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Does political ideology matter for environmental quality outcomes?

Abstract

The study tests the popular belief that Democrats (and more generally, liberals) are "green" while Republicans (more generally, conservatives) are "brown", for several measures of California air quality indicators. We employ two alternative econometric identification strategies on county-level cluster and yearly panel data that include proxy variables for political party preferences of the local populace, controlling also for the political party affiliations at the state-level legislative and executive branches. Generally, we do not find a consistent and statistically significant relationship between pollution outcomes and political variables. The popular belief is supported only for NO_2 and O_3, but not for any of the other pollutants, and even in these two cases the relationship only holds at the local regulatory level and not at the state policymaking level. At the state level, for most of the pollutants no significant effect of party affiliation is identified, and in the rare cases where such an effect exists, it is either too weak to be conclusive or is counter to popular belief.

Keywords: political party affiliation, environmental preferences, policymaking, air pollution.
JEL Classification: Q51, Q58, D78.

Introduction

Economic theory suggests that market outcomes in the presence of negative externalities, such as air pollution, will be inefficient without regulation. If efficiency were the objective, public legislative and regulatory bodies with appropriate power would attempt to enact policies that achieve the highest feasible social welfare level without favoring one group over another. But as many scholars (among them, Stigler (1971), Peltzman (1976, 1984), Becker (1983), Pashigian (1985)) have long argued, various political and information imperfections may cause regulatory bodies to deviate from that goal. In particular, in a democratic system characterized by two dominant political coalitions, pressure from these groups may influence policy, and hence pollution outcomes, in directions favorable to their affiliated political party stands[1].

California, a state strongly dominated by the Democratic party voters, is often recognized to be the trend-setter for environmental protection actions and policies both for other states and at the federal level. This appears to accord with the common belief that in the United States, the Democratic party and its affiliates are more pro-environment than their rival Republicans. This political party-affiliation divide ("party sorting") with respect to environmental quality issues is particularly noticeable when it comes to beliefs about global warming (its timing, seriousness, causes, consequences and scientists' belief)[2].

Various arguments are often forwarded to justify this belief. The main tenet of the argument, however, is that when there is trade-off between profits (or some other measure of economic activity) and environmental qualities, Republicans view pro-environmental regulatory actions as unacceptable costs that render corporations less competitive (domestically and internationally), leading to more unemployment, and reduced economic wellbeing[3]. Consistent with this view, it is commonly held that the "rich" (those with significant capital holdings) are more likely to be affiliated with the Republican party and to vote for the Republican party-affiliated representatives and policymakers than those with lower-incomes/less capital. Furthermore, it is often argued that while Republicans have the financial support of polluting firms to engage in vigorous lobbying against environmental regulations, the low and middle-income groups have to rely on grass-roots activism to influence pro-environment regulations and their outcomes[4].

Regardless of the arguments for its justification, if the popular belief that Democrats (and liberals) are environmentally "greener" than Republicans is actually valid, then one would expect that changes in party affiliation across space and over time, coupled perhaps with a growing partisan divide about environmental protection, should lead to changes in environmental outcomes. But, does empirical evidence support this common belief as a reality or does it reject it as myth?

This is an intriguing question, particularly when one notes that over the period of 1970-2008 (that is, over the 38 years that followed the birth of the "environ-

[1] Several authors have investigated the effect of alternative polity structures on environmental outcomes; for example, Lopez and Mitra (2000), Farzin and Bond (2006), Buitenzorgy and Mol (2011), and Arvin and Lew (2011), among others.

[2] See, for example, Dunlap and McCright (2008).

[3] For an analysis of the effects of environmental regulations on industry and social welfare, see, for example, Farzin (2003; 2004).

[4] Although an examination of the empirical evidence supporting this belief is outside the scope of this study, we note that in the November 2012 election, 8 of the 10 wealthiest counties in the country (in terms of income) voted for the Democratic candidate, including Marin County, CA (Toscano, 2012).

mental movement" in the United States in 1970), the U.S. president was affiliated with the Republican party for 26 years. Furthermore, the popular belief that Democrats are "green" while Republicans are "brown" tends to obscure the fact that it was Richard Nixon, a Republican president, who (under heavy pressure from environmental activists), created the Environmental Protection Agency (EPA) and signed many milestone environmental laws including the National Environmental Policy Act, the Clean Air Act, the Clean Water Act, and the Endangered Species Act.

In this paper, we would like to subject this popular belief to the scrutiny of empirical testing. Specifically, we test the hypothesis that the environmental quality is influenced by political party affiliation of the residents, of their representatives in political institutions, of policymakers and of policy practitioners. We conduct this test for several air quality indicators in California.

Despite its intellectual and policy importance, the research effort thus far spent on this important political economy question of environmental quality, while insightful, seems inadequate. Khan (2007) focuses on environmentalists' private consumer choice. He proxies a community's environmentalism by its share of Green Party registered voters and considers a range of private consumer choices including commuting modes, annual gasoline consumption, and vehicle choice. Using several California data sets, he tests whether there is a significant difference between environmentalists (the so called "greens") and non-environmentalists (the so called "browns") in their choices of transportation modes and consumption patterns. Controlling for a number of variables including community population density, Khan finds that California environmentalists are more likely to use public transit, consume less gasoline and purchase green vehicles (such as hybrids). This is an insightful result supporting the view that California environmentalist citizens, mainly comprised of greens and Democratic party constituents, are in fact pro-environment protection in their *private* consumption over the range of choices studied.

While these results can serve as a building block in investigating the differential environmental preferences of various societal groups, Kahn's work is limited to the investigation of private consumption choices at the individual level. In aggregate, however, environmental quality (for example, urban air quality) is largely a public good supplied for the nonexclusive benefit of a large group of people. As such, one cannot ignore the direct role of political ideology and preferences (expressed through political party affiliations at various levels of electorate constituents, policy legislation, regulation and implementation) in influencing environmental quality.

Attempting to address this reality, Khan and Matsusaka (1997) employ an indirect method to estimate the effect of political preferences of California citizens on their demand for environmental goods at the county level for the period of 1970-1994. Because of the public nature of these goods and hence the non-observability of quantities, prices, incomes, and preferences, they proxy the demand for the environmental good by the odds of a favorable vote cast in a county on the 16 initiatives (out of a total of 98 California initiatives voted on over this period) they identify as environmental in nature, involving the supply of pollution, natural resources, or wildlife. As indirect indicators of a voter's political preferences, the authors use the percentage of county voters registered as Democrats and the percentage of the vote received by the Democratic candidate in the current or preceding presidential election. Using income and several other variables as proxies for the perceived monetary costs of the proposed initiatives, their regression estimates lead them to conclude that "…it may be sensible to speak of an environmental "movement" in the sense of a general demand for environmental goods or a stable coalition of groups pushing for increased environmental amenities (p. 167)". However, they find that "…inclusion of a variable representing political ideology add relatively small amounts of explanatory power to the regressions (p. 167)".

These findings are valuable in that they suggest that the voters registered as Democrats are more likely to be pro-environment quality than Republicans, but, that, relative to price and income effects, their political preferences may not have a large effect on their *actual* demands for environmental quality. As such, this finding relates to what may be termed as the intensity of *private* demand for environmental quality (in a very general sense) and by a section of population with specific political preferences (Democrats). It, however, does not answer our question about the effects of political party affiliations of decision makers at different levels on aggregate demand for, and provision of, a specific environmental *public* good-air quality.

Neumayer (2003) studies the effects of the strength of the left-wing party and green or left-libertarian party on air pollution levels for a panel data of 18-21 countries of the Organization of Economic Corporation and Development (OECD) for the period 1980 or 1990-1999 and five air pollutants (SO_2, NO_2, CO, CO_2, and VOC). He finds that the effects differ depending on whether one considers the parliamentary (legislative) strength as opposed to cabinet (executive) strength of the parties: while he finds strong statistical evidence that the parliamentary strength (share of legislative seats) is associated with lower pollution levels for all five air pollutants, interestingly, the cabinet strength, if statistically significant at all, is associated with *higher* pollution levels. Further, he finds no evidence for a consistent impact of corporatism on pollution levels.

