Unintended Environmental Consequences of Investment Stimulus Policy

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Abstract

We study the unintended environmental consequences of "bonus depreciation," one of the largest investment tax incentives in US history. To do so, we pair emissions data from the EPA's Toxic Release Inventory and National Emissions Inventory with quasi-experimental policy variation in the extent to which establishments benefited from the policy. Differences-in-differences estimates show bonus depreciation increased annual emissions by 30%. To quantify aggregate damages associated with the policy we integrate our estimates into a pollution transport model. We estimate overall environmental damages at between $17 and 39 billion per year. These estimates represent between 56 and 125% of the policy's annual fiscal cost during the period we study. Damages differ by race and were 75% higher for African-Americans compared to the national average. More stringent environmental regulations decreased damages from bonus depreciation by 40%.

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1 Introduction

Governments around the world rely on investment stimulus policies to advance key economic objectives, including promoting growth, reducing unemployment, and stabilizing the macroeconomy. From 2004–2016, 98 different countries implemented policies that decreased the cost of physical capital (Steinmüller, Thunecke, and Wamser, 2019). A particularly prescient example is the recent US Tax Cuts and Jobs Act of 2017, which included more than $1 trillion in investment incentives (CBO, 2017). Due to their widespread use and immense fiscal cost, academic researchers have spent considerable energy understanding how investment stimulus policies affect a wide range of outcomes including investment, employment, and productivity. Missing from our understanding of these policies is any consideration of the environmental damages generated by the capital investment they stimulate. Given the magnitude of these policies, their unintended environmental consequences are potentially large and critical in any cost-benefit analysis of their efficacy.

In this paper, we estimate the environmental impact of "bonus depreciation," one of the largest tax investment incentives in US history (Curtis et al., 2021). Bonus depreciation lowers the cost of new capital investments by allowing firms to deduct the purchase price of new capital assets from their taxable income more quickly. We estimate the effect of bonus depreciation on emissions in the industrial sector using well-established, quasi-experimental variation in the policy and data from the Toxic Release Inventory and the National Emissions Inventory. By combining our reduced-form emissions response estimates with a pollution transport model, we quantify the total economic damages generated by the policy.

We find bonus depreciation has a large and positive effect on plant-level emissions. The third of plants that benefit most from the policy increased emissions 30% more than plants that benefit less after bonus depreciation was implemented. Using a pollution transport model, we estimate that the economic damages caused by these additional emissions amount to between $17 and $39 billion per year. These damages are concentrated in areas with lower average incomes and higher Black population shares suggesting that investment stimulus policies can exacerbate existing inequalities in exposure to pollution. Together, our results suggest that the environmental costs of investment stimulus policies can be sizable and that policymakers should consider these damages when evaluating the costs and benefits of capital investment incentives.

The policy we study, bonus depreciation, was first implemented to combat the 2001 recession and has been in nearly continuous use ever since. The Tax Cuts and Jobs Act extended a generous version of the incentive through 2022. The US Treasury estimates that the fiscal cost of the policy was more than a quarter of a trillion dollars over the last ten years. The policy allows firms to deduct an additional "bonus" percentage of the cost of new investments from their taxable income in the year the investments are made. As a result, the policy decreases the present-value cost of new investments because firms receive tax breaks sooner in the lives of capital assets. Past research has documented the policy has large effects on capital investment, employment, and output (House and Shapiro, 2008; Zwick and Mahon, 2017; Curtis et al., 2021).

While the aim of the policy was to stimulate investment and other attendant outcomes, there are two potential channels by which the policy might lead to unintended environmental consequences. First, additional capital investment and output due to the policy will increase emissions through the so-called "scale effect." Second, the policy might alter emissions intensity (emissions per unit of output), thereby changing total emissions via the "technique effect". This technique effect may reduce emissions intensity if firms replace older capital with newer, more efficient capital. On the other hand, the policy may induce firms to substitute toward more capital-intensive production or allow firms to produce more intermediate goods "in-house" resulting in more emissions per unit of output.[1] In sum, there is ample reason to believe pollution emissions are linked to bonus depreciation, but the strength and direction of the relationship is an empirical question.

To answer this question, we link plant-level emissions data from the Environmental Protection Agency's (EPA) Toxic Release Inventory (TRI) and industry-level, quasi-experimental variation in the generosity of bonus depreciation. In the absence of bonus depreciation, historic and largely arbitrary tax rules specify how quickly different types of capital assets may be deducted from a firm's taxable income. Bonus depreciation decreases the present value costs of investment more for firms in industries that typically invest in assets that are deducted from taxable income more slowly. Based on this variation, we follow Cummins, Hassett, and Hubbard (1994), House and Shapiro (2008), Zwick and Mahon (2017), and Curtis et al. (2021) in comparing plants in industries that benefit more from the policy to plants in industries that benefit less. Using a

[1] "In-housing" is a form of vertical integration and often referred to as the "make-buy" decision which has long been studied by economists (Joskow, 1985; Hortaçsu and Syverson, 2007; Atalay, Hortaçsu, and Syverson, 2014).

difference-in-differences framework, we find that the third of plants in industries that benefit most from bonus depreciation increased total chemical releases by 34.9% relative to plants in industries that benefit less after the policy was introduced in 2001.

This estimate represents the causal effect of bonus depreciation on emissions if the emissions of treated and control plants would exhibit parallel trends in the absence of the policy. We perform a number of tests designed to support the validity of this assumption. First, using dynamic difference-in-differences (DD) specifications, we show no differences in pre-period emissions trends between treated and control plants. The dynamic DD estimates also show large, positive differences in emissions starting in 2002, just after the policy was implemented. Second, we show that our estimates are robust to the inclusion of county-by-year and sector-by-year (2-digit NAICS) fixed effects. The county-by-year fixed effects eliminate concerns that time-varying geographic variation, such as changes in state-level policies or changes in county-level environmental regulations, are responsible for our results. With sector-by-year fixed effects, our estimates are identified using within-sector variation. Thus, time-varying, sector-level changes in factors such as technological innovation or sector-specific regulations also do not drive our results. Third, we show our estimates are stable when we directly control for industry-level variation in several other contemporary policies. Finally, relying on a subsample of plants that we are able to link to financial statement data from Compustat, we show that the policy caused a large increase in capital stocks that coincided with the emissions patterns we document. Together these tests provide support for our identifying assumption and suggest our estimates represent the causal effect of bonus depreciation on pollution emissions.

The matched TRI-Compustat sample also allows us to explore the overall impact of the technique effect on emissions by estimating responses of firm-level measures of emissions intensity to bonus depreciation. Both DD and dynamic DD specifications show that the policy did not decrease emissions intensity and may have even led to increases in emissions per unit of capital (or revenue). This finding suggests that the additional capital investment induced by the policy was not less emissions intensive than previously-installed capital. We infer that firms did not primarily respond to bonus depreciation by replacing existing capital with cleaner production technologies.

Given the important role of environmental policy in mitigating emissions, we explore whether existing environmental regulations have the power to temper or shape emissions responses to investment stimulus policies. To do so, we compare the emissions responses of plants in counties subject to the Clean Air Act's nonattainment standards to the responses of plants in counties subject to less stringent regulations. We find that bonus depreciation had a 29% smaller impact in nonattainment counties. Similar heterogeneity analysis provides suggestive evidence that county-level nonattainment standards may have achieved this result by decreasing the capital investment response to the policy. Taken together, these results suggest that environmental regulations may have the power to curb the emissions impacts of investment stimulus policies, but may do so at the expense of capital investment, itself.

