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Abstract

Growing cities, featuring more people with higher incomes who live and work in the suburbs and commute by private vehicle, should be a recipe for increased air pollution. Instead, California's major polluted urban areas have experienced sharp improvements in air quality. Technological advance has helped to "green" the average vehicle. Such quality effects have offset the rising quantity of miles driven. This paper uses several vehicle data sets to investigate how California's major cities have enjoyed air pollution gains over the last 20 years.

Introduction

In 2004, roughly 18 million people lived in the greater Los Angeles area. Given its geography and climate patterns and the scale of economic activity within the metropolitan area, the Los Angeles Basin suffers from the highest levels of air pollution in the United States. Most of this pollution is caused by vehicle emissions (Fujita [9], South Coast Air Quality Management District [37]). 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 Basin's 14 continuously operated monitoring stations declined 60% between 1980 and 2005, from 0.24 parts per million (ppm) to 0.094 ppm. The number of days per year exceeding the federal one-hour ozone standard declined by an even larger amount—from nearly 150 days per year at the worst locations during the early 1980s, down to fewer than 20 days per year today.[2] Across the United States, there has been significant ambient air pollution reductions as measured by decreases in ambient ozone, sulfur dioxide, carbon monoxide and lead pollution (see http://www.epa.gov/airtrends/econ-emissions.html).

Recent pollution gains are especially notable because the Los Angeles Basin's population grew by 42 percent between 1980 and 2000 (Cox [6]), and total automobile mileage grew by 88 percent (California Department of Transportation [4], Sherwood [34]). For air quality to improve as total vehicle mileage increases indicates that emissions per mile of driving must be declining sharply. Technological advance is

[2] Data source: 2007 California Ambient Air Quality Data CD, 1980-2005 (California Air Resources Board). This CD-ROM provides all air quality readings taken in the state during this time period. In this data set, the unit of analysis is a monitoring station.

helping to reduce an important external cost of urban living. In addition, emissions control equipment bundled into newer vehicle makes is more durable now than in the past.[3]

Such pollution reductions offer potentially large public health gains. The public health costs from vehicle emissions have been estimated to be as high as 3 cents per mile (see Small [35] and Small and Kazimi [36]). Recent California based research has documented the role of ambient carbon monoxide in increasing infant mortality risk (Currie and Neidell [7]).

A growing empirical literature has examined the external benefits of urban agglomeration (Rosenthal and Strange [32]). The future of cities also hinges on the external costs of urbanization (Glaeser [11], Henderson [16], Kahn [21], Tolley [40]). Technological advance offers the possibility of achieving the "win-win" of urban growth along with the reduction of classic Pigouvian externalities. Recent studies have documented that technological progress has led to reduction of other urban nuisances such as noise pollution (see McMillen [26]). New crime fighting technologies, such as the use of real time GIS maps for deploying police to "hot spots," have helped to reduce urban crime levels. Technological advance has permitted London's recent success with its time-of-day congestion pricing (Leape [23]). If technological advance can reduce the external pollution costs of "city bigness," then urban quality of life will sharply improve (Portney and Mullahy [31], Gyourko, Kahn and Tracy [14]).

In this paper, we examine why California has seen a "greening" of its vehicle fleet. Environmentalists tend to focus on the scale effects induced by urban growth

[3] We thank an anonymous reviewer for making this point.

(Wackernagel et al. [41]). In many growing cities, the population is moving to the suburbs and enjoying rising incomes. In addition, the urban form of these growing cities is conducive to travel by private vehicle (Bento et al. [1], Bertaud [2]). These trends help to explain why miles driven have soared. If the *quality* of driving (i.e., emissions per mile) did not improve, then suburban growth could sharply degrade local air quality. Technological advance, due to both government regulation and auto-manufacturer innovation, has significantly reduced the regional air pollution caused by driving. Because vehicles are durable goods, it takes several years for new-vehicle emissions improvements to reduce significantly 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 the vehicle fleet's emissions by vehicle model year. We document that in-fleet vehicle emissions decline sharply as new-vehicle emissions regulation is phased in. Vehicles built in the same year differ greatly with respect to their emissions. A distinctive feature of the California Random Roadside Emissions tests is that each driver's Zip Code of residence is included in the data set. We use this information to merge in Census data on average household income within each Zip Code. We document that if we control for a vehicle's model year and mileage, richer households pollute less per mile of driving.

