Urban Air Pollution Progress Despite Sprawl: The "Greening" of the Vehicle Fleet[1]

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Abstract

Growing cities, featuring more people with higher incomes who live and work in the suburbs and do not commute by public transit should be a recipe for increased air pollution. Instead, California’s major polluted urban areas have experienced sharp reductions in air pollution. Technological advance has helped to “green” the average in fleet vehicle. Such quality effects have offset the rising quantity of miles driven. This paper uses several data sets to investigate how California’s major cities have enjoyed environmental gains over the last 20 years despite ongoing growth.

Introduction

In 2004, roughly 18 million people lived in the greater Los Angels area. Given its geography and climate patterns and the scale of economic activity within this basin, the Los Angeles Basin suffers from the highest levels of air pollution in the United States. Much of this pollution is caused by vehicle emissions. But Los Angeles has made dramatic progress on air pollution over the last 25 years. For ambient ozone, a leading indicator of smog, the average of the top 30 daily peak one-hour readings across the county's 9 continuously operated monitoring stations declined 55% from 0.21 to 0.095 parts per million between 1980 and 2002. The number of days per year exceeding the federal one-hour ozone standard declined by an even larger amount—from about 150 days per year at the worst locations during the early 1980s, down to 20 to 30 days per year today.[2]

Recent pollution gains are especially notable because Los Angeles County's population grew by 29 percent between 1980 and 2000, while total automobile mileage grew by 70 percent (California Department of Transportation 2003). For air quality to improve as total vehicle mileage increases indicates that emissions per mile of driving must be declining sharply over time. This suggests that technological advance is helping to reduce an important external cost of urban living.

A growing empirical literature has examined the external benefits of urban agglomeration (Rosenthal and Strange 2004). The future of cities also hinge on the

[2] Data source: California Ambient Air Quality Data CD, 1980-2002 (California Air Resources Board). This CD-ROM provides all air quality readings taken in the state during this time period. In this dataset, the unit of analysis is a monitoring station.

external costs of urbanization (Tolley 1974, Glaeser 1998, Kahn 1999, Henderson 2002). Technological advance offers the possibility of achieving the "win-win" of urban growth without the exacerbation of classic pigouvian externalities. Recent studies have documented how technological progress has helped to mitigate other urban externalities such as noise pollution (see McMillen 2004) and traffic congestion (Olszewski and Xie 2005). New crime fighting technologies such as the use of real time GIS maps for deploying police to "hot spots" has helped to reduce urban crime levels. If technological advance can reduce the external pollution costs of "city bigness", then urban quality of life will sharply improve (Portney and Mullahy 1986, Small and Kazimi 1995, Gyourko, Kahn and Tracy 1999).

In this paper, we examine why there has been a "greening" of California's vehicle fleet. Environmentalists tend to focus on the scale effects induced by urban growth (Wackernagel et. al. 2002). In many growing cities, the population is suburbanizing and enjoying rising incomes. In addition, the urban form of these growing cities is conducive to travel by private vehicle (Bertaud 2003, Bento et. al. 2005). These trends help to explain why miles driven have soared. If the *quality* of driving (i.e emissions per mile) did not improve, then such urban growth could sharply degrade local air quality. Technological advance, both due to government regulation and vehicle company innovation, has significantly reduced the local air pollution impact of driving. Since vehicles are durable goods, it takes years for new vehicle emissions progress to significantly reduce the emissions of the average vehicle on the roads.

We use two waves of the California Random Roadside Emissions tests spanning the years 1997 to 2002 to estimate vehicle level emissions production functions. These regressions allow us to estimate infleet emissions by vehicle model year. We document that infleet vehicle emissions decline sharply as new vehicle emissions regulation is phased in. Controlling for a vehicle's model year and mileage, richer households pollute less per-mile of driving. By combining estimates of average vehicle emissions by model year and data on the age distribution of the vehicle fleet, we document the reduction in average vehicle emissions by calendar year. Our estimates of how the average vehicle's emissions have declined over time provide a measure of overall technological progress. Using California air pollution data for ambient carbon monoxide, nitrogen dioxide and ozone, we document that despite increased population, rising per-capita income and ongoing population sprawl, reductions in average emissions per-vehicle have helped to improve ambient air quality and hence raise urban quality of life.

Measuring Vehicle Emissions Progress Over Time

Private vehicle emissions are leading contributors to California's ambient carbon monoxide, nitrogen dioxide and ozone levels. Vehicles are durable goods. The median age of a vehicle in the United States is over 8 years old. In any calendar year t, the average vehicle's emissions represent a weighted average of emissions of each previous vintage weighted by that vintage's share of the fleet. Equation (1) shows this relationship using the identity that in year t a vehicle built in t-j is j years old.

$$E_t = \Sigma\gamma_j * E_{\text{model year t-j}} \qquad (1)$$

In equation (1), γ_j represents the share of the vehicle fleet that is j years old. These shares sum to one. $E_{\text{model year t-j}}$ represents vehicle emissions for the average vehicle built in year t-j. Equation (1) represents an aggregation equation mapping heterogeneous vehicles' emissions into an "average" vehicle's emissions in any calendar year.

In this paper, we will use a rich data set (described below) to estimate how $E_{model\ year\ t-j}$ varies a function of model year. Equation (2) reports our multivariate vehicle emissions production function. The unit of analysis is a vehicle. We estimate log-linear OLS regressions in order to explain vehicle i that is registered in zip code l's emissions.

$$Log(1+E_{il}) = c + \Sigma_j \beta_j * Model\_Year_j + Zipcode_l + controls_i + U_{il} \qquad (2)$$

In equation (2), ZipCode is a vector of zip code of vehicle registration fixed effects. These fixed effects allow us to control for socio-economic differences across communities. Controls include vehicle characteristics such as dummy variables for whether the vehicle is a light truck, built by a USA manufacturer, climate indicators for the day of the emissions test, engine size, log of mileage and a time trend indicating the month in which the vehicle was emissions tested in the Random Roadside test. Model year represents a set of dummy variables from 1966 to 2002.