To provide additional support for the emissions responses we document and to calculate the dollar value of economic damages due to the policy, we turn to the EPA's National Emissions Inventory (NEI) dataset. The NEI focuses on emissions of common air pollutants regulated under the Clean Air Act–the so-called "criteria" air pollutants. Using a similar identification strategy, we find bonus depreciation substantially increased these criteria air pollutants. Our point estimates are similar in magnitude to the responses we document using the TRI and therefore further corroborate our TRI findings.

While the emissions responses we document are concerning, ultimately, we want to know how these impacts translate into economic damages. To do so, we rely on a pollution transport model called the Intervention Model for Air Pollution or simply "InMAP" and our NEI estimates. Using the InMAP model, we calculate how increases in criteria air emissions due to bonus depreciation from a given plant lead to increased pollution exposure and economic damages across the US. Critically, the model accounts for both atmospheric transport and chemical reactions of pollution to determine damages at a fine degree of spatial resolution. InMAP has been increasingly embraced in the economic literature due to this spatial granularity which allows for more precise connections between environmental outcomes and demographic disparities (e.g. Hernandez-Cortes and Meng, 2023; Shapiro and Walker, 2020; Hernandez-Cortes, Meng, and Weber, 2022).

Estimates from the InMAP model suggest annual economic damages from bonus depreciation range between $17 and $39 billion USD, which corresponds to per-capita damages between $56 and $127 USD.[2] Economic damages are highly uneven over space and demographic groups, with

[2] This range corresponds to low and high estimates of the relationship between mortality and pollution concentration from Krewski D (2019) and Lepeule J (2012). Throughout, we assume the value of a statistical life is 9 million USD following the EPA's current standard.

some sub-populations incurring damages that far exceed the average. For the least affected counties, we estimate damages of $0.08 to $0.19 USD per capita. For the most affected counties our estimates range from $365 to $823 USD per capita.

Economic damages are also highly unequal across racial groups, with African Americans experiencing per-capita economic damages 75% higher than the national average. Counties with greater Black population shares incurred higher economic damages, even after controlling for median income and poverty rates. These results suggest that the policy exacerbated existing racial disparities in exposure to air pollution.

Finally, motivated by our findings that emissions responses are attenuated in counties subject to more stringent nonattainment regulations, we use the InMAP model to quantify the role of these regulations in reducing total damages caused by bonus depreciation. We find damages are approximately 40% lower as a consequence of existing environmental regulations.

This paper's findings represent four major contributions. First, the substantial unintended environmental costs of bonus depreciation that we document forces a reexamination of the relative costs and benefits of the policy and investment stimulus policies, broadly. A well-established literature has shown that federal bonus depreciation has large, positive effects on both capital investment and employment (House and Shapiro, 2008; Zwick and Mahon, 2017; Garrett, Ohrn, and Suárez Serrato, 2020; Curtis et al., 2021).[3] We estimate that incorporating the environmental costs of the policy increases its total annual cost by between 56% to 112%. These additional costs increase the cost-per-job figure from $50,000 (Garrett, Ohrn, and Suárez Serrato, 2020) to between $77,000 and $112,500. Unfortunately, our findings suggest the reliance on very similar policies to stimulate capital investment throughout the world—including in UK, China, Japan, Poland, and Canada (Maffini, Devereux, and Xing, 2018; Fan and Liu, 2020; Guceri and Albinowski, 2021)—may also result in large unintended environmental costs.

Second, our results show that investment stimulus policies—and fiscal policies in general—are important determinants of emissions and pollution in the United States.[4] Our findings therefore add to the large literature in environmental economics exploring the importance of various de-

[3]Ohrn (2019) and Tuzel and Zhang (2021) find that state accelerated depreciation policies increase capital investment. Most studies find no effect of bonus depreciation on wages, with the exception of Ohrn (2022), who finds bonus depreciation lead to large increases in compensation for the very highest paid executives at large, publicly traded firms.

[4]Kong, Xiong, and Qin (2022) find that a value added tax reform in China led to plant-level decreases in emissions.

terminants of industrial emissions, including trade and outsourcing, structural transformation, productivity growth, and environmental regulations (See e.g. Levinson, 2009, 2015; Shapiro and Walker, 2018; Najjar and Cherniwchan, 2021). Shapiro and Walker (2018) argue that environmental regulations are a key determinant of emissions and are primarily responsible for the decline in total emissions over the past 50 years. The environmental damages of the investment stimulus policy we study represent between 8.5% and 16.5% of the environmental benefits of the 1990 Clean Air Act Amendments (EPA, 2011). Thus, we find the environmental costs of investment stimulus policies are large even compared to the effects of major, historical environmental regulations. This paper also contributes directly to our understanding of the effects of environmental regulations on emissions (Greenstone, 2003; Hanna and Oliva, 2010; Martin, Muûls, and Wagner, 2016; Cropper et al., 2023). Our findings show that the effectiveness of environmental regulations can depend on the fiscal environment in which they are implemented.

Third, because bonus depreciation decreases the cost of investment and can alleviate financing frictions, this paper provides new evidence on the effects of financial conditions on environmental performance. A number of previous papers have explored these relationships, generally finding that removing credit constraints improves environmental outcomes (Aghion et al., 2022; Earnhart and Segerson, 2012; Andersen, 2016, 2017; Xu and Kim, 2021; Cohn and Deryugina, 2018). Motivated by increasing attention to sustainable (dis)investment trends, a related strand of research investigates the impact of capital costs on environmental performance, finding that increases in capital costs promote investment in dirty capital and increased emissions (Hartzmark and Shue, 2023; Edmans, Levit, and Schneemeier, 2022). Recently, several papers have found mixed results when exploring the effect of unconventional monetary policy on emissions via changes in the cost of capital (Goetz, 2019; Papoutsi, Piazzesi, and Schneider, 2022). Our study contributes to this literature by combining well-established quasi-experimental variation and plant-level emissions data to estimate the causal effects of changes in the cost of capital on emissions and emissions intensity. We find that decreases in the cost of capital lead to increases in emissions and do not decrease emissions intensity. Our findings caution generalizations that decreases in the cost of capital lead to greener investments and better environmental performance.

Finally, this paper also contributes to the large and growing environmental justice literature, which documents persistent inequalities in exposure to air pollution across racial-ethnic groups (Clark, Millet, and Marshall, 2017; Colmer et al., 2020; Chambliss et al., 2021; Liu et al., 2021;

Jbaily et al., 2022; Wang et al., 2022; Hernandez-Cortes, Meng, and Weber, 2022; Whittemore, 2017; Rosofsky et al., 2018; Lane et al., 2022). We find that bonus depreciation lead to more acute health effects for African Americans, which are not explained by differences in income. In doing so, we demonstrate that investment stimulus policies, and fiscal policies in general, can exacerbate pre-existing inequalities in pollution exposure.

The remainder of the paper proceeds as follows. Section 2 provides a more complete description of bonus depreciation. Section 3 describes our empirical framework and identification strategy. Section 4 details the data sources we use. In Section 5, we present our reduced form empirical estimates. Section 6 presents the aggregate damage estimates from the pollution transport model. Section 7 concludes.

2 Bonus Depreciation

When businesses make investments in new capital, typically they are not allowed to immediately deduct the full purchase price of the capital from their taxable income. Instead, tax rules govern how quickly the cost of the new investment can be "depreciated" and therefore deducted from a firm's taxable income.[5] All else equal, firms would prefer to depreciate capital more quickly and as a result deduct the investment costs from their taxable income sooner or even immediately. This would result in larger tax shields earlier in the life of a given asset and a lower after-tax present value cost of the investment. The policy we study, bonus depreciation, does exactly this.

