Does Environmental Policy Affect Income Inequality? Evidence from The Clean Air Act.

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Abstract

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Introduction.

This paper quantifies the impact of environmental policy on income inequality. We focus on the Clean Air Act (CAA). Prior research on the labor market effects of the CAA is inconclusive (Berman and Bui, 2001; Morgenstern et al., 2002; Greenstone, 2003), in part, because of the multiple channels through which the CAA affects firms and workers. On the one hand, exposure to local air pollution decreases labor productivity and increases absenteeism (USEPA, 2011). So, if the CAA reduces exposure, it might boost wages or employment opportunities. On the other hand, firms must take costly actions in order to comply with stricter environmental regulation. If firms shed labor in response to policy constraints, this would adversely affect labor market outcomes. In this setting, there has been little prior research on the distribution of labor markets impacts from environmental policy.

Our empirical analysis utilizes panel variation in the stringency of environmental regulation generated by the National Ambient Air Quality Standards (NAAQS). The NAAQS, established by the Clean Air Act (CAA), are annual county-level limits on the allowable concentrations of various air pollutants. We focus on the standards associated with fine particulate matter ($PM_{2.5}$) and tropospheric ozone (O_3) because, among common air pollutants, these two species result in the largest damage (USEPA, 2011; Muller, Mendelsohn, Nordhaus, 2011). The sample period considered for this analysis is 2005-2015. We focus on two specific policy changes: the 2006 $PM_{2.5}$ NAAQS (implemented in 2009) and the 2008 NAAQS for O_3 (implemented in 2012).

Annual, county-level attainment information with each of these standards allows us to quantify the impact of environmental policy on outcomes within a difference-in-differences (DD) framework. A county is "treated" in a given year if and only if this county is designated as being in "non-attainment" with the NAAQS standard. Using this DD framework, we consider three outcome variables: pollution levels, household income, and household income adjusted for the monetary damages associated with air pollution exposure (Nordhaus and Tobin, 1973; Muller, Mendelsohn, and Nordhaus, 2011; Muller, Matthews, Wiltshire-Gordon, 2018). We find that the 2006 $PM_{2.5}$ NAAQS reduced average levels and inequality in pollution levels and damages. We report no such evidence for the 2008 O_3 NAAQS. However, our results indicate that nonattainment with both standards increased income inequality for both market and pollution-adjusted measures of income. Though there may be sizable net benefits in aggregate from air quality regulations, our findings suggest that these benefits are tempered by an exacerbation of income inequality.

II. Methods.

Our analysis draws on publicly available data from numerous sources. First, we exploit modeled estimates of the annual concentration levels of fine particulates ($PM_{2.5}$) and ozone (O_3) in each census block group (CACES, 2018). Second, we employ annual zip-code level average market income from the Internal Revenue Service's Status of Income (SOI) data (NBER, 2018). In accord with prior literature, we employ the approach in (1) to calculate the monetary cost of premature mortality risk due to exposure to $PM_{2.5}$ and O_3 (USEPA, 2011; Muller and Mendelsohn, 2009; NAS NRC, 2010):

$$D_{i,t} = VSL_t \times M_{i,a,t}\left(\frac{1}{1-exp^{\left(\beta^s P_{i,t,s}\right)}}\right) \tag{1}$$

Where: VSL_t = value of a statistical life, expressed in year (t) dollars.
$M_{i,a,t}$ = baseline mortality rate among persons of age-cohort (a) in county (i) in year (t).
$P_{i,t,s}$ = pollution level for pollutant (s) in county (i) in year (t).
β^s = statistically estimated parameter linking exposure to mortality risk for pollutant (s).

The Centers for Disease Control and Prevention provide data on annual county-level mortality rate by age group (CDC Wonder, 2018). We adopt the USEPA's VSL of $7.4 million (in 2006 dollars), adjusting this VSL for inflation using the Consumer Price Index (CPI). The statistical relationship between $PM_{2.5}$ exposure and mortality risk is taken from Krewski et al., (2009). We adopt the findings from Bell et al., (2004) for O_3. The monetary damage $D_{i,t}$ is used to calculate zip-code-level average pollution-adjusted income for each year-of-sample.

Annual, county-level designations with each of the NAAQS are provided by the United States Environmental Protection Agency (USEPA, 2018a; 2018b). Based on these designations, our difference-in-differences (DD) framework takes the familiar form specified in (2).

$$\log(Y_{i,t}) = \alpha_i + \gamma_t + \beta NA_{i,t} + \varepsilon_{i,t} \qquad (2)$$

where: $Y_{i,t}$ = outcome of interest in county (i) in year (t).
α_i= county fixed effects.
γ_t = year fixed effects.
$NA_{i,t}$= indicator that's one if and only if county (i) is out of attainment with the relevant NAAQS standard in year (t).
$\varepsilon_{i,t}$ = error term.

