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Title: Do EPA Regulations Affect Labor Demand? Evidence from the Pulp and Paper Industry[1]

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Abstract

Many believe that environmental regulation must reduce employment, since regulations are expected to increase production costs, raising prices and reducing demand for output. A careful microeconomic analysis shows that this not guaranteed. Even if environmental regulation reduces output in the regulated industry, abating pollution could require additional labor (e.g. to monitor the abatement capital and meet EPA reporting requirements). Pollution abatement technologies could also be labor enhancing. In this paper we analyze how a particular EPA regulation, the “Cluster Rule” (CR) imposed on the pulp and paper industry in 2001, affected employment in that sector. Using establishment level data from the Census of Manufacturers and Annual Survey of Manufacturers at the U.S. Census Bureau from 1992-2007 we find evidence of small employment declines (on the order of 3%-7%), sometimes statistically significant, at a subset of the plants covered by the CR.

Keywords: cluster rule, regulatory costs, multimedia regulation, employment effects
Subject Areas: Economic Impacts; Air Pollution; Water Pollution
JEL Codes: Q52; Q53; Q58

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[1] Regarding data availability: This paper presents the results of research using confidential U.S. Census data. Owing to legal restrictions surrounding the Census data, we cannot simply make the data available to other researchers ourselves. Census data is made available to external researchers under strict security provisions. In particular, a researcher wishing to use the data must submit a proposal to the Census Bureau describing the use they wish to make of data, have the proposal approved, become a 'Special Sworn Employee' of the Census Bureau, and agree to the same serious penalties for disclosing confidential data that apply to regular Census employees. The data can then be accessed at the many Census Research Data Centers located around the country.

1. INTRODUCTION

Prior to 1970 environmental regulation was done principally by state and local agencies – for the most part with little enforcement activity. After the establishment of the Environmental Protection Agency (EPA) in the early 1970s, and the passage of the Clean Air and Clean Water Acts, the federal government took over the primary role in regulating environmental quality, imposing much stricter regulations with correspondingly stricter enforcement. Since the establishment of EPA the federal government has continually required U.S. manufacturing plants to further reduce their emission levels. Even though the stringency of environmental regulation has continually increased, U.S. manufacturing plants have only faced a moderate increase in their level of spending on pollution abatement – pollution abatement costs increased from roughly 0.3 percent of total manufacturing shipments in 1973 to only 0.4 percent in 2005. On the other hand, certain highly polluting, highly regulated industries face higher abatement costs – pulp and paper, steel, and oil refining each spend approximately 1% of their shipments to comply with environmental regulations in 2005 (PACE 2005[2]).

Although pollution abatement expenditures are a very small fraction of the manufacturing sectors' operating costs (even for the most highly regulated industries) the popular belief is that environmental regulation *must* reduce employment. The standard explanation for this effect is that such regulations increase production costs, which would raise prices and reduce demand for output, thus reducing employment (at least in a competitive market). Stricter regulations may encourage plants to adopt more efficient production technologies that are capital-intensive and thus reduce employment. Although

[2] "Pollution Abatement Costs and Expenditures: 2005" (MA200-2005) U.S. Dept of Commerce, Bureau of the Census, April 2008.

this effect might seem obvious, a careful microeconomic analysis shows that it is not guaranteed. Even if environmental regulation reduces output in the regulated industry, abating pollution could require additional labor (e.g. to monitor the abatement capital and meet EPA reporting requirements). It is also possible for pollution abatement technologies to be labor enhancing [see Berman and Bui (2001a) and Morgenstern et al (2002)]. Given current high unemployment rates, it is natural for policy-makers to be concerned that new, more stringent environmental regulations will lead to job loss, and hence important to test whether these concerns are well-founded.

In this paper we analyze how a particular EPA regulation, the so-called "Cluster Rule" (CR) imposed on the pulp and paper industry in 2001, affected employment in that sector. The CR was the first integrated, multi-media regulation imposed on a single industry. The goal of the CR was to reduce the pulp and paper industry's toxic releases into the air and water, driven in part by concerns about trace amounts of dioxin being formed at mills that used chlorine bleaching in combination with the kraft chemical pulping technology. The stringency of the CR varied across plants, with larger air polluters subject to MACT (maximum achievable control technology) technology standards, and chemical pulping mills subject to BAT (best available technology) technology standards for their water pollution discharges. By promulgating both air and water regulations at the same time EPA made it possible for pulp and paper mills to select the best combination of pollution prevention and control technologies, with the hope of reducing the regulatory burden. By imposing different requirements on plants within the same industry, the CR allows us to identify the size of that regulatory burden, specifically the impact (if any) that the CR had on employment at the affected plants.

Much of the existing literature relies on variations in environmental regulation across geographical areas or across industries to identify its effect on employment. In contrast, we are the first to use establishment level panel data within a single industry to rigorously examine the *net* employment effects of a specific regulation, the CR, on the directly regulated sector.[3] By identifying which plants are subject to the CR and when, we can construct accurate control groups, which allows us to estimate the effect of regulation on employment with more precision using difference-in-differences models. Second, the existing literature tends to measure the stringency of environmental regulation either with broad measures of all environmental regulations (e.g. total pollution abatement costs) or with measures targeting a single environmental medium (e.g. county non-attainment with specific National Ambient Air Quality Standards). In contrast, the CR is a uniquely multi-media regulation, whose employment effects may have important implications for future policy-making.

Using establishment level data from the Census of Manufacturers and Annual Survey of Manufacturers at the U.S. Census Bureau from 1992-2007, we find some evidence of *small* employment declines (on the order of 3%-7%) associated with the adoption of the CR, which are sometimes statistically significant. These declines are concentrated in plants covered by the BAT water pollution standards; employment effects at plants covered by only the MACT air rules are more often positive than negative,

[3] Environmental regulations may also produce jobs in other industries outside the directly regulated sector, e.g. in the environmental protection. Thus to calculate the *net* employment effect of any regulation for the entire economy requires estimating both the job gains as well as the job losses, if any, due to the imposition of that regulation. This exercise is beyond the scope of this paper, but we expect that in a full-employment economy that the number of jobs created by new pollution abatement spending would approximately equal the number of jobs lost in the regulated sector as resources are reallocated towards the environmental protection sector.

though generally insignificant.

Section 2 provides background information on pollution from the pulp and paper industry and a brief history of the Cluster Rule. Section 3 reviews the relevant literature. Section 4 outlines a theoretical framework of the impact of regulation on employment. Section 5 discusses the data and empirical methodology. Section 6 presents the results, followed by concluding comments in section 7.

2. REGULATING THE PULP AND PAPER INDUSTRY

Over the past 40 years the U.S. manufacturing sector has faced increasingly stringent environmental regulations with stricter enforcement and monitoring. The increasing stringency of environmental regulation has caused traditional ‘smokestack’ industries, like the pulp and paper industry, to devote more resources to pollution abatement. However, even though the pulp and paper industry is one of the most highly regulated industries, due to the inherent polluting nature of the production process, and spends a relatively large amount of resources on pollution abatement, it has historically spent less than 2% of its overall costs on pollution abatement.

The entire pulp and paper industry faces substantial levels of environmental regulation, however, plants in this industry are differentially affected by regulation, depending in part on their technology (pulp and integrated mills vs. non-integrated mills[4]), age, location, and the level of regulatory effort directed at the plant. Previous research, including Gray and Shadbegian (2003), has found that the main factor determining the extent of the regulatory impact on a plant is whether or not the plant

[4] Integrated mills produce their own pulp and non-integrated mills purchase pulp or use recycled wastepaper.

contains a pulping facility, since the pulping process (separating the fibers need to make paper from raw wood) is much more pollution intensive than the paper-making process.[5] Furthermore, different pulping processes generate different types of pollution: mechanical pulping is more energy intensive, producing air pollution from a power boiler, while chemical pulping could produce water pollution from spent chemicals, at least some of them potentially toxic. Moreover, to produce white paper the pulp must be bleached. The Kraft chemical pulping process initially considered to be relatively low-polluting in terms of conventional air and water pollution turned out to have other environmental concerns. In particular, when combined with elemental chlorine bleaching, the Kraft pulping process creates chloroform, furan, and trace amounts of dioxin (all potential carcinogens), raising concerns over toxic releases that contributed, at least indirectly, to the promulgation of the Cluster Rule.