Under bonus depreciation, firms are allowed to deduct a "bonus" percentage of the purchase price of new investments in the year they are made. The remaining costs are deducted according to existing tax rules. Figure 1, Panel (A) presents an example based on a "5-year" asset that is typically deducted from taxable income over a six-year period. In the absence of bonus depreciation, tax rules specify that 20% of costs are deducted in the first year, 32% are deducted in the second year, etc. With 50% bonus depreciation, 50% of the investment costs are deducted in the first year. The remaining 50% are deducted according to the typical tax rules. Assuming a 10% discount rate and a 35% tax rate (the rate during the period we study), bonus depreciation decreases the after-tax present value cost of the 5-year asset by 2.4%.

Figure 1, Panel (C) displays US bonus depreciation rates during our sample period. Bonus

[5] In the US, the tax rules that govern how quickly different types of assets can be deducted is called the Modified Accelerated Cost Recovery System (MACRS). IRS Publication 946 details the percent of investment costs that can be deducted in each year for each different type of capital investment.

was first implemented as part of the Job Creation and Worker Assistance Act of 2002. The bill allowed 30% bonus deprecation for investments made after September 10, 2001.[6] In May 2003, the bonus rate was increased to 50% for 2003 and 2004. The incentive was allowed to lapse in 2005. Congress reinstituted the policy at a 50% rate in 2008. The 50% rate was available through 2018 except for in 2011, when the bonus rate was 100% (sometimes referred to as full expensing).[7] Based on IRS Expenditure Estimates, Garrett, Ohrn, and Suárez Serrato (2020) conclude that bonus depreciation cost the US government approximately $30 billion per year on average during the treatment period we analyze.

While the policy was implemented in 2001 and again in 2008 as a countercyclical fiscal stimulus measure to promote business investment, in our empirical analysis we treat the policy as available in all years after 2001. We do this for two reasons. First, while the generosity of the policy varied over time, bonus depreciation was in nearly continuous use since its inception in 2001; the average rate from 2002-2012 was 39%. Second, while the policy was allowed to lapse, firms likely expected the policy to be reinstutited (it was often extended at the 11th hour) and retroactively available. Consistent with this contention, House and Shapiro (2008) estimate that firms acted as though the bonus depreciation rate in 2006 was between 25 and 50% even after the policy had expired. Further, prior research has shown that the capital investment and employment response to bonus depreciation implementation was persistent over the full 2002–2012 period Garrett, Ohrn, and Suárez Serrato (2020); Curtis et al. (2021).

3 Identification and Empirical Strategy

The key to identifying the effect of bonus depreciation on emissions is that the policy benefits firms in some industries more than others. In particular, firms in industries that invest in capital

[6]Given this retroactive implementation, we normalize outcomes in 2001 in our empirical analyses.

[7]During the time period we study, the US made use of a second accelerated depreciation policy referred to as Section 179 Expensing (§179). Under §179, firms are allowed to fully expense all capital investments costs below the §179 limit (applied at the firm-level annually). The §179 limit increased from $24,000 to $500,000 during our treatment period. Due to this limit, the policy applies only to smaller firms or those making fewer capital investments. Kitchen and Knittel (2016) find that §179 only applied to only about 12% of investment during our treatment period. Because the TRI and NEI datasets focus on large polluters, the §179 allowance is likely to apply to an even smaller percentage of capital investment and emissions in our sample. However, because both §179 and bonus depreciation provide larger benefits for firms that typically invest in capital that is depreciated more slowly according to tax rules, our identification strategy does not separately identify the effects of the two policies. Therefore, following Curtis et al. (2021), we interpret our estimates as responses to both accelerated depreciation policies. We refer to the combination of the two policies as simply bonus depreciation throughout the rest of the paper for simplicity.

that is depreciated more slowly according to IRS tax rules benefit more from the policy. For these firms, bonus depreciation accelerates tax deductions from further in the future and decreases the after-tax, present value cost of capital investments more.

Panels (A) and (B) of Figure 1 illustrate these differential effects. In both panels, the blue (left) bars show the tax depreciation schedule in the absence of bonus depreciation. The green (right) bars show how each asset is depreciated when bonus depreciation is applied at a 50% rate. Panel (A) shows the effect of 50% bonus depreciation on a 5-year asset while Panel (B) shows the effect of bonus depreciation on a 7-year asset. For both types of assets, bonus depreciation accelerates tax deductions and decreases the after-tax, present value cost of investment. Critically, however, bonus depreciation has a larger effect for the 7-year asset that is typically deducted more slowly. The reason is that, in the case of the 7-year asset, tax deductions are accelerated from further in the future, thereby decreasing the after-tax present value cost of the investment more.

Slightly more formally, let z_0 be the present value of tax deductions due to depreciation per \$1 of investment in the absence of bonus depreciation under typical tax rules. z_0 is the present value of the blue (left) bars in Panels (A) and (B) of Figure 1. z_0 is larger in Panel (A) because the value of the asset is deducted from taxable income more quickly. If b is the bonus depreciation rate, then b percent of the new asset is deducted immediately and the remaining $(1-b)$ is deducted according to typical tax rules. We can represent the tax deductions in the presence of bonus depreciation as $z = b + (1-b)z_0$. z is the present value of the tax deductions represented by the green (right) bars.

Taking the derivative of z with respect to bonus yields $dz/db = 1 - z_0$, meaning the value of bonus depreciation is larger for assets that are typically deducted more slowly according to typical tax rules. This simple math emphasizes that the benefit of bonus depreciation is larger for firms and industries that invest in assets that are typically depreciated more slowly and have lower z_0 measures. Using corporate tax return data, Zwick and Mahon (2017) calculate z_0 at the 4-digit NAICS industry-level. By comparing firms in industries with low z_0 (that typically invest in assets that are depreciated more slowly) to firms in industries with higher z_0 (that typically invest in assets that are depreciated more quickly), we identify the effect of bonus depreciation on emissions.

This identification strategy is particularly appealing because most of the variation in the

z_0 measure is determined not by the *type* of assets that are purchased, but by their *use*. For example, IRS Publication 946 states that assets used in the "Manufacture of Chemicals and Allied Products" are depreciated according to 5-year MACRS schedules. Assets used in the "Manufacture of Rubber Products" on the other hand, are depreciated over a 7-year period.[8] As a result, firms differ in the extent to which they benefit from bonus depreciation even if they are investing in the same types of capital. Further, firms are largely unable to change their tax depreciation schedules in response to the policy because doing so would entail changing industries. Because of this feature, a number of high-impact papers have examined the effect of bonus depreciation on various outcomes by comparing firms in low z_0 industries to firms in high z_0 industries over time (Cummins, Hassett, and Hubbard, 1994; House and Shapiro, 2008; Zwick and Mahon, 2017; Garrett, Ohrn, and Suárez Serrato, 2020; Curtis et al., 2021).

