

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

Christopher R. Knittel and Ryan Sandler*

November 9, 2011

Abstract

Efforts to reduce greenhouse gas emissions from transportation in the US have relied on Corporate Average Fuel Economy (CAFE) Standards and Renewable Fuel Standards (RFS). Economists often argue that these policies are inefficient relative to carbon pricing because they ignore existing vehicles and do not adequately reduce the incentive to drive. This paper presents evidence that the *net* social costs of carbon pricing are significantly less than previous thought. The bias arises from the fact that the demand elasticity for miles travelled varies systematically with vehicle emissions; dirtier vehicles are more responsive to changes in gasoline prices. This is true for all four emissions for which we have data—nitrogen oxides, carbon monoxide, hydrocarbon, and greenhouse gases—as well as weight. This reduces the net social costs associated with carbon pricing through increasing the co-benefits. Accounting for this heterogeneity implies that the welfare losses from a \$1.00 gas tax, or a \$110 per ton of CO₂ tax, are negative over the period of 1998 to 2008 even when we ignore the climate change benefits from the tax. Co-benefits increase by more than double relative to ignoring the heterogeneity that we document. In addition, accounting for this heterogeneity raises the optimal gas tax associated with local pollution, as calculated by Parry and Small (2005), by as much as 99 percent. While our empirical setting is California, we present evidence that the effects may be larger for the rest of the US.

*This paper has benefited from conversations with Severin Borenstein, Michael Greenstone, Jonathan Hughes, Dave Rapson, Nicholas Sanders, and Catherine Wolfram. We gratefully acknowledge financial support from the University of California Center for Energy & Environmental Economics. The research was supported by a grant from the Sustainable Transportation Center at the University of California Davis, which receives funding from the U.S. Department of Transportation and Caltrans, the California Department of Transportation, through the University Transportation Centers program. A portion of the paper was written while Knittel was a visitor at the Energy Institute at Haas. *Knittel*: William Barton Rogers Professor of Energy Economics, Sloan School of Management, MIT and NBER, *email*: knittel@mit.edu. *Sandler*: Department of Economics, University of California, Davis, *email*: rsandler@ucdavis.edu.

1 Introduction

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

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

In this paper we argue that the *net* social cost of GHG taxes have been *overstated*. The source of this bias comes from heterogeneity in how different types of vehicles respond to changes in gasoline prices. We show that vehicles with higher externalities, both in terms of local pollution and weight, respond more to gasoline prices. This is true for all three vehicle emissions for which we have data: carbon monoxide, hydrocarbons, and nitrogen oxides, as well as for vehicle weight and greenhouse gases. This heterogeneity increases the co-benefits from reductions in criteria pollutants¹ that are associated with a greenhouse gas tax.

We find that the average “two-year” elasticity of miles travelled is 0.26 across all vehicles (in absolute value), but the ratio of the elasticity for the dirtiest quarter of vehicles to the cleanest quarter of vehicles is 4.7, 4.5, and 3.4 for carbon monoxide, hydrocarbons, and nitrogen oxides, respectively. The ratio is 1.6 for greenhouse gases and 1.2 for vehicle weight. We also estimate how the hazard rate of scrapping a vehicle varies with criteria pollutant emissions. Here, the evidence is

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

more mixed.

We use these estimates to simulate the co-benefits from a carbon tax. For each vehicle in our data, we calculate the change in miles driven from the tax and the change in the vehicle's probability of survival and the resulting change in vehicle emissions. We do this across our entire time period and in each year. We then quantify these reductions using the estimated marginal damages in Muller and Mendelsohn (2009) and Matthews and Lave (2000). We find that once the heterogeneous response is accounted for, there is essentially no change in near-term deadweight loss from a \$110 CO₂ tax from 1998 to 2008; the welfare near-term co-benefits are nearly 20 percent greater than the deadweight loss from the tax increase. If one fails to account for the heterogenous response, the simulated co-benefits fall to 74 percent of the consumer welfare loss from the tax. We discuss reasons why these effects should be interpreted as strict lower bounds.

Given that the vehicle fleet has become cleaner over time, in terms of criteria pollutant emissions, we find that the co-benefits have fallen over our sample, but remain substantial even at the end. Early in the sample, we simulate that consumers would have been better off from the tax, with the co-benefits being twice as large as the welfare losses from the tax. In the last year of our sample, the co-benefits fall to 55 percent of the welfare losses from the tax. We argue that these are still substantial, reducing the cost per ton of carbon saved from \$83 to \$23. Again, not accounting for heterogeneity implies a net cost nearly twice as large as the net cost accounting for heterogeneity in the final year of our sample. To put these numbers into context, Greenstone, Kopits, and Wolverton (2011) estimate the social cost of carbon to be between \$21.40 and \$64.90, depending on the assumptions made.

Our results also have implications for the optimal gas tax in the presence of multiple market failures. Parry and Small (2005) calculate that the optimal gasoline tax within the US accounting for local and global pollution, accidents, congestion, and inefficiencies associated with income taxes. They find that the optimal tax is \$1.01 in the US, while it is \$1.62 in the UK. We calculate the optimal gas tax for California with and without heterogeneity; with heterogeneity the optimal tax increases from \$0.92 to \$1.05 in 1998 and from \$0.85 to \$0.90 in 2008. The relatively small increase is due, in large part, to the fact that the Pigouvian tax associated with congestion dominates the tax. The portion of the optimal tax attributed to local pollution increases from \$0.22 to \$0.33 in 1998 and from \$0.08 to \$0.13 in 2008, a change of 52 and 57 percent, respectively. We argue that these results should be viewed as strict lower bounds of the co-benefits for a variety of reasons.

We also present evidence that, while the marginal damages from NO_x and HCs are larger within California, Californian vehicles are, on average, much cleaner than the rest of the US. We show, using county-level data from the EPA on average vehicle emission rates, that the county-level average

per-mile externalities are roughly 30 percent *lower* in California compared to the rest of the US. Therefore, while we are unable to estimate elasticities outside of California, this suggests that provided the heterogeneity is somewhat similar to what we observe in California, the co-benefits may be larger for other states.

Finally, we also investigate several sources of the heterogeneity. At the most general level, we show that while the age of the vehicle contributes to 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 be more responsive to changes in gas prices. Second, it may come from within-household shifts in vehicle miles travelled, for example if a household has one newer and one older vehicle. As gas prices increase, they may shift miles away from the older vehicle and to the newer vehicle. Because age is, on average, correlated with both greenhouse gas and criteria pollutant emissions, this would lead to our result. Our data can speak to this. We find that while there is evidence of both a within household effect and an income effect, a significant amount of variation persists once these are accounted for.

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

2 Empirical Setting

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

The 1990 Clean Air Act Amendments required states to implement an enhanced inspection and maintenance program in areas with serious to extreme non-attainment of ozone limits. Several of California's urban areas fell into this category, and in 1994, a redesigned inspection program was

passed by California's legislature after reaching a compromise with the EPA. The program was updated in 1997 to address consumer complaints, and fully implemented by 1998. Among other improvements, California's new program introduced a system of centralized "Test-Only" stations and an electronic transmission system for inspection reports.² Today, more than a million Smog Checks take place each month.

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

Since 1998, the state has been divided into three inspection regimes (recently expanded to four), the boundaries of which roughly correspond to the jurisdiction of the regional Air Quality Management Districts. "Enhanced" regions, designated because they fail to meet state or federal standards for carbon monoxide (CO) and ozone, fall under the most restrictive regime. All of the state's major urban centers are in Enhanced areas, including the greater Los Angeles, San Francisco, and San Diego metropolitan areas. Vehicles registered to an address in an Enhanced area must pass a biennial Smog Check in order to be registered, and they must take the more rigorous Acceleration Simulation Mode (ASM) test. The ASM test involves the use of a dynamometer, and allows for measurement of NO_x emissions. In addition, a randomly selected two percent sample of all vehicles in these areas is directed to have their Smog Checks at Test-Only stations, which are not allowed to make repairs.³ Vehicles which match a "High Emitter Profile" are also directed to Test-Only stations, as are vehicles which are flagged as "gross polluters" (this occurs when a vehicle fails an inspection with twice the legal limit of one or more pollutant in its emissions). More recently some "Partial-Enhanced" areas have been added, where a biennial ASM test is required, but no vehicles are directed to Test-Only stations.

Areas with poor air quality that does not exceed legal limits fall under the Basic regime. Cars in a Basic area must have biennial Smog Checks as part of registration, but they are allowed to

²For more detailed background see <http://www.arb.ca.gov/msprog/smogcheck/july00/if.pdf>.

³Other vehicles can be taken to Test-Only stations as well if the owner chooses, although they must get repairs elsewhere if they fail.

take the simpler Two Speed Idle (TSI) test, and no vehicles are directed to Test-Only stations. The least restrictive regime, consisting of rural mountain and desert counties in the east and north of the state, is known as the Change of Ownership area. As the name suggests, inspections in these areas are only required upon change of ownership; no biennial Smog Check is required.

2.1 Automobiles, Criteria Pollutants, and Health

The tests report the emissions of three criteria pollutant: Nitrogen oxides, hydrocarbon, and carbon monoxide. All three of these pollutants are a direct consequences of the combustion process within either gasoline or diesel engines. Both NO_x and HCs are precursors to ground-level ozone, but, as with CO, have been shown to have negative health effects individually.⁴

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

3 Data

We bring together a number of large data sets. First, we have the universe of smog checks from 1996 to 2010 from California’s Bureau of Automotive Repair (BAR). These data report the location of the test, the vehicle’s VIN, odometer reading, the reason for the test, and test results. We decode the VIN to obtain the vehicles’ make, model, engine, and transmission. Using this, we match the vehicles to EPA data on fuel economy. Because the VIN decoding only holds for vehicles made after 1981, our data are restricted to these models. We also restrict our sample to 1998 and beyond given the large changes that occurred in the smog check test program in 1997. This yields roughly 120 million observations.

⁴CO has also been shown to speed up the smog-formation process. For early work on this, see Westberg, Cohen, and Wilson (1971).

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

We also estimate scrappage decisions. For this we use data reported to CARFAX Inc. for 32 million of the vehicles in the BAR data. These data contain the date and location of the last record 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 BAR data, we are able to match vehicles to given households using data come from confidential Department of Motor Vehicle records that track the registered address of the vehicle. We use this information to aggregate up to addresses, the stock of vehicles registered. Appendix A discusses how this is done. These data are from 2000 to 2008.

Finally, we use gasoline prices from EIA's weekly California average price series to construct average prices between Smog Check.

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

4 Preliminary Evidence

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

- significant variation exists in terms of vehicle externalities across vehicles within a year,

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

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

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

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

To understand how the distribution within a given vehicle changes over time, Figure 3 plots the distribution of the 1995 3.8L, front-wheel drive, Ford Windstar in 1999, 2001, 2004, and 2007.⁵ These figures suggest that over time the distributions shift to the right, become more symmetric, and the standard deviation grows considerably, relative to the mean. Across all vehicles, the ratio of the mean emission rate of NO_x and the standard deviation of NO_x has increased from 3.16 in 1998

⁵We chose this vehicle because the 1995 3.8L, front-wheel drive, Ford Windstar in 1999 is the second most popular entry in our data and it is old enough that we can track it over four 2-year periods.

to 4.53 in 2010. For hydrocarbons, this has increased from 3.59 to 5.51; and, has increased from 3.95 to 5.72 for CO.

These distributions demonstrate that there is 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 four quartiles of a given pollutant *within* a given year. We then plot how the log of daily miles driven has changed over our sample—a period where gas prices increased from roughly \$1.35 to \$3.20.

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

5 Vehicle Miles Travelled Decisions

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

$$\ln(VMT_{ijgt}) = \beta \ln(DPM_{ijgt}) + \gamma D_{truck} + \omega time + \mu_t + \mu_j + \mu_g + \mu_v + \epsilon_{igt} \quad (1)$$

where i indexes vehicles, j vehicle-types, g geographic locations, t time, and v vehicle age, or vintage. DPM_{ijgt} is the average dollars per mile of the vehicle between smog checks, D_{truck} is an indicator for whether the vehicle is a truck, and $time$ is a time trend.⁶

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

⁶Our dollars per mile variable uses the standard assumption that 45 percent of a vehicle miles driven are in the city and 55 percent are on the highway, along with the vehicles EPA fuel economy ratings.

ending with individual vehicle fixed effects.

We next differentiate the influence of gas prices by vehicle attributes related to the magnitude of their negative externalities—criteria pollutants, CO₂ emissions, and weight. We do this in two ways. First, we split vehicles up by the quartile the vehicle falls into with respect to the within-year emissions of nitrogen oxides (NO_x), hydrocarbons (HC), and carbon monoxide (CO), fuel economy (CO₂), and weight. Second, we include a linear interaction of the percentiles of these variables and the log of gas prices. Below we investigate, in a semi-parametric way, the actual functional form of this relationship.