Our empirical approach is to first estimate equation (2). This yields new estimates of how infleet vehicle emissions vary as a function of vehicle model year, type and vehicle owner attributes. We will use estimates of these regressions and combine this with data on the age distribution of California's vehicle fleet to compute estimates of the average vehicle emissions by calendar year (see equation 1). This will represent our overall emissions "progress" index. In the last section of the paper, we will document how this measure correlates with ambient California air pollution.

Vehicle Data

To measure vehicle emissions, we use the 1997 to 1999 and 2000 to 2002 waves of the California Random Roadside data. California's Bureau of Automotive Repair (BAR) collected emissions tests on more than 25,000 vehicles between February 1997 and October 1999 by pulling vehicles over at random at roadside sites in Enhanced Smog Check Program areas around the state.[3] The roadside equipment for these tests is the same as that used in the Enhanced Smog Check Program (the state's vehicle Inspection and Maintenance program). BAR collects these data as an on-road check of how well the Smog Check program is performing.

The data set provides detailed information on each vehicle's emissions of oxides of nitrogen, hydrocarbons, and carbon monoxide. The data used in this study were collected using the Acceleration Simulation Mode (ASM) test, which measures emissions as concentration in the exhaust. For each vehicle, the data set reports its type (i.e., car or light truck (i.e., SUV or pickup)), model year, mileage, make, weight, and other variables we will discuss below.

Table One reports the empirical distribution for the three pollutants for the 37,519 vehicles in our sample. Hydrocarbons and nitrogen oxide are measured in parts per million while carbon monoxide is measured as a percentage. The data are clearly heavily right skewed with the mean being more than twice as high as the median for hydrocarbons and nitrogen oxide and six times higher for carbon monoxide. The existence of super emitters is apparent from this table. Note that the ratio of the 99th

[3] An additional 12,000 vehicles were sampled in the 2000 to 2002 wave of the Random Roadside test.

percentile to the 95th percentile is roughly equal to two for all three pollutant measures.[4] These pollution measures are not highly correlated. The correlation between hydrocarbons and carbon monoxide equals .31 and the correlation between hydrocarbons and nitrogen oxide is .11. The correlation between carbon monoxide and nitrogen oxide is -.02.

Measuring Vehicle Emissions Progress by Model Year

In this section, we present new evidence on how vehicle emissions vary as a function of model year. The unit of analysis is a vehicle. Table Two reports three OLS estimates of equation (2). In column (1), the dependent variable is the log of vehicle hydrocarbon emissions. In columns (2) and (3), the dependent variables are the log of carbon monoxide emissions and the log of oxides of nitrogen, respectively. In these regressions, the omitted category is a 1966 imported non-luxury car tested between 1997 and 1999.[5]

The hydrocarbons regression results show that emissions have declined with respect to model year but the relationship is not linear. Note the sharp drop in vehicle

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[4] The fact that a small percentage of vehicles contribute a large share of the total stock of emissions suggests that effective inspection and maintenance programs could play a key role in reducing California smog. As documented by Hubbard (1997), private garages do not face the right incentives to pursue the public interest of reducing super-polluter's emissions. A more cost-effective means of reducing such vehicles' emissions would be to use remote sensing to identify likely gross polluters for required repair (see http://www.rppi.org/smogcheck.html).

[5] The luxury makes include: BMW, Ferrari, Alfa Romero, Lexus, Mercedes, Porsche, Rolls Royce, Saab, Audi, Jaguar and Cadillac.

emissions between 1974 makes and 1975 makes. California's new vehicle hydrocarbon emissions regulation tightened by 69% over this time period. In the late 1990s, vehicles built between 1975 and 1983 emit roughly the same amount of hydrocarbons. Starting with the 1984 makes there is a monotonic relationship between declining new vehicle emissions and model year. The model year estimates for the carbon monoxide regression reported in column (2) reveal a very similar pattern. Note the improvements in carbon monoxide emissions between 1974 makes and subsequent makes. In 1975, new vehicles were regulated to pollute 74% less carbon monoxide than pre-1975 makes. The oxides of nitrogen regression also indicate declining vehicle emissions with respect to model year but there is no clear observable sharp decline in any model years.[6]

Figure One graphs emissions patterns with respect to vehicle model year. To generate this figure, we predict vehicle emissions using the results from Table Two and then calculate average predicted emissions by model year. For each of the three pollutant measures we normalize the predictions by dividing through by the predicted value for 1966 model year vehicles. The Figure shows sharp improvement with respect to model year and documents emissions progress even during years when new vehicle regulation did not tighten. Table Three reports our estimates of average vehicle emissions by

[6] Unlike in the cases of hydrocarbon and carbon monoxide emissions, we do not see sharp reductions by model year in vehicle emissions (as shown in Table Two) lining up with the phase in of new vehicle regulation. For example, in California nitrogen oxide emissions regulation for new vehicles tightened significantly in 1975, 1977, 1980 and 1993. As shown in Table Two, only when we compare 1993 makes to 1992 makes do we see a large negative jump in emissions for this pollution measure.

model year as sampled in the 1997 to 2002 Random Roadside tests. These represent our estimates of $E_{\text{model year } t-j}$ that we will use to calculate equation (1).[7]

Could our estimates of lower vehicle emissions for more recent vintages of vehicles reflect aging effects?[8] Previous research has concluded that aging effects are not quantitatively important.[9] The results presented in Table Two control for vehicle mileage. We can test for the presence of aging effects because the California Random Roadside tests took place across 32 months between February 1997 and October 1999 and over 32 months in the second wave. In each of the regressions reported in Table Two, we include a time trend indicating what month each vehicle was tested in. In the hydrocarbons and carbon monoxide regressions we cannot reject the hypothesis that the coefficient on the time trend equals zero. The aging hypothesis would predict a positive

[7] It is important to note the small mileage elasticity estimates reported in Table Two. For example, the hydrocarbons regression indicates a mileage elasticity of only .07. We recognize that pre-1975 vehicles that are emissions tested in the late 1990s are likely to have high mileage relative to newer vehicles but these small elasticity estimates reduce our concern that we need to standardize vehicles with respect to mileage by calendar year.