A flood in Times Beach, Missouri (located near St. Louis) helped raise public awareness regarding the concerns about toxic pollutants in general, and in particular dioxin. On December 5th, 1982 the Meramec River flooded Times Beach, contaminating nearly the entire town with dioxin that had been deposited by spraying to alleviate dust in the early 1970's. The Center for Disease Control declared that the town was uninhabitable and in 1983 the US EPA bought Times Beach and relocated its residents, reinforcing the public perception of the dangers of dioxin.

As a result of the Times Beach incident two powerful environmental groups, the Environmental Defense Fund and the National Wildlife Federation, sued the EPA for not sufficiently protecting the U.S. public from the risks caused by dioxin. EPA, as part of a

[5] The two main environmental concerns during paper-making stage are air pollution if the mill has its own power plant and the residual water pollution generated during the drying process.

1988 settlement with the environmental groups, agreed to investigate the health risks of dioxin and to set regulations to reduce dioxin emissions. Ten years later, EPA implemented regulations that included dioxin reductions, as part of the Cluster Rule.

The Cluster Rule

EPA initially proposed the Cluster Rule on December 17, 1993. This was the agency's first integrated, multi-media regulation, designed to protect human health by decreasing toxic releases by pulp and paper mill's into both the air and water. By simultaneously promulgating both air and water regulations the EPA allowed pulp and paper mills to address multiple regulatory requirements simultaneously, attempting to diminish the overall regulatory burden on the mills. During the public comment period, many submissions were received from industry representatives, governmental entities, environmental groups, and private citizens. Industry comments asserted that EPA had underestimated the compliance costs of the proposed standards and raised the possibility of substantial negative impacts on the industry ($20 billion in compliance costs; 21,800 lost jobs). In response to these comments and additional data supplied by pulp and paper industry representatives, EPA made significant changes to the proposed rule, reducing control requirements for certain categories of plants and providing greater flexibility to plants in choosing control options.

The final version of the rule was promulgated in 1998. To address toxic air pollutants, EPA established maximum achievable control technology (MACT) standards (referred to as MACT I & III) for the pulp and paper industry that required mills to abate toxic air pollutant emissions that occurred during the pulping and bleaching stages of the manufacturing process.[6] The MACT I rule regulates mills that chemically pulp wood using kraft, semi-chemical, sulfite, or soda processes, while MACT III regulates mills that mechanically pulp wood, or pulp secondary fiber or non-wood fibers, or produce paper or paperboard. The MACT air regulations were expected to achieve substantial reductions in hazardous air pollutants (reduced by 59%), sulfur (47%), volatile organic compounds (49%) and particulate matter (37%).

To address water pollution EPA also established Best Available Technology Economically Achievable (BAT) effluent limits for toxic water pollutants created during the bleaching process. The BAT standards were based on substituting chlorine dioxide for chlorine in the bleaching process (i.e., using elemental chlorine-free bleaching [ECF]) or using totally chlorine-free (TCF) bleaching.[7] The BAT water regulations were expected to achieve a 96% reduction in dioxin and furan, and a 99% reduction in chloroform.

3. LITERATURE REVIEW: ENVIRONMENTAL REGULATION

The question of the impact of environmental regulation on U.S. manufacturing is not a new one. There is an extensive literature on the costs of complying with EPA regulations. Among the studies using plant-level data, many have examined the effect of EPA regulations on productivity [see Färe, Grosskopf and Pasurka (1986), Boyd and McClelland (1999), Berman and Bui (2001b), and Shadbegian and Gray (2005, 2006)]. Other studies have examined how regulations affected investment [see Gray and

[6] Technology based standard to limit hazardous air pollutants, <u>set without regard to cost</u>.
[7] Technology based standard to limit conventional and toxic discharges into water, which takes cost into consideration.

Shadbegian (1998)] and environmental performance [see Magat and Viscusi (1990), Laplante and Rilstone (1996), and Shadbegian and Gray (2003, 2006)]. However, only a limited of studies have examined the impact of environmental regulations on employment [see Berman and Bui (2001a), Greenstone (2002), Morgenstern, Pizer and Shih (2002), Cole and Elliott (2007), Walker (2011), and Gray and Shadbegian (2013)]. Given the high unemployment rate during the current economic crisis, and the government's continued efforts to reduce unemployment, policy-makers, industry, and the public are concerned that stringent environmental regulations may reduce employment and thus exacerbate the unemployment problem.

Berman and Bui (2001a) compiled a unique plant-level data set to estimate the impact of air pollution regulations on labor demand in the Los Angeles, CA area – South Coast Air Quality Management District (SCAQMD). The data set they constructed contains detailed information on all the changes in environmental regulation including adoption date, compliance date, date of increase in stringency, and the regulated pollutant for all the affected manufacturing plants in the SCAQMD. In their study Berman and Bui found that new air quality regulations introduced between 1979 and 1992 did not in fact reduce the demand for labor in Los Angeles, but may have actually increased it by a small amount.

Morgenstern, Pizer and Shih (2002) estimate a model (1979-1991) for four highly polluting/regulated industries (pulp and paper, plastic, petroleum refining, and steel) to examine the effect of higher abatement costs from regulation on employment. They conclude that increased abatement expenditures generally do *not* cause a statistically significant change in employment.

Cole and Elliot (2007) estimate a similar model to Berman and Bui (2001a) with a panel data set on 27 industries (1999-2003) from the United Kingdom. Cole and Elliot treat their measures of the stringency of regulation – pollution abatement operating costs as a percentage of gross value-added and pollution abatement capital expenditures as a percentage of total capital expenditures – both exogenously and endogenously and find, like Berman and Bui, that environmental regulations have no statistically significant effect on employment.

Gray and Shadbegian (2013), like Cole and Elliot (2007), use a similar model to Berman and Bui (2001a) with industry level data to analyze the impact of environmental regulation on employment in U.S. manufacturing (1973-1994). However, Gray and Shadbegian (2013) also examine whether or not differences in regulatory pressure across industries and over time affects how industry employment responds to regulatory pressure. They find that more stringent regulations (measured by pollution abatement operating costs relative to output) have a statistically significant yet quantitatively negligible effect on employment in most cases, with a somewhat larger effect in highly regulated industries. Gray and Shadbegian (2013) also find, as expected, that regulation has a smaller impact in employment in industries in which demand is growing faster. However, they unexpectedly find that employment is more sensitive to regulatory pressure in industries with less competition and that the sensitivity of employment to regulation is not significantly affected by an industry’s level of import competition.

Greenstone (2002), using a difference-in-differences model, examines the effect of county nonattainment status for the criteria pollutants – particulate matter, sulfur dioxide, ozone and carbon monoxide – on employment.[8] Polluting plants in non-attainment areas face stricter regulations than similar plants in attainment areas, thereby potentially raising their production costs and lowering economic activity. Greenstone combines county attainment status information with facility-level data from Census of Manufacturers (1972–1987) finds that nonattainment counties (relative to attainment ones) lost roughly 590,000 jobs. Walker (2011) also finds statistically significant employment losses in non-attainment counties (relative to counties in attainment), with employment falling by about 15% at plants in newly designated non-attainment areas due to new Clean Air Act regulations in the 1990s.

In sum, most past studies using plant-level data have found small or positive impacts of stricter environmental regulation on labor demand, with the exception of Greenstone (2002) and Walker (2011), who find more substantial reductions, looking at county non-attainment status. However, this does not mean that there is less *overall* employment due to more stringent environmental regulation, it simply suggests that the *relative* growth rate of employment in some sectors differs between attainment and non-attainment areas. Now we turn to our own analysis of employment impacts of the CR.