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

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

Table 3 focuses on nitrogen oxides. Moving from Models 1 to 5 illustrates the importance of controlling for vehicle-type fixed effects. Initially, the average elasticity falls from 0.394 to 0.141 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 0.161.⁷ In general, we find that the more finely we control for vehicle-type the larger the heterogeneity in terms of the dollar-per-mile elasticity, while the average elasticity does not change much once we control for the vehicle’s make. Focusing on Models 6 and 7, we find large heterogeneity. The DPM-elasticity for the cleanest vehicles, quartile one, is 0.018, while the DPM-elasticity for the dirtiest vehicles is over 13 times higher, at 0.242. To put these numbers in context, the average per-mile NO_x emissions of a quartile one vehicle is 0.163 grams, while the average per-mile NO_x emissions of a quartile four vehicle is 1.68 grams. Model 7 assumes the relationship is linear in centiles of NO_x and finds that each percentile increase in the per-mile NO_x emission rate is associated with a change in the elasticity of .003, from a base of essentially zero.

We find similar patterns across the three other pollutants. Table 4 reports the results for hydrocarbons. Here, the elasticity of the cleanest vehicles and the elasticity of the dirtiest vehicles differ by a factor of 13.65. Table 5 reports the results for carbon monoxide. Here the ratio is 15.41.

⁷This is much larger than that found in Hughes, Knittel, and Sperling (2008) reflecting the longer run nature of our elasticity.

Table 6 reports the results for fuel economy, or CO₂ emissions. The lowest quartile here are the most polluting vehicles. Their elasticity is 1.5 times as large as the cleanest vehicles. It is important to note that this is not driven by the fact that a given change in gas prices implies a larger change in the price per miles, since the independent variable is the log of the price per mile.⁸ The linear interaction implies that vehicles at the 100th percentile have an average elasticity of roughly zero. We come back to this below.

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

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

We next investigate the functional forms of these relationships in a semi-parametric way. For each externality, we define vehicles by their percentile of that externality. We then estimate equation 1 with separate elasticities for vehicles falling in the zero to first percentile, first to second, etc. Figure 6 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

⁸Also, note that this does not matter for the models with VIN fixed effects.

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”. Figure 7 plots the LOWESS smoothed lines under different bandwidths. The top left figure simply reports the 100 elasticities. There is some evidence that the relationship is not monotonic early on, but from the 5th percentile on, the relationship appears monotonic. Doing this exercise for the other criteria pollutants yields similar results.

5.1 The Source of the Heterogeneity

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

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

Tables 8 through 11 report the results across externality-type. These results suggest that while vintage is a factor in the externality-based heterogeneity, it is not the only source or even the most important source. Vehicles 10-15 years old are only slightly more elastic than newer vehicles, and vehicles 16 years and older are actually slightly less elastic than middle aged vehicles, although this point estimate is noisy. Older vehicles seem to have more heterogeneity over externalities, In all five externality types variation exists within age bin, and the heterogeneity is larger for older vehicles. Furthermore, with the exception of fuel economy and weight for the newest vehicles, this variation would appear to be economically significant.

For a sub-sample of our smog check vehicles, we are able to group them into households. This grouping comes from access to California Department of Motor Vehicles (DMV) data. A number of steps are undertaken to “clean” the address entries in the DMV records. These are discussed in Appendix A. Ultimately, however, the subsample of vehicles that we are able to match likely draw more heavily from households residing in single-family homes. Given this selection 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. In particular, they are larger than our base specification, but smaller than our usual sample over the same period suggesting that the elasticity may be correlated with income and increasing over time.⁹

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

If household shift usage from low MPG vehicles to high MPG vehicles, we would expect “Higher MPG in HH” to be negative and “Lower MPG in HH” to be positive. The results suggest that this is a mechanism, but not the only one. If there is a vehicle with higher fuel economy in the household, the elasticity is larger, while if there is a vehicle with a lower MPG, the elasticity is smaller. Column 2 of Table 13 adds these variables to our base specification. The point estimates suggest that a vehicle in the highest fuel economy quartile belonging to a household that also has a lower fuel economy vehicle has an elasticity that is more than a third lower. We cannot reject the null hypothesis that the sum of the interactions with quartile 4 and “Higher MPG in HH” is zero.¹⁰

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

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

⁹This is consistent with the results of Hughes, Knittel, and Sperling (2008).

¹⁰The 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 Scrappage Decisions

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

We determine whether a vehicle has been scrapped using the data from CARFAX Inc. We begin by assuming that a vehicle has been scrapped if more than a year has passed between the last record reported to CARFAX and the date when CARFAX produced our 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 which are at least 10 years old.

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

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

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

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 6th-order polynomial in odometer, and $h_{jv}^0(t)$ is the baseline hazard rate, which varies by time but not the other covariates. In some specifications, we will allow each vehicle type and vintage to have its own baseline hazard rate.

We estimate this model using semi-parametric Cox proportional hazards regressions, leaving

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

Tables 15 and 16 show the results of our hazard analysis. Models 1 and 2 assign all vehicles to the same baseline hazard function. Model 1 allows the effect of gas prices to vary by whether or not a vehicle failed a Smog Check. Model 2 also allows the effect of gas prices to vary by externality quartiles as well.¹¹ Models 3 and 4 are similar, but stratify the baseline hazard function, allowing each VIN prefix to have its own baseline hazard function. Finally, Model 5 allows the effect of gasoline prices to vary both by externality quartile and age group, separating vehicles 10 to 15 years old from vehicles 16 years and older.

Table 15 focuses on heterogeneity across emissions of NO_x . Models 1 and 2 indicate that increases in gasoline prices actually decrease scrapping on average, with the cleanest vehicles seeing the largest decreases. The effect is diminished once unobserved heterogeneity among vehicle types is controlled for, 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 5 cents, the hazard of scrappage decreases by about 23% for vehicles between 10 and 15 years old, while it increases by around 3% for vehicles age 16 and older, with little variation across NO_x quartiles within age groups. This suggests that when gasoline prices rise, very old cars are scrapped, increasing demand for moderately old cars and thus reducing the chance that they are scrapped. Results with HC and CO quartiles produce almost identical results.

Table 16 focuses on heterogeneity in fuel economy. Moving from model 2 to model 4, we see that heterogeneity appears when we stratify by VIN prefix, although the form is counter-intuitive. A 5-cent increase in DPM increases the hazard of scrappage by about 20% for the most fuel efficient vehicles, while decreasing the hazard of scrappage by about 15% for the most fuel efficient vehicles. Because we stratify by VIN prefix in model 4, this cannot be explained by differences in vehicle types, such as trucks surviving longer than cars. Model 5 shows that most but not all of these differences can be explained by differences in vehicle age. For vehicles age 16 and greater, where it seems that the hazard rate increases most for vehicles in the second and third quartiles.

In summary, increases in the cost of driving a mile over the long term increase the chance that old vehicles are scrapped, while middle aged vehicles are scrapped less, perhaps because of increased

¹¹Quartiles in these models are calculated by year among only vehicles 10 years and older.

demand. Although vehicle age is highly correlated with emissions of criteria pollutants, there is little variation in the response to gasoline prices across emissions rates within age groups.

7 Policy Simulations

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

7.1 Co-benefits and the Social Cost of Carbon Pricing

Our results indicate that a tax on gasoline will disproportionately affect the usage and, to a lesser extent, scrappage of cars with greater emissions of local pollutants. To quantify this, we use our data to simulate the change in emissions resulting from a \$1 increase in the tax on gasoline, or roughly a \$110 per ton of CO₂ tax.¹² We account for both the intensive and extensive margins, as well as all the dimensions of heterogeneity we have documented in Sections 5 and 6. For this simulation, we assume that the tax was imposed in 1998, and use our empirical models to estimate the level of gasoline consumption and emissions from 1998 until 2008, had gasoline prices been \$1 greater. Appendix C provides details of the steps we take for the simulation.

Tables 17, 18, and 19 show the results of our simulation for each year from 1998-2008, and the yearly average over the period. The two columns shows the total reduction in annual gasoline consumption and CO₂ emissions, in millions of gallons and millions of tons, respectively. The next two columns value the deadweight loss from the reduction in gasoline consumption. We approximate deadweight loss as $\frac{\Delta P \cdot \Delta Q}{2}$ and adjust for inflation. The next section of the table presents the social benefit resulting from the reduction in NO_x, HC, and CO due to the tax. Social benefits are valued using the marginal damages of each pollutant calculated by Muller and Mendelsohn (2009), based on the county each vehicle has its Smog Check in.¹³ Finally, the last column of the table shows the net cost of abating a ton of carbon dioxide, accounting for the reductions in criteria pollution.

Table 17 shows the results of a simulation that does not account for heterogeneity across emissions

¹²We 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.

¹³Note: 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.

profiles. The reduction in gasoline consumption declines slightly over time from around 510 million gallons in 1998 down to around 420 in 2008. The reduction in criteria pollutants declines quickly as the fleet becomes cleaner. Nonetheless, the co-benefits of a gasoline tax are substantial, averaging 34% of the deadweight loss over the ten year period.

Table 18 adds heterogeneity on the intensive margin, but not the extensive margins. The total change in gasoline consumption is smaller, declining from 190 million gallons in 1998 to 83 million gallons in 2008. This is a result of more fuel efficient vehicles having a higher average VMT. However, the reductions in criteria pollutants are much larger. In 1998 the co-benefits are over 60% of the deadweight loss, and the net cost of abating a ton of carbon is negative until 2004. On average, we estimate that on average benefits of a decrease in local air pollution from a gasoline tax would be greater than the deadweight loss between 1998 and 2008.

Finally, Table 19 adds heterogeneity on the extensive margins of scrappage and new car purchases. The net effect of the extensive margin is an increase in criteria pollutants, due to the decreased scrappage vehicles 10-15 years old, but an increase in greenhouse gas abatement. The annual reduction in gasoline consumption increases from 190 million gallons in 1998 to over 300 million gallons in 2008. The amount and value of the co-benefits is reduced compared to the figures in Table 18, but the difference is relatively small. Now over 84% of the deadweight loss is compensated for by the co-benefits. The net cost of the tax remains negative until 2001.

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

We argue that these results should be viewed as strict lower bounds of the co-benefits for a variety of reasons. First, we have valued the cobenefits 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 place upon mortality. Their baseline, used here in tables 17 to 19, assumes a VSL of \$2 million, weighted by remaining years of life, and they acknowledge this may not be the correct value. They also calculate a scenario with mortality valued as in the USEPA model, with a VSL of \$6 million, constant over ages. Tables 20 and 21 repeat the simulation without and with heterogeneity from tables 21 and 19, but value cobenefits as per Muller and Mendelsohn’s USEPA scenario. Now even without heterogeneity the average cobenefits are greater than the deadweight loss, but decline to just over 31% by 2008. With heterogeneity, the cobenefits average more than

three times the deadweight loss over the period, and remain greater until 2008, when the net cost per ton of CO₂ is estimated to be less than a dollar.

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 and the emissions of NO_x, HCs, and CO. Second, because of the rules of the Smog Check program many vehicles that emission standards are not required to be tested, leading to their omission in this analysis. Third, a variety of behaviors associated with smog check programs would lead the on-road emissions of vehicles to likely be higher than the tested levels. These include, but are not limited to, fraud, tampering with emission-control technologies between tests, failure to repair emission-control technologies until a test is required, etc.

When we account for the heterogeneity in the responses to changes in gasoline prices, we see that the co-benefits from reduced air pollution would substantially ameliorate the costs of an increased gasoline tax. The co-benefits would have been especially substantial in the late 1990s, but persist in more recent years as well, even though the fleet has become cleaner. To put these numbers into context, Greenstone, Kopits, and Wolverton (2011) estimate the social cost of carbon for a variety of assumptions about the discount rate, relationship between emissions and temperatures, and models of economic activity. For 2010, using a 3 percent discount rate, they find an average SCC of \$21.40, with a 95th percentile of \$64.90. Using a 2.5 percent discount rate, the average SCC is \$35.10. Our results suggest that once the co-benefits are accounted for, a \$1.00 gas tax (i.e., a \$110 per ton of CO₂ tax) would be nearly cost-effective even at the lower of these three numbers and well below the average social cost of capital using a 2.5 percent interest rate.¹⁴

The co-benefits vary considerably across counties. This variation comes from variation in the marginal damages, variation in the elasticities, and variation in the heterogeneity across vehicle types. Figure 8 illustrates the first two types of variation. Panels (a) and (b) map the variation in the marginal damages for NO_x and HC calculated by Muller and Mendelsohn (2009). While marginal damages for HC are positively correlated with population (correlation coefficient of 0.84), the marginal damage for NO_x are negatively correlated with both HC (0.49) and population (0.36). The reason for this has to do with the chemistry of ground-level ozone formation. Ground-level ozone, or smog, is formed in the presence of NO_x, HCs, heat, and sunlight. When the ratio of NO_x to HCs is not too large or small, the production function of smog, in the presence of sunlight and heat, is similar to that of a Leontiff production function. Therefore, a county can be in a region of

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

the level-set where increasing NO_x does not increase smog production because there are not enough HCs to mix with the additional NO_x . This is known as NO_x constrained. In contrast, a county may have so much HCs such that increasing HC does not lead to more smog. This is known as HC, or VOC, -constrained.¹⁵ Therefore, the marginal damages of NO_x and HC are negatively correlated.¹⁶ Given that vehicles emit roughly equal amounts of NO_x and HCs, in some respects the average (or total) of marginal damages across NO_x and HCs is more telling.