A study closely related to the present paper is that of McKitrick (2006). He uses panel data on air pollution in thirteen cities in Canada to test the effects of both provincial and Federal political affiliation on air quality, and concludes that the party in power is not a significant predictor of outcomes in the short run. We take a similar approach, but tailored for a different set of pollutants and governance structure, and conditional on the data available.

As such, we model and estimate California air pollution outcomes for CO, NO_2, SO_2, O_3, PM10, PM2.5, and PMFINE by county-level cluster and year over the 1992-2006 period, using panel data that include political proxy variables for environmental preferences of the local populace, as well as controlling for state-level legislative and executive branch composition. Our objective is to identify a likely structural relationship between pollution measures and the political variables. Our results suggest that, in general, such a relationship cannot unambiguously be identified for California. In particular, the popular belief receives little empirical support other than for NO_2 and O_3, and even in these two cases the relationship only holds at the local regulatory level and not at the state policy making level (with likely exception of PM2.5). At the latter level of decision making, in almost all cases no statistically significant relationship between pollution measures and political variables is identified, and in some cases where a relationship may exist, it is opposite to what is commonly believed.

The rest of the paper is organized as follows. Section 1 briefly describes the political governance structure and responsibilities of the California Air Resources Board (ARB). Data sources and definitions of the air quality, political affiliation, and socio-economic variables and their summary statistics are presented in section 2. Section 3 explains our econometric models and two alternative strategies to identify the relationship under investigation, which also serve as robustness check on estimation results. In section 4 for each of the pollutants we present the estimation results from the alternative estimation strategies and provide possible explanations for them. The final section concludes the paper.

1. Air quality regulation in California

In 1967, the state legislature passed (and Governor Reagan signed) the Mulford-Carrell Act, which merged two bureaus of the Department of Health to establish the California Air Resources Board (ARB), one of six organizations now under the umbrella of the California Environmental Protection Agency (CARBa, 2009).[1] The ARB is composed of eleven members appointed by the governor, six of whom are "experts" in related scientific fields, business, and/or law, while five others are elected officials from each of five regional air pollution control districts (CARBa, 2009)[2].

The ARB oversees the thirty-five local air quality districts which vary in size from single counties to large multi-county agencies (CARBa, 2009; CAPCOA, 2009). These districts implement emissions control rules, as well as perform monitoring, permitting, and enforcement roles related to air pollution related from commercial and industrial (point-source) pollution sources, and are governed by Boards consisting of primarily elected officials but staffed by professionals (CAPCOA, 2009; CARBa, 2009). In addition, the ARB is responsible for enforcement of mobile source pollutants, though local air quality districts can adopt control measures for non-point sources working in conjunction with state and federal regulators (CARBa, 2009).

The ARB reports enforcement on the basis of mobile source programs (Mobile Source Enforcement Branch, MSEB) and stationary source programs (Stationary Source Enforcement Branch, SSEB), as well as the greenhouse gas enforcement section (GGES) and training and compliance assistance branch (TCAB) (CARBg, 2010). The MSEB is focused on enforcement of programs to reduce exhaust emissions from vehicles and off-road engines, as well as aftermarket parts for vehicles, while the SSEB enforces regulations related to vehicle fuels and consumer products, provides oversight and assistance to local enforcement programs, and provides investigative services related to air pollution cases (CARBg, 2010). Many of the criteria pollutants used in this study are technical complements that arise primarily from one type of source or another, and as such, pollutant-level information is not readily available. In 2008, virtually all state-level ambient air quality standards for ozone, parti-

[1] The California EPA Office of the Secretary is the head of Cal/EPA and is an officer in the Governor's cabinet charged with coordination and supervision of the agency (CAL/EPA, 2010).

[2] These districts include the Los Angeles region, the San Francisco Bay region, San Diego, the San Joaquin Valley, and one other focused on more rural areas (CARBa, 2009).

culate matter, carbon monoxide, nitrogen oxide, sulfur dioxide, and lead were more restrictive than Federal requirements (CARBb, 2009).

The ARB and local air quality districts operate under a governmental structure that includes state-level executive, legislative (bicameral, Senate and Assembly), and judicial branches, with 58 counties governed by boards of supervisors that serves both legislative and executive roles (LWV, 2010). However, much of the rule making and enforcement of environmental standards is done through the ARB and local air quality districts. A very simplified conceptualization is provided in Figure 1 (see Appendix).

2. Data

2.1. Air quality data. The primary ambient air quality data used in the analysis comes from the California Air Quality Data DVD/CD published by the ARB Air Quality Data Branch, Air Quality and Statistical Studies Section (CARBb, 2009). This dataset includes information on a number of pollutants and pollutant measures, including criteria pollutants carbon monoxide (CO), nitrogen oxide (NO_2), sulfur dioxide (SO_2), ozone (O_3), and particulate matter (PM10, PM2.5, and PMFINE), for hourly and daily values and annual summaries from 1980-2007 at each monitoring site throughout the state. Annual summary data for sites, counties, and air basins typically includes maximum site values in the geographical unit over some time period (1 or 8 hrs), expected peak day concentrations (EPDC), which are calculated as the concentration expected to be exceeded once per year, on average, at the site in the geographic area with the maximum value, and designation values, which are the highest concentration values at any site in a geographic region over a three year period, excluding extreme concentration events (CARBb, 2009). This latter value is used in making state area designations in terms of attainment of a standard. Definitions of the air quality variables used in this study, as well as summary statistics, are provided in Table 1 (see Appendix).

While much of the county level data is straightforward, there are a few counties that lie within multiple California air basins. Specifically, El Dorado county spans the Lake Tahoe and Mountain air basins, Placer County lies in these plus the Sacramento Valley basins, while portions of San Bernardino and Los Angeles counties lie in the Mojave Desert and South Coast basins. Kern County spans the San Joaquin and Mojave Desert basins, and Riverside lies in South Cost, Salton Sea, and Mojave basins. Finally, Solano County spans the San Francisco Bay and Sacramento Valley air basins, while Sonoma lies in San Francisco and North Coast basins. In these cases, the ARB county pollution data is reported for each subsection of the county lying in each basin. In the absence of sub-county level political and economic data, we treat each of these regions as a separate geographical entity, with the political and economic data for each sub-county region matching the county.

Preliminary exploration of the relevant (1992-2006) county-level data through panel regression of each potential dependent pollutant measure against time suggests that pollution measures have almost always declined over time, with the exception of maximum 24 hour average concentrations PM10 (which have increased at an average rate of just under 16 ug/m^3/year). Other measures of PM10, however, have tended to decline.

2.2. Political data. Political affiliation data by county from 1992 through 2006 were collected from the CA Secretary of State's office (http://www.sos.ca.gov), and includes registration data by party for each even-numbered election year in this time period, plus data for the 2003 governor recall election. From this raw registration data, variables were created that describe the share of registered voters by county in each of three categories: Democratic and Green party members, Republican party members, and a catch-all "Other" category. While some may quarrel with this grouping, it seems apparent in American political discourse that the Democratic and Green parties are perceived as generally "pro-environment", while the Republican party is generally perceived as less interested in so-called "green". Furthermore, the "Other" category appears to be a collection of parties somewhat outside of the political mainstream, with shares of the registered electorate averaging just below 17%[1]. Mainstream party share data was linearly interpolated for off-years[2]. Summary statistics are provided in Table 2 (see Appendix).

An analysis of the broad trends of political affiliation over time by California county for the data used in this analysis showed that Democratic/Green affiliation declined over time (-0.0067 percentage points per year), with almost all of this decline attributable to the shift to non-mainstream parties (estimated share increases of 0.0069 percentage points per year). By contrast, Republican affiliation as a share

[1] The largest shares occur in San Francisco county, with values between 31-34% between 2002-2006. The smallest occurred in San Joaquin county in the early 1990's, with values just under 10%.

[2] In addition, data for Del Norte and Colusa counties did not include registration numbers for Democratic, Green, or Republican voters for 1992, and thus 1992 and 1993 years for these counties were omitted from the analysis.

of total registered voters remained relatively constant (a non-significant coefficient on the time dimension in a panel regression of Republican share against year).

Given that the ARB was authorized by the state legislature and reports (through the CAL/EPA Office of the Secretary) to the Governor, we include data (from the CA Secretary of State) on the democratic shares of the CA Assembly and CA Senate and the party of the governor to control for these influences on environmental outcomes. Summary statistics for these variables are also provided in Table 2.