The fact that bonus depreciation benefits some industries more than others naturally motivates a difference-in-differences (DD) empirical strategy. We compare emissions outcomes (Y_{it})—usually in logs—between plants that benefit most from bonus depreciation to plants that benefit less using the regression specification:

$$Y_{it} = \beta[\text{Bonus}_j \times \text{Post}_t] + \alpha_i + \lambda_t + \gamma \mathbf{X}_{icjt} + \varepsilon_{it} \tag{1}$$

where subscripts i, c, j and t denote plant, county, industry, and year. Bonus_j is an indicator equal to unity for plants in industries in the bottom tercile of the z_0 distribution.[9] Post_t is an indicator equal to one after policy implementation in 2002. α_i and λ_t are plant and year fixed effects which absorb time-invariant differences in plant-level emissions and aggregate trends in emissions.[10] $\mathbf{X}_{icjt}$ is a vector of fixed effects and controls that varies across specifications. Throughout the paper, we cluster standard errors at the 4-digit NAICS level following guidance provided by Bertrand, Duflo, and Mullainathan (2004) and Cameron and Miller (2015).

[8]MACRS class lives are based on the original Accelerated Cost Recovery System (ACRS) which was implemented in 1981. ACRS class lives were "not intended to reflect actual useful lives, or even some percentage of the useful lives" (Brazell, Dworin, and Walsh, 1989). The disconnect between depreciation schedules and how long different types of capital actually last assuage concerns that comparing low z_0 firms to higher z_0 firms captures differences in the types of capital utilized rather than arbitrary tax rules.

[9]In our baseline analysis, we use an indicator rather than continuous treatment variable for three reasons. First, the indicator is agnostic to assumptions about firms' discount rate. Second, there is a natural break in z_0 distribution at the 33rd percentile. Finally, as Callaway, Goodman-Bacon, and Sant'Anna (2021) point out, stronger assumptions are necessary to identify DD parameters when treatment variation is continuous. We come to very similar conclusions when we define treatment using alternative cutoffs or using the continuous variation in z_0. These results are presented in Table A2.

[10]To adjust our estimates to account for plants with vastly different emissions levels, we weight all plant-level regressions by outcome levels in 2001, just prior to bonus depreciation implementation.

β is our DD estimate, which represents the change in emissions in the most affected plants relative to less affected plants after bonus depreciation was implemented. This parameter represents the causal effect of bonus depreciation on emissions under the identifying assumption that, in the absence of the policy, emissions trends in the most affected plants would track emission trends in less affected plants. Throughout the paper, we implement a number of strategies to reinforce the validity of this identifying assumption. First, we augment our DD estimates with dynamic specifications of the form:

$$Y_{it} = \sum_{y=1997,\neq 2001}^{2012} \beta_y [[\text{Bonus}_j \times \mathbb{I}[y = t]] + \alpha_i + \lambda_t + \gamma \mathbf{X}_{icjt} + \varepsilon_{it}. \tag{2}$$

The time-varying coefficients β_y describe differences in emission outcomes between the most- and less-affected plants in each year relative to differences in 2001. If the identifying assumptions hold and bonus depreciation has a significant impact on emissions, then β_y should statistically indistinguishable from zero in years prior to 2002 and should then differ from zero upon bonus depreciation implementation in 2002.

Next, we include a number of fixed effects designed to mitigate concerns that other coincident shocks undermine the validity of our identifying assumption and bias our results. We show that our estimates are insensitive to the inclusion of county-year, sector-year, and even county-sector-year fixed effects in our regression models. County-year fixed effects absorb variation in emissions due to shocks that differently affect some counties and not others. These fixed effects assuage concerns that our estimates are due to policy or regulatory changes at the local level or localized effects of other shocks such as changes in trade and immigration policy. Sector-year fixed effects eliminate concerns that shocks affecting one sector and not another, such as changes in abatement technology or sector-specific regulations and incentives, drive our results.[11] County-sector-year fixed effects go one step further and control for changes in emissions due to shocks that differently affect specific county-sectors and not others.

As a final check, we directly control for industry-level exposure to other relevant shocks that occur during our analysis period. We are particularly concerned about other federal tax and trade policies that have been shown to have differential effects across industries. To this

[11] Data in our primary specifications include the utilities sector, manufacturing sector and a small number of oil and gas extraction sites. All plants in the utilities sector (NAICS 2-digit Sector 22) are defined as treated. As a result, when sector-year fixed effects are included in the model, estimates of the effect of bonus depreciation are not based on changes in emissions for plants in the utility sector.

end, we directly control for a federal tax incentive called the Domestic Production Activities Deduction (DPAD), which provided a tax benefit based on the percentage of income derived from manufacturing activities (Ohrn, 2018). We also control for industry level variation in trade exposure due to China's accession to the World Trade Organization (often referred to the "China Shock," Autor, Dorn, and Hanson, 2013).

Overall, while the identifying assumption underlying our empirical analysis is inherently untestable, our dynamic DD analyses—which display parallel trends in the pre-period and immediate differences in emissions upon policy implementation—together with the stability of our coefficient estimates across specifications that include a host of high-dimensional fixed effects and industry-level controls assuage concerns that the assumption is violated.

4 Data

To estimate the effects of bonus depreciation on emissions, we rely on a number of datasets. In this section, we describe our primary data sources, detail the construction of our main variables of interest, and present descriptive statistics for our main analysis sample. We begin with our two primary sources of emissions data.

4.1 Toxic Release Inventory

In our main analysis, we use plant-level emissions data from the Environmental Protection Agency's (EPA) Toxic Release Inventory (TRI). The TRI includes emissions data for approximately 650 toxic chemicals, which are known to cause significant adverse human heath impacts (e.g., cancer) or significant effects to the environment (or both). In particular, the dataset includes information on the annual quantity of emissions, the disposal media (air, surface water, landfill, other), and information regarding whether releases were on-site of transferred offsite.[12] Plants are required to self-report under the Emergency Planning Community Right-to-Know Act (EPCRA) of 1986 whenever they employ at least ten employees and release at least one toxic chemical in excess of the threshold. The EPA can assess civil penalties for not reporting or misreporting releases, and plants are generally not subject to emissions fees, which provides

[12] Emissions encompasses a wide-range of types of releases, such as emitting, discharging, dumping, leaking, leaching, and so on. Offsite emissions are transferred to geographically separate facilities, where chemicals are recycled, treated, or disposed. For more details, see https://www.epa.gov/toxics-release-inventory-tri-program/common-tri-terms.

incentives for accurate reporting.[13]

Using the TRI dataset, we construct several measures of pollution emissions. All measures are aggregated at the establishment-level based on total weight (in metric tons). Total Releases is the sum of all on-site and off-site chemical releases to all disposal media (air, water, land), and Total On-Site Releases is the sum of only on-site chemical releases to all disposal media). Our Total Releases variable reflects the sum of emissions generated, whereas Total On Site Releases reflects the sum of emissions released at the site of the establishment. Air Releases is the sum of all releases to the air, Water Releases is the sum of all releases to surface water, such as streams, rivers, lakes, and other water bodies and Land Releases is the sum of all releases to underground and above ground land, including landfills, surface holding areas, underground injection sites, and other leaks or spills. Finally, Clean Air Act Releases is the sum of chemicals covered under the Clean Air Act to air.

In analyzing the effects of bonus depreciation on emissions, we rely on log transformed pollution variables and winsorize outcomes at the 1st and 99th percentile to mitigate the effect of outliers on our results.