Panel (c) maps the absolute value of the elasticity of VMT across counties, calculated by estimating equation 1 and allowing the elasticity to vary by county of Smog Check. The absolute value of demand elasticities tend to be positively correlated with population, although the correlation coefficient is only 0.20.

This variation leads to the variation in the co-benefits in panel (d) of Figure 8. The distribution is slightly skewed with a non-population weighted mean of \$52.92 per ton of CO_2 and median of \$37.79; the standard deviation is \$63.97. More populated areas have greater co-benefits, on average. Figure 9 shows a scatterplot of the co-benefits across counties versus the log of the counties population.¹⁷ Los Angeles is clearly an outlier with benefits of \$367.28 per ton of CO_2 over our sample, although as noted the median is nearly \$38 with 75 percent of counties exceeding average co-benefits of over \$15.

7.2 Optimal Gasoline Tax in the Presence of Heterogeneity

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

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

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

where η_{MI} is the income elasticity of VMT, η_{FF} is the price elasticity of gasoline, η_{MF} is the price elasticity of VMT, $\beta \equiv \frac{\eta_{MF}}{\eta_{FF}}$, t_L is the tax on labor, M is total VMT, F is total fuel consumption,

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

¹⁶For California the correlation is -0.36.

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

MEB_L is the marginal excess burden of the tax on labor, and MEC_F is the marginal external cost of fuel use, defined by:

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

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

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

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

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

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

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

Table 22 compares the results of these calculations for California using both the baseline and USEPA valuations from Muller and Mendelsohn, as well as the figures calculated by Parry and Small for the United States as a whole. Accounting for heterogeneity dramatically increases the portion of the optimal gas tax associated with a Pigovian tax on local pollution. Whether this translates to a large change in the total optimal tax depends on the value placed on local pollution. With Muller and Mendelsohn's baselines valuation, the local pollution portion is quite small, and although it increases by upward of 70% when accounting for heterogeneity, the total tax increases by just 5.74% in 1998 and 2.8% in 2008. On the other hand, using the USEPA values, the local tax component

increases by a similar proportion when accounting for heterogeneity, but this amounts to a much larger change in the overall tax. Using these higher values, the optimal gasoline tax in 1998 increases from \$0.89 to \$1.22 when heterogeneity is accounted for, and from \$0.72 to \$0.86 in 2008.

8 California versus the rest of the US

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

The results in Muller and Mendelsohn (2009) provide a convenient way to test whether California differs in terms of marginal damages. Table 23 presents points on the distribution of marginal damages for NO_x , HCs, and the sum of the two, weighted by each county’s annual VMT.¹⁸ Figure 10 plots the kernel density estimates of the distributions. We present the sum of because counties are typically either “ NO_x constrained” or “VOC (HC) constrained” and the sum is perhaps more 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 23 also presents points on the per-mile emissions and Figure 11 plots the distributions.¹⁹ Mean county-level NO_x , HCs, and CO are 67, 36, and 31 percent lower in California, respectively. Other points in the distributions exhibit similar patterns.

Finally, we calculate the county-level average per-mile externality for each pollutant, as well as the sum of the three. Table 23 and Figure 12 illustrates these. As expected the HC damages are higher, but the average county-level per-mile externality from the sum the three pollutants is

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

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

30 percent lower in California compared to the rest of the country; the 25th percentile, median, and 75th percentile are 35, 30, and 9 percent lower, respectively. These calculations suggest that, provided the average VMT elasticities are not significantly smaller outside of California and/or the heterogeneity across vehicle types is not significantly different (in the reverse way), our estimates are likely to apply to the rest of the country.

9 Conclusions

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

These results should be viewed in light of the fact that existing policies used to reduce greenhouse gas emissions from transportation—CAFE standards, ethanol subsidies, and the RFS—fail to take advantage of these co-benefits, and can even increase criteria pollutant emissions, because they *reduce* the marginal cost of an extra mile travelled. Given that previous work that has analyzed the relative efficiency of these policies to gasoline or carbon taxes has ignored the heterogeneity that we document, such policies are less efficient than previous thought.

References

- Busse, Meghan, Christopher R. Knittel, and Florian Zettelmeyer. 2009. "Pain at the Pump: The Differential Effect of Gasoline Prices on New and Used Automobile Markets." Tech. rep., National Bureau of Economic Research, Cambridge, MA.
- Glazer, Amihai, Daniel B. Klein, and Charles Lave. 1995. "Clean on Paper, Dirty on the Road: Troubles with California's Smog Check." *Journal of Transport Economics and Policy* 29 (1):85–92.
- Greenstone, Michael, Elizabeth Kopits, and Ann Wolverton. 2011. "Estimating the Social Cost of Carbon for Use in U.S. Federal Rulemakings: A Summary and Interpretation." Working Paper 16913, National Bureau of Economic Research.
- Holland, Stephen P., Jonathan E. Hughes, Christopher R. Knittel, and Nathan C. Parker. 2011. "Some Inconvenient Truths About Climate Change Policy: The Distributional Impacts of Transportation Policies." Working paper, MIT.
- Hughes, Jonathan E., Christopher R. Knittel, and Daniel Sperling. 2008. "Evidence of a Shift in the Short-Run Price Elasticity of Gasoline Demand." *Energy Journal* 29 (1).
- Jacobsen, Mark. 2011. "Evaluating U.S. Fuel Economy Standards in a Model with Producer and Household Heterogeneity." Working paper, UC San Diego.
- Matthews, H. Scott and Lester B. Lave. 2000. "Applications of Environmental Valuation for Determining Externality Costs." *Environmental Science & Technology* 34 (8):1390–1395.
- Morrow, Silvia and Kathy Runkle. 2005. "April 2004 Evaluation of the California Enhanced Vehicle Inspection and Maintenance (Smog Check) Program." Report to the legislature, Air Resources Board.
- Muller, Nicholas Z. and Robert Mendelsohn. 2009. "Efficient Pollution Regulation: Getting the Prices Right." *American Economic Review* 99 (5):1714–39.
- Parry, Ian W. H. and Kenneth A. Small. 2005. "Does Britain or the United States Have the Right Gasoline Tax?" *American Economic Review* 95 (4):1276–1289.
- Westberg, Karl, Norman Cohen, and K. W. Wilson. 1971. "Carbon Monoxide: Its Role in Photochemical Smog Formation." *Science* 171 (3975):1013–1015.

A Steps to clean smog check data

A.1 Smog Check Data

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

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

First, we adjust odometer readings for roll-overs and typos. Many of the vehicles in our analysis were manufacturer 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 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.

²⁰For 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.

Emissions results from smog checks are given in either parts per million (for HC and NOx) or percent (O₂, CO, and CO₂). Without knowing the volume of air involved, there is no straightforward way to convert this to total emissions. Fortunately, as part of an independent evaluation of the Smog Check program conducted in 2002-2003, Sierra Research Inc. and Eastern Research Group estimated a set of conversion equations to convert the proportional measurements of the ASM test to emissions in grams per mile travelled. These equations are reported in Morrow and Runkle (2005) and are reproduced below. The equations are for HCs, NOx and CO, and estimate grams per mile for each pollutant as a non-linear function of all three pollutants, model year and vehicle weight. The equations for vehicles of up to model year 1990 are

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

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

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

Where

$$HC^* = \ln((Mode1_{HC} \cdot Mode2_{HC})^{.5}) - 3.72989$$

$$CO^* = \ln((Mode1_{CO} \cdot Mode2_{CO})^{.5}) + 2.07246$$

$$NO^* = \ln((Mode1_{NO} \cdot Mode2_{NO})^{.5}) - 5.83534$$

$$MY^* = modelyear - 1982.71$$

weight = Vehicle weight in pounds

TRUCK = 0 if a passenger car, 1 otherwise

And for model years after 1990 they are:

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

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

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

Where:

$$HC^* = \ln((Mode1_{HC} \cdot Mode2_{HC})^{.5}) - 2.32393$$

$$CO^* = \ln((Mode1_{CO} \cdot Mode2_{CO})^{.5}) + 3.45963$$

$$NO^* = \ln((Mode1_{NO} \cdot Mode2_{NO})^{.5}) - 3.71310$$

$$MY^* = modelyear - 1993.69$$

$$weight = \text{Vehicle weight in pounds}$$

$$TRUCK = 0 \text{ if a passenger car, } 1 \text{ otherwise}$$

B Steps to clean DMV data

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

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

C Details of the gas tax policy simulation

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

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

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

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

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

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

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

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

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

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

where MPG_k is the average fuel economy of vehicle of prefix k and 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, in which should be interpreted as a $H_{qkt} - 1$ probability that another vehicle of the same type would be on the road, but which was scrapped under “Business as Usual.” Since the hazard is the probability of scrappage in year t , conditional on survival to year t , this weight must be calculated iteratively, 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 which we have not estimated in this paper, that of new car purchases. To ensure that the total vehicle population is accurate, we apply an *ad hoc* correction based on Busse, Knittel, and Zettelmeyer (2009), who find that a \$1 increase in gas prices would decrease new car sales by 650,000 per year. Since California’s vehicle fleet makes up about 13% of the national total, we decrease the population of model years 1998 and later by 84500 when constructing the population weight for the counterfactual. We apply 40% of the decrease to trucks, and 60% to passenger cars. Denote the “new car effect” n_c .

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

t under “business as usual” are:

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

and under the counterfactual they are:

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

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

Figures and Tables

A Figures

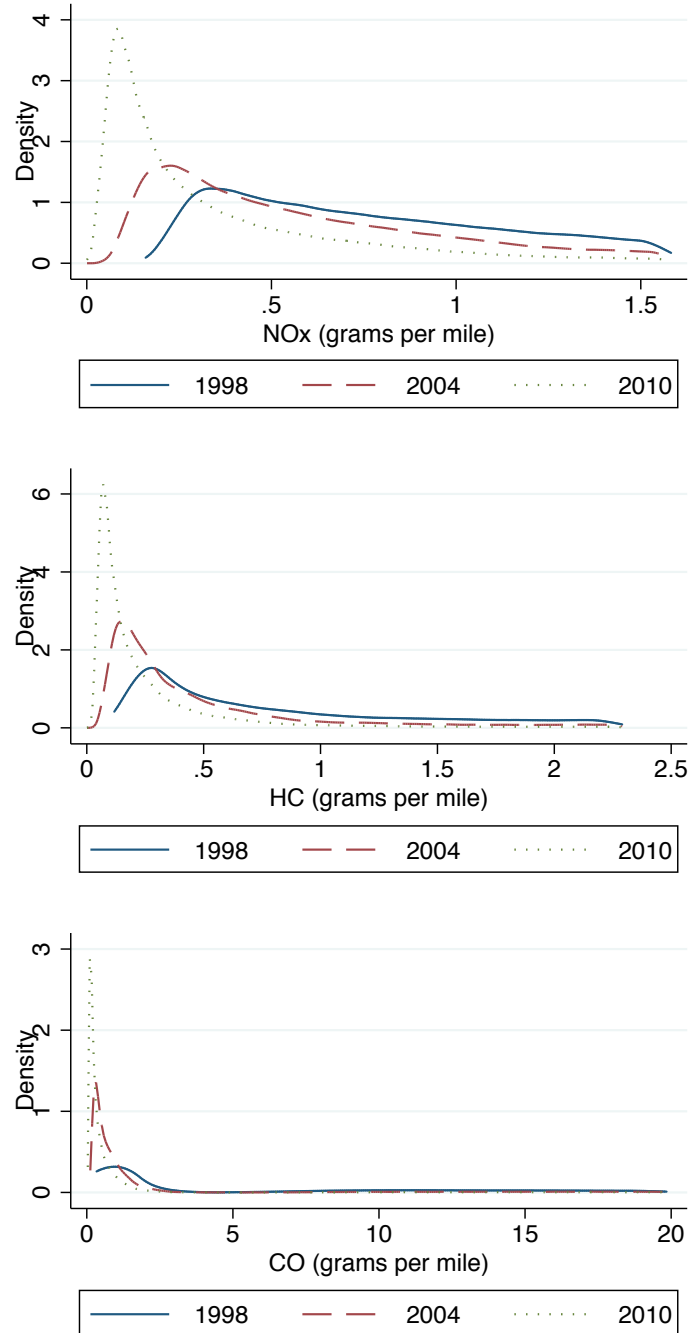


Figure 1: Distribution of three criteria pollutant emissions across all vehicles in 1998, 2004, and 2010 (observations above the 90th percentile are omitted)