2.3. Socio-economic data. As the Bureau of Economic Analysis (BEA) personal income and component data is "the only comprehensive annual measure of economic activity available for counties", we use the aggregate personal income per capita historical data (adjusted for inflation) as a proxy for economic activity (BEA, 2009). As shown in Table 2, mean per-capita income in the sample is \$31,855 in 2006 dollars, with real per-capita income increases of approximately \$560 per year from 1992 to 2006.

3. Methods

Pollution outcomes by county-level cluster and year are modeled using panel data that includes political proxy variables for environmental preferences of the local populace, as well as controlling for state-level legislative and executive branch composition. As implied by McKitrick (2006), if demand-side environmental preferences are correlated with Democratic or Green party registration and are appropriately expressed in the regulatory regime, or if supply-side enforcement or legislation related to environmental measures increases with a more liberal government (represented by these same parties) irrespective of these demand-side preferences, then one would expect to be able to indentify a structural relationship between pollution measures and the political variables. Here, we describe the models used to test these hypotheses.

As described above, the data spans up to fourteen years and sixty-two county or sub-county regions, depending on the pollutant. However, given the regulatory structure of the state, most enforcement (and legislation) related to air pollution takes place at the state or local level, and the political structure of the former is invariant across (sub)counties. As such, we pursue two identification strategies for the marginal effect of a change of these cross-sectional invariant variables.

The first strategy follows the two-stage procedure of McKitrick (2006), in which the structural pollution model includes time fixed effects in the first stage, followed by regression of the estimated time fixed effects coefficients on the cross-sectional invariant factors. More formally, we define the first stage model as

$$y_{it} = \alpha_i + \boldsymbol{x}'_{it}\boldsymbol{\beta} + \sum_{s=2}^{T}\gamma_s\delta_s + \varepsilon_{it}, \tag{1}$$

where y_{it} is pollution measure for (sub)county i in year t, $\boldsymbol{x}_{it}$ is an 1x4 vector of regressors including linear and squared county-level per captia income (to control for levels of economic activity by county) and the two political preference variables, $\boldsymbol{\beta}$ is a 4x1 vector of parameter estimates, α_i are county-specific individual effects (accounting for all factors that vary by county but not over time), δ_t is an indicator variable equaling one if $s = t$ and zero otherwise, with corresponding parameter estimates γ_s, and ε_{it} is a mean-zero error term (possibly exhibiting serial correlation and heteroskedasticity). This specification controls for all (unobservable) time-varying only effects, which is conceptually appealing as the only potential misspecification is the exclusion of a relevant cross-sectionally, time-varying regressor.

The second stage model is defined as

$$\hat{\gamma}_t = a + bt + \boldsymbol{z}'_t\boldsymbol{\varphi} + e_t,\ t = 2\ldots T, \tag{2}$$

where $\hat{\gamma}_t$ are coefficient estimates from the first stage, $\boldsymbol{z}_t$ is a 1x3 vector of cross-section invariant political variables, including the lagged democratic shares of the CA Assembly and CA Senate and the party of the governor in year t, t is a time trend to account for unobserved influences over pollution outcomes over time, and a, b, and $\boldsymbol{\varphi}$ are parameters to be estimated[1]. The primary problem with this specification, given the data, is the limited number of observations that results from only 14 years of data, resulting in low degrees of freedom and relatively large standard errors on the coefficients.

The second identification strategy trades the flexibility of time-specific fixed effects for increased observational information by including the time trend and county-invariant regressors from (2) directly into (1); namely,

$$y_{it} = \alpha_i + \boldsymbol{x}'_{it}\boldsymbol{\beta} + bt + \boldsymbol{z}'_t\boldsymbol{\varphi} + \varepsilon_{it}. \tag{3}$$

[1] The time trend was excluded from the first stage regressions in order to maximize degrees of freedom in the second stage; however, inclusion in the first stage and exclusion in the second yield similar results.

The cost of this decision is the possibility of misspecification if the pure time effect is non-linear, potentially inducing an endogeneity problem if a non-linear cross-sectional invariant effect is correlated with ε_{it}. However, one can empirically test for linear marginal effects of time from (1).

One concern with this approach might be the potential endogeneity of the political preference variables; that is, if the aggregate share of voters' party identification is correlated with the error term in each specification. While this certainly seems possible in the case of *individual* affiliation, the multi-dimensional nature of political outcomes coupled with aggregation to the county level suggests that average county-level shares are at least weakly exogenous here. It is plausible to think that, except perhaps for a small fringe of radical environmentalists, for most people the choice of political party affiliation is driven not so much by provision of environmental quality as by provisions of other public goods and services such as employment, health, education, national security, tax policy, and attitudes towards family values, gender equality, religious beliefs, etc.

In order to facilitate model interpretation, each pollutant measure was standardized such that over the sample, the mean is zero with a variance of one (McKitrick, 2006). As such, coefficients describe the marginal effect of a one standard deviation change in the air pollution measure. Equations (1) and (3) were estimated with the fixed-effects "within" estimator, accounting for potential heteroscedasticity and serial correlation in reported standard errors using the cluster-robust variance estimates presented in Wooldridge (2002) and Arellano (2003). Equation (2) was estimated using ordinary least squares. All estimation was performed using Stata version 9.2.

4. Results and discussion

Models were estimated for various measures of criteria pollutants carbon monoxide, nitrogen oxide, sulfur dioxide, ozone, and particulate matter for each identification strategy. We report the results of the two-stage estimations for each pollutant group in the tables, followed by each one-stage model in which at least one county-invariant political variable is significant at the 5% levels. As such, the two identification strategies serve as a robustness check of the overall results. Regardless of the model estimated, the political variables enter in identical manners, and are formed through a moving average over two years to account for lags in the policy process (McKitrick, 2006). The county-varying demand side registration data involves three constructed variables for share of the electorate formally registered to a party group (Democratic/Green, Republican, and Other). For ease of interpretation and to avoid perfect collinearity between share variables, the Democratic/Green and Other groups are introduced relative to the Republican share through differencing. More formally, define

$$\begin{aligned}(D/G\% - R\%)_{it} &= demgrn_{it} - rep_{it},\\ (Oth\% - R\%)_{it} &= oth_{it} - rep_{it},\end{aligned} \tag{4}$$

where the right-hand side variables of (4) are defined in Table 2. As such, the coefficient on, say, $(D/G\% - R\%)_{it}$ can be interpreted as (one hundred times) the change in the expected pollution measure (in standard deviation units) given a one percentage point change in registration from the Republican party to the Democratic party, keeping the share of the "Other" category constant.

For state-level Assembly, Senate, and Governor data, only Republican and Democratic shares are relevant over the time period. As such, the Republican share (or holding of the office in the case of the Governor) is treated as the base category. Share data is used as opposed to working majorities due to the fact that California as a whole has been Democratically dominated in terms of control of the State legislature.

Given these definitions, the hypotheses being tested are that (a) the sign on variables defined in (4) and on the California Assembly, Senate, and Governor variables are significantly different from zero; and (b) increases in Democratic or Democratic/Green shares decrease predicted pollution outcomes (i.e., the signs on these coefficients are negative).

4.1. Two-stage estimation results. *4.1.1. Carbon Monoxide.* Carbon monoxide (CO) is a colorless, odorless Clean Air Act criteria pollutant emitted from incomplete combustion of carbon in fuels (EPA, 2010). Motor vehicles and non-road engines are the major contributor, especially in cities, though other industrial and naturally-occurring phenomena (e.g., forest fires) contribute to ambient levels (EPA, 2010). Carbon monoxide affects health through a reduction of deliverable oxygen to the body, contributing to cardiovascular and nervous system effects (EPA, 2010).

Table 3 presents the two-stage model for six measurements related to CO, including maximum 8 hour and 1 hour average concentrations (*comax8n* and *comax1hr*), 8 hour and 1 hour average expected peak day concentrations (*coepdc8h* and *coepdc1h*), and 1 and 8 hour designation values (denoted *codsgh1* and *codsgh8*, a longer run average of the maximums). As seen in the sample size (*N*) and number of cross-sectional group (*Grps*) statistics, there is fairly good coverage of this pollutant across the state and across time.

