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Environmental Regulation and Labor Reallocation: Evidence from the Clean Air Act

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Environmental regulations limiting emissions of harmful ambient air pollution are designed with health benefits in mind. Associated with these benefits are the costs of abating pollution. The Pollution Abatement Costs and Expenditure Survey suggests that regulations pertaining to the Clean Air Act (CAA) in the United States account for almost $5 billion in capital expenditures and $20 billion in annual operating costs within the manufacturing industry alone (United States Census Bureau 2008). As a result, manufacturers often argue that these regulations place plants and industries at a competitive disadvantage, forcing plants to downsize or close. Implicit in this argument is that environmental regulations lead to job loss associated with industry-wide reductions in output.

Accordingly, various papers have looked at the implications of environmental regulation for regulated industries, generally finding negative effects of regulations on industry employment (J. Vernon Henderson 1996; Michael Greenstone 2002). However, regulation typically affects the distribution of employment among industries rather than the economy-wide employment level (Kenneth J. Arrow et al. 1996). As a result, the appropriate measure of regulatory costs to the workforce should not be characterized by jobs lost but by any transitional costs associated with reallocating production or workers (Arrow et al. 1996; Greenstone 2002). To the extent that workers simply transition from one employer to the next without losses pertaining to job-specific human capital or unemployment, it is not clear that job loss should be a net cost when evaluating regulations. Even though this fact has been pointed out in numerous papers, little to no work has attempted to understand the magnitudes of these frictions in the context of environmental regulation.

The goal of this paper is to begin to understand the degree to which changes in regulatory stringency over time from the CAA have contributed to costly job transitions by the affected workforce. Recent work linking plant-level job flow statistics to worker-level job turnover surveys has found a strong link between plant-level job destruction and involuntary worker-level job loss (Steven Davis, Jason Faberman, and John Haltiwanger 2006), where layoffs are likely to result both in significant nonemployment spells and earnings losses (see Till von Wachter, Jae Song, and Joyce Manchester 2007 for recent evidence). Thus, the margins of adjustment at the firm level have important distributional implications for the affected workforce. To the extent that firms adjust labor demand by increasing firing rates (job destruction), decreasing hiring rates (job attrition), reducing plant entry rates, or increasing plant exit rates, workers will be more or less affected in terms of job loss and/or losses pertaining to job-specific human capital.

This is the first paper to decompose net changes in employment due to environmental regulations into job flow components, offering new insight into the distributional impacts of regulation on the affected workforce. In doing so, I draw upon the most detailed and comprehensive data available on plant-level regulatory status over time: a confidential establishment-level, longitudinal database from the United States Census Bureau that I am able to link to a plant-level regulatory database from the Environmental Protection Agency. I can explicitly observe *plant*-level regulatory status over time and observe how these plants respond to environmental regulatory changes. Previous work inferring regulatory stringency is based on two- and four-digit nationwide industry classifications.

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A further contribution is that no research has evaluated the most recent amendments and changes to the CAA on employment. Previous work estimating the costs of the CAA focuses on earlier time horizons, when pollution levels were much higher and technological constraints greater. Thus, previous estimates of the cost of regulation may no longer be applicable in today's economy. I exploit changes in regulations following the CAA Amendments of 1990, in which the Environmental Protection Agency (EPA) adopted new and more stringent pollution standards. My estimates from these most recent revisions are arguably more applicable to current policy debates, and are particularly important in light of the EPA's recent proposal to further strengthen emissions standards (Environmental Protection Agency 2010).

The results suggest that the recent strengthening of emissions standards in the early 1990s led to a persistent decline in employment in affected sectors. Sector-level models suggest that the size of the newly regulated, polluting sector fell by more than 15 percent in the ten years following the change in regulation. These changes in employment are driven primarily by an increase in the plant-level job destruction rate, suggesting that these plant-level downsizings are associated with significant worker-level adjustment costs pertaining to involuntary job loss.