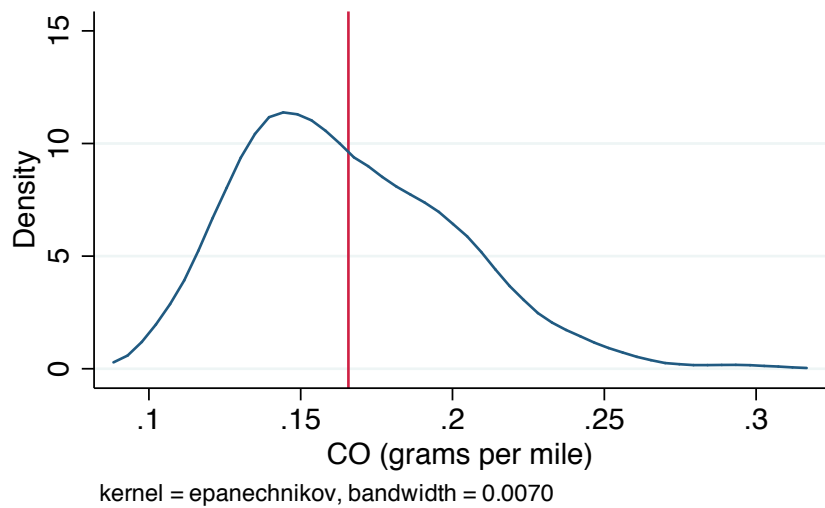
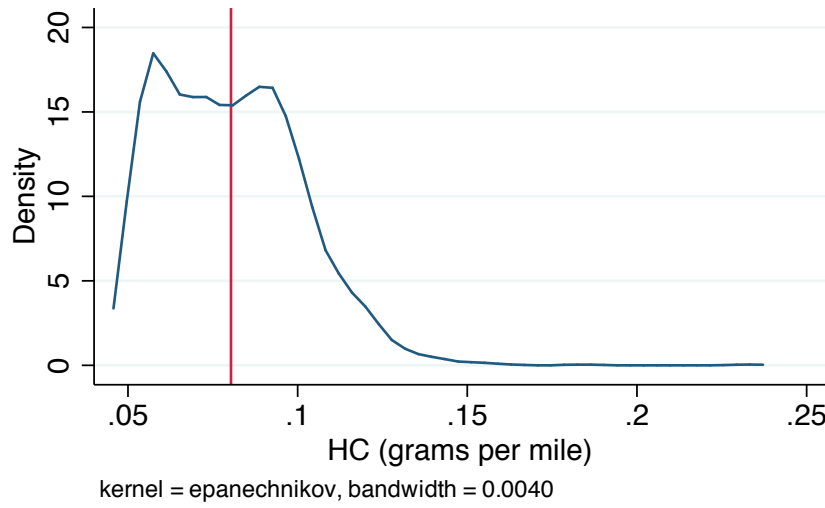
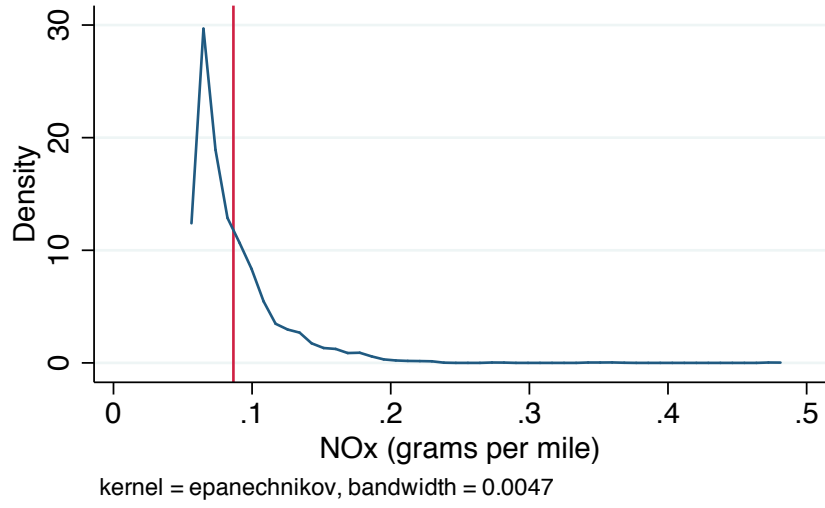


Figure 2: Distribution of three criteria pollutant emissions of a 2001 4-door, 1.8L, Toyota Corolla in 2009

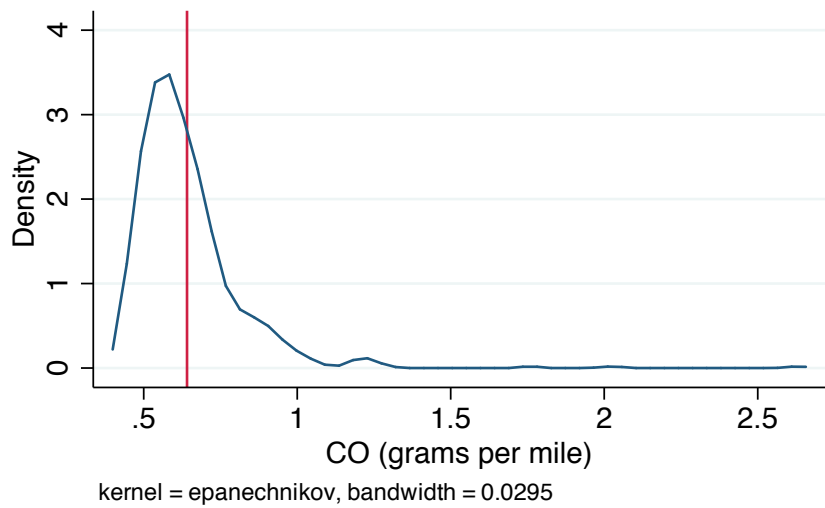
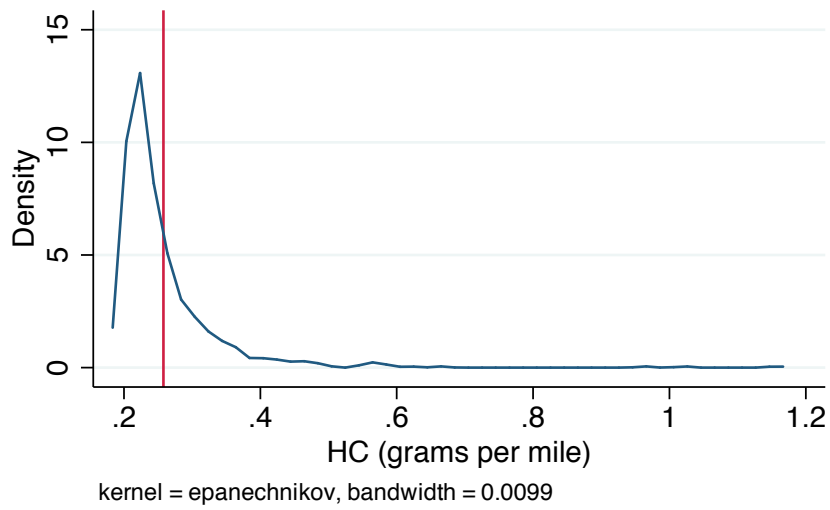
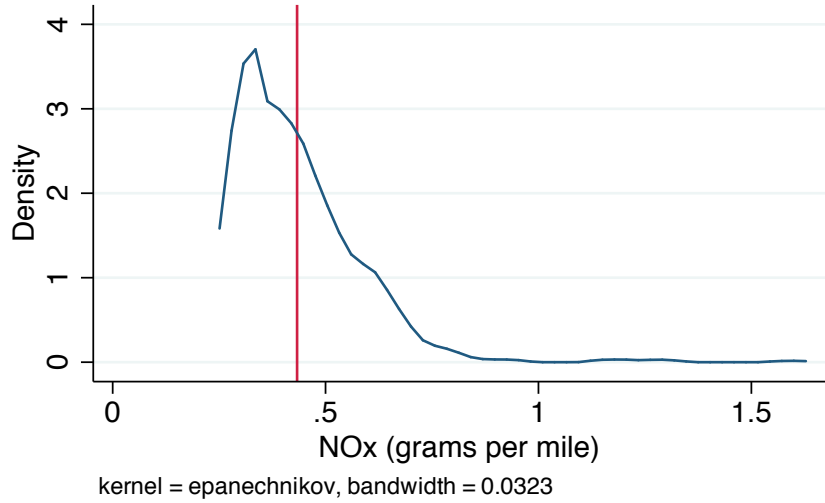


Figure 3: Distribution of three criteria pollutant emissions of a 1995 3.8L, FWD, Ford Windstar in 1999, 2001, 2005, and 2009 (observations above the 95th percentile are omitted)