However, it appears that neither changes in the percentage of registered voters within a county nor the state-level governance variables are consistently correlated with any of the measures of CO pollution outcomes[1]. Given the seriousness of health hazards traced to CO emissions, and political sensitivity of citizens to this pollutant, it may well be that in order to avoid risking their political party support by otherwise adopting significantly different stands on control of this pollutant, the state and local government legislators and regulation makers have been continually aiming to reduce the CO emissions, regardless of their political party affiliation.

Similarly, scale of economic activity (*Inc/cap*) is also insignificant at the 5% level across all six models. While the estimated coefficients for (*Inc/cap*) and squared (*Inc/cap*) hint at a likely Environmental Kuznets Curve (EKC) relationship between per capita income and measures of CO emissions, the turning point of the curve lies well outside of the sample mean for CO. Accordingly, they suggest that the growth of economic activity, as proxied by income per capita, is quite likely to raise CO emissions level (as measured by *comax8n*) for a considerably high levels of per capita income before the direction of this effect is reversed. One interpretation of this result could be that while reduced CO is a normal environmental good, the demand for it may not be highly income elastic at the sample per capita income levels. An alternative interpretation is that residents of every county have been persistently demanding reduced levels of CO pollution so that over time all counties have nearly converged to similarly stringent CO emissions standards, irrespective of counties' differences in income per capita and political party affiliation.

On the other hand, the estimation results are consistently and strongly dominated by a significant negative time trend effect which appears to be independent of the explanatory variables that vary by county and the state level political variables. Most likely, this result reflects improvements over time in abatement technology (equipment efficiency), in monitoring and/or enforcement of the prevailing environmental regulations and standards, or increases in stringency of CO standards over time. In fact, at the national level, various motor vehicle controls (such as fuel economy standards, the use of catalytic converters, fuel technologies, etc.) have been enacted over the past thirty years, reducing CO emissions from on-road vehicles by over forty percent (EPA, 2010), and California has been experiencing this trend strongly. Current California standards for CO are 9 ppm for eight hours and 20 ppm for one hour (CARBf, 2010).

4.1.2. Nitrogen dioxide. Nitrogen dioxide (NO_2) is the primary indicator for the larger class of nitrogen oxides (NO_X), and contributes to ozone and PM, in addition to directly affecting respiratory activity in humans (EPA, 2010). It can be directly emitted or formed via chemical conversion of nitrous oxide (NO) (Kado, et al., 2007). Nitrogen dioxide concentrations can be higher near major roadways, and as such, the EPA increased the stringency of the National Ambient Air Quality Standard (NAAQS) for NO_2 in January 2010, in addition to additional monitoring and reporting requirements to account for the areas of predicted maximum concentrations (EPA, 2010). Primary sources of NO_2 in California are automobiles and power plants, with higher emitted levels on weekdays (Kado et al., 2007). Currently, the short-term one-hour average ambient air quality standard for this pollutant is .18 ppm, with annual average of .03 ppm (Kado et al., 2007).

Two-stage model results for NO_2 measures are presented in Table 4 for maximum 1-hour concentrations (*no2max1h*), annual arithmetic mean concentrations (*no2aams*), 1-hour average expected peak day concentrations (*no2epdch*), and 1-hour designation values (*no2dsgh1*). Like the CO results, none of the models indicate a significant impact for the *state-level* political variables, and there tends to be evidence of a negative time trend. However, unlike CO, there does seem to be some evidence that changes in the percentage of registered Democratic/Green voters in each county do translate into less pollution, at least in terms of the three variables related to maximum concentrations. This county-level political party effect which is in accord with common belief may derive from the facts that (a) NO_2 emission sources are more diverse than those of CO in that in addition to urban transport (motor vehicles in cities), power plants, and industry are also significant sources of NO_2 emissions; and (b) these additional sources are geographically more local and less mobile than urban transportation sources. So, both the beneficiaries from these activities (who may be more affiliated with the Republican Party) and their pollution victims (who may be more affiliated with the Democratic and Green parties) are likely to be particularly politically assertive and influential at the *local* politics level.

[1] One exception is the positive and significant coefficient on the *Other* share (*Oth% – R%*) for maximum 1-hour concentrations, which is not replicated across the other pollutant measures.

4.1.3. Sulfur dioxide. Like NO_2, sulfur dioxide (SO_2) is a criteria pollutant emitted mostly as a result of fossil fuel combustion from power plants and industrial facilities, which can cause adverse respiratory effects from short term exposure, especially among the most susceptible populations (children, the elderly, and asthmatics) (EPA, 2010). In addition, it can be emitted by mobile sources such as locomotives, ships, and off-road diesel equipment that burn high-sulfur fuel (CARBe, 2010). Currently, the 24-hour SO_2 standard statewide is 0.4 ppm (enacted in 1991) and the 1-hour SO_2 standard is .25 ppm, originally adopted in 1984, which are considerably more strict than the 1959 values (CARBe, 2010).

Table 4 presents two-stage model results for maximum concentrations, arithmetic means, and EPDCs of sulfur dioxide, including all of the time dummies that were significant at the 5% level (insignificant coefficients on time dummies are noted with "— "). The dummies are for the fixed time effects by year and allow for a non-linear trend, as the marginal effect of time from year to year can change.

Unlike the previous two pollutants, there is only a weak time trend statistically identifiable for expected peak day concentrations, though it should be noted that coverage of this pollutant is scarcer both spatially and temporally. The only political relationship that can be detected is a negative one between share of Democratic/Green voters and 1 hour EPDC, which is negative, though the corresponding 8 hour EPDC has a weak correlation with this same political variable (significance slightly greater than 10%). Interestingly, the share of Democrats in the State Assembly exhibits a positive correlation with 24-hour maximum concentrations, and there is a weak relationship between this variable and hourly maximum concentration too. The intuition for the negative relationship between the share of Democratic + Green voters at the county level and the EPDC measures of SO_2 ambient concentration is similar to that mentioned above for NO_2: it may reflect the facts that the major SO_2 emissions are point-sources (power plants and industrial facilities), the emissions and their impacts are spatially more spread than those of CO, and the associated adverse health effects are less immediately visible, thus making the regulation and control of SO_2 emissions more open to political party affiliation bias in accord with the common belief. Furthermore, the result that the emission-reducing effect of the time-trend variable is not as strong as for CO and NO_2, may also partly reflect the relatively stronger political party contest over SO_2 emissions control, and the sluggish strengthening of SO_2 emissions standards observed over the sample period.

Perhaps related to this observation is the counter-to-common belief result that an increase in the share of Democrats in the State Assembly is likely to *increase* the daily and hourly maximum SO_2 concentration. One possible explanation could be a difference in the effect of political party affiliation at the *local* decision making where regulatory making, implementation and enforcement decisions are made versus the effect at the *state* legislation making level. As Miller (2002) notes, in the United States, "For a variety of reasons, most of the significant environmental policy is made at the regulatory level rather than at the legislative level (p. 51)." Whether for SO_2 ambient standards setting this differential political party effect has been so strong to explain our counter intuitive result at the State Assembly level is subject to speculation. Whatever the explanation, the important point to note is that the popular belief that Democrats are "Green" while Republicans are "Brown" may not be necessarily valid at every policy making level, nor may it be true for every pollutant.

4.1.4. Ozone. Ozone (O_3) is a local criteria pollutant formed in the atmosphere through a chemical reaction with nitrogen oxides (NO_X) and/or carbon monoxide (CO), and volatile organic compounds (VOCs), occurring during daylight and more readily formed on hot, sunny days (Drechsler et al., 2005). It is the primary component of smog, and often considered a "summertime" pollutant associated with urban areas (EPA, 2010). The precursor emissions originate from both point and non-point sources, including power plants and factories, motor vehicles, and consumer products such as paint (Drechsler et al., 2005). In some areas of the state, up to 50% of ozone-creating pollutants are from point sources (CARBg, 2010). Exposure to ozone can affect lung function and respiratory function, and has also been shown to adversely affect crops, trees, and other materials (Drechsler et al., 2005). The current state-level 1-hour ozone standard in California is .09 ppm, with a relatively new (as of May 2006) 8-hour average standard of .07 ppm (Drechsler et al., 2005).