[8] We recognize that the scrappage of durables raises the issue of selection bias. In calendar year 1998, the set of 1970 model year vehicles on the roads are 28 years old. Assuming that vehicle emissions and engine performance are negatively correlated, then high emissions vehicles would be more likely to be scrapped and would be *under sampled* when the Random Roadside tests take place. Thus, in 1998 the dirtiest 1970 vehicles are less likely to observed on the roads. This means that we are under-estimating the infleet average emissions progress over time.

[9] Research investigating whether model year effects or age effects better explains why older vehicles pollute more has concluded that aging effects are small compared to intrinsic improvements with each successive model year (Schwartz 2003; Pokharel et al. 2003). For example, data from vehicle inspection programs and on-road remote sensing have sampled given vehicle model years in each of several calendar years, allowing comparison of different model years at a given age. These data show that with each successive model year, the average automobile is starting out and staying cleaner than vehicles from previous model years. As a result, the average emissions of the vehicle fleet are declining even as the age of the average vehicle increases over time.

coefficient controlling for vehicle model year. It is true that for nitrogen oxide emissions we find a positive and quite large time trend. When we investigated this by graphing average emissions with respect to the month of the Random Roadside test we observed enormous outliers for vehicles tested in two months in early 1998.[10]

Measuring Vehicle Emissions Progress by Calendar Year

Equation (1) provides a simple aggregation approach that links average vehicle emissions by model year to average vehicle emissions by calendar year. We use the results reported in Table Three as our estimate of $E_{\text{model year}}$. As shown in equation (1), we need data on the age distribution of California's vehicle fleet. We have data from the R.L Polk Company over the years 1978 to 1988 for Los Angeles County. In each year, the data report the count of vehicles registered in Los Angeles County by vehicle model year. This allows us to construct the γ in equation (1). In Figure Two, we graph the empirical age distribution of the fleet for calendar years 1978, 1982 and 1988. Figure Two shows that there have not been quantitatively large fleet aging effects over the years 1978 to 1988. This is important because California new vehicle emissions regulation tightened for 1981 makes. An influential environmental economics literature has posited that an unintended consequence of new vehicle emissions regulation is that households keep their used vehicles longer than they would have in the absence of the regulation

[10] The positive coefficient estimates on the variable "Dummy for Tested in 1997 to 1999" provide additional evidence against the importance of vehicle aging. If vehicle aging raises vehicle emissions, then we should observe that holding vehicle model year constant that vehicles tested in the early period (1997 to 1999) should have *lower* emissions than observationally identical vehicles tested in the later Random Roadside test (2000 to 2002). As shown at the bottom of Table Two, for both hydrocarbons and oxides of nitrogen emissions we reject this hypothesis.

(Gruenspecht 1982, Stavins 2006).[11] Figure Two does show some evidence of California fleet aging between 1978 and 1982 but not between 1982 and 1988. The observed aging effects are not quantitatively large.

Given that the vehicle age distribution does not change much over time, we use the 1980 fleet age distribution for calculating γ_j in equation (1). The estimates of how the average vehicle's emissions change by calendar year (over the years 1982 to 2002) are reported in Table Four. The table shows overall progress in the "greening" of the average vehicle. For example, the index for hydrocarbon emissions declines between 1982 and 2002 from 124 parts per million to 14.4 parts per million. For all three emissions indicators, the average vehicle is much lower emitting in calendar year 2002 than in calendar year 1982. In a section below, we will use the data reported in Table Four to explain overall ambient air pollution trends.

Explaining Vehicle Emissions Heterogeneity Within Model Year

In this section, we estimate additional vehicle emissions production functions based on equation (2). Instead of including zip code of registration fixed effects, we now include two zip code level variables. We estimate these regressions to document the role of rising household income and household environmentalism as determinants of vehicle emissions.

[11] Some government studies have claimed that emissions control regulation has added over $2,000 to the price of a new vehicle while other researchers have disputed this arguing that new vehicle emissions regulation actually raises the quality of the driving experience (see Bresnahan and Yao 1985).

The first variable proxies for a vehicle's owner's income. We include the log of average household income in the zip code of registration.[12] In Table Five, we report three estimates of equation (2) using the 1997 to 1999 California Random Roadside test data. We include the same vehicle and climate data on the emissions testing day that we included in the specifications reported in Table Two. As shown in the top row of Table Five, higher income households pollute less. Controlling for vehicle model year, all three income elasticity estimates are roughly -.23. We believe that this is a substantial under-estimate of the income elasticity due to the measurement error issue introduced by using average zip code income.

Vehicle emissions represent a classic negative externality. All urbanites have little incentive to internalize the social consequences of their vehicle emissions. Potentially offsetting this self interested logic, recent research has documented evidence that people who reveal themselves as environmentalists engage in greater "civic restraint" and degrade the commons less (see Kotchen and Moore 2004).