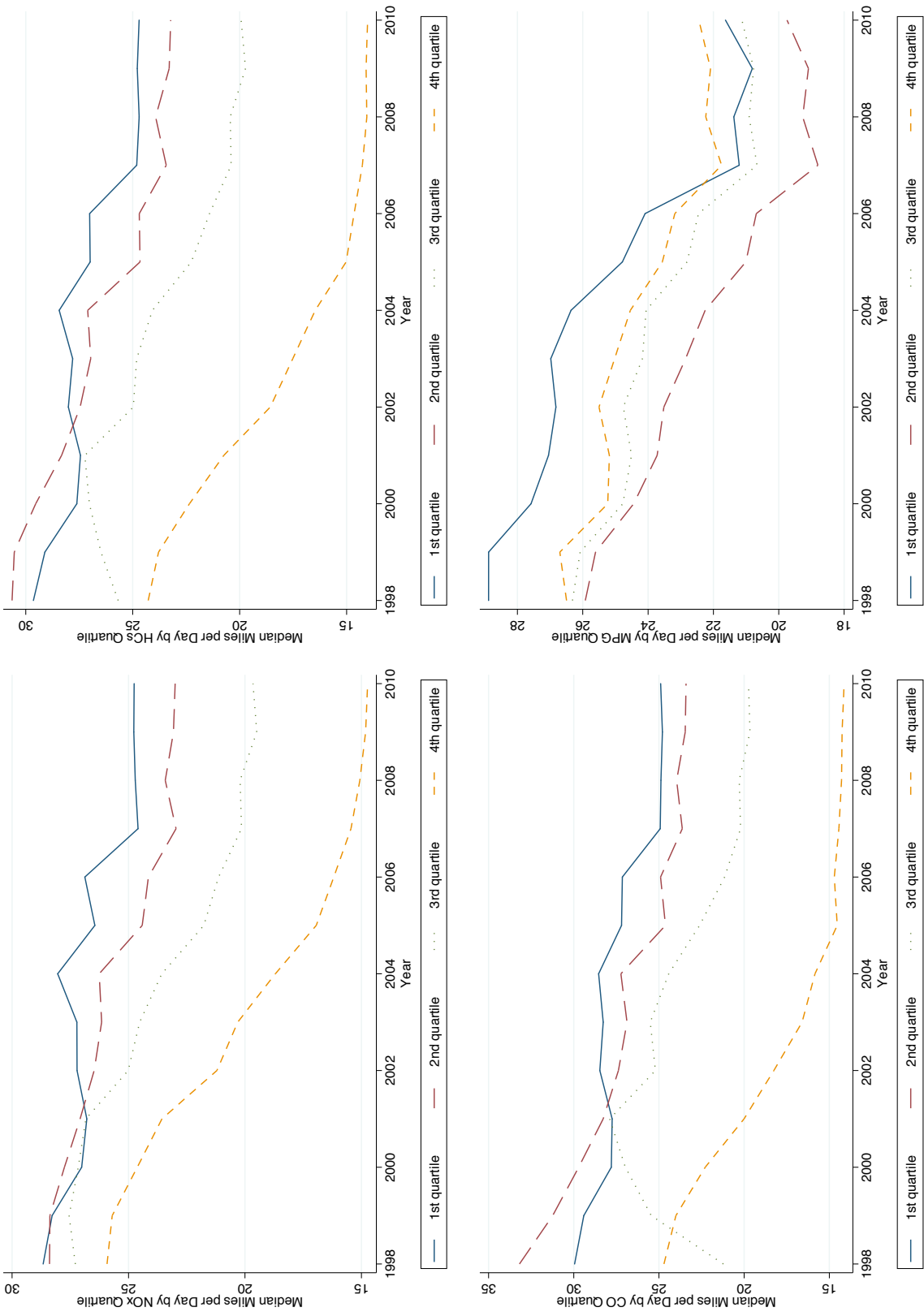


Figure 4: Change in VMT over sample by pollutant quartile

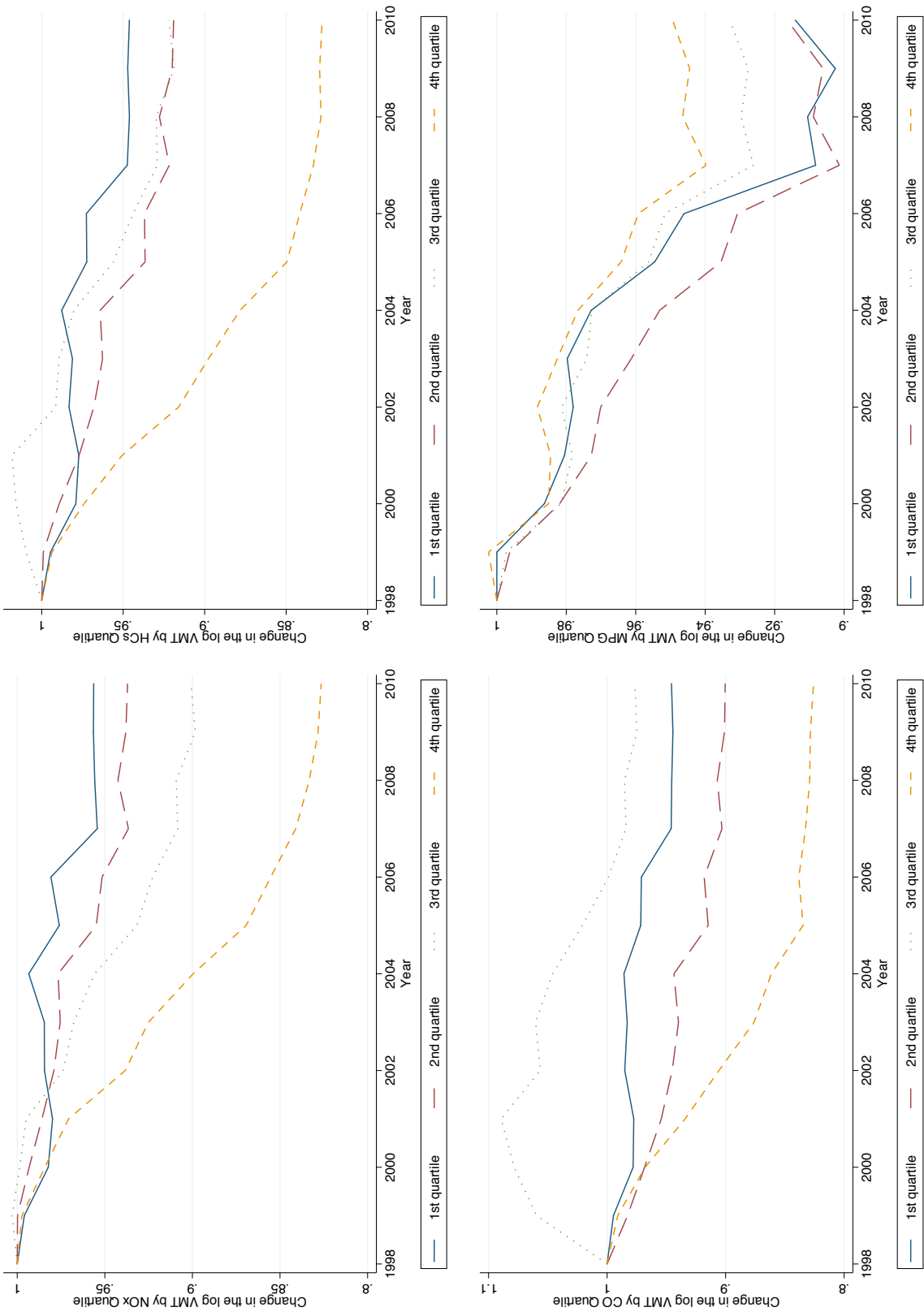


Figure 5: Change in the log of VMT over sample by pollutant quartile

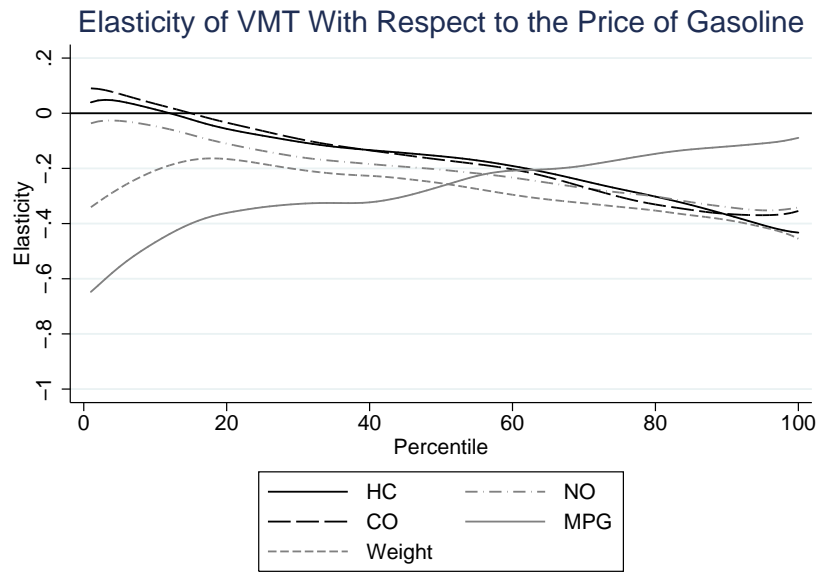


Figure 6: Non-parametric relationships between elasticity and externality

Elasticity of VMT over Centiles of g/mile HC

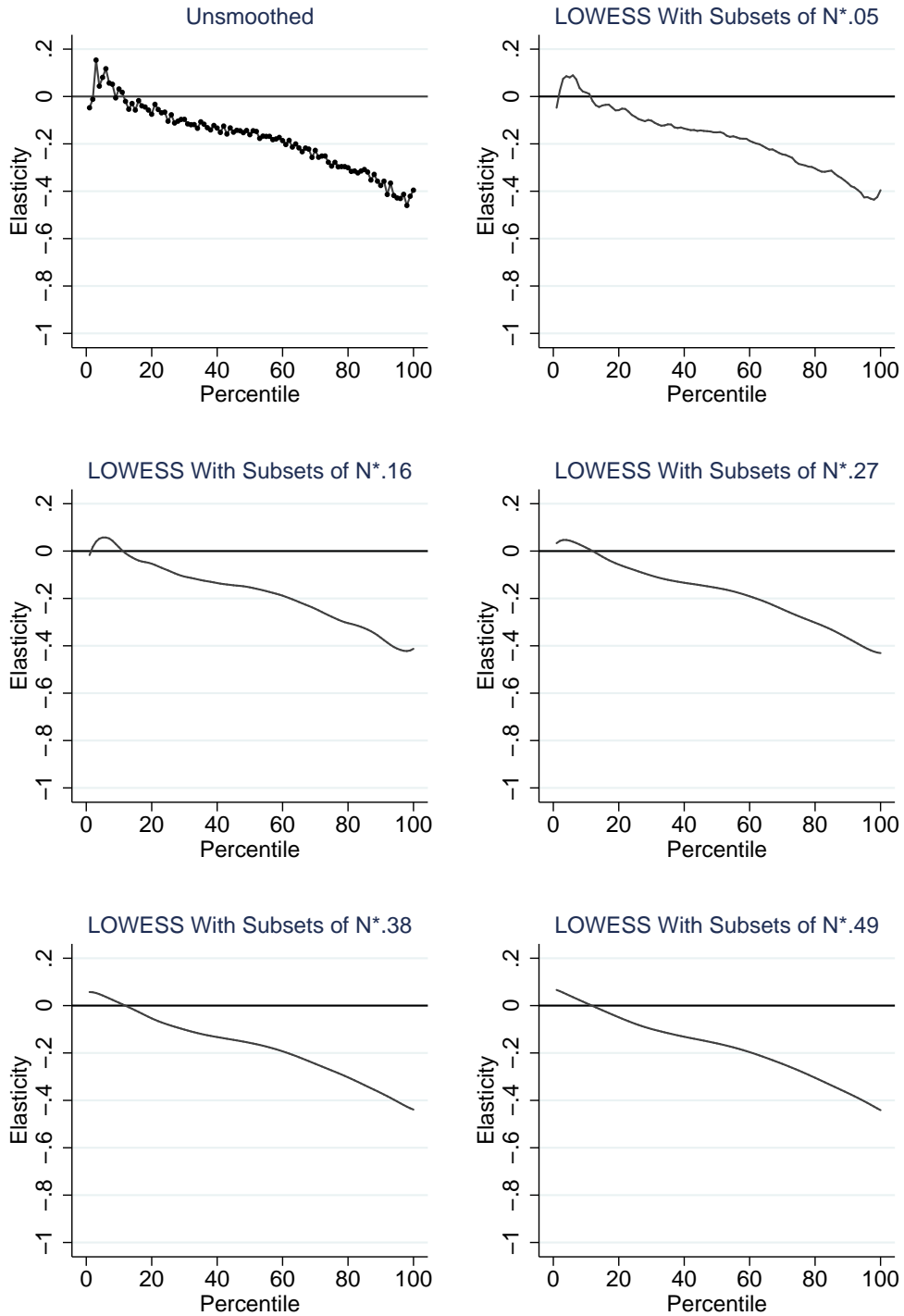
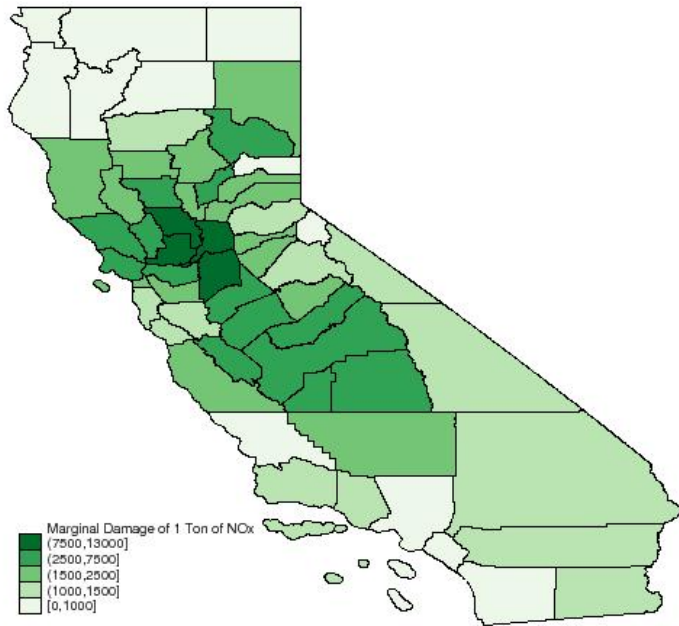
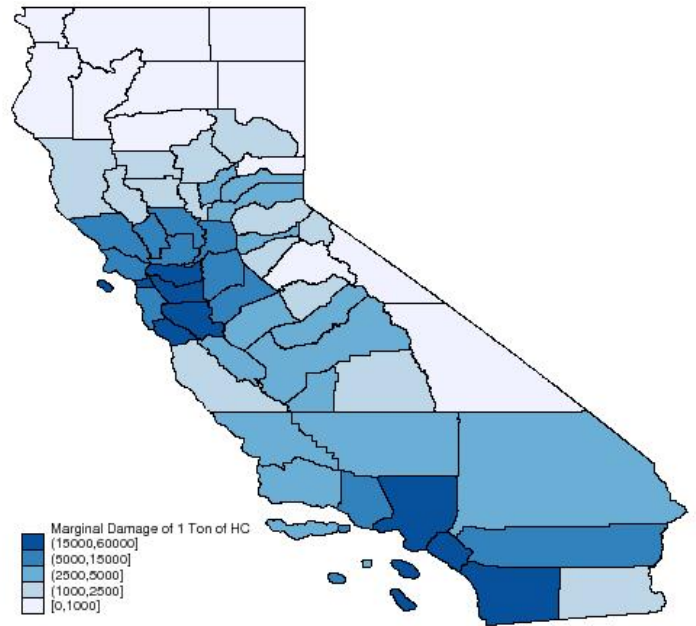