4.2 National Emissions Inventory

In addition to the TRI, we also rely on data from the EPA's National Emissions Inventory (NEI). The NEI data are helpful for two reasons. First, we use this alternative data source to corroborate our findings based on the TRI. Second and more importantly, we use estimates based on the NEI to quantity the aggregate and distributional consequences of bonus depreciation. The NEI includes detailed emissions data for criteria air pollutants and precursors from both point and non-point sources. The NEI was collected in 1990, every year between 1996 and 2000, and every third year starting in 2003 (i.e., 2003, 2005, 2008, and so on). We focus on particulate matter 2.5 ($PM_{2.5}$, which are particles in the air that are 2.5 microns or less in width), sulphur dioxide (SO_2), nitrogen oxides (NO_x), and volatile organic compounds (VOC), from point sources (i.e., larger sources at fixed locations). Emissions data are collected by state and local agencies and submitted to the EPA according to emissions thresholds determined by the Air Emissions Reporting Rule (AERR). While reporting requirements are based on the emissions potential of

[13] Misreporting is generally a concern whenever data are self-reported; however, the EPA finds that changes in pollution concentration are correlated with changes in reported emissions (U.S. Environmental Protection Agency, 1993). See Marchi and Hamilton (2006) for an in-depth analysis of misreporting and accuracy of the TRI dataset.

each facility, the reporting thresholds vary over time and by county.[14]

The primary advantage of the NEI is that it is a comprehensive measure of criteria air pollutants and precursors, which are the primary air pollutants responsible for harming human health and the environment. Moreover, the NEI includes detailed emissions-release data, including stack height, diameter, temperature, and velocity. As a consequence, the NEI is particularly well suited to estimating aggregate economic damages of pollution, and several pollution-transport models use NEI emissions data as inputs. The primary disadvantages of the NEI dataset (and the reason we first look to the TRI) is that the NEI is not collected every year and facilities do not have consistent identifiers across survey years.

We use the NEI in two primary ways. First, we construct annual (for years in the sample) county-by-industry measures of emissions for $PM_{2.5}$, SO_2, NO_x, and VOCs, which we employ as dependent variables. Second, we use facility-level emissions data (and stack characteristics) for $PM_{2.5}$, SO_2, NO_x, and VOCs, combined with our coefficient estimates, to estimate aggregate damages using the InMAP pollution-transport model.

4.3 Compustat

In supporting analyses, we explore the effect of bonus depreciation on capital investment and emissions intensity, which we measure as firm-level emissions per dollar of capital or firm-level emissions per dollar of revenue. To do so, we match emissions data from the TRI to capital stock and other financial statement data from Compustat's North American Annual Fundamentals database (Standard & Poor's, 1997-2012) using the matching procedure developed in Andersen (2016). We successfully match 3,923 TRI plants of our TRI sample to Compustat firms. A large majority of plants (just over 3,900), are the only plant link to a given Compustat firm.

4.4 Bonus Depreciation Variation

As we note in Section 3, we rely on 4-digit NAICS-level measure of z_0 to classify plants as most- or less-affected. Our z_0 measures come from Zwick and Mahon (2017), who construct the industry averages using administrative tax return data. First, for each asset class, Zwick and Mahon

[14]These thresholds vary due to county-level attainment status and voluntary reporting decisions. Changes in reporting thresholds have the ability to bias our results, however, our estimates are stable using only within-county-year variation (when county-year fixed effects are included) and are very similar when we use the TRI dataset, which is not affected by these same thresholds.

(2017) calculate z_0. Then, they construct industry-level average z_0 based on the percentage of investment in each asset-class in non-bonus years using data from IRS form 4562. As discussed above, we transform this z_0 variation into a discrete indicator to identify plants in industries that benefit most from the policy.

4.5 Descriptive Statistics

Table 1 presents descriptive statistics for our main TRI analysis sample. In total, we observe just under 5,800 treated plants (Bonus = 1) and just over 12,000 untreated plants. While treated plants, on average, produce more emissions, both treatment and control plants show very similar ratios of on-site releases, air releases, water releases, land releases, and releases governed under the CAA relative to total releases. Approximately 40% of both control and treatment plants are located in a county designated under Non-attainment according to CAAA standards during the sample period. We are able to link approximately 25% of plants in the treatment and 24% of plants in the control groups to Compustat. Compustat firms with treated plants have slightly larger capital stocks in 2001 than firms with control plants. Overall, while there exist some differences between treated and control plants, our DD and event study DD empirical strategies account for such time-invariant differences.

5 Effects of Bonus Depreciation on Emissions

We now measure the effect of bonus depreciation on toxic releases. We start by estimating baseline DD models. We then show that our estimates are robust to the inclusion of a number of fixed effects designed to assuage concerns that our results are influenced by other shocks that manifest at the local or industry level. Next, we implement dynamic DD models to test for pre-period trends and uncover the timing of the policy impacts. We then present estimates for different types of chemical releases: on-site releases, releases to air, releases to water, releases to land, and releases regulated by the CAA. To reinforce that the environmental impacts we document are due to investment stimulus, we estimate the effect of the policy on capital stocks for a subsample of plants. For these plants, we are also able to test whether bonus depreciation affected emissions intensity. Next, we explore whether environmental regulation had the power to mitigate the environmental impacts of the policy. Finally, we show that bonus depreciation elicited very similar responses in terms of criteria air pollutants using NEI data.

5.1 Baseline Impacts and Robustness

Table 2 Specification (1) present estimates the effect of bonus depreciation on emissions in the presence of plant and year fixed effects. The Bonus $\times$ Post coefficient is equal to 0.314 and is statistically significant at the 1% level. The estimate indicates that total releases for plants that benefit most from bonus depreciation increase by 31.4% relative to plants that benefit less after 2002 when the policy was first implemented. Specifications (2)–(6) progressively add more advanced levels of fixed effects in an effort to isolate variation due only to bonus depreciation. Specifications (2) and (3) replace the year fixed effects with county-year and sector-year fixed effects, respectively. Specification (4) includes both county-year and sector-year fixed effects. We base further analyses on this specification as it is the most parsimonious model that controls for time-varying shocks to emissions that differentially affect some counties or sectors more than others. Specification (5) includes county-sector-year fixed effects. Finally, Specification (6) reverts to the combination of county-year and sector-year fixed effects and additionally directly controls for industry-level exposure to other federal tax and international trade policies.[15]

The DD estimates across all six specifications are positive, statistically significant, and stable, ranging from 0.314 to 0.349. That the estimated effects are generally invariant indicates that our estimation strategy is not contaminated by shocks to counties or sectors that covary with bonus depreciation. Overall, the Table 2 findings indicate that the investment stimulus policy had a large, positive effect on chemical releases.

5.2 Dynamic DD Analysis

To further assess the validity of these estimates, we implement a dynamic DD analysis based on Specification (4) from Table 2. Panel (A) of Figure 2 displays these event study estimates and corresponding 95% confidence intervals. Estimates in pre-treatment years 1997–2001 are small, statistically insignificant, and display no concerning trends. Starting in 2002, the year of bonus depreciation implementation, coefficients are positive, statistically significant, and generally increasing in magnitude. Together, these findings indicate that differences in emissions between

[15]To control for the DPAD, we measure the value of the deduction at the 4-digit NAICS industry based on data from Ohrn (2018). We control for the China Shock by measuring industry-level changes in Chinese import penetration between 1999 and 2007 Autor, Dorn, and Hanson (2016). To avoid a bad controls problem, we create quintile bins of exposure to each control, then include interactions between these quintile bins and year fixed effects.

plants that benefited the most from bonus depreciation and plants that benefited less increase dramatically after bonus was first implemented. These findings also reinforce the validity of our empirical design; the absence of differential trends prior to 2002 and the immediate and observable differences in emissions after policy implementation provide strong evidence that the DD effects we estimated in Table 2 are caused by bonus depreciation.[16]

To place the magnitude of these effects in context, Panel (B) of Figure 2 maps our reduced-form estimates onto trends plant-level average log emissions. The resulting figure presents two plots, one describing the evolution of the log of total chemical releases for plants that benefited most from bonus depreciation and another describing the evolution of the same outcome for the plants that benefited less from the policy.[17] Toxic releases for the most- and less-affected plants track each other in the years 1997 to 2001 then diverge starkly after policy implementation in 2002. While both series show the dramatic decreases in total releases documented by Shapiro and Walker (2018) over the full period, declines for plants that benefited most from the policy were substantially curbed after 2001.