In any given calendar year, average vehicle emissions for vehicles on the roads depend on average vehicle emissions by model year and the age distribution of the fleet. We construct estimates of the average vehicle's emissions by calendar year, and this technique provides us with a measure of overall technological emissions progress. Using ambient air pollution data, we report new estimates of air pollution production functions. We document that despite population growth and rising per-capita income, reductions in average emissions per vehicle have improved California's ambient air quality.

Measuring Vehicle Emissions Progress

Private vehicle emissions are the largest contributor to carbon monoxide (CO) and volatile organic compounds (VOC), and major contributors to oxides of nitrogen (NOx) (Fujita et al. [9]; South Coast Air Quality Management District [37]). Because NOx and VOC, and, to a lesser extent CO, contribute to ozone formation, automobile emissions are therefore a major contributor to California's ozone levels. In this paper, we use a rich data set (described below) to estimate how vehicle emissions vary as a function of model year. Equation (1) reports our multivariate vehicle emissions production function. For each vehicle in our data set, we observe its emissions of carbon monoxide, hydrocarbons and oxides of nitrogen. The unit of analysis is a vehicle. We estimate log-linear OLS regressions in order to explain the emissions level of vehicle i built in model year j that is registered in Zip Code l.

$$Log(1+E_{ijl}) = c + \Sigma_j \beta_j * Model\_Year_{ij} + \delta * Zipcode_l + \theta * controls_i + U_{il} \quad (1)$$

In equation (1), 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 (using dummy variables for whether the vehicle is a light truck or if it was 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.

We first report estimates of equation (1). These regression results are useful for understanding how in-fleet vehicle emissions vary as a function of vehicle model year and vehicle type. Based on our regression estimates of equation (1), we predict how average vehicle emissions vary by model year. Let $E_{\text{model year t-j}}$ stand for our prediction of the average emissions for a vehicle built in year t-j.[4]

Vehicles are durable goods. The median automobile in the United States is more than 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 (2) shows this relationship using the identity that in year t a vehicle built in t-j is j years old.

$$E_t = \Sigma\gamma_j * E_{\text{model year t-j}} \qquad (2)$$

In equation (2), E_t represents the average vehicle's emissions in calendar year t. In the last section of the paper, we will document how this emissions "progress" index correlates with ambient California air pollution. In equation (2), γ_j represents the share of the vehicle fleet that is j years old. These shares sum to one. Equation (2) highlights how we use our predicted estimates of vehicle emissions by model year combined with the fleet age distribution to estimate average vehicle emissions by calendar year.

[4] For each vehicle, we use its observable attributes and the regression coefficient estimates to predict the log of its emissions. We take this index and then calculate its exponent and finally average this by model year to generate our prediction of average vehicle emissions by model year. We have also generated predictions of vehicle emissions by model year using a linear regression version of equation (1). The correlation of predicted vehicle emissions based on the log-linear and the linear regressions is .90.

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.[5] 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 (NOx), hydrocarbons (HC; a subset of VOC), and carbon monoxide (CO). The data used in this study were collected from 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 [SUV or pickup]), model year, mileage, make, weight, and other variables we will discuss below.