Environmentalists may be more willing to invest in vehicle maintenance to reduce their emissions. This group may intentionally not want to pollution. To test this hypothesis requires an observable ideology measure. As our environmental ideology measure we use the Green Party's share of registered voters in a person's zip code.[13] Kahn (2006) documents this variable's explanatory power with respect to household differences in aggregate gasoline consumption and the propensity to purchase hybrid

[12] By merging on a zip code average, we recognize that this is a noisy measure of a household's true income. Thus, we are underestimating the effect of income on vehicle emissions.
[13] For details documenting this party's commitment to environmental issues see http://cagreens.org/platform/ecology.htm.

vehicles such as the Toyota Prius.[14] As shown in Table Five, all else equal, vehicles registered in Green Party areas emit less. A one percentage point increase in the share of zip code voters who are registered in the Green Party reduces hydrocarbon emissions by 5% and oxides of nitrogen emissions by 22%.

The final hypothesis we test is whether vehicles recently tested in California's inspection and maintenance program pollute less. In Table Five, we create a dummy variable that equals one if a vehicle tested in the 1997 to 1999 Random Roadside test has participated in the inspection and maintenance program within the last 50 days.[15] If recent regulation is effective, then such "treated" vehicles should have lower emissions. We find evidence of small negative effects. Relative to observationally identical vehicles that have not been recently emissions tested, the "treated vehicles" have 8% lower hydrocarbon emissions and 11% lower carbon monoxide emissions.

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[14] The Berkeley IGS (see http://swdb.berkeley.edu/) provides data for each California census tract on its count of registered Green Party Voters. We use a Geocorr mapping of tracts to zip codes to create the percentage of each California zip code's voters who are registered in the Green party.

[15] California currently operates three different variations of the Smog Check program in different areas of the state (see http://www.smogcheck.ca.gov/ftp/pdfdocs/program_map.pdf for a map). The "Enhanced" program operates in the state's major metropolitan areas and requires biennial and change-of-ownership testing of automobiles using the "BAR97" test. In the BAR97 test, cars are placed on a treadmill-like machine called a dynamometer, allowing cars to be tested under conditions that simulate on-road driving. The Enhanced program began in June of 1998. The "Basic" program operates in smaller metropolitan areas and rural areas near metropolitan areas and requires biennial and change-of-ownership testing using the "BAR90" test. In the BAR90 test, cars are tested at idle without the engine in gear. The BAR90 test was also used in Enhanced areas before the beginning of the Enhanced program. Finally, the "Change-of-Ownerhip" program operates in the most rural and remote areas of the state. This program also uses the BAR90 test, but requires cars to be tested only when they change owners.

Urban Air Pollution Progress as a Function of Average Vehicle Emissions

In Table Four, we documented how the "average" vehicle's emissions have declined over time. In this section, we use data on ambient air pollution at multiple monitoring stations in California over the years 1982 to 2000 to test whether our estimate of average vehicle emissions levels predicts actual urban air pollution levels.

To study this, we estimate urban ambient air pollution functions. The unit of analysis is monitoring station j located in county l's time t average ambient pollution level. Our ambient air pollution data is from the California Ambient Air Quality Data CD, 1980-2002 (California Air Resources Board). This CD-ROM provides all air quality readings taken in the state during this time period.

Equation (3) reports the functional form of our ambient pollution production function.

$$Log(Ambient\ Pollution_{jlt}) = \Phi_j + \beta_1 * Population_{lt} + \beta_2 Income_{lt} + \beta_3 * E_t + U_{jlt} \quad (3)$$

In equation (3), the "E_t" term represents average vehicle emissions in calendar year t (see Table Four). The monitoring station fixed effect, Φ, controls for the geography of a specific location and its average climate conditions. The error term U reflects unobserved time varying variables such as climate variation at the monitoring station. For example, during hotter summer months we would expect higher ambient ozone levels. All else equal, pollution is an increasing function of the number of people who live in the county where the monitoring station is located, and of per-capita income. The data source for the county attributes is the Bureau of Economic Analysis' REIS county data. We have estimated versions of equation (3) where we include monitoring station fixed effects and a time trend. Based on these regressions, we find that ambient ozone is declining by 1.7% per year, ambient nitrogen oxide is declining by 2.6% per year and ambient carbon monoxide is declining by 3.9% per year.

Table Six reports three estimates of equation (3). In each of these regressions, the dependent variable is based on the annual arithmetic mean at a monitoring station in a specific year. The standard errors are clustered by calendar year because the average vehicle emissions index (see Table Four) only varies across calendar years. All three regressions highlight the tension between scale and technique effects. For example, consider the ambient carbon monoxide regression reported in Table Six. The elasticity of county population on pollution is .36 and the elasticity of county per-capita real income on pollution is .45. These two facts suggest that urban growth will increase ambient carbon monoxide levels. But, offsetting these effects is the technique effect. The elasticity of the vehicle carbon monoxide emissions index (see Table Four) on ambient carbon monoxide is .65.

As the average vehicle's carbon monoxide emissions declines over time, ambient carbon monoxide improves. A similar pattern is observed for ambient nitrogen oxide. The results for ambient ozone are not as strong. Note that the elasticity estimates are small and I cannot reject the hypothesis that the proxies for scale (county population and county per-capita income) are statistically insignificant. This makes sense because the formation of ozone as a byproduct of hydrocarbon emissions and xx does not respect physical boundaries and can float away imposing downwind externalities.[16] Still, it must

[16] We acknowledge that for certain ambient pollutants such as ozone, the relationship between emissions and ambient pollution can have very unusual isoquants (see the NRC

be noted that even in the case of ambient ozone, the vehicle hydrocarbon index is statistically significant in explaining its dynamics. Average vehicle emissions declines have helped to offset the increased scale of economic activity in sprawling California.