Ozone models are presented in Table 6 (see Appendix), where it is clear that both a negative time trend and political affiliations of the citizenry are correlated with pollution outcomes. For each measure (1 and 8 hour maximum concentrations and EPDC), the share of Democratic/Green voters relative to the Republican share is negative and significant, while the share of Other voters is positive and significant. No relationship is detected with the state level governance variables.

As ozone is often associated with urban environments, one might be tempted to explain this result through the concentration of Democratic voters in highly polluted urban centers (e.g., Los Angeles). However, recall that the panel nature of the estimation controls for fixed county-level effects, and thus this relationship suggests that a change in registration *within the county unit* has the tendency to result in less peak levels of ozone.

Since O_3 is a highly local pollutant, one would expect that the battle over its regulation and control to be particularly intense at the local regulatory bodies, thus the significance of the party affiliation variable found at the county level. At the same time, O_3 is a serious health hazard, with both immediate and short-term adverse health effects. As such, at the state legislation level, the elected representatives from both parties would be sensitive to the health hazards of this pollutant and avoid a political party divide when it comes to legislating environmental statures that reduce the risks to their constituents' health.

4.1.5. Particulate matter. Particulate matter (PM) is a form of pollution consisting of small particles directly emitted from a variety of sources and indirectly formed through chemical processes in the atmosphere. Direct sources of PM include vehicles, power plants and refineries, burning of vegetative material, construction, tillage, and natural sources, while secondary particulates can be formed from reactions of NO_x and ammonia and sulfur dioxide and ammonia (BAAAMD, 2008). PM is measured and regulated in two sizes, PM10 and PM2.5, with the latter measuring smaller particles of 2.5 micron or less (CARBc, 2010). PM has been linked to increased incidence of "respiratory disease, lung damage, cancer, and increased mortality", and generally reduces visibility where present in significant concentrations (CARBc, 2010). California standards are more strict than those of the Federal EPA, with annual averages of 20 $\mu g/m^3$ and 12 $\mu g/m^3$ for PM10 and PM2.5, respectively and a 24-hour average standard of 50 $\mu g/m^3$ for PM10 (CARBd, 2010). As of June 2005, only Lake County and Siskiyou County air districts met the PM10 standards, and all fourteen air basins were in non-compliance of the 24-hour standard (Velasco et al., 2005). Most air basins were designated as nonattainment regions for the PM2.5 standards as well (Velasco et al., 2005).

Given the variety of sources of PM, regulation across the state currently takes many forms, including both point and non-point source regulations. These regulations include vehicle emission inspections (the Motor Vehicle Emission Control Program), bans on burning vegetative material, and nearly one hundred other measures that could be implemented by air quality management districts in accordance with Senate Bill 656 (BS 656), passed in 2003 (for more information regarding potential control measures, see http://www.arb.ca.gov/pm/pmmeasures/pmmeasures.htm).

Particulate matter models are presented in Table 7 for PM10 and Table 8 (see Appendix) for smaller particulate matter measures. The explanatory power of the PM10 models is low, and neither a time trend nor political relationships appear to be significant. The smaller particle models of Table 8 tell a similar story, save for the 3-year annual average concentration of PM2.5, in which a negative time trend is coupled with positive and significant relationships between Democratic share of the State Assembly, Senate, and Governor's office. Notice, however, that this model is only estimated using seven observations due to data limitations, and is thus suspect due to low power, but is included here for completeness.

Taking the estimation results reported in Table 7 and Table 8 at their face value, the lack of a statistically significant relationship between any of the PM10 emission measures and the explanatory variables seems puzzling. This is so because, given that PM10 is a local pollution, highly hazardous to health (at least in the medium to long run) and emitted from diverse industrial and agricultural sources, one would have expected that its regulation and control to be subject to political contest, at least at the local regulatory design and implementation level. However, the facts that since 2003 more than one hundred regulations of one form or the other had been passed at the State level to control this pollutant and yet by 2005 almost all air basins were in non-compliance suggest that at the State level there may have been a *bipartisan* sentiment to legislate regulations but that there has been a failure at the local level to effectively implement and enforce the regulations. In short, the air quality standards for this pollutant seem to have been set with no significant political affiliation bias at the State level, but the standards themselves have been rather stagnant over the data period and ineffectively implemented at the local level.

4.2. One-stage estimation results. The estimation results for the one-stage model are presented in Table 9 (see Appendix). Over all, these results are in accord with those reported for the two-stage models in that they are generally mixed and suggest only a weak statistical support for the effect of political party affiliation on air quality indicators as commonly believed. For example, it is seen from Table 9 that only for one of the PM 2.5 measures (PM25aoq) there is a consistent statistical support for the hypothesis that an increase in the Democratic party affiliation of decision makers (whether at the county level or the State assembly, senate and governor level) is associated with a lower level of air pollution.

Table 10 provides an aggregation of the empirical evidence compiled in this study. In short, for the air quality indicators studied here, the results are mixed and in some cases counter to popular belief. For example, while for the ozone concentration measures *ozepdc1h* and *ozepdc8h* we find the expected (negative) relationships for the Democratic party affiliation variables at the *county* level and the state *assembly* level, the relationship found for the State Governor variable is opposite of what is commonly thought. On the other hand, there is no significant party affiliation effect at the county level for CO, NO, SO, and almost any of the PM measures and yet at the state *Senate* level there are significant party effects in the expected direction for these air pollutants. Nevertheless, the standard interpretation of a pure monotonic relationship between political identification and environmental outcomes is not supported by the evidence compiled in this study. There are likely many competing hypotheses as to why this might be the case, and we have offered some preliminary explanations. Future research is needed, however, to more fully uncover the complex behavioral, regulatory, and physical processes at work in translating preferences for environmental public goods into environmental outcomes.

Conclusions

We have examined the likely effect of political party affiliations of environmental decision makers on environmental quality outcomes. Specifically, for California air quality, we have subjected the popular belief that Democrats are "green" while Republicans are "brown" to empirical scrutiny. We have used panel data for several air pollutants at the county level and for political party affiliations of the regulatory and legislative bodies both at the local level (air resources districts/counties) and the state (assembly, senate, and the governor) level. Controlling for the effects of economic activity level and explanatory variables that may exogenously change over time, we have employed two alternative (one-sage and two-stage) estimation strategies to identify the likely effect of political ideology variables on various emission measures of CO, NO_2, SO_2, O_3, PM10, and PM2.5. As qualitatively summarized in Table 10 (see Appendix), the results from our two alternative estimation strategies are largely consistent, thus adding to the internal validity of the conclusions. That is, similar to McKitrick (2006) – though at different level of analysis and for a different country – we generally do *not* find strong and consistent empirical support for the popular belief. Rather, both our one-stage and two-stage models generate mixed estimation results, suggesting that (1) the political party effect on air quality outcomes is likely to differ for different pollutants depending on sources of a pollutant emissions, seriousness of its health hazards, and the spatial dimension of its impacts, and (2) whereas for some of the pollutants (O_3 and NO_2) a statistically significant effect exists in support of the popular belief at the *local* (county/district) regulatory and enforcement level, at the *state* legislation level, such an effect is mostly absent, or in a very few cases where it exists it is too weak to be conclusive, or is even counter to what is commonly believed.

That at the state legislation level we do not find the expected political ideology effect may come as a surprise, at least at first sight. This is because legislators are elected representatives of their constituents, serve for a rather short-tem, and are subject to reelection. As such, they are directly responsible to reflect their constituents' environmental preferences. In contrast, at the local level, the regulators are administrative personnel with more or less tenured positions and hence are likely to be less subject to external pressures from special interests and advocacy groups (Miller, 2002). So, one might have expected the political party affiliation effect to be more pronounced at the state legislation level than at the local regulatory and implementation level.

However, this argument should be balanced with the fact that legislators are responsible for making environmental *laws*, which are mostly bipartisan because of many political compromises and policy priorities and trade-offs which are involved at the state legislative level. On the other hand, the pollution *outcomes* (as opposed to environmental legislations) are likely to be more influenced by local regulators who are actually in charge of formulating the standards and specifying ways of compliance with them in order to achieve the policy objectives of environmental laws.