For a variety of reasons we believe that "real-world" vehicle data, such as the data we use for the present study, provide a more relevant sample of vehicle emissions than the data sets used by the U.S EPA and the California Air Resources Board (CARB) to

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

develop mobile-source emissions inventories and determine emission reduction credit for states' Clean Air Act State Implementation Plans.[6]

Table One reports the empirical distribution for the three pollutants for the 38,691 vehicles in our sample. Hydrocarbons and oxides of nitrogen are reported in parts per million, and carbon monoxide is reported in percentages (i.e., parts per hundred).[7] The data are clearly heavily right skewed, with the mean more than twice as high as the median for hydrocarbons and nitrogen oxide and six times as high for carbon monoxide. The existence of super-emitters is apparent from this table. Note that the ratio of the 99th percentile to the 95th percentile is roughly equal to two for all three pollutant measures.[8] These pollution measures are not highly correlated. The correlation between

[6] The EPA uses "emission factor" models to estimate emissions from the vehicle fleet in air pollution non-attainment areas around the country. These models are also used to develop emission inventories for Clean Air Act State Implementation Plans (SIPs) and to evaluate the likely effects from various regulations. The EPA's model is known as MOBILE. Model validation studies have shown that MOBILE generally fails to accurately predict vehicle emissions as measured on the road (Gertler and Pierson [10]; Pierson et. al. [28]). A review of MOBILE by a National Academy of Sciences Panel concluded that the model is not sufficiently accurate for the regulatory tasks for which it is used (National Research Council [27]).

[7] Oxides of nitrogen (NOx) are the sum of nitric oxide and nitrogen dioxide (NO_2). The ASM test actually measures nitric oxide (NO). The vast majority of NOx comes out the tailpipe as NO, but NO and NO_2 are interconverted in the atmosphere in the chemical reactions that form ozone.

[8] The fact that a small percentage of vehicles contributes a large share of the total stock of emissions suggests that effective inspection and maintenance programs could significantly reduce California smog. Unfortunately, private garages and motorists do not face the right incentives to diagnose and repair vehicles with extremely high emissions (Hubbard [17]). A more cost-effective means of reducing such vehicles' emissions would be to use remote sensing to identify high polluters for required repair (see http://www.rppi.org/smogcheck.html).

hydrocarbons and carbon monoxide equals .31, and the correlation between hydrocarbons and nitrogen oxide is .11. The correlation between carbon monoxide and oxides of nitrogen is -.02.[9]

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 (1). 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.[10]

The hydrocarbons regression results show that emissions have declined with respect to model year but the relationship is non-monotonic. Note the sharp drop in vehicle emissions between 1974 makes and 1975 makes. California's new vehicle hydrocarbon emissions standard tightened by 69% over this time period. In the late

[9] The relatively low correlation between pollutants is due to differing engine conditions that result in high emissions of a particular pollutant and also to the lognormal distribution of emissions. For example, too high a fuel to air ratio tends to cause high CO and HC, but high HC without high CO can be caused by conditions, such as misfires, that allow fuel to go through the cylinder and out the tailpipe without being burned. High NOx can result from too low a fuel to air ratio or a malfunctioning exhaust gas recirculator (EGR).

[10] The luxury makes include BMW, Ferrari, Alfa Romeo, Lexus, Mercedes, Porsche, Rolls Royce, Saab, Audi, Jaguar, and Cadillac. We have also estimated additional specifications where we broaden the luxury vehicle category to include Acura, Infiniti, and Volvo as well. The regression results based on this broader definition are similar to the ones reported in Table Two.

1990s, vehicles built between 1975 and 1983 emitted 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, regulations required that new vehicles emit 74% less carbon monoxide than pre-1975 makes. The oxides of nitrogen regression also indicates declining vehicle emissions with respect to model year, but there is no clear sharp decline in any model year.[11]

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 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 (2).[12]

[11] 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 NOx emissions regulation for new vehicles tightened significantly in 1975, 1977, 1980, and 1993. As Table Two shows, only when we compare 1993 makes to 1992 makes do we see a large drop in emissions for this pollution measure.