Figure 7: The effect of bandwidth on the non-parametric function



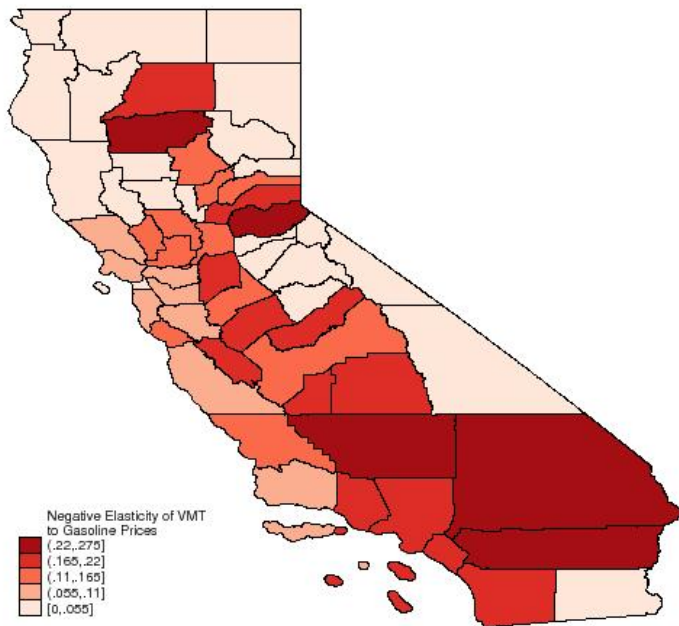
Source: Muller and Mendelsohn (2009)

(a) NO_x Damage



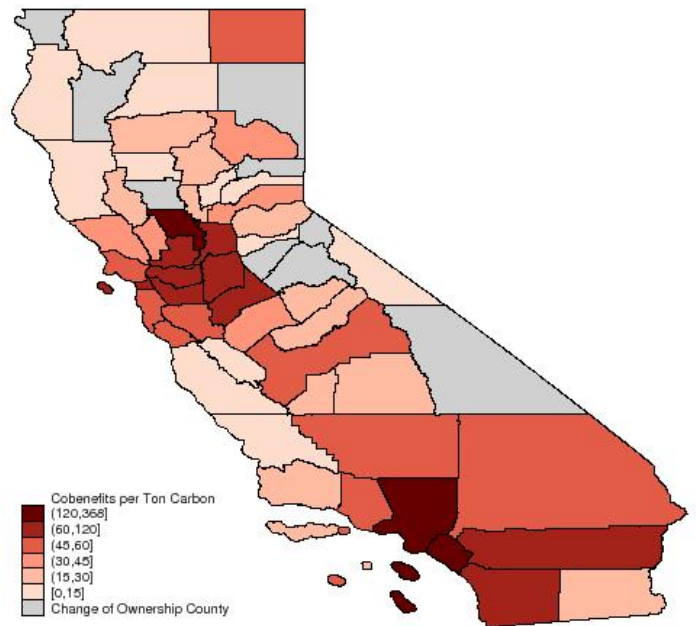
Source: Muller and Mendelsohn (2009)

(b) HC Damage



Source: Authors' Calculations

(c) VMT Elasticity



Source: Authors' Calculations

(d) Estimated Co-benefits

Figure 8: Social Damages of Pollution, VMT Elasticity and Cobenefits of a Gasoline Tax, By County

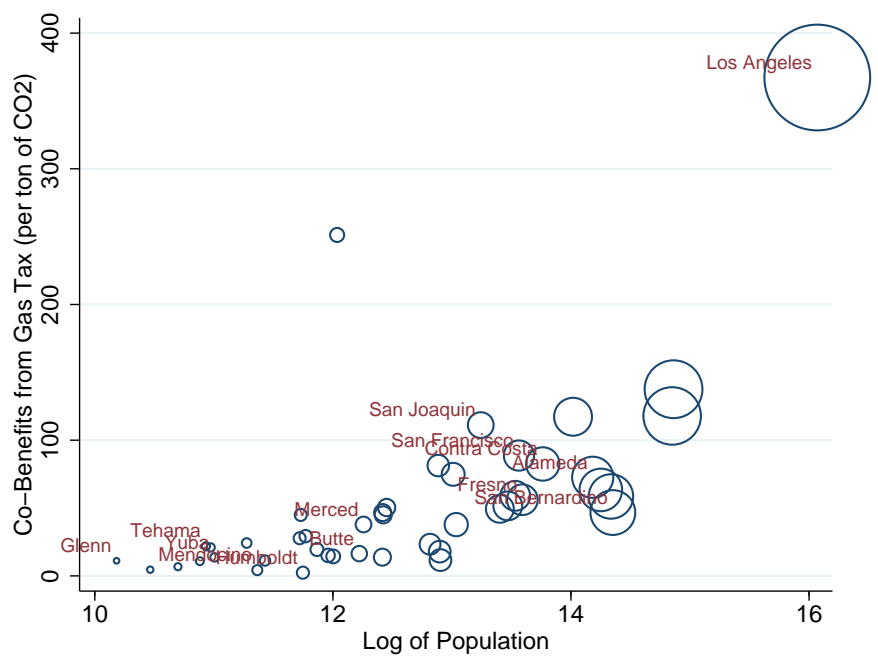


Figure 9: Estimated county-level co-benefits verse the log of county population

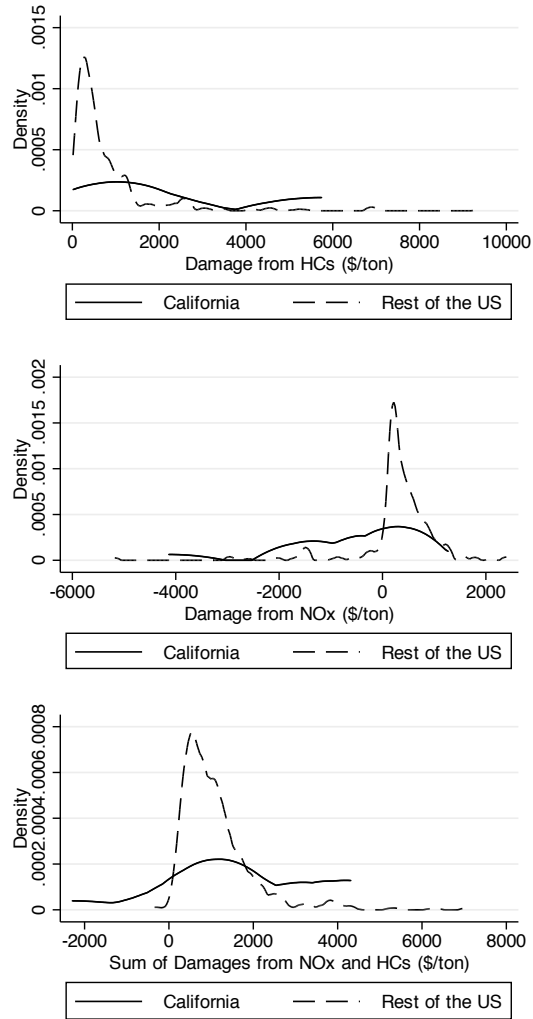


Figure 10: Distributions of marginal damages from Muller and Mendelsohn (2009) for California and the rest of the US

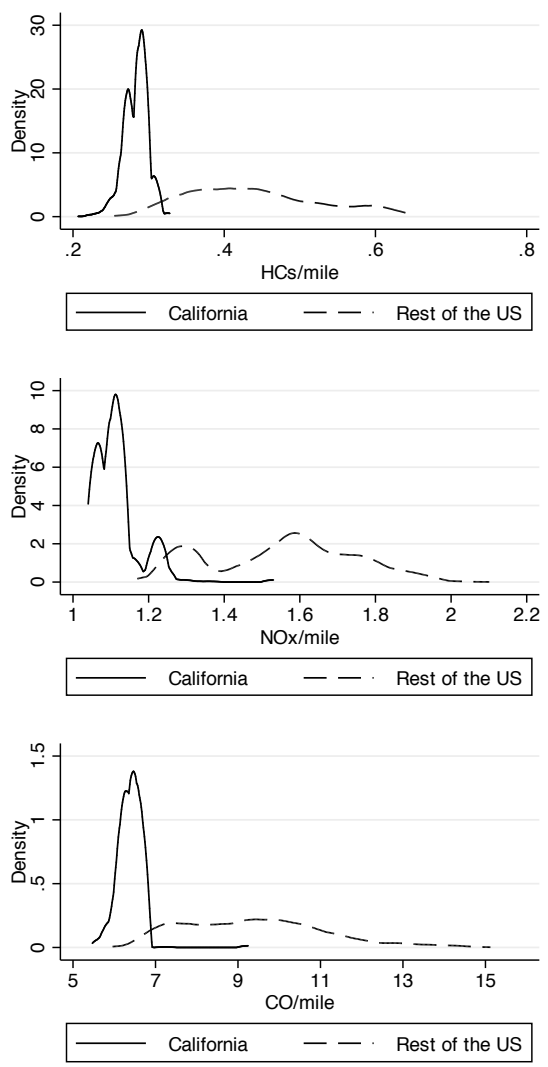


Figure 11: Distributions of per-mile emissions for California and the rest of the US

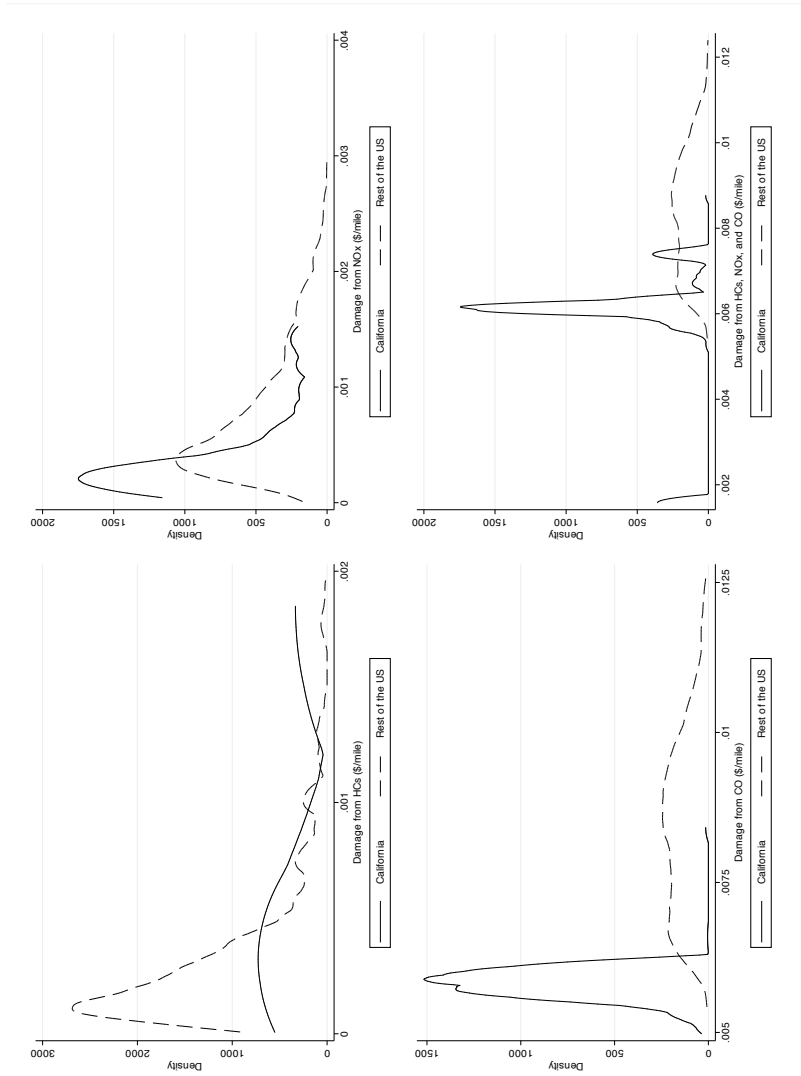


Figure 12: Distributions of per-mile damages for California and the rest of the US

B Tables

Table 1: Summary Statistics

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

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

Table 2: Average Pollutant Rates Per Mile Traveled by Year

Year	Nitrogen Oxides			Hydrocarbons			Carbon Monoxide			Gasoline		
	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
<i>N</i>	10432374			10432374			10666348				13397795	

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

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
ln(DPM)	-0.394** (0.066)	-0.141** (0.039)		-0.183** (0.023)	-0.161** (0.027)		0.001 (0.030)
ln(DPM) * NO Q1			-0.098** (0.014)			-0.018 (0.025)	
ln(DPM) * NO Q2			-0.150** (0.013)			-0.101** (0.028)	
ln(DPM) * NO Q3			-0.178** (0.013)			-0.164** (0.027)	
ln(DPM) * NO Q4			-0.203** (0.013)			-0.242** (0.025)	
ln(DPM)*NO Centile							-0.003** (0.000)
NO Q2			-0.006 (0.015)			-0.164** (0.019)	
NO Q3			0.047* (0.020)			-0.271** (0.030)	
NO Q4			0.142** (0.024)			-0.392** (0.036)	
NO Centile							-0.003** (0.001)
Truck	0.124** (0.042)	0.098* (0.048)	0.074** (0.010)	0.038 (0.075)			
Time Trend	0.055 (0.047)	-0.086** (0.027)	-0.120** (0.027)	-0.089** (0.020)	-0.021 (0.032)	-0.086* (0.040)	-0.097* (0.040)
Time Trend-Squared	-0.001* (0.000)	0.000 (0.000)	0.001* (0.000)	0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
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	0.141	0.159	0.172	0.083	0.109	0.105	0.106