One possible explanation for not finding a significant relationship between the political party affiliations and air pollution outcomes could be the fact that barely does a single political party affiliation dominate at all (local and state) levels of decision making for a long time period. So that, even if one were to assume a significant effect to exist at each and every level of decision making, the *net* effect on emissions *outcomes* could be expected to be weak or insignificant. Another reason for lack of a significant effect could relate to California's specific socioeconomic features. That is, the county average income per capita, the average education and environmental awareness, and the degree of openness of political institutions have risen to such high levels in California that they have raised the constituents' demands for higher air quality standards irrespective of their political party affiliations. A third, more technical, reason for lack of a consistent effect might be due to statistical limitations; that is, the available data is not sufficient to uncover the effect implied by the conventional wisdom. Finally, it may be that the prevailing popular belief that Democrats are "green" and Republicans are "brown" is, in fact, mistaken when it comes to public-good related local environmental outcomes. Whatever the reasons for the lack of empirical evidence, our findings ought to be treated with due caution and should *not* be extended to (a) other states or to national level, (b) global air pollutants such as greenhouse gases (especially CO_2 emissions) about which there appears to be a significant and growing partisan divide in the United States, and (c) other environmental pollutants, such as water or soil pollutants. Whether our findings for California can extend to these cases is a question for future research.

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Appendix

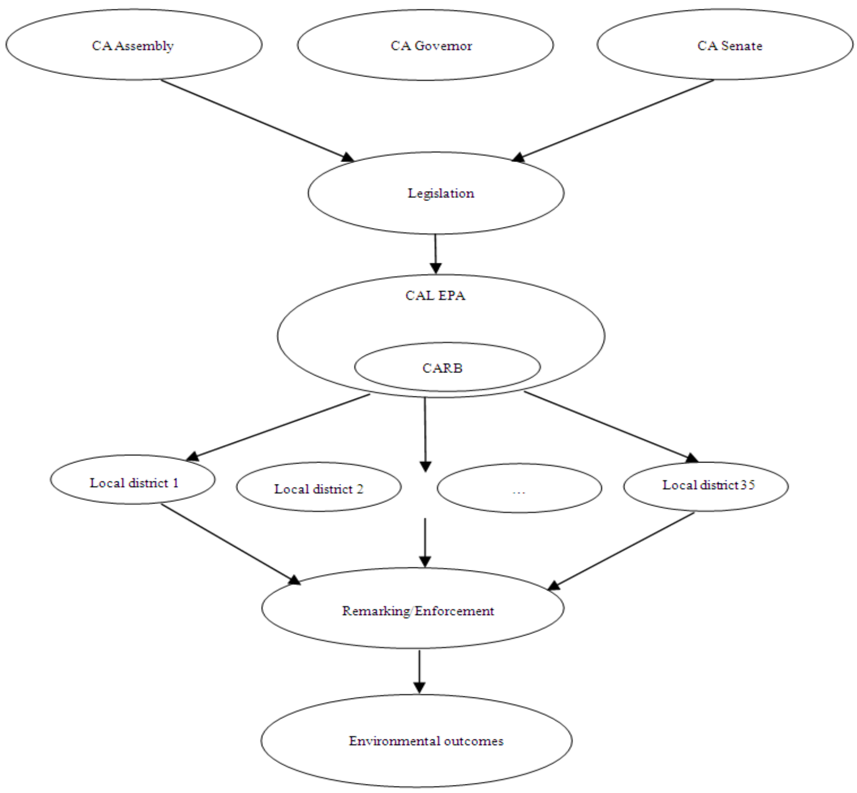

Fig. 1. Conceptualization of the environmental governance structure of the state of California

Table 1. Pollutant measures used as dependent variables

Variable	Definition	# obs	Mean	Std. dev.
comax8n	max 8-hr CO, ppm	601	4.061	2.972
comax1hr	max 1-hr average CO, ppm	601	6.671	4.316
coepdc8h	EPDC 8 hr avg CO, 3 yr pd, ppm	589	4.401	3.093
coepdc1h	EPDC 1 hr avg CO, 3 yr pd, ppm	589	7.111	4.655
codsgh1	Designation value CO, 1 hr avg, ppm	601	7.050	4.647
codsgh8	Designation value CO, 8 hr avg, ppm	601	4.284	3.081
no2max1h	max 1-hr average NO_2, ppm	577	0.0919	0.0454
no2aams	annual arithmetric mean NO_2, ppm	519	0.0181	0.0080
no2epdch	EPDC 1 hr avg, 3 yr pd NO_2, ppm	570	0.0910	0.0396
no2dsgh1	Designation value, 1 hr avg NO_2, ppm	577	0.0907	0.0427
ozmax1hr	max 1-hr average ozone, ppm	870	0.1196	0.0355
ozmx8st	max 8-hr avg ozone, ppm	870	0.0979	0.0255
ozepdc1h	EPDC 1 hr avg, 3 yr pd ozone, ppm	866	0.1167	0.0330
ozepdc8h	EPDC 8 hr avg, 3 yr pd ozone, ppm	866	0.1009	0.0258
so2max1h	max 1-hr average SO_2, ppm	244	0.0466	0.0574
so2mx24s	max 24 hr SO2, ppm	244	0.0109	0.0085
so2aam	annual arithmetric mean SO_2, ppm	244	0.0020	0.0013
so2epdch	EPDC 1 hr avg, 3 yr pd SO_2, ppm	238	0.0346	0.0325
so2epdcd	EPDC 8 hr avg, 3 yr pd SO_2, ppm	238	0.0110	0.0069
pm10mx24	max 24 hr PM10, ug/m3	839	192.85	875.53
pm10anxs	annual avg PM10, ug/m3	663	31.19	16.04
pm10x3ys	max annual average PM10, 3 yrs, ug/m3	757	34.12	18.45
pm10aoq	avg quarterly means PM10, ug/m3	855	30.64	15.91
pm25mx24	max 24-hr avg PM2.5, ug/m3	389	57.18	32.84
pm25aoq	avg quarterly means PM2.5, ug/m3	293	13.04	5.48
pm25mas	annual avg PM2.5, ug/m3	212	12.44	4.87
pm25ma3s	annual avg, 3 yr avg PM2.5, ug/m3	276	13.27	5.20
pmfmx24	max 24 hr PMFINE, ug/m3	111	62.05	23.89
pmfaoq	avg quarterly means PMFINE, ug/m3	106	16.56	5.70

Source: California Air Quality Data database, California Air Resources Board (CARBb, 2009).

Table 2. Party share, county-level income, and county invariant regressors

Variable	Definition	# obs	Mean	Std. dev.
demgrn[a]	Registered Democratic/Green party share by county	934	0.441	0.077
rep[a]	Registered Republican party share by county	934	0.390	0.083
other[a]	Registered Other party share by county	934	0.169	0.042
demasbly	Share of Democrats in State Assembly	15	0.58	0.05
rasbly	Share of Republicans in State Assembly	15	0.42	0.05
dsen	Share of Democrats in State Senate	15	0.60	0.03
rsen	Share of Republicans in State Senate	15	0.40	0.03
gover	Party of governor (1 = Democratic)	15	0.33	0.49
pcinc	Per capita income by county (real $)	934	31855	9822

Source: CA Secretary of State and Bureau of Economic Analysis. [a] Interpolated data for non-election years.