[12] 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 were emissions tested in the late 1990s are likely to

Could our estimates of lower vehicle emissions for more recent vintages of vehicles reflect aging effects?[13] Previous research suggests that aging effects are of minor importance when compared with technique effects—a result we confirm here.[14] 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 as well. In each of the regressions reported in Table Two, we include a time trend indicating in what month each vehicle was tested. 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 coefficient after controlling for vehicle model year. It is true that for NOx emissions we find a large, positive time trend. When we investigated this result by graphing average emissions with

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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.

[13] We recognize that some vehicles are scrapped, and this fact raises selection bias issues. In calendar year 1998, the set of 1970 model year vehicles on the roads were 28 years old. Assuming that vehicle emissions and engine performance are negatively correlated, then high-emission vehicles would be more likely to be scrapped and would be *under-sampled* when the Random Roadside tests take place. Therefore in 1998 the dirtiest 1970 vehicles are less likely to be observed on the roads. This attrition means that we are underestimating the in-fleet average emissions progress over time.

[14] Research investigating whether model year effects or age effects better explain why older vehicles pollute more has concluded that aging effects are small compared to intrinsic improvements with each successive model year (Schwartz [33]; Pokharel et al. [30]). 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.

respect to the month of the Random Roadside test, we observed enormous outliers for vehicles tested in two months in early 1998.[15]

Measuring Vehicle Emissions Progress by Calendar Year

Equation (2) 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 (2), 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. We use this information to construct γ for each age category in equation (2).[16]

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

[15] 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, if we hold vehicle model year constant, vehicles tested in the early period (1997 to 1999) 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.

[16] The Polk data go back 16 years in any given calendar year. For example, in calendar year 1978 the data report the count of registered vehicles built between 1962 and 1978. As our Random Roadside Test data's earliest model year is 1966, we are implicitly assuming that all pre-1966 makes have an emissions level equal to the average 1966 make.

have in the absence of the regulation (Gruenspecht [13], Stavins [38]).[17] Such households recognize that they can delay paying the new vehicle regulatory "tax" by keeping their original vehicle. The environmental economics literature has claimed that if this substitution effect is large enough, new vehicle regulation can *lower* air quality in the short run. 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 large. We have also examined Los Angeles vehicle registrations by model year in calendar year 2000.[18] Between calendar years 1980 and 2000, the fleet has aged, but the effects are not large. In 1980, 76% of Los Angeles's vehicle fleet was under ten years old; in the year 2000, 66% of Los Angeles's vehicle fleet was under ten years old.

Given that the vehicle age distribution does not change much over time, we use the 1980 fleet age distribution for calculating $\gamma_{j.}$ in equation (2). 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 ppm to 14.4 ppm—a reduction of 88%. For all three emissions indicators, the average vehicle polluted much less in calendar year 2002 than in calendar year 1982. During the same period, total automobile miles driven increased 74% (Texas

[17] Some government studies have claimed that emissions control regulation has added more than $2,000 to the price of a new vehicle; other researchers have disputed this claim, arguing that new vehicle emissions regulation actually raises the quality of the driving experience (see Bresnahan and Yao [3]).

[18] We have also estimated equation (2) using data on the vehicle age distribution based on year 2000 Los Angeles county data, and our results are not much different.

Transportation Institute [39]).[19] Below, we will use the data reported in Table Four to explain overall ambient air pollution trends. It should be noted that recent California regulations such as mandating sales of zero emissions vehicles will further contribute to reducing the average vehicle emissions index as reported in Table Four.

Explaining Vehicle Emissions Heterogeneity Within Model Year

In this section, we estimate additional vehicle emissions production functions using equation (1). Instead of including Zip Code of registration fixed effects, we now include two Zip Code–level variables. These two variables are the log of average household income in the Zip Code of registration and the Zip Code's share of registered voters who are members of the Green Party. In Table Five, we report three estimates of equation (1) 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.