I. Environmental Regulations in the United States

Air pollution regulation in the United States is coordinated under the CAA, where regulatory stringency varies at the county level. Regulations primarily affect densely populated areas where people live and work and where the potential benefits from abatement are larger. While regulation varies across counties, it also varies across seven "criteria air pollutants." Areas with high levels of a specific air pollutant are regulated only for that pollutant. The threshold for excessive pollution varies for each pollutant but is applied uniformly across the United States. In any given year, some counties find themselves over these thresholds, while others do not.

Ambient air pollution is measured by EPA pollution monitors that take hourly/daily pollution readings for various pollutants. Monitor location is not subject to manipulation by local authorities. When a county is out of attainment for one of the regulated pollutants, the EPA forces local plants that emit that pollutant to adopt "lowest achievable emission rates" (LAER) technologies without regard to costs. Furthermore, the EPA forces any new polluting plants that wish to locate in that particular county to offset their emissions from another polluting source within the county. In contrast, in areas designated as "attainment," large polluting plants must use "best available control technology" (BACT), which is significantly less costly than LAER technology (Randy Becker 2005). In summary, in nonattainment areas, firms are subject to regulations designed to reduce emissions without regards to costs; counties in attainment are more lightly regulated.

In 1990, Congress passed the CAA Amendments of 1990, which created a new criteria pollutant class for particulates, PM-10.[1] Furthermore, the EPA formally reviewed all county nonattainment designations for all criteria pollutants. As a result, 177 counties switched into nonattainment in 1991.

II. Longitudinal Plant-Level Employment and Regulatory Data

The primary source of data for this project is the Census Bureau Longitudinal Business Database (LBD), an establishment-level database that covers the universe of US establishments. Annual information on employment, payroll, and firm age, and detailed industry, location, and entry/exit years for the respective establishments are all included. I link the LBD to plant-level regulatory and permit data from the EPA, formally known as the Air Facility Subsystem (AFS), using a name and address matching algorithm.[2]

The AFS provides permit information detailing the regulatory program(s) for which the plant is regulated, as well as the specific pollutants for which the permit is issued. A limitation of the AFS is that it does not provide any information as to when these permits were issued. Fortunately, the regulatory structure of the CAA allows one to infer the timing based on county nonattainment

[1] Previously, the EPA regulated particulates in the form of Total Suspended Particulates (TSPs), which are larger and thought to be less pernicious than the smaller forms of particulates.

[2] See Reed Walker (2010) for details.

Table 1—County and Plant Characteristics in Year Prior to CAA Amendments

	Polluting sector			Nonpolluting sector		
	Attain	Nonattain	Switch	Attain	Nonattain	Switch
County employment (1990)	1,249.6	6,421.1	6,041.2	1,798.2	13,522.6	17,514.5
Plant employment (1990)	281.3	289.7	285.2	152.0	132.2	137.4
Employment growth (1985–1990)	0.408	0.280	0.333	0.199	0.107	0.170
Job creation rate (1985–1990)	0.511	0.433	0.456	0.581	0.553	0.592
Job destruction rate (1985–1990)	0.104	0.153	0.123	0.382	0.446	0.422
Plant age (1990)	9.874	10.74	10.63	8.257	8.492	8.075
Plants (1990)	8,507	9,488	3,915	38,692	59,755	34,599

Notes: Plant-level growth rates and labor reallocation rates are constructed using denitions from Davis and Haltiwanger (1992), and are described further in Section IV. Number of counties per category: attain 2,265, nonattain 392, switch 177.

status. Specifically, I define a plant as regulated if the plant has an operating permit in the AFS database and resides in a county that is in nonattainment for the specific pollutant on the permit. This is the first longitudinal, national dataset that includes plant-level regulatory status. Previous research proxied regulation by two- and four-digit SIC level national pollution estimates (Greenstone 2002; Becker 2005).

I limit the sample to establishments within the manufacturing and utility sectors.[3] I also exclude establishments with a maximum employment of fewer than 50 employees over the sample frame and any establishments with a lifespan of fewer than 3 years. Since EPA regulations primarily apply to major sources with potential to emit of more than 100 tons per year, excluding these smaller establishments has little effect on the estimates.

I create a second dataset that aggregates this plant-level micro data to the county by sector (i.e., polluting or nonpolluting) and by year for the years 1985 to 2005. This eases the computational burden and provides aggregate statistics that reflect both changes in employment for continuing plants as well as any changes pertaining to plant entry or exit.