4. THEORETICAL FRAMEWORK

Popular wisdom holds that environmental regulation must reduce employment, because such regulation raises the cost of production, thereby decreasing output. Nevertheless, standard neoclassical microeconomic analysis demonstrates that this is *not* necessarily true. Even though it is indeed possible for environmental regulation to result in less production, it is also possible that pollution abatement technologies are labor enhancing.

[8] Greenstone also examines the effect of county non-attainment status on capital stock and output.

Therefore, we adopt a model derived by Berman and Bui (2001a) that allows environmental regulation to affect labor demand via two channels: the output elasticity of labor demand and the marginal rate of technical substitution between labor demand and pollution abatement activity. The model developed by Berman and Bui (2001a) was based on the partial static equilibrium model (PSEM) of Brown and Christensen (1981). The key component of Brown and Christensen's PSEM is that it allows the levels of some "quasi-fixed" factors (e.g. pollution abatement investment) to be set by exogenous constraints (e.g. environmental regulation), instead of purely by cost minimization.[9] In our case, we regard pollution abatement capital and operating costs, as well as environmental regulatory variables as "quasi-fixed." We treat all other "productive" factors as variable.

Assume that a perfectly competitive polluting plant minimizes costs by choosing levels of the *M* variable inputs and *Q* "quasi-fixed" inputs. We can write the variable cost function as follows:[10]

$$(1) \qquad CV = F(Y, P1, \ldots, Pm, Z1, \ldots, Zn)$$

where Y is output, P_m are the prices of the variable factors, and Z_n are the levels of the "quasi-fixed" inputs. Using Shephard's lemma produces the following set of variable input factor demands as a function of output, prices, and the level of the "quasi-fixed" inputs:

$$(2) \qquad L = \alpha + \rho_y Y + \sum_{k=1}^{K} \beta_k Z_k + \sum_{j=1}^{J} \gamma_j P_j$$

The direct effect of regulation on L_i is

[9] This approach permits us to model the plant's behavior with a variable cost function which is minimized with respect to a subset of input factors conditional on both output and the levels of the "quasi-fixed" factors.

[10] Our notation is largely adopted from Berman and Bui (2001a).

(3) $$\frac{dL}{dR} = \rho_{yi}\frac{dY}{dR} + \sum_{k=1}^{K}\beta_k\frac{dZ}{dR} + \sum_{j=1}^{J}\gamma_j\frac{dP_j}{dR} = \mu$$

The first term in equation (3) indicates the effect of regulation on labor demand through its effect on output. The “output” effect of environmental regulation is typically assumed to be negative, however Berman and Bui (2001a) note that neoclassical microeconomic theory provides no definitive sign. For example, if plants comply with regulations by investing in abatement capital that decreases marginal costs, *dY/dR* can be positive. The second term indicates the effect regulation has on labor demand through its effect on the demand for quasi-fixed abatement activities, *Z*, and the marginal rates of technical substitution between pollution abatement activities and labor. The change in demand for pollution abatement activity caused by more stringent regulation, *dZ/dR*, must be positive. The β_k coefficients cannot be signed a priori, since they depend on whether labor and pollution abatement activity are substitutes or complements. This is the key reason why the sign of μ, the overall employment effect of regulation, cannot be predicted from theory alone. Finally, if input factor markets are competitive and the regulated industry makes up only a small portion of those markets, any change in regulatory stringency for the industry will not affect the price of its inputs, thus the final term in equation (3) will drop out.

Citing data limitations, Berman and Bui (2001a) estimated the impact air pollution regulations have on labor demand in the SCAQMD between 1979 and 1992 with the following reduced-form version of equation (3):

$$(4) \qquad L = \delta + \mu R$$

Following Berman and Bui (2001a) we estimate a similar version of equation (4), augmented with several plant characteristics as well as county and state level variables described below.[11]

5. DATA AND EMPIRICAL METHODOLOGY

We seek to estimate the causal effect of the CR on employment in the pulp and paper industry. However, plants covered by the CR may be systematically different from plants not covered by the rule, biasing a simple comparison of covered and non-covered plants. We adopt a difference-in-differences (DiD) estimator to help control for any systematic differences between covered and non-covered plants and any other potentially confounding factors that changed around the time of the promulgation of the CR.

One potential concern with a DiD analysis is the possibility that the treatment and control groups are experiencing different trends which can be misinterpreted as a different impact of the treatment when both groups are compared with their pre-treatment values. Figures 1-3 address this issue, showing the trends for total employment, production workers, and production worker hours for all three groups of plants: BAT plants, MACT-only plants, and the control group. Looking at the pre-promulgation period, we see relatively stable employment for all three groups – if anything, there seems to be a bit of a decline in the treated groups relative to the control group in the earlier period, which might lead the DiD analysis to overstate employment reductions in

[11] Cole and Elliot (2007) and Gray and Shadbegian (2013) estimate a similar model using industry level data.

the treatment groups.

To implement our DiD estimator we use establishment level data from the Census of Manufacturers and Annual Survey of Manufacturers at the U.S. Census Bureau from 1992-2007. These datasets are linked together using the Longitudinal Business Database, as described in Jarmin and Miranda (2002). Our Census data include three measures of employment: total employment, number of production workers, and production worker hours. The data also include the total value of shipments from the plant, materials inputs (including energy usage), and new capital investment. We combine the Census data with data from the Lockwood Directory for various years, identifying whether or not the plant includes a pulping process and the plant's age.

As mentioned above, the stringency of the CR varied across plants. Out of 490 pulp and paper mills that EPA originally estimated would be subject to the new CR MACT regulations only 155 mills had to comply with the Air Toxics (MACT) regulations.[12] Furthermore, of the 155 plants that were covered by the MACT regulations 96 of them chemically pulp wood so they also needed to comply with the Water Toxics (BAT) standards. The remaining 335 mills did not need to comply with either the MACT or BAT requirements of the CR. Plants needed to comply with the MACT regulations by April 2001, while those covered by the BAT regulations had to comply as soon as their water pollution discharge National Pollutant Discharge Elimination System (NPDES) permit was renewed. Given that most water NPDES permits last for five years, the effective BAT compliance dates were spread over 1998-2002. Thus we have a set of regulations affecting multiple pollution media, with

[12] EPA also separately tightened up its rules regarding hazardous air pollutants from pulp and paper mills, including those not subject to the CR, but those rules are not as stringent as the CR.

different stringency levels across plants. This allows us multiple dimensions along which to test the impact of the Cluster Rule.

We examine whether changes in employment at plants that had to comply with the CR before and after it became effective are similar to changes in employment at plants that did not have to comply with the CR. Factors other than the CR also affect employment levels. The demand conditions in the pulp and paper industry may fluctuate over time, along with the prices of inputs, supply of materials, and production technology, all leading to changes in employment levels. The plants in the control group need to satisfy two conditions. First, these plants should not be affected by the CR, which we ensure by using EPA lists of the affected plants. Second, these plants should otherwise be very similar to the treatment group. Because plants in the control group were in the same industry, producing similar products to the treatment group, we expect the two groups be reasonably similar in the factors affecting their employment other than the CR, satisfying the second condition. We limit the control group to those plants which include some kind of pulping process, to avoid the less-comparable plants which use recycled paper or purchase market pulp. Thus the DiD approach allows us to control for any time-invariant unobserved heterogeneity as well as any changes over time that affect both groups similarly.