We hypothesize that richer drivers should pollute less, even after we control for vehicle age. Affluent drivers buy higher quality automobiles, which are correlated with lower pollution emissions, and have a private incentive to maintain their vehicles and to invest in upkeep. As shown in the top row of Table Five, higher income households do pollute less (see Harrington [15]). When we control for vehicle model year, all three

[19] It should be noted that these emissions trend estimates pertain to "hot stabilized" emissions (emissions when a car is warmed up). I/M programs do not measure "cold start" emissions or non-tailpipe HC emissions (i.e., from evaporation or leaks). These emissions have declined as well as a result of the movement to computer control, fuel injection, and other technological enhancements; improvements in evaporative emission control systems; and shortening of the cold start warm-up period for catalytic converters.

income elasticity estimates are roughly -.23. We believe that this underestimates the true income elasticity, due to the measurement error issue introduced by using average Zip Code income.[20]

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 [22], Kahn [20]).

Environmentalists may be more willing to invest in vehicle maintenance to reduce their emissions. This group may intentionally want not to pollute. Testing this hypothesis requires an observable measure of environmentalism. As our environmental ideology measure, we use the Green Party's share of registered voters in a person's Zip Code.[21] Kahn [20] documents this variable's explanatory power with respect to explaining household differences in aggregate gasoline consumption and the propensity to purchase hybrid vehicles such as the Toyota Prius.[22] 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%.

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[20] By merging on a Zip Code average, we recognize that we are using a noisy measure of a household's true income.

[21] For details documenting this party's commitment to environmental issues, see http://cagreens.org/platform/platform_toc.shtml.

[22] 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.

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.[23] If recent regulation is effective, such "treated" vehicles should have lower emissions. We find evidence of small effects. Relative to observationally identical vehicles that have not been emissions tested recently, the "treated vehicles" have 8% lower hydrocarbon emissions and 11% lower carbon monoxide emissions.

Urban Air Pollution Progress as a Function of Average Vehicle Emissions

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 question, we estimate urban ambient air pollution functions. The unit of analysis is monitoring station j located in county l's average ambient pollution

[23] 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 1998. The "Basic" program operates in smaller metropolitan areas and rural areas near metropolitan areas; it 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. The "Change-of-Ownership" 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.

level at time t. 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. If we control for monitoring station fixed effects, we see that ambient pollution in California declined sharply between 1980 and 2002. Ambient 1-hour ozone declined by 1.7% per year, ambient nitrogen dioxide [the ambient data measures nitrogen dioxide (NO_2), a component of NOx (NOx = NO + NO_2)] declined by 2.6% per year, and ambient carbon monoxide declined by 3.9% per year.

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

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

In equation (3), the "E_t" term represents average vehicle emissions in calendar year t (see Table Four and equation (2)). We estimate equation (3) to document that our emissions index (E_t) is positively correlated with ambient pollution levels. The elasticity regression coefficient, β_3, is useful for understanding how changes in the average vehicle emissions index translate into ambient pollution gains. In estimating equation (3), we attempt to control for other relevant factors. County average per-capita income and population are meant to proxy for the scale of local economic activity. The monitoring station fixed effect, Φ, controls for the geography of a specific location and its average climate conditions. The error term 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. The data source for the county attributes is the Bureau of Economic Analysis's REIS county data.

Table Six reports four estimates of equation (3). In each of these regressions, the dependent variable measures a different ambient air pollutant at a specific monitoring station in a given calendar year. The standard errors are clustered by calendar year because the average vehicle emissions index (see Table Four) varies only 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 decline over time, the ambient carbon monoxide level improves. A similar pattern is observed for ambient nitrogen dioxide.