As outcome variables, we consider the mean and dispersion of the following variables: household income, $PM_{2.5}$ and O_3 concentration levels, and pollution-adjusted household income. Our measures of dispersion are the Gini Coefficient, the ratio of the 90th percentile to the median, and the ratio of the 90th percentile to the 10th percentile. Note that all of these outcome variables are expressed in logs in our primary specifications. We include county fixed effects and year fixed effects. Standard errors are clustered by county. Finally, our primary specifications weight by annual county-level population, taken from the Survey of Epidemiology and End Results (SEER).

III. Results.

This section presents our results pertaining to the impact of environmental policy on the mean and dispersion of pollution, market income, and augmented income. The DD framework relies on the following assumption: counties that will eventually shift into nonattainment with the standard have the same average trend in outcomes over time as counties that are always in attainment (the "common trends" assumption). We relegate the plots of these trends to Appendix Section B.

[Put Table 1 here.] Columns (1), (3), and (4) in the top panel of Table 1 indicates that nonattainment with the 2008 O_3 NAAQS results in declines in the dispersion of within-county ozone levels, though the regression coefficients are imprecisely estimated. However, noncompliance slightly increases average O_3 levels. While this may seem counterintuitive, O_3 is formed through complex non-linear processes. Thus, efforts to reduce O_3 can increase average annual O_3 levels (Seinfeld, Pandis, 1998). Further, average O_3 levels have remained roughly constant for decades (see Figure A.1 and Muller, Ruud, 2017).

The bottom panel of Table 1 indicates that the 2006 $PM_{2.5}$ NAAQS unambiguously reduced $PM_{2.5}$ levels. In nonattainment counties, the mean $PM_{2.5}$ level is 3.5 percent lower than in attainment counties ($p < 0.01$). Further, noncompliance with the 2006 NAAQS reduced the within-county inequality of $PM_{2.5}$. The Gini coefficient is 9.3 percent lower in nonattainment counties on average ($p < 0.01$). Both the 90-50 and 90-10 ratios are about 12 percent lower in counties out of attainment with the 2006 $PM_{2.5}$ NAAQS ($p < 0.01$).

Table 1 suggests that the standards did not appreciably affect average O_3 readings. Due to this, any effect on income inequality is likely through firms' compliance behavior rather than improvements in workers' health and labor productivity. In contrast, the 2006 $PM_{2.5}$ NAAQS clearly impacted both the level and distribution of $PM_{2.5}$. Income inequality may be affected both due to improvements in worker welfare and changes in firm behavior.

[Put Table 2 here.] In Table 2, we quantify the effect of NAAQS compliance status on market income. The top two panels of Table 2 focus on the 2008 O_3 NAAQS. Non-attainment with the 2008 O_3 NAAQS exacerbates inequality in market income. Specifically, the Gini coefficient is 7 percent larger in non-attainment counties ($p < 0.01$). Both the 90-10 and the 90-50 ratios are also positively affected by nonattainment status ($p < 0.01$). Table 2 indicates that compliance with the 2008 O_3 NAAQS induced a large, 18 percent, increase in mean income ($p < 0.01$). However, Appendix Figure B.3 suggests that "common trends" assumption required to interpret this coefficient estimate causally is unlikely to hold. We see a large dip in average income in nonattainment counties roughly 4-5 years before the standard kicks in. We pose the following mechanism for these results. Compliance with binding standards requires that polluting firms allocate additional resources to abatement. In doing so, they likely reduce the usage of variable inputs such as labor. This results in an increase in income inequality to the extent that firms are relatively likely to fire low-productivity, low-wage earners.

The second panel in Table 2 also includes attainment status with the prior 1997 O_3 NAAQS to assuage concerns that the marginal effect of noncompliance with the 2008 NAAQS may be affected by prior standards. The coefficients associated with the 2008 NAAQS remain largely unchanged. In addition, all of the coefficient estimates pertaining to the 1997 NAAQS controls are negative, though only the effect for the Gini coefficient is precisely estimated. The estimated effect on the Gini coefficient suggests being out of attainment with the 1997 NAAQS induces a 2.9 percent *decrease* in the Gini coefficient. This in turn suggests a nonlinearity in the effect of environmental policy on income inequality: environmental regulations are progressive up to a certain level of stringency but become regressive if these regulations are tightened further. This may manifest from rising marginal costs of abatement.