5.3 Effects on Different Types of Toxic Releases

Table 3 displays estimates describing the effect of bonus depreciation on different types of toxic releases. Specification (1) shows the effect of bonus depreciation on the log of Total On-site Releases. The coefficient is 0.366, indicating the effect on on-site releases is very similar to effect on total releases, meaning firms did not shift to—or away from—off-site releases in response to the policy. Therefore, to the extent that off-site pollution represents recycling or clean-up efforts, we do not see a proportional increase in these efforts in response to the policy. Next, we measure the effect of bonus depreciation on total releases to air, water, and land (recall most releases are to air). Specifications (2), (3), and (4) indicate bonus had a large statistically significant effect on air and water, but not land releases (perhaps due to small number of plants that make land releases). Specification (5) shows bonus depreciation has a positive and statistically significant effect on CAA releases that is approximately 70% as large as the corresponding total releases estimate (Specification (4), Table 2). The smaller effect for these more stringently regulated

[16] Appendix Figure A1 displays event study estimates corresponding to the Specifications (1), (5), and (6) from Table 2. All three plots show statistically insignificant differences in emissions in the pre-period and immediate, large differences in emissions after bonus implementation in 2002.

[17] To construct these plots we add or subtract 0.5 $\times$ our coefficient estimates from Panel (A) to the average log of log of total chemical releases for the balanced sample of plant we observe.

pollutants suggests a role for environmental regulation in mitigating the effects of investment stimulus policies on emissions. We further explore this hypothesis in Section 5.6.

5.4 Attributing Emissions Responses to Bonus Depreciation

To reinforce that the environmental consequences we document are due to bonus depreciation, we now turn to the sample of plants that we successfully match to firm-level capital stock data from financial statements. We begin by repeating our total releases analysis for the matched plants. Figure 3 presents dynamic DD estimates. As was the case for the full sample, the dynamic DD analysis shows that releases between the most- and less-affected plants trended similarly between 1997 and 2001. Toxic releases for treated plants then increased dramatically relative to control plants beginning in 2002. Appendix Table A3 presents DD coefficients using the same set of specifications as Table 2 for the set of plants we successfully match to Compustat. As was the case for the full sample, bonus depreciation has a large and positive effect on total emissions regardless of the model. Our preferred specification indicates total releases increase by 55% for the most-affected plants relative to the less-affected plants after the policy was introduced. These larger estimates indicate that bonus depreciation has a slightly larger effect for plants owned by publicly traded corporations than for other plants.

If the emissions response we document is due to the investment stimulus policy, then we should observe a coincident capital investment response for this subsample. We test this hypothesis using firm-level data and a slightly-modified dynamic DD design.[18] The outcome is the log of capital stock.[19] Figure 4, Panel (A) shows our baseline dynamic DD specification. Coefficient estimates indicate that prior to bonus implementation, differences in capital stock are relatively small but with some oscillation around zero. In years after implementation, capital stocks for the most-treated firms show a large statistically significant increase relative to firms that benefit less from the policy. Specification (2) of Table 4, which includes firm fixed effects and firm-size by year fixed effects, displays the DD estimate based on this specification.The coefficient indicates that bonus deprecation increases capital stock at treated plants by 29% relative to control plants. Specifications (1), (3), and (4) include alternative fixed effects that force identification to be

[18] Consistent with the timing of capital investment responses documented in Zwick and Mahon (2017), we now omit 2000 rather than 2001 from the analysis.

[19] Capital stocks are measured using the financial statement variable "property, plant, and equipment net of depreciation".

based on firms of similar sizes, similar leverage, and similar capital stocks by including binned pre-treatment measures of each of these variables interacted with year fixed effects. Specifications (1)–(4) all show positive and statistically significant effects of bonus depreciation on capital stock. To directly address any concerns due to the pre-period dynamic DD estimates, Specification (5) directly includes controls for pre-period trends in capital stock by including quintile bins representing firm-level capital stock growth from 1997–2000 interacted with year fixed effects. The Specification (5) estimate continues to show positive and statistically significant effects of bonus depreciation on capital stocks. That we find positive effects of the policy on capital stocks while directly controlling for pre-period trends in this outcome allays concerns that pre-period trends drive the our estimates. The capital stock response that we document echos the findings of House and Shapiro (2008), Zwick and Mahon (2017), and Curtis et al. (2021) and reinforces the conclusion that the emissions response we document is due to the investment stimulus policy rather than some other shock to toxic emissions.

We can also use the capital stock results to disentangle role of the scale and technique effects in generating the overall emissions response. By definition, the overall emissions response is the sum of the scale and technique effects. This implies that the scale effect for this subsample of firms represents 53% (= 29%/55%) of the total emissions response. Therefore, the remaining 47% of the emissions response is due to the technique effect. As a result, we would expect bonus depreciation to increase emissions per unit of capital by 26%(= 47% × 55%). This simple calculation suggests that bonus depreciation increased emissions intensity. We more directly explore this hypothesis in the following section.

5.5 Effects on Emissions Intensity and Energy Efficient Investments

We return to the matched TRI-Compustat sample to directly explore the effect of bonus depreciation on emissions intensity. Using this sample, we construct a firm-level measure of emissions intensity equal to the sum of total releases for all plants owned by a firm divided by firm-level capital stock.[20] We then log-transform this ratio so our estimates can be interpreted as percentage changes. The resulting variable describes the annual emissions per dollar of capital stock.

[20]We rely primarily on emissions scaled by capital stock because bonus depreciation is designed to stimulate investment in capital assets. We also construct a measure of emissions intensity as emissions scaled by revenue. Results based on this outcome are presented in Appendix Figure A2 and Appendix Table A4. We find very similar results for both measures of emissions intensity.

DD estimates describing the effect of bonus depreciation on emissions intensity are presented in Table 5. The specifications mimic those in Table 4. Consistent with the relative size of the emissions and capital investment responses we find, the DD estimates are always positive, suggesting the technique effect increases emissions intensity. The DD estimates range from 0.152 to 0.308 and are statistically significant across most of the specifications, including when we add quintiles of pre-period growth in emissions intensity interacted with year fixed effects in Specification (5). This specification directly controls for any differential pre-period trends in the outcome and suggests that bonus depreciation increased emissions intensity by approximately 30%. Across most specifications, the estimates are remarkably close to the 26% emissions intensity response we inferred based on the calculations in the preceding section.

Panel (B) of Figure 4 presents dynamic DD estimates based on Specification (2) from Table 5 which includes only firm and firm-size-bins-by-year fixed effects. The dynamic DD estimates in years after policy implementation are generally positive, but are statistically insignificant in most years. This more parsimonious dynamic specification also shows that emissions intensity for firms benefiting most from the policy may have been increasing slightly during the years 1997–2001. This slight pre-trend emphasizes the importance of the Table 5 Specification (5) results, which directly address this potential concern.

Overall, the evidence presented in Table 5 and Figure 4 Panel (B) shows that bonus depreciation increased emissions intensity. However, given some of the concerns we highlight above, such as statistical imprecision, a more conservative conclusion based on this evidence is that bonus depreciation certainly did not decrease emissions intensity.