The results for ambient ozone are not as strong. Note that the elasticity estimates are small. We cannot reject the hypothesis that the proxies for scale (county population and county per-capita income) are statistically insignificant. Ground-level ozone is formed by a chemical reaction between volatile organic compounds and oxides of nitrogen (NOx) in the presence of sunlight. These emissions do not respect physical boundaries and can float away, imposing downwind externalities. Still, it must be noted that even in the case of ambient ozone, the vehicle hydrocarbon index is statistically significant in explaining its dynamics.[24] Average vehicle emissions declines have helped to offset the increased scale of economic activity in sprawling California. In column (4) of Table Six, we present our results when we use PM10 as the dependent variable. Public health research has documented that particulate exposure raises mortality risk (Chay and Greenstone [5]). The results show that our NOX index is positively correlated with this outcome indicator.[25]

Conclusion

Growing cities, featuring more people with higher incomes who live and work in the suburbs, should be a recipe for increased air pollution. Instead, California's most polluted urban areas have experienced sharp reductions in air pollution.[26] This paper has used two novel micro-data sets to report new explanations for why these gains have taken place. We have shown that technological advance has been central to reducing the average vehicle's emissions. These emissions reductions have been sufficient to offset more urban driving brought about by population and income growth.

[24] The comparatively smaller decline in ozone relative to other pollutants is not unexpected. First, the reactions that produce ozone are nonlinear, and reductions in NOx and VOC do not necessarily result in monotonic reductions in ozone. For example, the ratio of VOC to NOx is a principal determinant of the effectiveness of precursor reductions in reducing ozone. At low VOC/NOx ratios, reducing NOx actually increases ozone. The Los Angeles Basin has one of the lowest VOC/NOx ratios in the U.S., and recent research suggests that NOx reductions there are likely slowing progress in reducing ozone (Marr and Harley [25]; Fujita et al. [9]). Second, there is evidence that as ozone levels decline, additional incremental ozone reductions become progressively more difficult to achieve (Lefohn et al. [24]). Third, the background level of ozone is significantly greater than zero. Some ozone is produced by natural VOC and NOx emissions, and both ozone and ozone precursors are also transported into the Los Angeles area from elsewhere, including as far away as Asia (Hudman et al. [18]; Jaffe et al. [19]).

[25] Here we must acknowledge that particulate matter comes from many sources such as diesel buses and trucks and these mobile sources are not in our data set.

[26] We focused on data from 1980 onward, but ozone records in the Los Angeles area go back as far as the mid-1950s. These records show that ozone was declining in the decades leading up to 1980, though not as quickly as it did during the 1990s (Ellsaesser [8]).

By documenting the role of 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 some cities to start road pricing programs, reducing the transaction costs of tracking which vehicle has entered what zone at what time (Leape [19]). Under Mayor 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 details on this debate see Glaeser [11]). Our results suggest that improvements in emissions control technology have helped to reduce one major cost of urbanization and hence enhances the "consumer city's" quality of life (Glaeser, Kolko and Saiz [12]).