Table 3. Two-stage carbon monoxide (CO) models

First stage regression						
	comax8n	*comax1hr*	*coepdc8h*	*coepdc1h*	*codsgh1*	*codsgh8*
D/G% – R%	-4.356	-5.200	-4.029	-5.333	-4.858	-4.048
	(2.94)	(3.11)	(2.86)	(3.26)	(3.36)	(3.06)
Oth% – R%	2.551	4.077**	2.819	3.447	3.002	2.465
	(2.10)	(1.80)	(2.17)	(2.32)	(2.32)	(2.23)
Inc/cap	0.085*	0.084	0.033	0.046	0.073	0.049
	(0.05)	(0.07)	(0.05)	(0.06)	(0.06)	(0.05)
(*Inc/cap*)^2	-0.000	-0.001	-0.000	-0.000	-0.000	-0.000

Table 3 (cont.). Two-stage carbon monoxide (CO) models

First stage regression						
	comax8n	*comax1hr*	*coepdc8h*	*coepdc1h*	*codsgh1*	*codsgh8*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
N	556	556	549	549	556	556
Grps	46	46	44	44	46	46
Avg Grp *N*	12.1	12.1	12.5	12.5	12.1	12.1
Within *R*-Sq	0.505	0.504	0.619	0.656	0.630	0.565
Second stage regression						
Year	-0.153***	-0.130***	-0.133***	-0.140***	-0.142***	-0.138***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
Asbly % (D)	0.018	-0.311	1.124	0.239	0.008	0.686
	(1.02)	(1.47)	(0.75)	(0.86)	(0.92)	(1.04)
Sen % (D)	-2.507	-7.987	-4.231	-4.879	-4.685	-3.542
	(3.11)	(4.49)	(2.28)	(2.63)	(2.81)	(3.16)
Gov (D)	0.024	0.095	0.009	0.041	-0.001	0.002
	(0.08)	(0.11)	(0.06)	(0.07)	(0.07)	(0.08)
N	13	13	13	13	13	13
R-Sq	0.995	0.992	0.997	0.997	0.996	0.994

Notes: Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All time dummy variables (not shown) significant at the 5% level, except *comax1hr* for Dum 2005.

Table 4. Two-stage nitrogen dioxide (NO_2) models

First stage regression				
	no2max1h	*no2aams*	*no2epdch*	*no2dsgh1*
D/G% – R%	-4.008*	-1.529	-4.296**	-5.722**
	(2.07)	(1.42)	(1.71)	(2.37)
Oth% – R%	1.640	0.498	1.018	1.277
	(1.50)	(1.09)	(1.32)	(1.50)
Inc/cap	0.049	-0.021	0.034	0.093
	(0.04)	(0.03)	(0.05)	(0.06)
(*Inc/cap*)^2	-0.000	0.000	-0.000	-0.000
	(0.00)	(0.00)	(0.00)	(0.00)
N	542	489	536	542
Grps	43	40	41	43
Avg Grp *N*	12.6	12.2	13.1	12.6
Within *R*-Sq	0.291	0.520	0.470	0.401
Second stage regression				
Year	-0.118*	-0.042*	-0.118**	-0.137***
	(0.05)	(0.02)	(0.04)	(0.03)
Asbly % (*D*)	0.036	0.111	1.468	1.449
	(2.40)	(0.99)	(1.66)	(1.36)
Sen % (*D*)	-1.664	-4.341	-2.557	-3.175
	(7.31)	(3.01)	(5.05)	(4.14)
Gov (*D*)	0.187	0.115	-0.037	-0.050
	(0.18)	(0.07)	(0.12)	(0.10)
N	13	13	13	13
R-Sq	0.950	0.974	0.975	0.988

Notes: Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All time dummy variables (not shown) significant at the 5% level, except Dum 2004 for *no2aams* and Dum 2005 for n*o2max1h* and *no2aams*.

Table 5. Two-stage sulfur dioxide (SO_2) models

First stage regression					
	so2max1h	*so2mx24s*	*so2aam*	*so2epdch*	*so2epdcd*
D/G% – R%	-0.688	-1.643	-8.059	-5.144**	-6.745
	(2.90)	(2.74)	(4.93)	(1.89)	(4.12)

Table 5 (cont.). Two-stage sulfur dioxide (SO_2) models

First stage regression					
	so2max1h	*so2mx24s*	*so2aam*	*so2epdch*	*so2epdcd*
Oth% – R%	0.184	-1.746	3.372	-4.874	-4.871
	(4.17)	(4.85)	(3.57)	(3.11)	(4.57)
Inc/cap	-0.319**	-0.111	0.147	-0.052	0.088
	(0.14)	(0.10)	(0.22)	(0.11)	(0.12)
(*Inc/cap*)^2	0.003**	0.001	-0.001	0.001	-0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Dum 1995	--	--	2.104**	--	--
			(0.97)		
Dum 1998	--	--	1.394**	--	--
			(0.57)		
Dum 1999	--	--	1.429***	--	--
			(0.46)		
Dum 2000	--	--	1.205***	--	--
			(0.39)		
Dum 2001	--	--	0.998**	--	--
			(0.39)		
N	227	227	227	222	222
Grps	20	20	20	19	19
Avg Grp *N*	11.4	11.4	11.4	11.7	11.7
Within *R*-Sq	0.158	0.145	0.185	0.260	0.256
Second stage regression					
Year	-0.075	-0.073	0.025	-0.044**	-0.061*
	(0.06)	(0.05)	(0.09)	(0.02)	(0.03)
Asbly % (*D*)	4.156	6.801**	0.091	1.234	2.261
	(2.68)	(2.13)	(3.87)	(0.82)	(1.35)
Sen % (*D*)	5.843	-2.486	-20.799	4.196	-2.012
	(8.16)	(6.50)	(11.80)	(2.51)	(4.11)
Gov (*D*)	0.064	-0.051	-0.119	0.008	0.052
	(0.20)	(0.16)	(0.29)	(0.06)	(0.10)
N	13	13	13	13	13
R-Sq	0.587	0.805	0.906	0.575	0.924

Notes: Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Only time dummies significant at 5% shown.

Table 6. Two-stage ozone (oz) models

First stage regression				
	ozmax1hr	*ozmx8st*	*ozepdc1h*	*ozepdc8h*
D/G% – R%	-6.194***	-4.508***	-5.635***	-4.155***
	(1.63)	(1.26)	(1.46)	(1.29)
Oth% – R%	3.228**	2.509**	2.639**	2.247*
	(1.34)	(1.07)	(1.23)	(1.24)
Inc/cap	0.052	0.012	0.040	0.033
	(0.03)	(0.03)	(0.03)	(0.03)
(*Inc/cap*)^2	-0.000	0.000	-0.000	-0.000
	(0.00)	(0.00)	(0.00)	(0.00)
N	811	811	809	809
Grps	62	62	61	61
Avg Grp *N*	13.1	13.1	13.3	13.3
Within *R*-Sq	0.315	0.279	0.385	0.306
Second stage regression				
Year	-0.185**	-0.139**	-0.116***	-0.105***
	(0.06)	(0.06)	(0.03)	(0.03)
Asbly % (*D*)	-3.878	-3.932	1.114	1.224
	(2.62)	(2.69)	(1.20)	(1.20)
Sen % (*D*)	8.350	7.580	-2.503	-0.434

Table 6 (cont.). Two-stage ozone (oz) models

First stage regression				
	ozmax1hr	*ozmx8st*	*ozepdc1h*	*ozepdc8h*
	(7.99)	(8.19)	(3.66)	(3.65)
Gov (*D*)	0.381*	0.370	0.003	0.016
	(0.20)	(0.20)	(0.09)	(0.09)
N	13	13	13	13
R-Sq	0.956	0.919	0.987	0.978

Notes: Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All time dummy variables (not shown) significant at the 5% level, except Dum 2004 for *ozmax1hr* and *ozmx8st*.

Table 7. Two-stage particulate matter 10 (PM10) models

First stage regression				
	pm10mx24	*pm10anxs*	*pm10x3ys*	*pm10aoq*
D/G% – R%	1.783	0.351	2.019	1.968
	(1.42)	(1.08)	(1.31)	(1.35)
Oth% – R%	1.288	1.623	0.839	1.072
	(1.68)	(1.34)	(1.25)	(1.13)
Inc/cap	-0.028	-0.103	-0.035	0.059
	(0.09)	(0.07)	(0.05)	(0.09)
(*Inc/cap*)^2	-0.000	0.001	0.000	-0.001
	(0.00)	(0.00)	(0.00)	(0.00)
Dum 2000	--	--	0.239**	--
			(0.12)	
Dum 2001	--	--	0.254**	--
			(0.11)	
Dum 2002	--	0.272***	0.225**	0.251***
		(0.10)	(0.10)	(0.09)
Dum 2003	--	--	0.178**	--
			(0.07)	
Dum 2004	--	--	0.210**	--
			(0.09)	
Dum 2005	--	-0.260***	0.025	-0.247***
		(0.09)	(0.06)	(0.07)
N	782	628	716	798
Grps	64	59	59	64
Avg Grp *N*	12.2	10.6	12.1	12.5
Within *R*-Sq	0.040	0.095	0.075	0.105
Second stage regression				
Year	0.043	0.036	0.042	-0.018
	(0.05)	(0.05)	(0.06)	(0.05)
Asbly % (*D*)	0.328	-0.086	0.988	-1.918
	(2.15)	(2.03)	(2.58)	(2.17)
Sen % (*D*)	-1.682	-4.359	-4.054	1.253
	(6.56)	(6.19)	(7.88)	(6.61)
Gov (*D*)	0.143	0.297*	0.033	0.286
	(0.16)	(0.15)	(0.19)	(0.16)
N	13	13	13	13
R-Sq	0.743	0.734	0.419	0.535

Notes: Standard errorsare in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Only time dummies significant at 5% shown.