These conclusions beg the question, "did bonus depreciation lead to *any* adoption of cleaner production technologies?" Unfortunately, recent data on pollution abatement investments are scarce.[21] To provide some tangentially related evidence on this question, we turn to the Manufacturing Energy Consumption Survey (MECS) from the Department of Energy.[22] Using the MECS, we construct industry-by-year aggregates of the share of surveyed firms who made investments in seven categories of capital to increase energy efficiency. We also construct the share of establishments who underwent a voluntary energy audit and who installed or retrofitted an

[21] The Pollution Abatement Cost Expenditures (PACE) survey was conducted annually from 1973–1994 (except for 1987) and 1999 and 2005. Variables from PACE are also unreliable and inconsistent across years, limiting our ability to examine changes over time (Ross et al., 2004).

[22] In Appendix D, we provide more description of the MECS survey and our analysis.

energy source. We use these measures in a simple DD framework that includes industry and year fixed effects. Appendix Table A6 presents our results. We find that bonus depreciation did lead to increased investments in several categories of energy efficient investments, including compressed air systems, machine drive systems, and process cooling systems. Additionally, the results show bonus increased the likelihood of plants undertaking an energy audit and increased installations or retrofits of an energy source. Overall, we take this as suggestive evidence that bonus depreciation may have stimulated some investments in greener technologies. Combining these findings with the emission intensity effects presented above, we conclude that while bonus depreciation could have stimulated some "greener" technology adoption, the overall technique effect did not decrease emissions intensity and likely increased emissions per unit of capital.

5.6 Can Environmental Policies Mitigate Emissions Effects?

Given the important role of environmental policy as a determinant of overall emissions Shapiro (2022) , we empirically whether CAA environmental regulations led to heterogeneous emissions responses to bonus depreciation. To do so, we compare emissions responses across plants in attainment and non-attainment counties. We focus on air pollutants covered under the CAA as these pollutants would be subject to the relevant regulations. During the sample period, there were two amendments (for Ozone and Particulate Matter) to the CAA, which led to a significant increase in the number of non-attainment counties in 2004 and 2005. We use a time-invariant measure of non-attainment, defining a county as in non-attainment if was in non-attainment following the 2004 and 2005 reforms.[23]

As a prelude to the attainment status heterogeneity analysis, Figure 5, Panel (A) shows dynamic DD estimates of the effect of bonus depreciation on the Log of CAA Releases. As was the case with total emissions, estimates from 1997–2001 show differences in CAA releases between treated and control plants are statistically insignificant and stable. The dynamic DD estimates also show large increases in CAA releases for those plants benefiting most from bonus depreciation relative to other plants after 2002. These estimates reinforce the finding in Specification (5) of Table and show bonus depreciation had a large, positive impact on the emissions regulated by the CAA.

[23] Almost all counties in non-attainment status prior to the 2004 and 2005 reforms remained in non-attainment status following these reforms which introduced more strict guidelines. Data on county-level attainment status can be found at https://www.epa.gov/green-book.

Panel (B) shows dynamic DD estimates describing the effect of bonus depreciation on CAA emissions separately for plants in attainment and non-attainment counties. Both plots show insignificant and stable pre-trends, and statistically significant and positive coefficients after bonus depreciation was implemented. Importantly, prior to 2005, the effects of bonus depreciation were nearly identical for non-attainment and attainment counties, but the effects diverged at the exact same time that the new non-attainment standards went into effect. In particular, the emissions response for plants in non-attainment counties grew slower than those in attainment counties after 2005, suggesting the more strict regulations mitigated the emissions response to bonus depreciation.

To quantify this heterogeneity, Table 6 provides regression estimates in which we include interactions between Bonus × Post and an indicator equal to one for plants in non-attainment counties.[24] Specification (1) focuses on the CAA Releases outcome variable. The Bonus × Post coefficient is positive and statistically significant. Its magnitude indicates that bonus depreciation increases CAA Releases by 48.2% for plants in counties that were less severely regulated. The interaction coefficient is negative and statistically significant and indicates that bonus depreciation decreased the emissions response to bonus depreciation by approximately 30% (0.286=0.138/0.482) in non-attainment counties.

We also test in Specification (2) whether there is a heterogeneous response to bonus depreciation using On-Site Releases. We focus on On-Site Releases as, unlike Total Releases, we know with certainty the location and can therefore determine whether the releases would be covered under non-attainment regulations. There are two reasons we perform this test. First, it is important to know whether the regulations also mitigated the response of a broader set of emissions. Second, by comparing the heterogeneous responses for CAA Releases and On-Site Releases, we can infer whether the non-attainment standards caused a shift from regulated to unregulated emission (Gibson, 2019).

The Specification (2) interaction term remains negative and statistically significant. The fact that the heterogeneous effect coefficients are nearly identical for CAA releases and On-Site Releases suggests that non-attainment standards did indeed temper responses to bonus depreciation for a broader set of emissions. This result also suggests that non-attainment standards did not

[24]For these regressions, we exclude county-year fixed effects because the goal of the analysis is to uncover differences in response among counties over time depending on their CAA status. Estimates based on regressions that include county-year fixed effects yield similar estimates in terms of sign, magnitude, and statistical significance.

cause a significant shift from regulated and unregulated emissions. This is consistent with the co-generation of regulated and unregulated pollutants (Burtraw et al., 2003).

A potential explanation for the non-attainment heterogeneity results is that capital investment is also less responsive to bonus depreciation in more regulated counties. In Appendix Table A5, we compare capital investment responses to bonus depreciation for firms that have plants in non-attainment counties to responses for firms that do not using a regression specification similar to those used in Table 6.[25] All interaction coefficients are negative and economically significant in magnitude but are imprecisely estimated, likely owing to the smaller TRI-Compustat, firm-level sample. These results suggest that environmental regulation may have the ability to temper emissions responses to investment stimulus policies, although they may do so by undermining the ability of the policy to actually stimulate investment.

Overall, based on the heterogeneity evidence presented in Figure 5 and 6, we conclude that the CAA played a significant role in mitigating emissions responses to bonus depreciation. In Section 6.4, we provide further evidence for this conclusion using NEI data. That the CAA mitigated emissions responses to bonus depreciation suggests environmental policy can play a vital role in shaping environmental responses to fiscal stimulus policies.

5.7 Effects on NEI Criteria Air Emissions

We now turn to the NEI to estimate the effect of bonus depreciation on criteria air pollutants. This analysis provides both corrobarating evidence for our TRI results and allows us to quantify aggregate economic damages due to policy's unintended environmental consequences, which we do in the following section.

We slightly modify the empirical strategy described in Section 3 to identify the effects of bonus depreciation on county-industry NEI emissions. In particular, we estimate the following DD specifications:

$$Y_{cjt} = \beta[\text{Bonus}_j \times \text{Post}_t] + \alpha_{cj} + \gamma \mathbf{X}_{cjt} + \varepsilon_{cjt}. \tag{3}$$

where Y_{cjt} is the log of annual aggregate emissions of $PM_{2.5}$, SO_2, NO_x, and VOCs in county-industry cj. We follow our preferred TRI analysis in using observation-level (county-industry) fixed effects as well as county-year and sector-year fixed effects in all specifications. We continue to cluster standard errors at the four-digit-NAICS industry level.

[25] We define a firm as Non-Attainment if at least one of its plants is located in a non-attainment county.