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
ln(DPM)	-0.394** (0.066)	-0.141** (0.039)		-0.183** (0.023)	-0.161** (0.027)		0.044 (0.031)
ln(DPM) * HC Q1			-0.110** (0.014)			-0.020 (0.028)	
ln(DPM) * HC Q2			-0.134** (0.014)			-0.096** (0.027)	
ln(DPM) * HC Q3			-0.148** (0.013)			-0.160** (0.029)	
ln(DPM) * HC Q4			-0.204** (0.014)			-0.273** (0.026)	
ln(DPM)*HC Centile							-0.003** (0.000)
HC Q2			0.075** (0.015)			-0.152** (0.014)	
HC Q3			0.198** (0.021)			-0.258** (0.030)	
HC Q4			0.222** (0.025)			-0.472** (0.039)	
HC Centile							-0.006** (0.001)
Truck	0.124** (0.042)	0.098* (0.048)	0.071** (0.010)	0.038 (0.075)			
Time Trend	0.055 (0.047)	-0.086** (0.027)	-0.108** (0.027)	-0.089** (0.020)	-0.021 (0.032)	-0.079* (0.040)	-0.092* (0.039)
Time Trend-Squared	-0.001* (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
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	0.141	0.159	0.170	0.083	0.109	0.104	0.105

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
ln(DPM)	-0.394** (0.066)	-0.141** (0.039)		-0.183** (0.023)	-0.161** (0.027)		0.037 (0.033)
ln(DPM) * CO Q1			-0.044** (0.015)			-0.017 (0.030)	
ln(DPM) * CO Q2			-0.083** (0.014)			-0.102** (0.029)	
ln(DPM) * CO Q3			-0.108** (0.013)			-0.167** (0.030)	
ln(DPM) * CO Q4			-0.144** (0.015)			-0.262** (0.027)	
ln(DPM)*CO Centile							-0.003** (0.000)
CO Q2			0.046** (0.016)			-0.167** (0.014)	
CO Q3			0.156** (0.022)			-0.270** (0.029)	
CO Q4			0.242** (0.028)			-0.423** (0.047)	
CO Centile							-0.004** (0.001)
Truck	0.124** (0.042)	0.098* (0.048)	0.050** (0.010)	0.038 (0.075)			
Time Trend	0.055 (0.047)	-0.086** (0.027)	-0.133** (0.027)	-0.089** (0.020)	-0.021 (0.032)	-0.079* (0.040)	-0.092* (0.040)
Time Trend-Squared	-0.001* (0.000)	0.000 (0.000)	0.001* (0.000)	0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
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	2979507	3640433	3640433	2979507	2979507
R-squared	0.141	0.159	0.170	0.083	0.109	0.104	0.105

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
ln(DPM)	-0.394** (0.066)	-0.141** (0.039)		-0.183** (0.023)	-0.161** (0.027)		-0.326** (0.031)
ln(DPM) * MPG Q1			-0.279** (0.022)			-0.192** (0.022)	
ln(DPM) * MPG Q2			-0.241** (0.022)			-0.181** (0.023)	
ln(DPM) * MPG Q3			-0.175** (0.022)			-0.140** (0.026)	
ln(DPM) * MPG Q4			-0.151** (0.019)			-0.128** (0.025)	
ln(DPM)*MPG Centile							0.003** (0.001)
Truck	0.124** (0.042)	0.098* (0.048)	0.100** (0.010)	0.038 (0.075)			
Time Trend	0.055 (0.047)	-0.086** (0.027)	-0.060* (0.024)	-0.089** (0.020)	-0.021 (0.032)	-0.022 (0.032)	-0.025 (0.033)
Time Trend-Squared	-0.001* (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
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	3640433	3640433	3640433	3640433	3640433
R-squared	0.141	0.159	0.159	0.083	0.109	0.110	0.111

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
ln(DPM)	-0.394** (0.066)	-0.141** (0.039)		-0.183** (0.023)	-0.161** (0.027)		-0.059* (0.029)
ln(DPM) * Weight Q1			-0.179** (0.016)			-0.142** (0.027)	
ln(DPM) * Weight Q2			-0.223** (0.017)			-0.148** (0.024)	
ln(DPM) * Weight Q3			-0.258** (0.017)			-0.169** (0.024)	
ln(DPM) * Weight Q4			-0.267** (0.016)			-0.187** (0.022)	
ln(DPM)*Weight Centile							-0.002** (0.000)
Truck	0.124** (0.042)	0.098* (0.048)	0.095** (0.010)	0.038 (0.075)			
Time Trend	0.055 (0.047)	-0.086** (0.027)	-0.050* (0.024)	-0.089** (0.020)	-0.021 (0.032)	-0.021 (0.032)	-0.020 (0.032)
Time Trend-Squared	-0.001* (0.000)	0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
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	3640411	3640433	3640433	3640411	3640411
R-squared	0.141	0.159	0.160	0.083	0.109	0.110	0.110

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

	(1)	(2)	(3)	(4)	(5)	(6)
	4-9	10-15	16-27	4-9	10-15	16-27
ln(DPM)	-0.115**	-0.149**	-0.124+			
	(0.020)	(0.029)	(0.065)			
ln(DPM) * NO Q1				-0.077**	-0.063*	-0.006
				(0.023)	(0.027)	(0.069)
ln(DPM) * NO Q2				-0.105**	-0.128**	-0.044
				(0.019)	(0.027)	(0.065)
ln(DPM) * NO Q3				-0.126**	-0.168**	-0.143+
				(0.021)	(0.029)	(0.074)
ln(DPM) * NO Q4				-0.140**	-0.201**	-0.180*
				(0.024)	(0.031)	(0.068)
NO Q2				-0.055*	-0.119**	-0.050
				(0.025)	(0.025)	(0.032)
NO Q3				-0.093**	-0.183**	-0.239**
				(0.026)	(0.032)	(0.039)
NO Q4				-0.107**	-0.234**	-0.282**
				(0.039)	(0.040)	(0.054)
Time Trend	-0.139**	-0.007	-0.034	-0.094+	-0.061	-0.089
	(0.042)	(0.058)	(0.149)	(0.049)	(0.062)	(0.147)
Time Trend-Squared	0.001*	-0.000	-0.001	0.001	0.000	-0.000
	(0.000)	(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	0.040	0.064	0.083	0.038	0.066	0.081

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

	(1)	(2)	(3)	(4)	(5)	(6)
	4-9	10-15	16-27	4-9	10-15	16-27
ln(DPM)	-0.115** (0.020)	-0.149** (0.029)	-0.124+ (0.065)			
ln(DPM) * HC Q1				-0.090** (0.022)	-0.073* (0.028)	0.031 (0.067)
ln(DPM) * HC Q2				-0.114** (0.020)	-0.134** (0.028)	-0.029 (0.057)
ln(DPM) * HC Q3				-0.117** (0.021)	-0.165** (0.027)	-0.134+ (0.073)
ln(DPM) * HC Q4				-0.146** (0.023)	-0.199** (0.034)	-0.224** (0.076)
HC Q2				-0.042+ (0.023)	-0.114** (0.017)	-0.100* (0.050)
HC Q3				-0.038 (0.024)	-0.166** (0.028)	-0.318** (0.076)
HC Q4				-0.089** (0.028)	-0.230** (0.039)	-0.491** (0.101)
Time Trend	-0.139** (0.042)	-0.007 (0.058)	-0.034 (0.149)	-0.090+ (0.049)	-0.056 (0.062)	-0.075 (0.144)
Time Trend-Squared	0.001* (0.000)	-0.000 (0.001)	-0.001 (0.002)	0.001 (0.001)	0.000 (0.001)	-0.000 (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	0.040	0.064	0.083	0.038	0.066	0.081

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

	(1) 4-9	(2) 10-15	(3) 16-27	(4) 4-9	(5) 10-15	(6) 16-27
ln(DPM)	-0.115** (0.020)	-0.149** (0.029)	-0.124+ (0.065)			
ln(DPM) * CO Q1				-0.071** (0.020)	-0.065* (0.028)	0.029 (0.069)
ln(DPM) * CO Q2				-0.109** (0.021)	-0.134** (0.028)	-0.051 (0.064)
ln(DPM) * CO Q3				-0.124** (0.019)	-0.166** (0.030)	-0.144* (0.068)
ln(DPM) * CO Q4				-0.148** (0.025)	-0.199** (0.033)	-0.199* (0.080)
CO Q2				-0.084** (0.016)	-0.123** (0.016)	-0.145** (0.050)
CO Q3				-0.107** (0.020)	-0.178** (0.037)	-0.325** (0.081)
CO Q4				-0.146** (0.032)	-0.223** (0.043)	-0.419** (0.113)
Time Trend	-0.139** (0.042)	-0.007 (0.058)	-0.034 (0.149)	-0.097+ (0.049)	-0.072 (0.062)	-0.076 (0.143)
Time Trend-Squared	0.001* (0.000)	-0.000 (0.001)	-0.001 (0.002)	0.001 (0.001)	0.000 (0.001)	-0.000 (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	1215774	1269415	494318
R-squared	0.040	0.064	0.083	0.038	0.066	0.081

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

	(1)	(2)	(3)	(4)	(5)	(6)
	4-9	10-15	16-27	4-9	10-15	16-27
ln(DPM)	-0.115** (0.020)	-0.149** (0.029)	-0.124+ (0.065)			
ln(DPM) * MPG Q1				-0.120** (0.019)	-0.159** (0.028)	-0.170** (0.060)
ln(DPM) * MPG Q2				-0.120** (0.020)	-0.157** (0.029)	-0.126* (0.063)
ln(DPM) * MPG Q3				-0.113** (0.020)	-0.141** (0.028)	-0.097 (0.066)
ln(DPM) * MPG Q4				-0.109** (0.019)	-0.138** (0.026)	-0.105 (0.068)
Time Trend	-0.139** (0.042)	-0.007 (0.058)	-0.034 (0.149)	-0.139** (0.042)	-0.007 (0.058)	-0.022 (0.148)
Time Trend-Squared	0.001* (0.000)	-0.000 (0.001)	-0.001 (0.002)	0.001* (0.000)	-0.000 (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	1548634	1535833	555966
R-squared	0.040	0.064	0.083	0.040	0.064	0.083

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

	(1)	(2)	(3)	(4)	(5)	(6)
	4-9	10-15	16-27	4-9	10-15	16-27
ln(DPM)	-0.115** (0.020)	-0.149** (0.029)	-0.124+ (0.065)			
ln(DPM) * Weight Q1				-0.114** (0.019)	-0.139** (0.028)	-0.101 (0.066)
ln(DPM) * Weight Q2				-0.112** (0.020)	-0.144** (0.027)	-0.098 (0.063)
ln(DPM) * Weight Q3				-0.117** (0.020)	-0.152** (0.027)	-0.132* (0.062)
ln(DPM) * Weight Q4				-0.119** (0.020)	-0.162** (0.028)	-0.163** (0.057)
Time Trend	-0.139** (0.042)	-0.007 (0.058)	-0.034 (0.149)	-0.140** (0.042)	-0.007 (0.058)	-0.033 (0.147)
Time Trend-Squared	0.001* (0.000)	-0.000 (0.001)	-0.001 (0.002)	0.001* (0.000)	-0.000 (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	1548620	1535828	555963
R-squared	0.040	0.064	0.083	0.040	0.064	0.083

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

	(1)	(2)	(3)
ln(DPM) * MPG Q1	-0.204*** (0.0399)	-0.205*** (0.0399)	-0.219*** (0.0400)
ln(DPM) * MPG Q2	-0.201*** (0.0399)	-0.203*** (0.0399)	-0.217*** (0.0401)
ln(DPM) * MPG Q3	-0.154*** (0.0398)	-0.158*** (0.0398)	-0.172*** (0.0400)
ln(DPM) * MPG Q4	-0.147*** (0.0402)	-0.153*** (0.0401)	-0.167*** (0.0403)
ln(DPM) * Higher MPG in HH		-0.0266*** (0.00397)	-0.0274*** (0.00397)
Dollars per Mile * Lower MPG in HH		0.0539*** (0.00410)	0.0537*** (0.00410)
Higher MPG in HH		-0.0691*** (0.00920)	-0.0708*** (0.00920)
Lower MPG in HH		0.126*** (0.0104)	0.126*** (0.0104)
ln(DPM) * HH Income Q2			-0.00251 (0.00451)
ln(DPM) * HH Income Q3			0.0176*** (0.00469)
ln(DPM) * HH Income Q4			0.0280*** (0.00511)
Year Fixed Effects	Yes	Yes	Yes
Within-Year Time Trends	Yes	Yes	Yes
Vintage Fixed Effects	Yes	Yes	Yes
Demographics	Yes	Yes	Yes
Vehicle Fixed Effects	Yes	Yes	Yes
Observations	7549359	7549359	7549359
R-squared	0.106	0.106	0.106