Model Specification

To obtain a raw DiD effect of the CR on plants' employment, we can estimate the following baseline model:

$$(5)\ \ln EMP_{pt} = \beta_0 + \beta_1 MACT_p + \beta_2 BAT_p + \beta_3 MACT_p{*}CR\_YEAR_{pt} + \beta_4 BAT_p{*}CR\_YEAR_{pt} + \delta_t + \eta_s + u_{pt}$$

where p indexes plants and t indexes years and η_s is a vector of state dummy variables. The dependent variable ln*EMP* is the log of one of our employment measures; *MACT* is a dummy indicating plants that must comply with the MACT regulations of the Cluster Rule; *BAT* is a dummy indicating plants that must comply with the BAT regulations of the Cluster Rule (a proper subset of the MACT plants); and *CR_YEAR* is a dummy variable indicating when a plant must begin to comply with the requirements of with the Cluster Rule. Thus $MACT_p*CR\_YEAR_{pt}$ and $BAT_p*CR\_YEAR_{pt}$ capture the change in employment at the CR-covered plants, relative to non-covered plants, during the post-cluster rule years. The coefficients β_3 and β_4 thus measure the DiD effect of the CR on employment. While β_3 measures the CR effect on the MACT plants relative to the control group, β_4 measures the differential effect on the BAT plants relative to the MACT plants, so $(\beta_3+\beta_4)$ measures the CR effect on the BAT plants relative to the control group.

We use several alternative measures of employment at the plant level. First, we examine TE, the *total employment* at the plant, which includes both production and non-production workers. Although this measure has been the primary focus for researchers and policy-makers, we might expect the impact of a regulation on employment to differ between the two groups. Rules involving paperwork and procedural compliance might require additional non-production workers to deal with those changes, while increases in production costs that reduced demand for the firm’s product might have a greater impact on production worker employment. Thus, we also considered a second employment measure - PW, the *number of production workers.* By comparing the results for TE and PW, we could test for evidence of differential effects across labor types. Finally, plants may express a change in production labor demand through changing the hours worked instead of the number of workers. Thus we also examine a third employment measure - PH, the *production worker hours per year*.

In defining the "post-CR" period, we consider both the announcement and effective dates of the rule. The CR was announced at the end of 1997. Covered plants had to comply with MACT regulations before April 2001, while the compliance date of BAT regulations varied over several years, depending on when plants renewed their water discharge permit. Although we have information on the compliance dates of each plant, we suspect that they may not be the appropriate basis to define the post-CR period. It takes time for plants to adjust, which was why the compliance date of the CR was set for years after it was announced. We expect that, as soon as the rule was announced, plants started planning for the adjustment, including adoption of new technology and possibly adjusting their employment levels. If the CR had an impact on employment, the change could occur before 2001, once the announcement was made. Supporting this concern, Gray and Shadbegian (2008) found that reductions in pollution emissions from pulp and paper mills began before the Cluster Rule's 2001 compliance date. Based on these earlier results, we consider two break points, using the Cluster Rule's 1997 announcement date as one break point (making 1998-2007 the post-CR treatment period – CR_1998) and the 2001 enactment date as the other (making 2001-2007 the post-CR treatment period – CR_2001)[13], and estimate models using one or the other or both break points.

To isolate the effect of the CR on employment, we also need to control for plant

[13] An alternative would be to find out how long it would take for plants to install the necessary equipments to comply with the CR so as to get a rough estimate of when plants might start the adjustment process. However, plants may vary in the timing of the adoption of technology. Furthermore, the timing of the adoption of technology may not be indicative of the timing of the potential employment adjustment, further complicating this approach.

characteristics that are constant over time as well as other time-variant factors that might affect employment differently between the covered and non-covered plants. As mentioned before, plant characteristics play an important role in determining pollution levels. These characteristics may determine whether a plant is subject to the CR and may also have a direct effect on employment levels. For example, older plants have higher pollution levels and may be more likely to be in the treatment group. These plants may also have different labor demand and elasticity of substitution among factors of production and could have changed employment levels differently from non-covered plants over time. In addition, local labor market conditions can affect a plant's hiring decisions, so we include a set of control variables measuring local labor market conditions: local wages, unemployment rates, and per-capita income, measured at the county level[14]. We also include state fixed effects to control for any other time-invariant state-level unobserved heterogeneities that may affect employment.[15]

When we include these control variables, our model can be written as:

$$(6)\ \ln EMP_{pt} = \beta_0 + \beta_1 MACT_p + \beta_2 BAT_p + \beta_3 MACT_p{*}CR\_YEAR_{pt} + \beta_4 BAT_p{*}CR\_YEAR_{pt} + \mathrm{Z}_{\mathrm{pt}}\Gamma + \eta_{\mathrm{s}} + \delta_t + u_{pt}$$

Here Z is a set of plant characteristics, including *OLD*, a dummy variable indicating whether or not the plant was started before 1960, and a set of county-level labor market conditions that change over time, including log wage rate, log unemployment rate, and log per capita income.

[14] Income and wage data came from the Bureau of Economic Analysis (BEA) website (http://www.bea.gov/regional/reis/), while unemployment data came from the Bureau of Labor Statistics (BLS) website (http://www.bls.gov/lau/).

[15] Including these additional regressors can also increase the efficiency of our estimator.

One final set of analyses include plant-specific fixed effects:

$$\text{(7) } \ln EMP_{pt} = \beta_0 + \beta_3 MACT_p{*}CR\_YEAR_{pt} + \beta_4 BAT_p{*}CR\_YEAR_{pt} + Z_{\mathrm{pt}}\Gamma + \delta_t + \alpha_{\mathrm{i}} + u_{pt}$$

Including α_i accounts for fixed characteristics of the plant affecting the average employment level, but also eliminates variables (e.g. *MACT*, *BAT*, and *OLD*) which do not vary over time.

6. RESULTS

Baseline models

Table 1 displays the summary statistics and variable definitions. We exclude observations with missing values for value of shipments (TVS), overall employment (TE), production worker employment (PW), production worker hours (PH), or plants that seem to match to two different Census records. None of those restrictions results in much loss of sample size. We also exclude non-pulping plants from the analysis, about 40% of the plants in the Census data, to ensure that the control group is as similar to the treatment group as possible (all CR plants include a pulping process). The resulting dataset used for the analysis is an unbalanced panel, with 2,593 observations over the 1993-2007 period. About two-thirds of the observations are covered by the MACT air requirements, while 43% are covered by the BAT water requirements. Most of the plants (three-quarters) had been in operation since 1960, and about 60% of them include a pulping process. The majority of employment consists of production workers, though there is also substantial non-production employment (about one-fifth of the total).

Tables 2A-2C show the results for our baseline DiD regression as described in equation (5) for each employment measure, comparing employment effects for both BAT and MACT plants and allowing effects to occur at the promulgation date (1998), the effective date (2001), or both. As suggested by Bertrand et al (2004), our basic DiD results allow for correlations in errors across years for the same plant by using standard errors that are robust to within-plant correlations over time. Plants covered by the BAT water regulations have employment almost two-thirds larger than plants covered only by the MACT air regulations, which are in turn about 10% larger than control plants (though the latter difference is not significant) for all three dependent variables.

The key variables for our analysis, the DiD terms interacting the treatment categories with promulgation or adoption date, are reasonably consistent across model specification and employment measures, though only occasionally statistically significant. Plants covered by only MACT air regulations tend to show positive employment changes in the post-CR period, relative to the control group, with magnitudes on the order of 5%-10% depending on the employment measure and the time period chosen. The BAT interacted dummies, on the other hand, are consistently negative, with magnitudes on the order of 5%-10%, indicating that plants covered by the BAT water regulations tend to have negative employment changes in the post-CR period, relative to the MACT-only plants. Since the BAT changes relative to the control group are the sum of these two coefficients (which are similar in magnitude, but opposite in sign) they tend to be near zero, and are not statistically significantly different from zero.