The third panel of Table 2 examines the 2006 $PM_{2.5}$ NAAQS. As with O_3, we find that noncompliance with the 2006 $PM_{2.5}$ standard exacerbates income inequality. Nonattainment increases the Gini coefficient by 5 percent ($p < 0.01$), and the 90-50, and 90-10 by between 25 and 15 percent ($p < 0.01$). We also detect a large increase in mean household income of 17 percent ($p < 0.01$). The fourth panel of Table 2 controls for compliance status with the 1997 $PM_{2.5}$ NAAQS. The coefficients on the 2006 $PM_{2.5}$ NAAQS remain robust to this additional covariate. However, the parameter estimates associated with noncompliance with the 1997 NAAQS are all negative and economically significant ($p < 0.01$). For instance, noncompliance with the 1997 NAAQS is associated with a 6 percent reduction in the Gini Index, a 12 percent reduction in mean income, a 20 percent reduction in the 90-50 ratio, and a 16 percent reduction in the 90-10 ratio (all $p < 0.01$). Appendix Table A.3 demonstrates that the 1997 $PM_{2.5}$ NAAQS significantly reduced by levels and inequality in $PM_{2.5}$ readings. As with O_3, the fourth panel of Table 2 suggests that the effect of additional environmental policy on income inequality depends on the initial level of regulatory stringency.

[Put Table 3 here.] Table 3 reports the effects of NAAQS nonattainment on the measure of income that deducts per capita pollution damage from adjusted gross income. This table reveals that for both pollutants, the effects have the same sign as for market income. The evident difference is that the effects of noncompliance on augmented income is considerably larger. For example, nonattainment status with the 2008 O_3 NAAQS is associated with a 12 percent increase to the adjusted income Gini ($p < 0.01$). (The effect on market income was 6 percent.) Similarly, noncompliance with the 2006 $PM_{2.5}$ NAAQS induces a 10 percent increase in the augmented income Gini ($p < 0.01$). The corresponding effect on market income was about 5 percent. We note, first, that pollution-adjusted income is distributed much less equally than market income because low-income households tend to be in high pollution areas and they have higher baseline mortality risks (Muller, Matthews, Wiltshire-Gordon, 2017). To the extent that policy reduces exposure and damage, it does so in cities, which tend to have higher income, on average, than rural areas. And, recall that we find the NAAQS enhance market income inequality. If damages fall mainly in cities, policies can make pollution-adjusted income inequality worse because low income households bear the brunt of adverse labor market effects without concomitant damage reductions.

This is especially likely for the O_3 NAAQS since table A.1 in the appendix reports that the O_3 NAAQS did not reduce damages. In contrast, the 2006 $PM_{2.5}$ reduced both the mean damage (down 2 percent, $p < 0.01$), and both the 90-50 and 90-10 ratios ($p < 0.01$). The worsening of inequality from the PM NAAQS suggests that labor market effects overwhelm this slight reduction and equalization in damage. Finally, while the 2008 O_3 NAAQS and the 2006 $PM_{2.5}$ NAAQS appear to have enhanced inequality in both market and augmented income, the 1997 NAAQS for both pollutants had the opposite effect. And, for the 1997 $PM_{2.5}$ NAAQs, the result of nonattainment was a large and statistically significant attenuation of income levels and inequality.

We conclude by noting that further research is required to fully explore and document the mechanisms through which large scale environmental policies may affect the distribution of income. Our results offer a provocative glimpse of the intersection between the CAA, labor markets, and human health effects. While the $PM_{2.5}$ NAAQS have attenuated pollution levels and monetary damage, both NAAQS appear to distort the distribution of economic resources in complex, and at times unfortunate, ways

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Tables.

Table 1. The Effect of NAAQS Attainment on Ambient O_3 and $PM_{2.5}$.

	(1)	(2)	(3)	(4)
O_3 2008 NAAQS	-0.003^{+}	0.023$^{***,+}$	0.025^{+}	0.032^{+}
	(0.024)	(0.007)	(0.024)	(0.024)
Number of Obs.	33,715	34,177	33,714	33,715
R^2	0.744	0.842	0.690	0.737
$PM_{2.5}$ 2006 NAAQS	-0.093$^{***,+}$	-0.035$^{***,+}$	-0.121$^{***,+}$	-0.124$^{***,+}$
	(0.020)	(0.006)	(0.022)	(0.020)
Number of Obs.	30,650	31,070	30,650	30,650
R^2	0.874	0.916	0.774	0.839

Standard errors clustered by county in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$
$^{+}$ indicates common trends, ^{x} indicates lack of common trends

Dependent variables:

1 = Log of Gini Coefficient.
2 = Log of Average Pollution.
3 = Log of the Ratio of the 90th percentile of pollution/median pollution.
4 = Log of the Ratio of the 90th percentile of pollution/ 10th percentile of pollution.