Standard errors in parentheses

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

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

	40% Sample of HHs	10% Sample of VINs
ln(DPM) * HH Income Q1	-0.190*** (0.0400)	-0.341*** (0.0682)
ln(DPM) * HH Income Q2	-0.192*** (0.0400)	-0.340*** (0.0684)
ln(DPM) * HH Income Q3	-0.173*** (0.0399)	-0.338*** (0.0681)
ln(DPM) * HH Income Q4	-0.164*** (0.0400)	-0.316*** (0.0682)
Year Fixed Effects	Yes	Yes
Within-Year Time Trends	Yes	Yes
Vintage Fixed Effects	Yes	Yes
Demographics	Yes	Yes
Vehicle Fixed Effects	Yes	Yes
Observations	7549359	2489373
R-squared	0.105	0.088

Standard errors in parentheses

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

Table 15: Hazard of Scrappage: Cox Proportional Hazard Model

	Model 1	Model 2	Model 3	Model 4	Model 5
Dollars per Mile	0.917*		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 16: 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**	1.091**	1.085**	1.124**	
	(0.029)	(0.033)	(0.021)	(0.022)	
Failed Last Smog Check	7.293**	7.438**	8.282**	7.713**	
	(0.234)	(0.243)	(0.187)	(0.173)	
DPM * MPG Quartile 1		0.964		0.803**	
		(0.048)		(0.033)	
DPM * MPG Quartile 2		0.976		0.891**	
		(0.050)		(0.038)	
DPM * MPG Quartile 3		0.968		0.986	
		(0.059)		(0.062)	
DPM * MPG Quartile 4		1.024		1.155*	
		(0.072)		(0.074)	
Vehicle Ages 10-15					
DPM * MPG Quartile 1					0.714**
					(0.053)
DPM * MPG Quartile 2					0.724**
					(0.062)
DPM * MPG Quartile 3					0.835+
					(0.087)
DPM * MPG Quartile 4					0.909
					(0.162)
Failed Smog Check					6.490**
					(0.377)
DPM * Failed Smog Check					1.181**
					(0.044)
Vehicle Ages 16+					
DPM * MPG Quartile 1					0.957*
					(0.018)
DPM * MPG Quartile 2					1.060*
					(0.028)
DPM * MPG Quartile 3					1.130**
					(0.051)
DPM * MPG Quartile 4					1.104**
					(0.037)
Failed Smog Check					9.408**
					(0.412)
DPM * Failed Smog Check					1.049**
					(0.017)
Station ZIP Code Characteristics	Yes	Yes	Yes	Yes	Yes
Quadratic Time Trend in Days	Yes	Yes	Yes	Yes	Yes
Vehicle Characteristics	Yes	Yes	Yes	Yes	Yes
Stratified on Vin Prefix	No	No	Yes	Yes	Yes
Observations	3170553	3170553	3170553	3170553	3170553

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

Table 17: Cobenefits of a Gasoline Tax, No Heterogeneity, Muller and Mendelsohn (2009) Baseline Values

	Δ Consumption		Δ CO2 (Tons)	DWL (\$)	Criteria Benefit					Net Cost (Per CO2)	
	(Gallons)	(Tons)			(NOx \$)	(HC \$)	(CO \$)	(Total \$)	(% DWL)		(Per CO2)
1998	510.3	4.899	4.899	350.4	-0.326	53.55	61.16	113.7	71.96	51.47	20.06
1999	519.3	4.985	4.985	346.4	-0.0740	59.16	65.27	124.0	65.41	45.45	24.04
2000	484.9	4.655	4.655	311.8	-0.0379	52.49	54.86	107.1	58.96	39.50	27.49
2001	421.2	4.044	4.044	260.6	0.0808	36.95	37.61	74.52	49.65	32.00	32.44
2002	463.5	4.449	4.449	279.9	0.322	48.34	47.20	95.73	37.73	23.74	39.18
2003	506.5	4.862	4.862	299.0	0.509	40.20	37.66	78.25	29.71	18.27	43.23
2004	519.1	4.984	4.984	298.6	0.699	30.61	28.41	59.61	22.11	13.25	46.67
2005	489.7	4.701	4.701	271.7	0.596	20.45	17.61	38.57	16.11	9.308	48.48
2006	407.3	3.911	3.911	217.5	0.457	14.09	10.87	25.35	13.29	7.391	48.23
2007	464.6	4.460	4.460	240.2	0.496	10.17	6.567	17.20	8.183	4.407	49.45
2008	424.8	4.078	4.078	212.4	0.316	7.280	3.553	11.13	6.139	3.197	48.89
Average	473.8	4.548	4.548	280.8	0.276	33.93	33.71	67.74	34.48	22.54	38.92

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

	Δ Consumption		Δ CO ₂		DWL		Criteria Benefit				Net Cost
	(Gallons)	(Tons)	(Tons)	(\$)	(NOx \$)	(HC \$)	(CO \$)	(Total \$)	(% DWL)	(Per CO ₂)	(Per CO ₂)
1998	190.2	1.826	1.826	130.6	-0.472	106.6	135.8	240.6	186.6	133.4	-61.91
1999	156.6	1.504	1.504	104.5	-0.484	92.75	115.4	207.1	195.9	136.1	-66.65
2000	206.7	1.984	1.984	132.9	-0.142	86.74	105.2	191.5	145.5	97.47	-30.49
2001	188.3	1.807	1.807	116.5	0.141	68.61	84.54	153.0	133.9	86.29	-21.85
2002	171.0	1.642	1.642	103.3	0.251	54.99	66.36	121.4	117.8	74.11	-11.20
2003	161.2	1.547	1.547	95.15	0.378	47.19	55.89	103.3	108.9	66.99	-5.497
2004	153.7	1.476	1.476	88.43	0.595	35.79	43.50	79.72	90.41	54.18	5.745
2005	108.4	1.041	1.041	60.14	0.480	24.34	29.07	53.75	89.79	51.89	5.903
2006	103.4	0.993	0.993	55.22	0.394	18.72	21.58	40.59	73.88	41.09	14.53
2007	76.18	0.731	0.731	39.38	0.304	14.54	16.60	31.37	80.15	43.16	10.69
2008	83.37	0.800	0.800	41.69	0.284	12.08	13.33	25.63	61.75	32.16	19.92
Average	145.4	1.396	1.396	87.98	0.157	51.12	62.48	113.4	116.8	74.27	-12.80

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 19: 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)	(\$)	(NOx \$)	(HC \$)	(CO \$)	(Total \$)	(% DWL)	(Per CO2)	(Per CO2)	(Per CO2)	
1998	190.2	1.826	130.6	-0.472	106.6	135.8	240.6	186.6	133.4	133.4	-61.91	
1999	178.2	1.711	118.9	-0.217	92.44	115.0	206.6	172.0	119.5	119.5	-50.06	
2000	228.1	2.190	146.7	-0.150	85.51	103.6	188.5	147.8	99.03	99.03	-32.05	
2001	272.3	2.614	168.4	0.118	69.33	84.13	153.3	95.66	61.65	61.65	2.794	
2002	252.3	2.422	152.4	0.278	56.62	66.71	123.4	81.18	51.08	51.08	11.84	
2003	287.2	2.757	169.5	0.430	50.04	57.21	107.5	63.69	39.17	39.17	22.33	
2004	332.8	3.195	191.5	0.618	40.36	46.73	87.53	45.88	27.49	27.49	32.43	
2005	288.2	2.767	159.9	0.562	29.24	33.84	63.49	39.87	23.04	23.04	34.75	
2006	259.5	2.491	138.5	0.498	24.04	27.54	51.93	37.72	20.98	20.98	34.64	
2007	298.0	2.861	154.1	0.491	20.86	23.54	44.78	29.24	15.75	15.75	38.11	
2008	310.0	2.976	155.0	0.418	18.74	20.73	39.77	25.80	13.44	13.44	38.64	
Average	263.4	2.528	153.2	0.234	53.98	64.98	118.8	84.14	54.96	54.96	6.501	

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 20: Cobenefits of a Gasoline Tax, No Heterogeneity, Muller and Mendelsohn (2009) USEPA Values

	Δ Consumption		Δ CO2		DWL		Criteria Benefit					Net Cost
	(Gallons)	(Tons)	(\$)	(NOx \$)	(HC \$)	(CO \$)	(Total \$)	(% DWL)	(Per CO2)	(Per CO2)		
1998	510.3	4.899	350.4	12.57	352.0	61.16	425.1	269.0	192.4	-120.8		
1999	519.3	4.985	346.4	16.33	388.7	65.27	469.9	248.0	172.3	-102.8		
2000	484.9	4.655	311.8	14.28	344.8	54.86	413.8	227.8	152.6	-85.58		
2001	421.2	4.044	260.6	11.00	242.7	37.61	291.2	194.0	125.0	-60.59		
2002	463.5	4.449	279.9	16.56	317.5	47.20	381.2	150.2	94.53	-31.61		
2003	506.5	4.862	299.0	15.41	264.0	37.66	317.0	120.3	74.01	-12.51		
2004	519.1	4.984	298.6	14.53	201.1	28.41	243.9	90.49	54.22	5.700		
2005	489.7	4.701	271.7	11.19	134.4	17.61	163.1	68.09	39.35	18.44		
2006	407.3	3.911	217.5	8.429	92.54	10.87	111.8	58.59	32.59	23.03		
2007	464.6	4.460	240.2	7.606	66.83	6.567	80.97	38.52	20.74	33.11		
2008	424.8	4.078	212.4	5.465	47.83	3.553	56.83	31.35	16.33	35.76		
Average	473.8	4.548	280.8	12.12	223.0	33.71	268.6	136.0	88.55	-27.08		

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 21: 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)	(\$)	(NOx \$)	(HC \$)	(CO \$)	(Total \$)	(% DWL)	(Per CO2)	(Per CO2)	(Per CO2)	
1998	190.2	1.826	130.6	21.26	700.6	135.8	856.3	664.1	475.0	475.0	-403.5	
1999	178.2	1.711	118.9	20.39	607.3	115.0	742.1	618.0	429.4	429.4	-359.9	
2000	228.1	2.190	146.7	17.81	561.7	103.6	682.6	535.4	358.7	358.7	-291.7	
2001	272.3	2.614	168.4	16.13	455.4	84.13	555.4	346.6	223.3	223.3	-158.9	
2002	252.3	2.422	152.4	14.85	371.9	66.71	453.2	298.2	187.6	187.6	-124.7	
2003	287.2	2.757	169.5	14.31	328.6	57.21	399.9	237.0	145.7	145.7	-84.24	
2004	332.8	3.195	191.5	13.93	265.1	46.73	325.6	170.7	102.3	102.3	-42.34	
2005	288.2	2.767	159.9	11.23	192.1	33.84	237.0	148.8	85.99	85.99	-28.20	
2006	259.5	2.491	138.5	9.566	157.9	27.54	194.8	141.5	78.72	78.72	-23.10	
2007	298.0	2.861	154.1	8.854	137.0	23.54	169.3	110.5	59.53	59.53	-5.674	
2008	310.0	2.976	155.0	7.906	123.1	20.73	151.6	98.40	51.25	51.25	0.836	
Average	263.4	2.528	153.2	14.20	354.6	64.98	433.4	306.3	199.8	199.8	-138.3	

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 22: Optimal Gasoline Tax in Cents, With and Without Heterogeneity

	PS 2005	Our Estimates, Valued By:			
		MM Baseline		MM USEPA	
		1998	2008	1998	2008
Marginal Pollution Damage (Cents/mile) (E^{PM})	2	0.87	0.51	7.02	2.41
Elasticity of VMT (η^{MF})	0.22	0.117	.140	0.117	.140
Pigovian Tax on Local Pollution					
No Heterogeneity	16	3.87	1.73	34.29	13.36
With Heterogeneity	-	6.70	3.19	64.66	26.11
% Difference	-	73.1%	84.06%	88.55%	95.45%
Total Optimal Gasoline Tax					
No Heterogeneity	101	55.20	59.04	89.08	72.16
With Heterogeneity	-	58.37	60.69	122.54	86.47
% Difference	-	5.74%	2.80%	37.57%	19.84%

Notes: PS 2005 denotes Parry and Small (2005), while MM Baseline and MM USEPA denote the baseline and USEPA scenarios, respectively, of Muller and Mendelsohn (2009). Marginal pollution damages and VMT elasticity for our estimates are calculated using the weighted average of the vehicle stock with Smog Checks in the given year; changes from 1998 to 2008 are due to changes in the composition of the fleet.

Table 23: 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.