We have some concerns with data quality, therefore we also present "RobustDiD" results estimating an iteratively reweighted least squares model to reduce the influence of individual data points on the coefficient estimates and correct for possibly non-normal residuals, providing a more robust estimation.[16] Focusing on the key DiD interactions, the robust BAT*CR_YEAR coefficients are almost always close to the non-robust coefficients in sign and magnitude, while the robust MACT*CR_YEAR coefficients tend to be larger, showing more positive impacts of the CR on employment. Summarizing the BAT and MACT interactions from the various models, we see that MACT-only plants have 7% to 14% higher total employment, production worker employment, and production worker hours as compared to either the BAT plants or the control group, with the latter two groups being relatively similar. The only statistically significant results come from the robust DiD models. Comparing the results across years, the 2001 change seems to be a bit larger than the 1998 ones, though not significantly so.

In Tables 3A-3C we turn to models based on equation (6), which include a series of control variables, including the OLD dummy and various county labor market characteristics. The control variables give similar results for all three employment measures. Older plants show about 40% higher employment for all three measures. Plants in high-wage counties have higher employment, with similar magnitudes in both the regular and robust models, although only the robust results are statistically significant. Neither county per-capita income nor county unemployment rates are significant, though the signs are similar for all three employment measures. Adding the control variables had essentially no impact on any of the other variables in the model, with employment at MACT-only plants rising in the post-CR period relative to the control group, while employment at BAT plants is lower (sometimes significantly so), and roughly comparable to employment at plants in the control group.

In Tables 4A-4C we now turn to fixed-effect models, based on equation (7), that

[16] Implemented using the rreg procedure in Stata.

control for any differences across plants that remain fixed through our sample period. As noted earlier, these models cannot include any variables that remain fixed, such as OLD, MACT, and BAT. The county-level labor market variables now depend on within-county variation over time, not variation across counties, and are only significant in the robust models, although the signs are consistent between the regular and robust models. As in Table 3, wage and unemployment rates are positively associated with employment, while per-capita income is negatively related to employment.

For the key DiD interaction coefficients, the main difference compared with the results in Tables 2 and 3 is that the post-CR coefficients for MACT plants are smaller and not always positive, indicating that their employment experience is not much different from the plants in the control group. The post-CR MACT coefficients also tend to be more negative for the 2001 cutoff than for the 1998 cutoff, which may reflect relatively little anticipatory investment at those plants before the CR effective date. The negative post-CR coefficients for BAT plants are somewhat smaller in magnitude than those in Tables 2 and 3, but the reduction in the MACT coefficients is larger, so the net (MACT+BAT) effects are more negative than in the earlier tables. The change is especially pronounced for the robust models, which had shown mostly positive (though insignificant) effects for BAT plants in the earlier tables. They now show statistically significant reductions of 3%-7% in employment at BAT plants in the post-CR period, with the effects on total employment being slightly larger than on the production worker related measures.[17]

A potential concern with the DiD estimator is that it is most suitable when the

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[17] We estimated a set of comparable models using the log of output as the dependent variable and the results are qualitatively similar to the employment results.

treatment is random, or when observable characteristics can be used to adjust for selection into treatment. In our case, the MACT and BAT regulations are not randomly assigned to pulp and paper mills. Rubin (2008) notes that one can approximate a randomized experiment by selecting a suitably-matched control group to eliminate or at least reduce this bias. In our case, we can reduce selection bias due to differences in observable covariates by choosing a control group with comparable covariate distributions to the pulp and paper mills covered by the MACT and BAT portions of the CR (Stuart (2010)). To choose such a control group we use a version of the propensity score matching (PSM) estimator developed by Rosenbaum and Rubin (1983).[18] Because we have two treatment groups (MACT-only and BAT) we ran the matching twice - once for each group. The same set of control plants was used for each matching (with replacement) and the final dataset included the matched pairs of treatment and control plants. We tested a variety of specifications before achieving the desired "balance" of matching variables between our treatment and control groups. The final matching model for the BAT group included the plant's energy cost ratio and age, the county unemployment rate, and an index of the state's pro-environmental Congressional voting. The matching model for the MACT-only group included the same variables plus the county non-attainment status for PM, SO2, and NOx and county log income.

Unfortunately, while the DiD estimator with matching provides us with a more appropriate control group, it also changes our sample as a few treatment plants (and about one-third of the control plants) are not included in the matched sample. This raises complications for releasing those results due to Census Bureau rules designed to protect

[18] To estimate the propensity score and produce our matched control group we employ the psmatch2 algorithm in Stata, developed by Leuven and Sianesi (2003).

data confidentiality. However, the estimated effects of MACT and BAT on employment in our DiD analysis with matching estimators are quite similar to our main DiD results presented above, in both magnitude and significance. This provides us with some assurance that our results are not being driven by any observable differences between our treatment and control groups.

7. CONCLUDING REMARKS

In this paper we examine the impact of the Cluster Rule on employment at plants in the pulp and paper industry. The Cluster Rule, promulgated in the end of 1997 was EPA's first integrated, multi-media regulation. Using a sample of pulp and paper mills, we use a DiD approach to estimate the causal effect of the Cluster Rule on employment. We consider alternative starting points for the post-CR period (1998 and 2001), alternative measures of employment (total employment, number of production workers, and production worker hours), and both regular and robust estimators.

Our results suggest that the Cluster Rule had relatively small effects on employment, with different effects for plants covered by only the MACT air requirements as compared to plants that were also covered by the BAT water requirements. The MACT-only plants show small positive employment effects post-CR in most models, though these are often insignificant. In contrast, the BAT plants show small negative employment effects relative to the MACT-only plants and (in some models) relative to the control group, also often insignificant. For our final preferred models, which include plant-specific fixed effects and other control variables, the robust estimator shows statistically significantly, yet moderately lower employment for the BAT plants as compared to both the MACT-only plants and the control group. In particular, BAT plants have on the order of 3%-7% less employment than the control group (the non-robust results are similar in magnitude, but not significant).

These results should be interpreted with some degree of caution. As noted, most of the models we estimated had insignificant coefficients on the DiD term measuring the CR effects. Despite our efforts to develop an appropriate control group (including our confirming the results with matching DiD estimators), there could still remain some issues of comparability of treatment and control plants. Future research is needed to link an employment analysis of the sort conducted here with other measures of the plant's activities (both in terms of emissions and production), to get a more complete picture of how the Cluster Rule affected pulp and paper mills.

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Table 1
Descriptive Statistics
(1993-2007, N=2593)

Variable	Mean (std dev)	Description
TE	618.63 (405.16)	Average employment at plant - Census
PW	482.40 (319.51)	Average production workers at plant - Census
PH	1040.82 (698.61)	Annual production worker hours at plant, in 000s - Census
LOGTE	6.20 (0.74)	Log(TE)
LOGPW	5.94 (0.76)	Log(PW)
LOGPH	6.71 (0.76)	Log(PH)
MACT	0.68 (0.47)	Dummy variable =1 if the plant is covered by EPA Cluster Rule MACT requirements
BAT	0.43 (0.49)	Dummy variable =1 if the plant is covered by EPA Cluster Rule BAT requirements
MACT*CR_1998	0.43 (0.49)	Dummy variable =1 after 1997 for plants covered by EPA Cluster Rule MACT requirements
MACT*CR_2001	0.29 (0.45)	Dummy variable =1 after 2000 for plants covered by EPA Cluster Rule MACT requirements
BAT*CR_1998	0.27 (0.44)	Dummy variable =1 after 1997 for plants covered by EPA Cluster Rule BAT requirements
BAT*CR_2001	0.18 (0.39)	Dummy variable =1 after 2000 for plants covered by EPA Cluster Rule BAT requirements
OLD	0.74 (0.44)	Dummy variable =1 if the plant was in operation in 1960
INCOME	23834 (5779)	Average per-capita income in county - BEA
WAGE	27957 (5226)	Average per-job wages in county - BEA
LOG(INCOME)	10.05 (0.24)	Log of income
LOG(WAGE)	10.22 (0.18)	Log(Average per-job wage in county)- BEA
UNEMPLOYMENT	6.17 (2.16)	Unemployment rate in county - BLS