Table 2: The Effect of Non-Attainment on the Distribution of Adjusted Gross Income.

	(1)	(2)	(3)	(4)
O_3 2008	$0.068^{***,+}$	$0.192^{***,x}$	$0.284^{***,+}$	$0.230^{***,+}$
NAAQS	(0.008)	(0.015)	(0.027)	(0.022)
Number of Obs.	33,313	33,388	33,368	33,387
R^2	0.814	0.903	0.867	0.879
O_3 2008	0.064^{***}	0.191^{***}	0.282^{***}	0.230^{***}
NAAQS	(0.008)	(0.015)	(0.028)	(0.023)
O_3 1997	-0.029^{***}	-0.007	-0.015	-0.001
NAAQS	(0.008)	(0.014)	(0.020)	(0.015)
Number of Obs.	33,313	33,388	33,368	33,387
R^2	0.815	0.903	0.867	0.879
$PM_{2.5}$ 2006	$0.053^{***,+}$	$0.167^{***,+}$	$0.213^{***,+}$	$0.161^{***,+}$
NAAQS	(0.012)	(0.027)	(0.033)	(0.028)
Number of Obs.	30,296	30,358	30,339	30,357
R^2	0.810	0.893	0.853	0.867
$PM_{2.5}$ 2006	0.061^{***}	0.184^{***}	0.241^{***}	0.182^{***}
NAAQS	(0.013)	(0.029)	(0.034)	(0.029)
$PM_{2.5}$ 1997	-0.060^{***}	-0.119^{***}	-0.207^{***}	-0.156^{***}
NAAQS	(0.011)	(0.025)	(0.034)	(0.029)
Number of Obs.	30,358	30,339	30,357	30,296
R^2	0.893	0.855	0.868	0.811

Standard errors clustered by county in parentheses
*** p<0.01, ** p<0.05, * p<0.1
$^{+}$ indicates common trends, ^{x} indicates lack of common trends

Dependent variables:

1 = Log of Gini Coefficient of Income.
2 = Log of Average Income.
3 = Log of the Ratio of the 90th percentile of income/median income.
4 = Log of the Ratio of the 90th percentile of income/ 10th percentile of income.

Table 3. The Effect of Non-Attainment on the Distribution of Adjusted Gross Income Less Pollution Damage.

	(1)	(2)	(3)	(4)
O_3 2008 NAAQS	$0.127^{***,+}$	$0.198^{***,x}$	$0.323^{***,x}$	$0.304^{***,x}$
	(0.013)	(0.015)	(0.031)	(0.026)
Number of Obs.	30,447	30,447	33,147	33,154
R^2	0.836	0.871	0.846	0.859
O_3 2008 NAAQS	0.123^{***}	0.196^{***}	0.320^{***}	0.301^{***}
	(0.0139)	(0.0148)	(0.0310)	(0.0252)
O_3 1997 NAAQS	-0.030^{**}	-0.019	-0.019	-0.023
	(0.012)	(0.018)	(0.024)	(0.019)
Number of Obs.	30,447	30,447	33,147	33,154
R^2	0.836	0.871	0.846	0.859
$PM_{2.5}$ 2006 NAAQS	$0.101^{***,+}$	$0.216^{***,x}$	$0.311^{***,x}$	$0.291^{***,x}$
	(0.024)	(0.032)	(0.038)	(0.034)
Number of Obs.	27,633	27,633	30,133	30,140
R^2	0.830	0.859	0.831	0.846
$PM_{2.5}$ 2006 NAAQS	0.112***	0.237^{***}	0.344^{***}	0.323^{***}
	(0.026)	(0.034)	(0.039)	(0.035)
$PM_{2.5}$ 1997 NAAQS	-0.081^{***}	-0.158^{***}	-0.240^{***}	-0.237^{***}
	(0.019)	(0.027)	(0.044)	(0.039)
Number of Obs.	27,633	27,633	30,133	30,140
R^2	0.830	0.860	0.832	0.847

Standard errors clustered by county in parentheses
*** p<0.01, ** p<0.05, * p<0.1
$^{+}$ indicates common trends, ^{x} indicates lack of common trends

Dependent variables:

1 = Log of Gini Coefficient of Pollution-Adjusted Income.
2 = Log of the Ratio of the Mean Pollution-Adjusted Income.
3 = Log of the Ratio of the 90^{th} percentile of pollution-adjusted income/median pollution-adjusted income.
4 = Log of the Ratio of the 90^{th} percentile of pollution-adjusted income/ 10^{th} percentile of pollution-adjusted income.