A. *Summary Statistics*

Since the CAA is administered on a county by year basis and only polluting plants are regulated in that county-year, there is a tremendous amount of regulatory variation in the data. It is therefore instructive to understand the degree to which these sources of variation are orthogonal to plant or county observables. If there are significant differences across counties or plants pertaining to preregulatory observed differences, then the nature of these differences should motivate the choice of a proper empirical specification. Table 1 presents sample statistics by polluting and nonpolluting sectors for both county and plant samples, where each column shows the characteristics for attainment counties, nonattainment counties, and counties that switched nonattainment status in 1991. Nonattainment counties tend to be more urban and economically larger, and relying on cross-sectional variation alone might confound regulations with other sources of heterogeneity across counties. Similarly, purely relying on time-series variation in regulated plants is suspect, given that the recession in the early 1990s occurred at the same time as the CAA Amendments of 1990. Within-county comparisons between plants in the same county rely on the fact that polluting and nonpolluting plants are similar except for regulatory status. Table 1 shows that polluting plants tend to be older and larger than their counterparts, and have slower growth rates ex ante. Failing to account for these differences might lead to confounding regulation with plant age or plant vintage effects, a point not addressed in the previous literature.

Credible identification requires accounting for all these sources of observed and unobserved confounders. Fortunately, the richness of the data permit me to flexibly control for most unobserved shocks, while still being able to recover precise estimates.

[3] Specifically, one-digit and two-digit 1987 SIC code categories 2 (manufacturing), 3 (manufacturing), and 49 (electric, gas, and sanitary services). These are the most widely represented sectors in the AFS.

III. Sector-Level Dynamics

In order to understand the dynamic effects of CAA regulations on sector-level employment, I turn to a generalized triple-difference model of the form

$$(1)\quad L_{jct} = \sum_{k=-5}^{10} \beta_k (N_c \times P_j \times 1(\tau_t = k)) + \delta_{jc} + \eta_{ct} + \rho_{jt} + \gamma_t + u_{jct},$$

where L_{jct} represents the log of sector j employment in county c for year t. N_c are indicators for those counties that switched nonattainment after the 1990 CAA Amendments, P_j is a sector-level indicator for the polluting sector, and τ_t and represents years before and after the policy change. The lower-order interaction terms of a standard triple-difference estimator are implicit in the "switching county" by year fixed effects (η_{ct}), polluting sector by year fixed effects (ρ_{jt}), and the county-by-sector fixed effects (δ_{jc}). The excluded time category is $k = -1$ so that estimates are measured relative to the year before the change in policy.

The parameters of interest are the β_ks which provide an estimate of the semi-elasticity of employment with regard to changes in environmental regulations. Estimates of the β_ks are identified by *within*-sector comparisons over time for those sectors that experienced changes in regulatory stringency. This specification controls for any observed or unobserved permanent county-by-sector characteristics as well as any unobserved shocks to those counties that switched nonattainment or unobserved shocks to the polluting sector. To account for potential correlation across sectors within the same county, standard errors are clustered at the county level. Lastly, regressions are weighted by the total employment for each county/sector in 1985.

Figure 1 plots the coefficients from a version of equation (1) for the five years prior and ten years after the changes to the 1990 CAA Amendments. Specifically, the plotted coefficients are the difference in event time indicators for the polluting sectors in counties that switched nonattainment status in 1991 relative to the polluting sector in those counties that did not switch.[4]

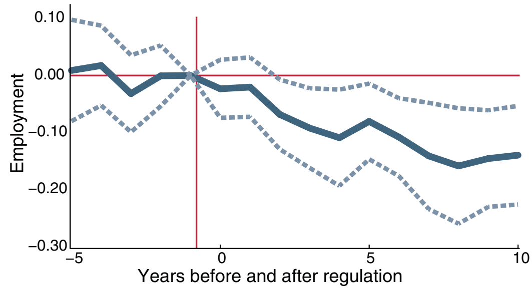

FIGURE 1. SECTOR-LEVEL EMPLOYMENT ESTIMATES BEFORE AND AFTER REGULATION

Note: Plotted are the coefficient estimates from a version of equation (1). See text for details. The dashed lines represent 95 percent conficence intervals.