Table 2A
Total Employees - Only Cluster Rule Effects

	OLS-DiD			Robust-DiD		
Model	**1**	**2**	**3**	**4**	**5**	**6**
MACT	0.096 (0.118)	0.102 (0.113)	0.096 (0.118)	0.016 (0.047)	0.026 (0.039)	0.015 (0.047)
MACT* CR_1998	0.058 (0.075)		0.018 (0.061)	0.105+ (0.056)		0.032 (0.075)
MACT* CR_2001		0.071 (0.080)	0.059 (0.073)		0.130* (0.055)	0.110 (0.074)
BAT	0.637** (0.097)	0.619** (0.095)	0.637** (0.097)	0.589** (0.043)	0.571** (0.035)	0.590** (0.043)
BAT* CR_1998	-0.094+ (0.050)		-0.051+ (0.031)	-0.103+ (0.053)		-0.053 (0.071)
BAT CR_2001		-0.096 (0.064)	-0.063 (0.064)		-0.107* (0.052)	-0.073 (0.069)
Adj R^2	0.426	0.426	0.425	0.458	0.459	0.458

All models include a set of state dummy variables; 2593 plant-year observations; (Standard Errors)
+=p<0.10, *=p<0.05, **=p<0.01

Table 2B
Production Workers – Only Cluster Rule Effects

	OLS-DiD			Robust-DiD		
Model	**1**	**2**	**3**	**4**	**5**	**6**
MACT	0.114 (0.121)	0.116 (0.115)	0.114 (0.121)	0.034 (0.048)	0.041 (0.041)	0.033 (0.048)
MACT* CR_1998	0.039 (0.080)		0.005 (0.064)	0.080 (0.058)		0.022 (0.077)
MACT* CR_2001		0.053 (0.085)	0.050 (0.076)		0.101+ (0.057)	0.087 (0.076)
BAT	0.629** (0.099)	0.610** (0.097)	0.629** (0.099)	0.570** (0.045)	0.551** (0.037)	0.571** (0.045)
BAT* CR_1998	-0.084+ (0.050)		-0.055+ (0.031)	-0.087 (0.055)		-0.056 (0.073)
BAT* CR_2001		-0.079 (0.065)	-0.044 (0.065)		-0.081 (0.053)	-0.046 (0.071)
Adj R^2	0.404	0.404	0.403	0.440	0.440	0.439

All models include a set of state dummy variables; 2593 plant-year observations; (Standard Errors)
+=p<0.10, *=p<0.05, **=p<0.01

Table 2C
Production Worker Hours - Only Cluster Rule Effects

	OLS-DiD			Robust-DiD		
Model	**1**	**2**	**3**	**4**	**5**	**6**
MACT	0.104 (0.120)	0.100 (0.114)	0.104 (0.120)	0.033 (0.048)	0.033 (0.040)	0.032 (0.048)
MACT* CR_1998	0.043 (0.080)		-0.010 (0.066)	0.067 (0.057)		0.002 (0.077)
MACT* CR_2001		0.072 (0.084)	0.079 (0.075)		0.100+ (0.057)	0.099 (0.076)
BAT	0.626** (0.098)	0.611** (0.096)	0.626** (0.098)	0.566** (0.044)	0.549** (0.036)	0.567** (0.044)
BAT* CR_1998	-0.077 (0.053)		-0.043 (0.035)	-0.073 (0.054)		-0.048 (0.072)
BAT* CR_2001		-0.078 (0.066)	-0.050 (0.064)		-0.066 (0.053)	-0.035 (0.071)
Adj R^2	0.405	0.405	0.405	0.443	0.443	0.443

All models include a set of state dummy variables; 2593 plant-year observations; (Standard Errors)
+=p<0.10, *=p<0.05, **=p<0.01

Table 3A
Total Employees – Cluster Rule Effects with Control Variables

	OLS-DiD			Robust-DiD		
Model	**1**	**2**	**3**	**4**	**5**	**6**
MACT	0.098 (0.120)	0.106 (0.116)	0.098 (0.120)	-0.009 (0.043)	-0.001 (0.036)	-0.013 (0.043)
MACT* CR_1998	0.060 (0.074)		0.024 (0.059)	0.100* 0.051)		0.027 (0.068)
MACT* CR_2001	0.069 (0.080)	0.054 (0.073)			0.128* (0.050)	0.110 (0.067)
BAT	0.640** (0.098)	0.622** (0.096)	0.640** (0.099)	0.562** (0.040)	0.544** (0.033)	0.562** (0.039)
BAT* CR_1998	-0.089+ (0.050)		-0.049 (0.031)	-0.102* (0.048)		-0.052 (0.064)
BAT* CR_2001	-0.090 (0.064)	-0.058 (0.063)			-0.108* (0.047)	-0.075 (0.062)
OLD	0.331** (0.093)	0.331** (0.093)	0.331** 0.093)	0.410** (0.024)	0.412** (0.024)	0.414** (0.024)
Log(WAGE)	0.462 (0.398)	0.463 (0.398)	0.462 (0.398)	0.471** (0.106)	0.474** (0.106)	0.473** (0.106)
Log(INCOME)	-0.045 (0.320)	-0.047 (0.320)	-0.048 (0.320)	0.113 (0.102)	0.111 (0.102)	0.113 (0.102)
UNEMPLOYMENT	0.005 0.017)	0.005 (0.017)	0.005 (0.017)	0.005 (0.007)	0.006 (0.007)	0.006 (0.007)
Adj R^2	0.458	0.458	0.458	0.540	0.541	0.542

All models include a set of state dummy variables; 2593 plant-year observations; (Standard Errors)
+=p<0.10, *=p<0.05, **=p<0.01

Table 3B
Production Workers – Cluster Rule Effects with Control Variables

	OLS-DiD			Robust-DiD		
Model	**1**	**2**	**3**	**4**	**5**	**6**
MACT	0.112 (0.121)	0.115 (0.116)	0.111 (0.122)	0.029 (0.044)	0.036 (0.037)	0.028 (0.044)
MACT* CR_1998	0.041 (0.079)		0.010 (0.062)	0.075 (0.053)		0.022 (0.070)
MACT* CR_2001		0.053 (0.085)	0.046 (0.076)		0.095+ (0.052)	0.081 (0.069)
BAT	0.635** (0.099)	0.616** (0.097)	0.635** (0.099)	0.530** (0.041)	0.512** (0.034)	0.531** (0.041)
BAT* CR_1998	-0.080 (0.051)		-0.053+ (0.031)	-0.083+ (0.050)		-0.055 (0.066)
BAT* CR_2001		-0.075 (0.065)	-0.040 (0.064)		-0.077 (0.049)	-0.041 (0.065)
OLD	0.370** (0.094)	0.370** (0.094)	0.370** (0.094)	0.437** (0.024)	0.436** (0.024)	0.437** (0.024)
Log(WAGE)	0.466 (0.403)	0.468 (0.403)	0.466 (0.403)	0.509** (0.110)	0.509** (0.110)	0.508** (0.110)
Log(INCOME)	-0.109 (0.330)	-0.110 (0.330)	-0.111 (0.330)	0.098 (0.105)	0.096 (0.105)	0.097 (0.105)
UNEMPLOYMENT	0.004 (0.017)	0.004 (0.017)	0.004 (0.017)	0.005 (0.007)	0.005 (0.007)	0.005 (0.007)
Adj R^2	0.441	0.441	0.441	0.518	0.518	0.518

All models include a set of state dummy variables; 2593 plant-year observations; (Standard Errors)
+=p<0.10, *=p<0.05, **=p<0.01