Conclusion

Growing cities, featuring more people with higher incomes who live and work in the suburbs and do not commute by public transit should be a recipe for increased pollution and rising public health challenges. Instead, since 1980 California's major polluted urban areas have experiences sharp reductions in air pollution. This paper has used two novel micro data sets to report new facts on why these gains have taken place. We have shown how technological advance has played a key role in reducing the average vehicle's emissions over time. These emissions reductions have been sufficient to offset the rising scale of urban driving brought about by population and income growth.

By documenting the role played by technological advance and diffusion of technologies in reducing vehicle emissions, this paper touches on a broader theme in urban economics. Technological advance has reduced many of the social costs of city bigness. It has reduced both air emissions and noise emissions associated with urban economic activity. Information technology has allowed cities to start road pricing programs reducing the transaction costs of tracking which vehicle has entered what zone at what time. Under Rudy Giuliani, New York City started to use a spatial mapping program called "CompStat" to monitor the spatial distribution of crime. Some futurists have argued that information technology would reduce the benefits of urbanization (for

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1990). Here we simply want to document the positive correlation between our average vehicle emissions indices and ambient pollution levels.

details on this debate see Glaeser 1998). In this paper, we have argued that technological advance reduces the cost of urbanization and hence enhances the “consumer city’s” quality of life (Glaeser, Kolko and Saiz 2001).

References

Bertaud, Alain. Clearing the *Air* in Atlanta: Transit and Smart Growth or Conventional Economics? *Journal of Urban Economics*, vol. 54, no. 3, November 2003, pp. 379-400

Bento, Antonio M., Maureen Cropper, Ahmed Mushfiq Mobarak and Katja Vinha. 2005. "The Impact of Urban Spatial Structure on Travel Demand in the United States" Review of Economics and Statistics, 87(3) 466-478

Bresnahan, Timothy F; *Yao*, Dennis A The Nonpecuniary Costs of Automobile Emissions Standards *RAND Journal* of Economics, vol. 16, no. 4, Winter 1985, pp. 437-55

California Department of Transportation. (2003). Motor Vehicle Fuel, Stock and Travel Report. November 2003.

Glaeser, Edward L, 1998, Are cities dying? Journal of Economic Perspectives, 12(2), 139-160.

Glaeser, Edward L, Jed Kolko, and Albert Saiz. 2001. "Consumer City." *Journal of Economic Geography* 1, no. 1: 27–50.

Gruenspecht, Howard K. Differentiated Regulation: The Case of Auto Emissions Standards American Economic Review, vol. 72, no. 2, May 1982, pp. 328-31

Gyourko, Joe and Matthew Kahn and Joe Tracy. Quality of Life and the Environment. Handbook of Regional and Urban Economics, edited by Paul Cheshire and Edwin Mills. Volume 3. North Holland Press. 1999.

Henderson, Vernon, 2002, Urban primacy, external costs, and quality of life, Resource and Energy Economics, 24(1-2), 95-106.

Hubbard, Thomas. Using Inspection and Maintenance Programs to Regulate Vehicle Emissions" (Contemporary Economic Policy, April 1997, p. 52-62

Kahn, Matthew E. Do Greens Drive Hybrids or Hummers? Environmental Ideology as a Determinant of Consumer Choice

Kahn, Matthew E.The Silver Lining of Rust Belt Manufacturing Decline. Journal of Urban Economics, 46, 360-376 1999

Kotchen, Matthew and Michael Moore (2004) Conservation Behavior. From Voluntary Restraint to a Voluntary Price Premium. Willams College Working Paper.

McMillen, Daniel, P:"Airport Expansions and Property Values: The Case of Chicago O'Hare Airport" Journal of Urban Economics Vol. 55 (2004) pp. 627-640.

National Research Council. 2000. Modeling Mobile-Source Emissions. Washington, DC: National Academy Press.

National Research Council. 1992 Washington, DC: National Academy Press. Rethinking the Ozone Problem in Urban and Regional Air Pollution

Olszewski, Piotr; Xie, Litian Modelling the Effects of *Road Pricing* on Traffic in Singapore Transportation Research: Part A: Policy and Practice, vol. 39, no. 7-9, Aug.-Nov. 2005, pp. 755-72

Pokharel, Sajal, Gary Bishop, Donald Stedman and Robert Slott. (2003) Emissions Reductions as a Result of Automobile Improvement. Environmental Science and Technology. 37, 5097-5101.

Portney, Paul R; Mullahy, John Urban Air Quality and Acute Respiratory Illness Journal of Urban Economics, vol. 20, no. 1, July 1986, pp. 21-38

Rosenthal, Stuart and Will Strange. (2004) Evidence on the Nature and Sources of Agglomeration Economics. In *Handbook of Urban and Regional Economics*, vol. 4: *Cities and Geography*, edited by Vernon Henderson and Jacques-François Thisse. Amsterdam: Elsevier North-Holland.

Schwartz, Joel. (2003). No Way Back: Why Air Pollution Will Continue to Decline. Washington, DC: American Enterprise Institute.

Singer and Harley, A fuel-based inventory of motor vehicle exhaust emissions in the Los Angeles area during summer 1997," *Atmospheric Environment,* 34(11)1783-1795 (2000)

Small, Kenneth A., and Camilla Kazimi, "On the Costs of Air Pollution from Motor Vehicles," *Journal of Transport Economics and Policy*, 29 (1995), pp. 7-32.

Stavins, Robert. "Vintage-Differentiated Environmental Regulation." *Stanford Environmental Law Journal*, Volume 25, Number 1 (Winter 2006), pp. 29-63.

Tolley, George S. 1974 The welfare economics of city bigness. Journal of Urban Economics, 1(3), 324.

Wackernagel, Mathis, and others. 2002. “Tracking the Ecological Overshoot of the Human Economy.” Proceedings of the National Academy of Science 99, no. 14: 9266–71.