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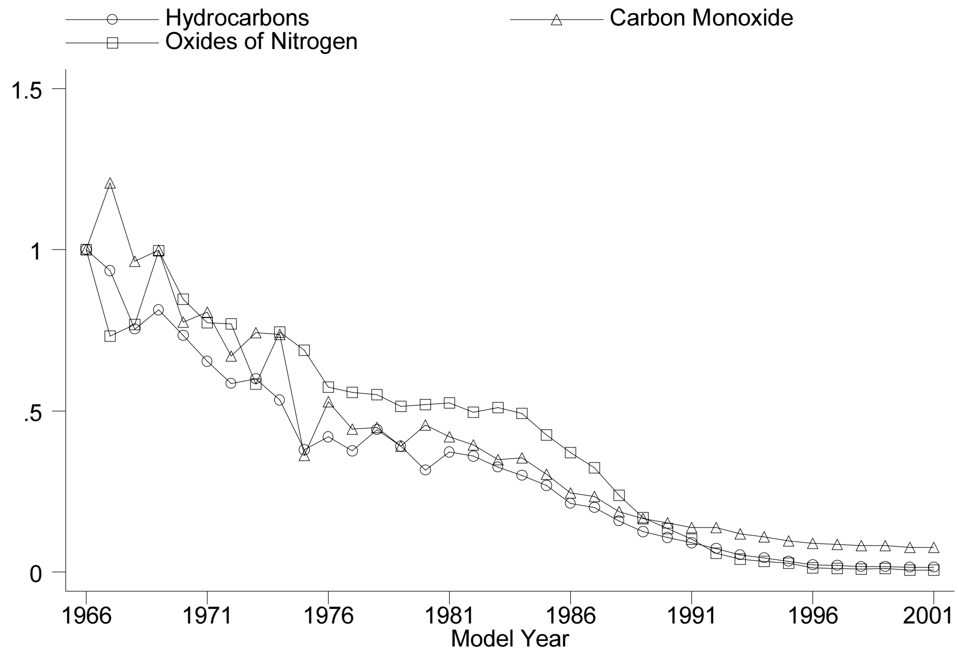
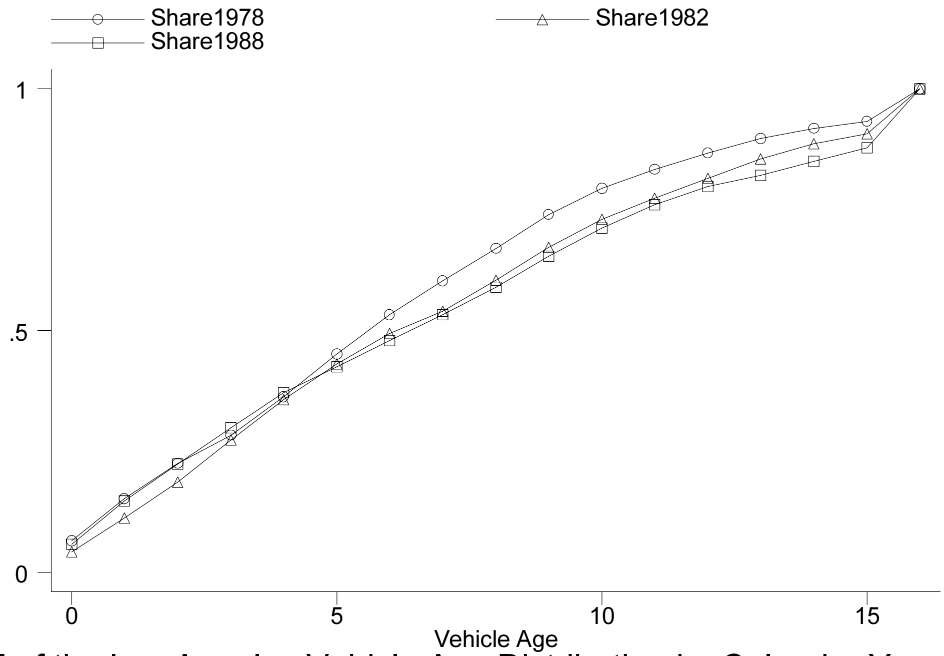
Figure One



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 (1) 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 (2) 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 (1) 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 under the Random Roadside test program. 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)		Log(PM10)	
Column	(1)		(2)		(3)		(4)	
	beta	s.e	beta	s.e	beta	s.e	beta	s.e
log(county population)	0.0507	0.1067	0.2452	0.1256	0.3612	0.1682	0.0471	0.1452
log(vehicle hydrocarbon index)	0.1932	0.0318						
log(vehicle nitrogen oxide index)			0.3194	0.0387			0.2779	0.0485
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	0.3686	0.1380
constant	-4.4922	2.4707	-10.3106	2.2019	-6.5646	3.2980	-2.2778	2.6482
Monitoring Station Fixed Effects	Yes		Yes		Yes		Yes	
Observations	4343		2670		2502		1148	
Adjusted R2	0.703		0.851		0.747		0.914	

In columns (1-3) the dependent variable represents the ambient maximum one hour reading at a monitoring station during a calendar year. The unit of analysis is a monitoring station/year. In column (4), the dependent variable is the annual average of particulate matter readings at a monitoring station. Standard errors are clustered by calendar year.
The three explanatory variables measuring vehicle emissions by calendar year are based on the data reported in Table Four. These variables vary across calendar years but not within calendar years.