There are two important features from this figure. First, the trends in employment in the polluting sectors for the years prior to the change are remarkably similar (as reflected by the zero pretrend differences). Second, beginning with the year of the regulatory change, the employment of polluting sectors in newly regulated counties begins to fall for the next eight years to 15 percent below 1990 employment levels. Recall that these estimates are all relative to polluting sectors in counties that did not switch regulatory status in 1990, and thus any cyclical differences pertaining to the recession in the early 1990s should be accounted for (conditional on the control group evolving similarly). Figure 1 summarizes the paper's primary finding: namely, that there is a strong and persistent relationship between nonattainment designation and sector-level employment.

I next turn to plant-level data to look at differences in employment growth and labor reallocation rates over five-year intervals for affected plants. The focus on medium- to long-run differences abstracts away from the short-run dynamics, while allowing me to compare my estimates to the previous literature using the Census of Manufacturers (Henderson 1996; Greenstone 2002).

[4] The online Appendix presents the estimated parameters and standard errors, as well as employment trends for each sector, rather than the difference in trends presented here. http://www.aeaweb.org/articles.php?doi=10.1257/aer.101.3.442.

Table 2—Effect of Nonattainment Designation on Plant Level Five-Year Labor Reallocation Rates

	Employment growth	Job creation rate	Job destruction rate
Panel A. Model 1			
$\text{Nonattainment}_{ct-5} \times \text{Polluter}_i$	−0.142***	−0.037***	0.105***
	(0.043)	(0.014)	(0.039)
Panel B. Model 2			
$\text{Nonattainment(CO)}_{ct-5} \times \text{Polluter}_i$	−0.031	−0.012	0.019
	(0.076)	(0.023)	(0.063)
$\text{Nonattainment}(O_3)_{ct-5} \times \text{Polluter}_i$	−0.099***	−0.035*	0.064*
	(0.035)	(0.019)	(0.033)
$\text{Nonattainment(PM10)}_{ct-5} \times \text{Polluter}_i$	−0.133***	−0.007	0.126***
	(0.030)	(0.013)	(0.024)
$\text{Nonattainment}(SO_2)_{ct-5} \times \text{Polluter}_i$	−0.246**	−0.114***	0.132*
	(0.118)	(0.044)	(0.077)

Notes: This table reports several estimates pertaining to equation (2), where each column of each panel is a separate regression. See text for details. $N = 470{,}958$. Reported in parentheses are robust standard errors that are clustered at the county level.
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

IV. Plant-Level Labor Reallocation Rates

In keeping with the literature, I define plant employment growth as the difference in employment between t and $t-5$, divided by the average employment in those two periods. To better understand the margins of firm adjustment, employment growth is decomposed into two separate components: one measuring the growth rate from expanding establishments (i.e., the job creation rate) and the other measuring the rate at which contracting establishments are shrinking (i.e., the job destruction rate).[5] I estimate various forms of the following plant level model:

$$(2) \quad y_{ijct} = \alpha + \theta(N_{ct-5} \times P_i) + \delta_{jt} + \eta_i + \zeta_{ct} + \gamma_{it} + u_{ijct},$$

where N_{ct-5} is a lagged indicator for whether county c is in nonattainment five years prior, and P_i is a plant-level indicator for polluting status. The parameter, θ, provides an estimate of the effect of plant-level nonattainment designation on the five-year plant employment growth and labor reallocation rates. Equation (2) also controls for annual fluctuations by industry with two-digit SIC × year fixed effects (δ_{jt}); any permanent observed or unobserved plant characteristics with plant fixed effects (η_i); and any local economic shocks to plants that affect both polluting and nonpolluting plants similarly by including county-by-year fixed effects (ζ_{ct}). Since plant age is an important determinant of growth rates and job flows, I also include a set of plant age indicators (γ_{it}). Lastly, estimates are weighted by plant-specific median employment over the sample.