Figure One

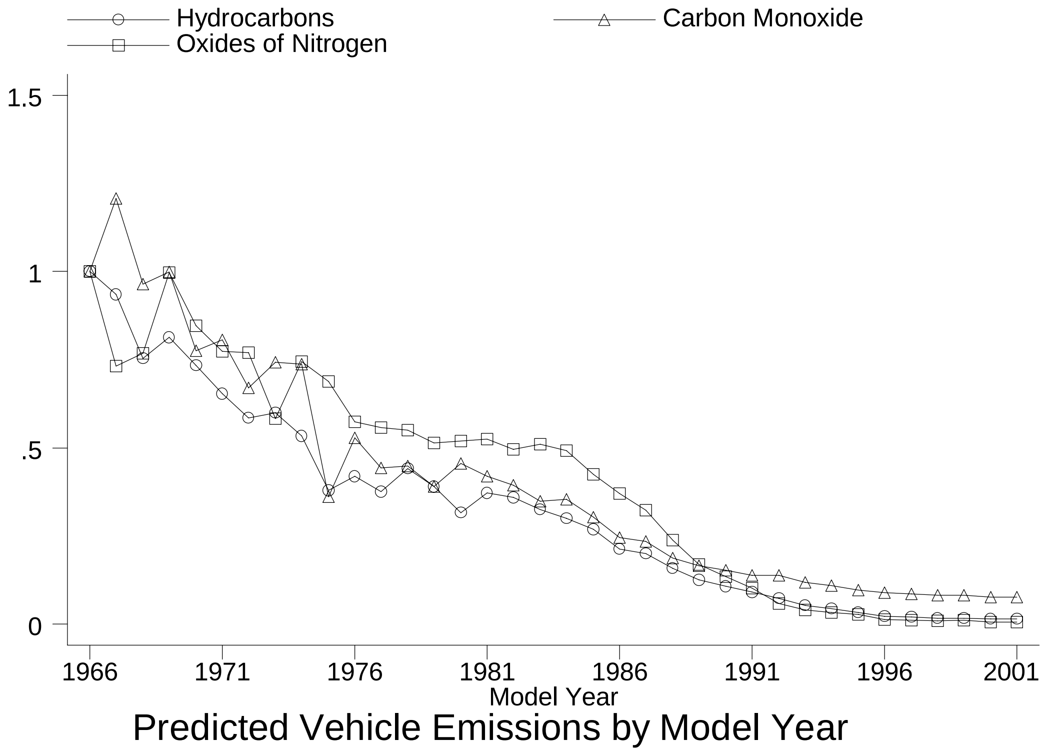
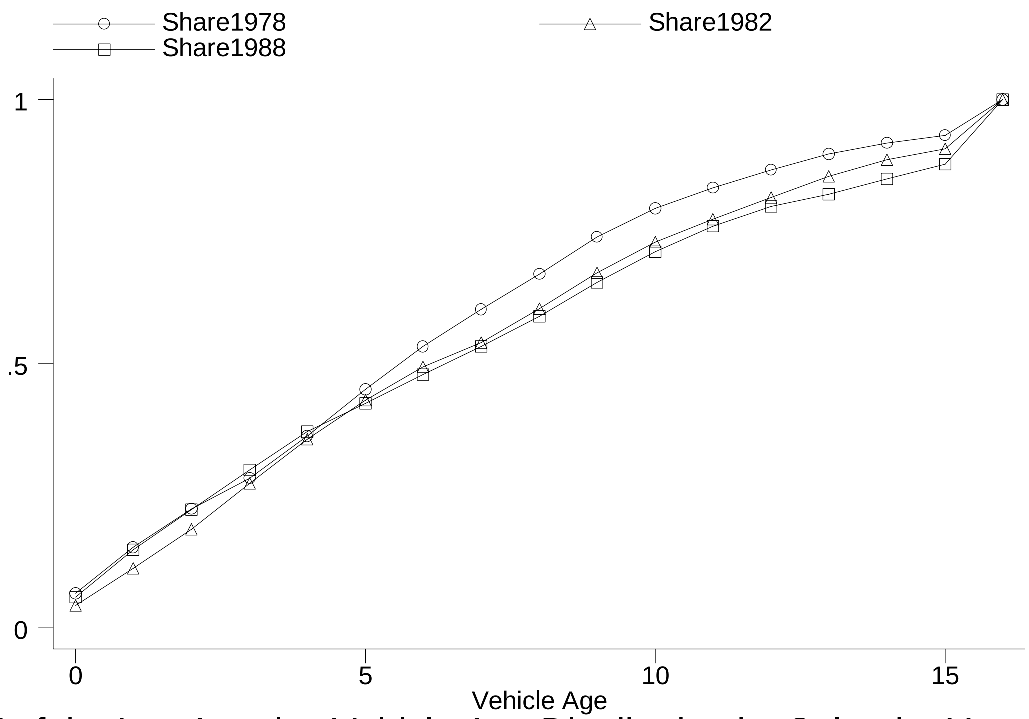

Hydrocarbons
Carbon Monoxide
Oxides of Nitrogen
1.5
1
.5
0
1966
1971
1976
1981
1986
1991
1996
2001
Model Year
Predicted Vehicle Emissions by Model Year

Figure Two



CDF of the Los Angeles Vehicle Age Distribution by Calendar Year

Table One Empirical Distribution of Vehicle Emissions

Percentile	Hydrocarbons (ppm)	Carbon Monoxide (Percentage)	Nitrogen Oxide (ppm)
1%	0	0	0
5%	2	0	0
10%	6	0	5
25%	15	0.02	82
50%	44	0.12	313
75%	114	0.49	827
90%	206	2.18	1587
95%	278	4.28	2306
99%	791	8.43	4304
mean	102.687	0.723	622.687
standard deviation	306.281	1.620	843.886