Table 3C
Production Worker Hours – Cluster Rule Effects with Control Variables

	OLS-DiD			Robust-DiD		
Model	**1**	**2**	**3**	**4**	**5**	**6**
MACT	0.112 (0.121)	0.105 (0.115)	0.106 (0.120)	0.031 (0.044)	0.033 (0.037)	0.029 (0.044)
MACT* CR_1998	0.041 (0.079)		-0.004 (0.063)	0.070 (0.052)		0.010 (0.069)
MACT* CR_2001		0.070 (0.084)	0.073 (0.075)		0.098+ (0.052)	0.092 (0.069)
BAT	0.635** (0.099)	0.614** (0.097)	0.628** (0.099)	0.518** (0.040)	0.503** (0.033)	0.518** (0.040)
BAT* CR_1998	-0.080 (0.051)		-0.041 (0.034)	-0.066 (0.049)		-0.046 (0.065)
BAT* CR_2001		-0.072 (0.066)	-0.045 (0.063)		-0.059 (0.048)	-0.029 (0.064)
OLD	0.370** (0.094)	0.363** (0.093)	0.363** (0.093)	0.434** (0.024)	0.434** (0.024)	0.435** (0.024)
Log(WAGE)	0.466 (0.403)	0.525 (0.401)	0.523 (0.401)	0.571** (0.109)	0.571** (0.109)	0.570** (0.109)
Log(INCOME)	-0.109 (0.330)	-0.082 (0.315)	-0.083 (0.316)	0.120 (0.104)	0.121 (0.105)	0.121 (0.105)
UNEMPLOYMENT	0.004 (0.017)	0.004 (0.016)	0.004 (0.016)	0.006 (0.007)	0.006 (0.007)	0.006 (0.007)
Adj R^2	0.442	0.442	0.441	0.522	0.522	0.522

All models include a set of state dummy variables; 2593 plant-year observations; (Standard Errors)
+=p<0.10, *=p<0.05, **=p<0.01

Table 4A
Total Employees – Fixed Effect Cluster Rule Models

	OLS-DiD			Robust-DiD		
Model	**1**	**2**	**3**	**4**	**5**	**6**
MACT* CR_1998	0.036 (0.053)		0.063 (0.041)	0.009 (0.009)		0.006 (0.011)
MACT* CR_2001		-0.005 (0.063)	-0.045 (0.060)		0.006 (0.009)	0.003 (0.011)
BAT* CR_1998	-0.064 (0.046)		-0.044* (0.022)	-0.057** (0.008)		-0.026* (0.010)
BAT* CR_2001		-0.058 (0.062)	-0.031 (0.060)		-0.067** (0.008)	-0.053** (0.010)
Log(WAGE)	0.098 (0.485)	0.073 (0.482)	0.072 (0.480)	0.257** (0.068)	0.269** (0.066)	0.269** (0.067)
Log(INCOME)	-0.575 (0.388)	-0.558 (0.384)	-0.550 (0.387)	-0.193** (0.062)	-0.228** (0.061)	-0.238** (0.061)
UNEMPLOYMENT	0.001 (0.009)	-0.001 (0.009)	-0.001 (0.009)	0.004** (0.002)	0.004** (0.002)	0.004** (0.002)
Adj R^2	0.889	0.889	0.889	0.988	0.989	0.989

All models include a set of state dummy variables; 2593 plant-year observations; (Standard Errors)
+=p<0.10, *=p<0.05, **=p<0.01

Table 4B
Production Workers – Fixed Effect Cluster Rule Models

	OLS-DiD			Robust-DiD		
Model	**1**	**2**	**3**	**4**	**5**	**6**
MACT* CR_1998	0.020 (0.056)		0.055 (0.041)	0.008 (0.009)		0.006 (0.012)
MACT* CR_2001		-0.022 (0.066)	-0.057 (0.062)		0.006 (0.009)	0.002 (0.011)
BAT* CR_1998	-0.051 (0.047)		-0.042+ (0.022)	-0.038** (0.008)		-0.022* (0.011)
BAT* CR_2001		-0.039 (0.063)	-0.013 (0.061)		-0.042** (0.008)	-0.029** (0.011)
Log(WAGE)	0.061 (0.499)	0.036 (0.496)	0.034 (0.495)	0.333** (0.069)	0.341** (0.069)	0.333** (0.069)
Log(INCOME)	-0.608 (0.429)	-0.582 (0.426)	-0.576 (0.429)	-0.201** (0.063)	-0.207** (0.063)	-0.211** (0.063)
UNEMPLOYMENT	-0.003 (0.009)	-0.004 (0.009)	-0.004 (0.009)	0.005** (0.002)	0.004** (0.002)	0.004** (0.002)
Adj R^2	0.872	0.872	0.872	0.988	0.988	0.988

All models include a set of state dummy variables; 2593 plant-year observations; (Standard Errors)
+=p<0.10, *=p<0.05, **=p<0.01

Table 4C
Production Worker Hours – Fixed Effect Cluster Rule Models

	OLS-DiD			Robust-DiD		
Model	**1**	**2**	**3**	**4**	**5**	**6**
MACT* CR_1998	0.034 (0.057)		0.051 (0.043)	-0.006 (0.012)		-0.002 (0.015)
MACT* CR_2001		0.004 (0.066)	-0.028 (0.061)		-0.011 (0.012)	-0.010 (0.015)
BAT* CR_1998	-0.047 (0.049)		-0.035 (0.027)	-0.034** (0.011)		-0.024+ (0.014)
BAT* CR_2001		-0.039 (0.064)	-0.017 (0.061)		-0.031** (0.011)	-0.018 (0.014)
Log(WAGE)	0.098 (0.521)	0.084 (0.519)	0.083 (0.517)	0.400** (0.091)	0.404** (0.091)	0.394** (0.091)
Log(INCOME)	-0.698 (0.466)	-0.689 (0.463)	-0.683 (0.467)	-0.241** (0.083)	-0.228** (0.083)	-0.237** (0.083)
UNEMPLOYMENT	-0.002 (0.009)	-0.002 (0.009)	-0.002 (0.009)	0.003 (0.002)	0.002 (0.002)	0.002 (0.002)
Adj R^2	0.861	0.861	0.860	0.979	0.979	0.980

All models include a set of state dummy variables; 2593 plant-year observations; (Standard Errors)
+=p<0.10, *=p<0.05, **=p<0.01