Panel A of Table 2 presents regression estimates pertaining to equation (2). Similar to the findings in the previous literature, plant-level employment growth declines with changes to plant-level regulatory status. Interestingly, the results suggest that most of this adjustment is occurring through increases in the job destruction rate (i.e., the rate at which plants with negative employment growth shed jobs). The job destruction rate nearly doubles for newly regulated plants, suggesting there may be significant costs to the affected workforce from these plant-level reductions in employment.

[5] These statistics are created using the standard job flow definitions from Davis and Haltiwanger (1992). Importantly, all of these measures account for entry and exit at the plant level, whereas measures using log differences are not defined for plants entering or exiting the sample.

Since counties can be regulated for various sources of pollution, and the regulations are applied such that only plants emitting the pollutant in question are regulated, I can estimate a model that jointly identifies the regulatory effects for each pollutant (Greenstone 2002). I estimate a version of equation (2) where there are four parameters of interest, θ^p for $p \in \{CO, PM10, O_3, SO_2\}$, conditional on the respective nonattainment indicators, N^p_{ct-5} being equal to one.[6] Thus, the regulatory effects are identified off of changes to the plant-level regulatory status for each pollutant p, conditional on that plant emitting pollutant p. Panel B of Table 2 presents results from the joint pollutant estimation. Changes in the plant-level regulatory status have significant effects on plant-level employment growth and labor reallocation rates across most pollutant classes.

V. Conclusion

Evidence here suggests that firms primarily respond to regulatory pressure by destroying jobs rather than reducing their hiring rates. This has important distributional implications for the affected workforce. It is not entirely clear, however, how to monetarize these effects. While the jobs might disappear, the workers certainly do not, and thus the true costs should be characterized by the adjustment costs associated with reallocating the workforce.

Future work should try to explicitly estimate these costs. Specifically, longitudinal micro data could yield considerable insight into the magnitude of the earnings losses pertaining to reallocation for the affected workforce in both the short and long run. Since most of these regulations occur in relatively thick labor markets, and since these shocks are very sector specific, the actual costs to the workforce could be quite modest relative to the estimated benefits of the policy. See Walker (2010) for evidence suggesting this to be the case.

[6] Only the pollutants CO, PM-10, O_3, and SO_2 experience significant amounts of regulatory variation in the sample.

REFERENCES

Arrow, Kenneth J., Maureen L. Cropper, George C. Eads, Robert W. Hahn, Lester B. Lave, Roger G. Noll, Paul R. Portney et al. 1996. *Benefit-Cost Analysis in Environmental, Health and Safety Regulation*. Washington, DC: American Enterprise Institute.

Becker, Randy A. 2005. "Air Pollution Abatement Costs under the Clean Air Act: Evidence from the PACE Survey." *Journal of Environmental Economics and Management*, 50(1): 144–69.

Davis, Steven J., and John C. Haltiwanger. 1992. "Gross Job Creation, Gross Job Destruction, and Employment Reallocation." *Quarterly Journal of Economics*, 107(3): 819–63.

Davis, Steven J., R. Jason Faberman, and John Haltiwanger. 2006. "The Flow Approach to Labor Markets: New Data Sources and Micro-Macro Links." *Journal of Economic Perspectives*, 20(3): 3–26.

Environmental Protection Agency. 2010. "National Ambient Air Quality Standards for Ozone." *Federal Register*, 75(11): 2938–3052.

Greenstone, Michael. 2002. "The Impacts of Environmental Regulations on Industrial Activity: Evidence from the 1970 and 1977 Clean Air Act Amendments and the Census of Manufactures." *Journal of Political Economy,* 110(6): 1175–1219.

Henderson, J. Vernon. 1996. "Effects of Air Quality Regulation." *American Economic Review*, 86(4): 789–813.

United States Census Bureau. 2008. Pollution Abatement Costs and Expenditures: 2005. *Current Industrial Reports*. Washington, DC, April.

Von Wachter, Till, Jae Song, and Joyce Manchester. 2007. "Long-Term Earnings Losses Due to Job Separation during the 1982 Recession: An Analysis Using Longitudinal Administrative Data from 1974 to 2004." Columbia University Economics Discussion Paper 0708-16.

Walker, Reed. 2010. "The Transitional Costs of Policy: Evidence from the Clean Air Act and the Workforce." Unpublished.