38691 observations

Table Two: Vehicle Emissions Regressions

	Hydrocarbons		Carbon Monoxide		Nitrogen Oxide	
Column	(1)		(2)		(3)	
	beta	s.e	beta	s.e	beta	s.e
Built in 1967	-0.0747	0.1379	0.1786	0.1287	-0.3155	0.2199
Built in 1968	-0.2940	0.1274	-0.0551	0.1189	-0.2736	0.2032
Built in 1969	-0.2357	0.1288	-0.0227	0.1201	-0.0413	0.2053
Built in 1970	-0.3148	0.1257	-0.2844	0.1172	-0.1153	0.2004
Built in 1971	-0.4279	0.1312	-0.2788	0.1223	-0.1932	0.2091
Built in 1972	-0.5669	0.1183	-0.4458	0.1103	-0.2672	0.1886
Built in 1973	-0.5374	0.1159	-0.3376	0.1081	-0.5455	0.1848
Built in 1974	-0.6438	0.1174	-0.3610	0.1095	-0.2918	0.1872
Built in 1975	-1.0081	0.1236	-1.0729	0.1153	-0.3953	0.1971
Built in 1976	-0.9000	0.1143	-0.6908	0.1066	-0.5692	0.1822
Built in 1977	-1.0074	0.1063	-0.8556	0.0992	-0.6114	0.1695
Built in 1978	-0.8270	0.1048	-0.8434	0.0978	-0.6439	0.1671
Built in 1979	-0.9487	0.1031	-0.9759	0.0962	-0.7155	0.1644
Built in 1980	-1.1181	0.1050	-0.8638	0.0979	-0.6923	0.1674
Built in 1981	-0.9597	0.1030	-0.9371	0.0961	-0.6920	0.1643
Built in 1982	-1.0137	0.1017	-1.0098	0.0948	-0.8103	0.1621
Built in 1983	-1.1076	0.1007	-1.1255	0.0939	-0.7877	0.1605
Built in 1984	-1.2072	0.0991	-1.1193	0.0925	-0.8462	0.1580
Built in 1985	-1.3222	0.0985	-1.2660	0.0919	-1.0242	0.1570
Built in 1986	-1.5678	0.0982	-1.4963	0.0916	-1.1849	0.1565
Built in 1987	-1.6384	0.0994	-1.5328	0.0927	-1.3795	0.1585
Built in 1988	-1.8875	0.0994	-1.7586	0.0927	-1.6892	0.1584
Built in 1989	-2.1277	0.0990	-1.8764	0.0924	-2.0518	0.1578
Built in 1990	-2.2678	0.0992	-1.9493	0.0925	-2.2875	0.1582
Built in 1991	-2.4266	0.0993	-2.0404	0.0926	-2.5611	0.1583
Built in 1992	-2.6569	0.1044	-2.0979	0.0974	-3.0041	0.1665
Built in 1993	-2.9904	0.1047	-2.2640	0.0977	-3.2827	0.1670
Built in 1994	-3.1769	0.1039	-2.3450	0.0969	-3.5051	0.1656
Built in 1995	-3.4355	0.1034	-2.4635	0.0965	-3.6360	0.1649
Built in 1996	-3.7544	0.1047	-2.5149	0.0977	-4.2601	0.1669
Built in 1997	-3.8481	0.1087	-2.5479	0.1014	-4.3668	0.1733
Built in 1998	-4.0278	0.1219	-2.5463	0.1137	-4.7680	0.1944
Built in 1999	-4.0459	0.1446	-2.4598	0.1348	-4.8986	0.2305
Built in 2000	-4.0924	0.1518	-2.5127	0.1416	-5.4331	0.2420
Built in 2001	-4.0695	0.1522	-2.4751	0.1419	-5.4489	0.2426
Light Truck	0.1874	0.0133	0.1766	0.0124	0.2281	0.0212
Engine Size	-0.0071	0.0049	-0.0243	0.0045	-0.0945	0.0077
Luxury Car	-0.2220	0.0258	-0.2546	0.0241	0.0628	0.0411
log(miles)	0.0719	0.0068	0.0279	0.0064	0.1201	0.0109
Vehicle Built by USA maker	0.1842	0.0140	-0.0381	0.0130	0.2742	0.0223
Time Trend (months)	0.0047	0.0009	-0.0016	0.0008	0.0282	0.0014
Dummy for Tested in 1997 to 1999	0.1862	0.0339	-0.0225	0.0316	0.4245	0.0540
Constant	4.3635	0.1441	0.1361	0.1344	5.2065	0.2297
climate controls	yes		yes		yes	
zip code fixed effects	yes		yes		yes	
observations	37519		37519		37519	
Adjusted R2	0.394		0.245		0.314	

This table reports three OLS estimates of equation (2) in the text. In Column (1), the dependent variable equals the log of 1 plus the vehicle's hydrocarbons emissions. In Column (2), the dependent variable equals the log of .1 + the vehicle's carbon monoxide emissions. In Column (3) the dependent variable equals the log of 1 + the vehicle's nitrogen oxide emissions. The omitted category is a non-luxury foreign car built in 1966 and tested in the 1999 to 2002 Random Roadside Tests. Zip code fixed effects are based on each vehicle's zip code of registration.
Climate controls include a measure of the temperature, humidity and barometric pressure on the day of the emissions test.