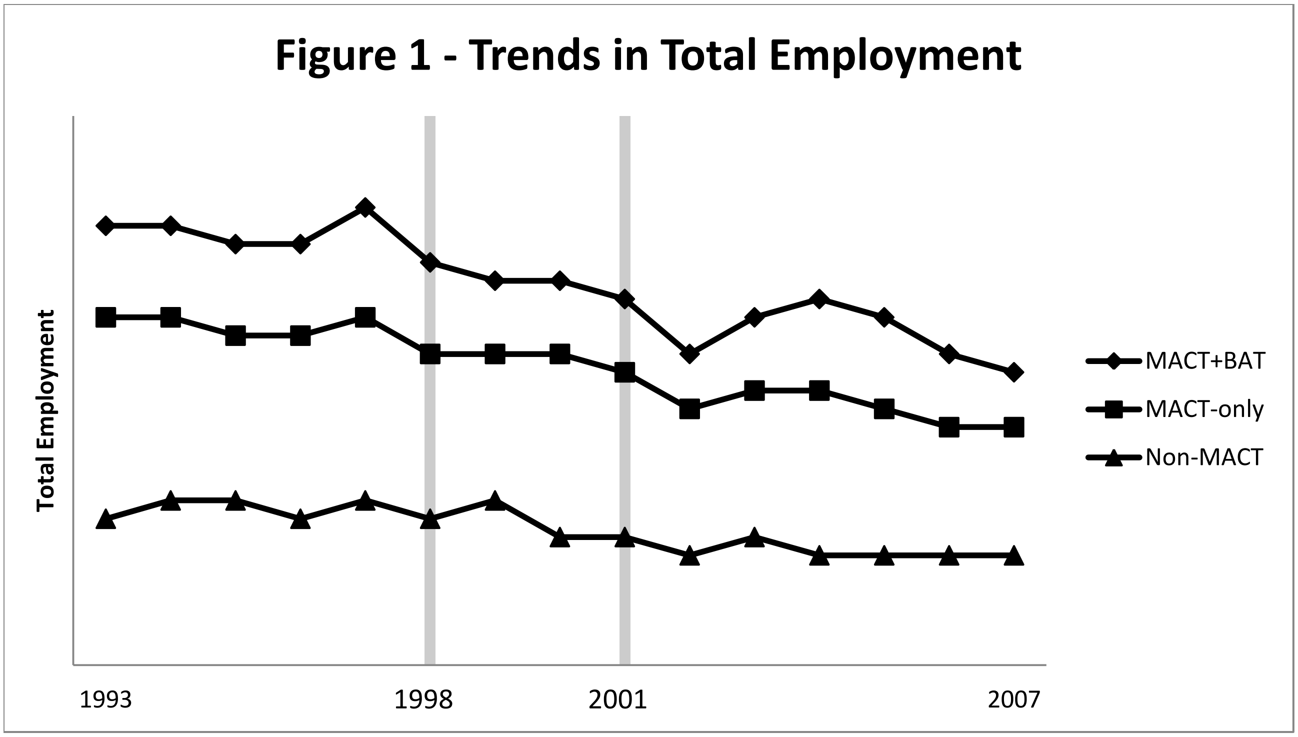

Figure 1 - Trends in Total Employment
Total Employment
1993
1998
2001
2007
MACT+BAT
MACT-only
Non-MACT

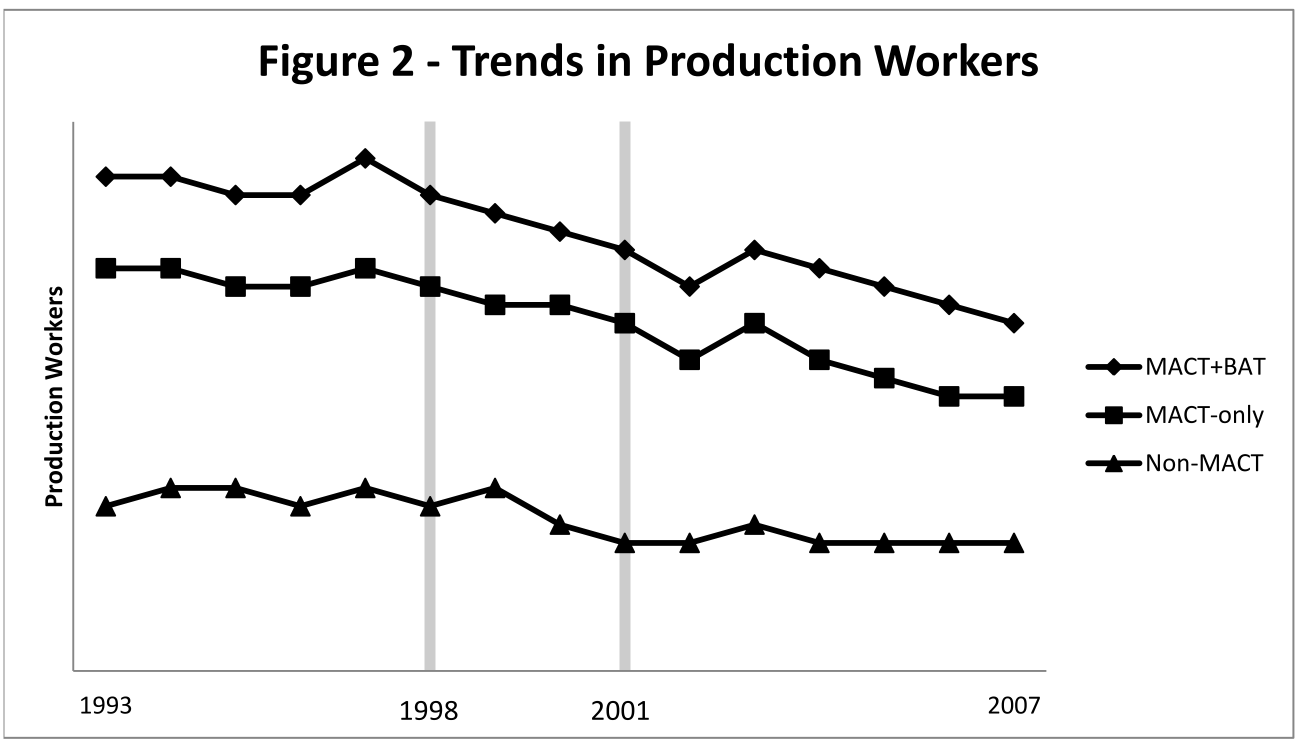

Figure 2 - Trends in Production Workers
Production Workers
1993
1998
2001
2007
MACT+BAT
MACT-only
Non-MACT

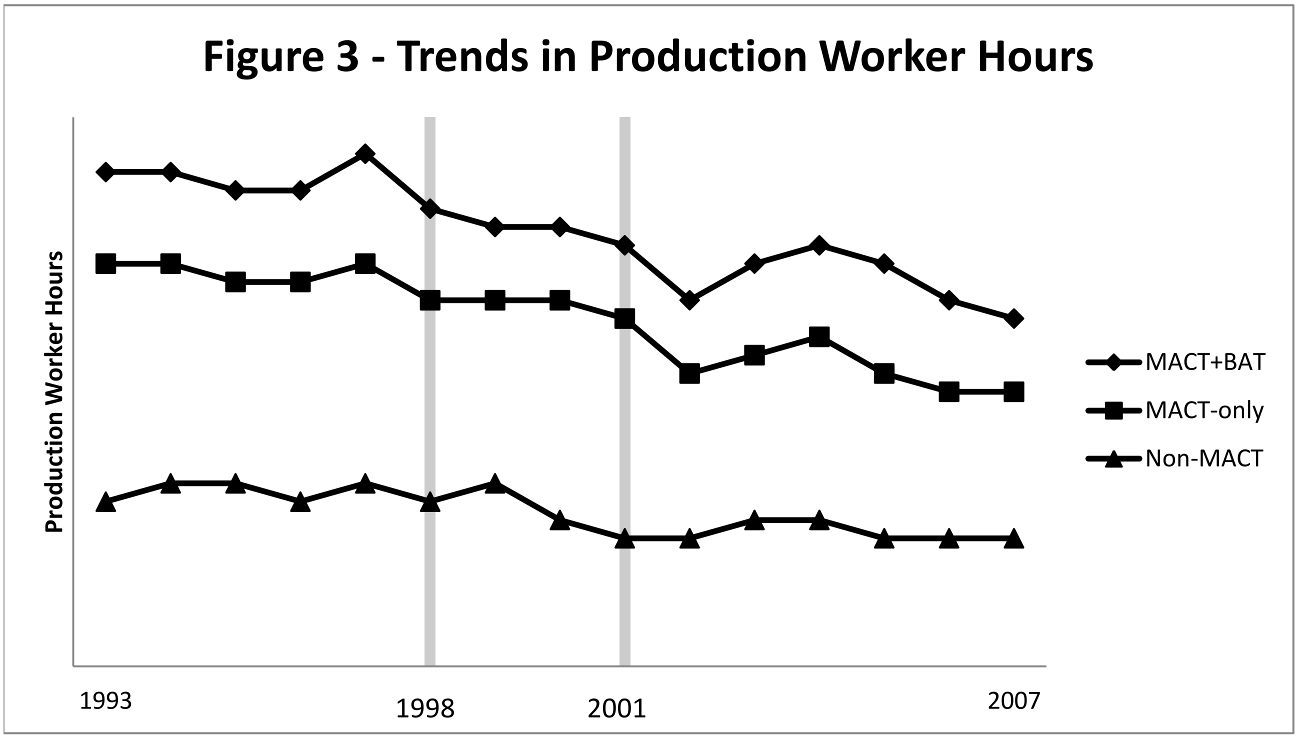
Figure 3 - Trends in Production Worker Hours
Production Worker Hours
1993
1998
2001
2007
MACT+BAT
MACT-only
Non-MACT