Table 8.Two-stage fine particulate matter (PM2.5 and Fine) models

First stage regression						
	pm25mx24[a]	*pm25aoq*[b]	*pm25mas*[b]	*pm25ma3s*[b]	*pmfmx24*[c]	*pmfaoq*[c]
D/G% – R%	3.087	-0.861	-0.288	2.489	11.830	-1.780
	(2.28)	(1.11)	(2.51)	(1.77)	(12.02)	(8.02)

Table 8 (cont.). Two-stage fine particulate matter (PM2.5 and Fine) models

First stage regression						
	pm25mx24[a]	*pm25aoq*[b]	*pm25mas*[b]	*pm25ma3s*[b]	*pmfmx24*[c]	*pmfaoq*[c]
Oth% – R%	2.002	2.282**	2.373	0.872	-16.500	-1.306
	(1.88)	(1.12)	(2.02)	(1.65)	(13.52)	(7.60)
Inc/cap	0.122*	-0.023	-0.023	-0.023	-0.008	0.021
	(0.07)	(0.08)	(0.07)	(0.08)	(0.13)	(0.14)
(*Inc/cap*)^2	-0.001*	0.000	-0.000	-0.000	0.001	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
N	389	293	212	276	96	91
Grps	52	46	46	46	17	16
Avg Grp *N*	7.5	6.4	4.6	6.0	5.6	5.7
Within *R*-Sq	0.092	0.630	0.516	0.364	0.359	0.443
Second stage regression						
Year	0.056	-0.184	-0.089	-0.219***	0.502	0.105
	(0.13)	(0.13)	(0.14)	(0.00)	(0.32)	(0.16)
Asbly % (*D*)	-3.457	-15.671	-13.106	4.794***	30.755	13.535
	(4.49)	(8.43)	(8.98)	(0.15)	(17.81)	(9.11)
Sen % (*D*)	-10.714	-8.204	-10.585	26.475***	-84.778	-48.169
	(16.33)	(19.38)	(20.64)	(0.35)	(48.61)	(24.87)
Gov (*D*)	0.159	-0.212	-0.080	0.297***	-0.017	-0.276
	(0.21)	(0.37)	(0.40)	(0.01)	(1.54)	(0.79)
N	8	7	7	7	6	6
R-Sq	0.805	0.969	0.946	1.000	0.961	0.981

Notes: Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Time dummies not shown. [a] Data from 1997-2005 only. [b] Data from 1998-2005 only. [c] Data from 1992-1998 only.

Table 9. One stage models, significant cross-section invariant political regressors only

	comax1hr	*no2aams*	*so2aam*	*ozmx8st*	*ozepdc1h*	*ozepdc8h*	*pm10anxs*	*pm25aoq*	*pm25mas*	*pm25ma3s*	*pmfmx24*	*pmfaoq*
D/G% – R%	-4.877	-1.104	-7.300	-4.338***	-5.124***	-3.688***	0.737	-2.050*	-1.496	1.628	14.334	-0.274
	(3.00)	(1.30)	(4.77)	(1.25)	(1.44)	(1.27)	(1.03)	(1.07)	(2.15)	(1.73)	(11.70)	(8.00)
Oth% – R%	3.871**	0.068	2.915	2.431**	2.093*	1.748	1.301	2.976***	3.210*	1.439	-19.593	-2.954
	(1.67)	(1.03)	(3.48)	(1.04)	(1.20)	(1.19)	(1.32)	(1.10)	(1.79)	(1.62)	(13.16)	(7.48)
Inc/cap	0.085	-0.008	0.193	0.024	0.056*	0.050*	-0.098	-0.032	-0.035	-0.007	0.061	0.010
	(0.06)	(0.03)	(0.20)	(0.03)	(0.03)	(0.03)	(0.07)	(0.07)	(0.06)	(0.08)	(0.13)	(0.14)
(*Inc/cap*)^2	-0.001	0.000	-0.001	-0.000	-0.000	-0.000	0.001	0.000	-0.000	-0.000	0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Year	-0.139***	-0.055***	-0.045	-0.071***	-0.117***	-0.096***	0.025	0.088***	0.125**	-0.030	0.667***	0.147
	(0.04)	(0.02)	(0.07)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.05)	(0.04)	(0.21)	(0.15)
Asbly % (*D*)	3.733**	1.085**	0.726	-0.265	-1.247*	-1.594**	2.671**	-6.800***	-4.404**	-2.247**	45.976***	26.061***
	(1.84)	(0.53)	(3.36)	(0.83)	(0.63)	(0.64)	(1.08)	(1.48)	(1.99)	(0.89)	(14.56)	(8.57)
Sen % (*D*)	-10.413**	-3.418*	-16.204**	-4.154**	-0.131	0.887	-5.746**	-34.443***	-35.454***	-0.043	-86.889**	-54.631***
	(4.61)	(1.81)	(7.12)	(1.86)	(1.64)	(1.66)	(2.47)	(4.56)	(6.61)	(4.67)	(31.95)	(16.79)
Gov (*D*)	-0.177	0.012	-0.175	-0.056	0.100***	0.135***	0.150	-0.437***	-0.479***	0.182	-4.583***	-0.116
	(0.11)	(0.04)	(0.24)	(0.06)	(0.04)	(0.04)	(0.14)	(0.09)	(0.11)	(0.11)	(1.17)	(0.72)
N	556	489	227	811	809	809	628	293	212	276	96	91
Grps	46	40	20	62	61	61	59	46	46	46	17	16
Avg Grp *N*	12.1	12.2	11.4	13.1	13.3	13.3	10.6	6.4	4.6	6.0	5.6	5.7
Within *R*-Sq	0.493	0.491	0.149	0.196	0.370	0.286	0.073	0.566	0.439	0.331	0.346	0.434

Notes: Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 10. Summary of empirical results for time trend and political variables, two stage/(one stage) evidence relative to expectations

	CO	PM10	PM2.5&Fine	SO_2	NO_2	Ozone
	(6 measures)	(4 measures)	(6 measures)	(5 measures)	(4 measures)	(4 measures)
Time trend	All yes[a]	No[c]	1 yes	2 yes	All yes	All yes

Table 10 (cont.). Summary of empirical results for time trend and political variables, two stage/(one stage) evidence relative to expectations

	CO	PM10	PM2.5&Fine	SO_2	NO_2	Ozone
	(Yes)[b]	(No)	(No)	(No)	(Yes)	(All yes)
Local level						
D/G% – R%	No	No	No	1 yes, 4 no	3 yes, 1 no	4 yes
	(No)	(No)	(No)	(No)	(No)	(3 yes)
State level						
Asbly % (D)	No	No	1 + ![d]	1 + !	No	No
	(1 + !)	(1 + !)	(2 + !, 3 yes)	(No)	(1 + !)	(1 yes)
Sen % (D)	No	No	1 +!	No	No	No
	(1 yes)	(1 yes)	(1 no, 4 yes)	(1 yes)	(1 yes)	(No)
Gov (D)	No	1 + !, 3 no	1 + !	No	No	1 + !
	(No)	(No)	(2 no, 3 yes)	(No)	(No)	(No)

Notes: [a] "Yes" denotes a significant (10%) estimated relationship in accordance with conventaional wisdom (a negative relationship). [b] First row for each variable indicates two-stage results. Second row indicates one-stage results. [c] "No" denotes no significant effect at the 10% level. [d] "+!" denotes significant effect (10%) contrary to conventional wisdom (a positive relationship).