Table Three: Predicted Vehicle Emissions by Model Year

Model Year	Hydrocarbons	Carbon Monoxide	Nitrogen Oxide
1966	236.9953	1.3782	898.9576
1967	221.6225	1.6644	658.3838
1968	178.8013	1.3292	690.2068
1969	192.8907	1.3764	896.6134
1970	173.9023	1.0691	760.6028
1971	155.0531	1.1121	696.3637
1972	138.7080	0.9242	692.8679
1973	142.3556	1.0236	523.6857
1974	126.6037	1.0157	670.1350
1975	90.2401	0.4987	619.4551
1976	99.3738	0.7301	516.1871
1977	89.2408	0.6109	502.2860
1978	104.7666	0.6187	495.7888
1979	92.5475	0.5403	462.7075
1980	75.1192	0.6282	467.6595
1981	88.1976	0.5788	472.3607
1982	85.5538	0.5450	446.2201
1983	77.4158	0.4813	459.6384
1984	71.2808	0.4895	443.3663
1985	63.9697	0.4197	382.2768
1986	50.5751	0.3388	333.8940
1987	47.5818	0.3231	290.4994
1988	37.4939	0.2579	214.1250
1989	29.6746	0.2279	151.6714
1990	25.6150	0.2105	120.9348
1991	21.8785	0.1924	92.1153
1992	17.4768	0.1903	52.7604
1993	12.4799	0.1643	36.4930
1994	10.3391	0.1507	29.9606
1995	7.8321	0.1331	25.1842
1996	5.4181	0.1246	12.6761
1997	4.7418	0.1177	11.1579
1998	4.0301	0.1148	9.6878
1999	4.1307	0.1131	10.1320
2000	3.8052	0.1062	5.5300
2001	3.7669	0.1074	5.3621

This table's entries for predicted emissions are generated using the regression coefficients reported in Table Two. For each vehicle, we predict its log(emissions) based on its observable attributes. We then calculate the anti-log and average this prediction by vehicle model year.

Table Four: Predicted Average Vehicle Emissions by Calendar Year

Calendar Year	Hydrocarbons	Carbon Monoxide	Nitrogen Oxide
1982	124.0120	0.8327	592.7613
1983	115.9955	0.8019	556.7698
1984	107.5361	0.7359	542.6200
1985	103.0065	0.6951	537.4724
1986	95.0150	0.6296	505.0494
1987	87.7633	0.5949	476.1184
1988	81.3736	0.5464	448.7502
1989	76.1200	0.5139	408.5739
1990	69.3089	0.4766	388.5949
1991	61.5315	0.4116	353.7858
1992	57.1082	0.3990	315.2044
1993	51.3500	0.3618	283.2889
1994	47.1625	0.3344	252.7107
1995	41.2004	0.3027	221.1146
1996	35.3204	0.2829	193.1058
1997	31.8538	0.2553	167.2449
1998	27.6735	0.2325	141.5550
1999	23.5349	0.2104	120.5795
2000	20.0032	0.1951	100.1234
2001	16.8992	0.1767	80.1658
2002	14.4175	0.1634	67.2371

This table uses equation (1) in the text to calculate average vehicle emissions by calendar year. Predicted vehicle emissions by model year are reported in Table Three. The age distribution of Los Angeles County vehicles in calendar year 1980 is used to measure the age distribution.

Table Five: Explaining Within Model Year Variation in Vehicle Emissions

	Hydrocarbons		Carbon Monoxide		Nitrogen Oxide	
Column	(1)		(2)		(3)	
	beta	s.e	beta	s.e	beta	s.e
log(zip code Average Income)	-0.2211	0.0390	-0.2346	0.0289	-0.2530	0.0629
Zip Code Green Party Share of Registered Voters	-0.0522	0.0229	-0.0261	0.0180	-0.2233	0.0556
I/M Tested in Last 50 Days	-0.0800	0.0301	-0.1071	0.0269	-0.0689	0.0532
Constant	5.5205	0.4355	1.2839	0.3343	7.7881	0.7888
Vehicle Model Year Fixed Effects	Yes		Yes		Yes	
Vehicle Attribute Controls	Yes		Yes		Yes	
Emissions Test Day Climate Controls	Yes		Yes		Yes	
observations	19577		19577		19577	
Adjusted R2	0.319		0.219		0.232	

This table reports three estimates of equation (2) based on the 1997 to 1999 Random Roadside Sample.
The zip code variables are based on the vehicle's zip code of registration. These explanatory variables vary across zip codes but not within zip codes. The standard errors are clustered by zip code. The dummy variable "I/M tested in last 50 days" equals one if the vehicle's last inspection and maintenance test was within fifty days of the date when the vehicle was tested by the Random Roadside test.
The variable "Zip Code Green Party Share of Registered Voters" is measured in percentage points.
It has a mean of .80 and a standard deviation of .52.

Table Six: The Determinants of California Ambient Pollution from 1982 to 2000

Dependent Variable	Log(Ozone)		Log(Nitrogen Dioxide)		Log(Carbon Monoxide)	
	beta	s.e	beta	s.e	beta	s.e
log(county population)	0.0507	0.1067	0.2452	0.1256	0.3612	0.1682
log(vehicle hydrocarbon index)	0.1932	0.0318				
log(vehicle nitrogen oxide index)			0.3194	0.0387		
log(vehicle carbon monoxide index)					0.6513	0.0598
log(county real per-capita income)	0.1030	0.1376	0.2946	0.1407	0.4469	0.1596
constant	-4.4922	2.4707	-10.3106	2.2019	-6.5646	3.2980
Monitoring Station Fixed Effects	Yes		Yes		Yes	
Observations	4343		2670		2502	
Adjusted R2	0.703		0.851		0.7470	

Each ambient pollutant is measured by the maximum one hour reading at a monitoring station during a calendar year. The unit of analysis is a monitoring station/year. Standard errors are clustered by calendar year.
The three explanatory variables measuring vehcile emissions indices are based on the data reported in Table Four. These variables vary across calendar years but not within calendar years.