Table 7 presents our DD estimates for the four NEI criteria air pollution outcomes. The DD coefficients are economically large and statistically significant at the 10% level or better for the outcomes $PM_{2.5}$, SO_2, and NO_x. Bonus depreciation does not have a statistically significant effect on VOCs, but the coefficient is large and positive. For the statistically significant effects, the magnitudes are remarkably similar in size to the TRI coefficients, with estimates ranging from 0.301 to 0.348, indicating that county-industries benefiting the most from bonus depreciation increased their emissions of these criteria air pollutants by between 30 and 35% after the policy was implemented in 2002.

As with the TRI analysis, we estimate dynamic DD models for each criteria air pollutant.[26] Figure 6 presents the dynamic DD estimates for each of the four outcomes. All four plots show relatively small and stable differences in emissions between treated and control units in the pre-period, indicating that differential trends are not responsible for the effects we estimate. The plots also show large, positive increases in differences in emissions between treated and control units in the years after bonus depreciation implementation. Together, these dynamic DD estimates reinforce the plant-level TRI findings presented in Figures 2 and 5 Panel (A) and indicate that bonus depreciation had a large, positive effect on emissions of criteria air pollutants.[27] Ultimately, that we find such similar results from two very different data sources reinforces the validity of our conclusion that bonus depreciation had a large positive effect on emissions.

6 Aggregate Economic Damages

While the emissions responses we document suggest investment stimulus policies can have large unintended effects on emissions, ultimately, policymakers must know how the emissions responses translate into reduced environmental quality and economic damages in order to properly compare the costs and benefits of a given policy. To this end, we now quantify the aggregate economic damages caused by bonus depreciation and explore whether these damages are concentrated among certain socioeconomic or demographic groups.

The procedure to estimate the economic damages consists of four steps. First, we need to

[26]We omit the 2000 interaction term—rather than 2001 as in our TRI analysis—because NEI data was not collected in 2001.

[27]Across all four event study plots presented in Figure 6, coefficients in years 1996–1998 and coefficients in years 1999 and 2000 are very similar. In Appendix C, we investigate these similarities and show that our results are robust to limiting the analysis to a subsample that excludes years with highly correlated responses to the NEI survey.

estimate changes in criteria air pollutants due to the policy. Second, we use these estimates as inputs for a pollution transport model to map source emissions changes to changes in destination (receptor) $PM_{2.5}$ pollution concentrations.[28] Third, we calculate excess mortality due to increased exposure to local pollution concentrations. Fourth and finally, using a standard value of statistical life estimate, we translate excess mortality into a dollar value of economic damages due to the policy.

6.1 Calculating Emissions Changes

We use the coefficient estimates from Table 7 to quantify the changes in criteria air pollutant emissions due to the policy. We calculate emissions changes for a given pollutant, ΔY_i, as:

$$\Delta Y_i = \beta \mathbb{I}[\text{Bonus}_j] \times Y_i \tag{4}$$

where Y_i is the baseline emissions from facility i, and $\mathbb{I}[\text{Bonus}_j]$ is a dummy variable equal to one for facilities we classify as most affected by the policy in the analysis above.[29] β is the estimated effect of bonus depreciation, which differs by pollutant type. This procedure implicitly assumes the group of control plants experience no increase in emissions due to the policy. This approach results in a conservative estimate of the emissions changes due to the policy. Our estimates are also conservative because we assume bonus depreciation has no effect on a given criteria air pollutant if we do not estimate a statistically significant effect at the 10% level or better, which is the case for VOCs.

Table 8 presents baseline pollution emissions and our estimates of total pollution emissions (in metric tonnes) of criteria air pollutants generated by bonus depreciation. The first row (Total Emissions) is total baseline emissions for all point-source emissions sources. The total amount of $PM_{2.5}$ emissions was around 101 thousand, SO_2 emissions was around 1.8 million,

[28] Around 85% of the economic costs associated increased pollution concentrations are due to increased mortality risk from particulate pollution (EPA, 2011). The use of a sophisticated pollution transport model is necessary in this situation because actual pollution concentrations are subject to complex modes of atmospheric transport and chemical reactions (Deschenes and Meng, 2018; Hernandez-Cortes, Meng, and Weber, 2022). Moreover, quantifying economic damages from ambient pollution concentrations requires a precise understanding of the health effects of exposure to particular pollutants.

[29] We rely on the 2008 NEI dataset for baseline emissions levels for several reasons. The first is that—consistent with the choices we make elsewhere—the later year yields more conservative estimates. This is because i) ambient pollution concentrations (from NEI sources and all other sources) have generally declined over the sample period and ii) the stringency of environmental regulations, such as minimum stack heights, has increased during the sample period. As a result, the 2008 data provide a smaller base and an environment where the same changes lead to smaller aggregate damages. We opt to use 2008 rather than later years in our sample, due to concerns that these estimates may be influenced by the Great Recession.

NOx emissions was around 896 thousand, and VOC was around 180 thousand. The second row (Δ Emissions (Average)) presents total estimated emissions changes due to bonus depreciation (following equation 4) using the coefficients from Table 7. The remaining rows are discussed in Section 6.4.

6.2 From Emissions Changes to Economic Damages

We map emissions changes (ΔY_i) from their sources to their destination $PM_{2.5}$ concentrations using the InMAP pollution transport model.[30]

We then calculate aggregate damages based on the number of additional deaths attributable to the increase in $PM_{2.5}$ pollution, which depends on the number of individuals exposed and the population-specific mortality rate. Following the epidemiological literature (and the InMAP model), we estimate excess deaths using Cox proportional-hazard models. A key parameter in this calculation is the "concentration-response relationship," which is defined as the increased risk of all-cause mortality associated with a 10 $\mu g/m^3$ increase in $PM_{2.5}$. To account for uncertainty with respect to this key parameter, we follow standard InMAP practice and provide a range of damages based on a range of concentration-response estimates from 4% (Krewski D, 2019) to 14% (Lepeule J, 2012). To translate these estimates into monetary damages, we multiply the number of deaths attributed to bonus depreciation by the standard value of statistical life, $9 million USD (the EPA's standard).

Table 9 presents our estimates of annual aggregate economic damages due to bonus depreciation for the United States as a whole and by racial groups. Aggregate economic damages are expressed in terms of total damages (Million $) and damages per capita ($/pop). The "Low" columns use the 4% concentration-response parameter and the "High" columns use the 14% parameter. Annual aggregate economic damages range from $17 to 39 billion US, which corresponds to per capita damages between $56 and $127. These economic damages are highly disproportionate across racial groups, with Black populations incurring per-capita economic damages that are 75% higher than the national average.

[30] In order to retain computational tractability, we use the source-receptor matrix (SRM) InMAP model developed by Goodkind et al. (2019).

6.3 Disparate Impacts of Bonus Depreciation Emissions

To closer examine the disparate impacts of emissions generated by bonus depreciation across geography, socioeconomic status, and racial groups, we aggregate economic damages to the county level. We then merge aggregate damages with county-level data on median income, poverty rates, and racial composition from the United States Census Bureau's Small Area Income and Poverty Estimates.[31]

Panel (A) of Figure 7 maps aggregate per-capita economic damages using the lower concentration-response parameter of 4%. The map demonstrates that economic damages are highly uneven across counties, with higher damages more concentrated in the South, Midwest, and Mid-Atlantic. County-level per-capita economic damages range from as low as $0.08 to as high as $365.

To better understand relationships between income and damages, Panel (B) displays per-capita economic damages as a fraction of median income. The geographic patterns in the distribution of per-capita economic damages remain largely the same and range from $0.15 per $100,000 income to $933 per $100,000 income.[32] Both maps show significant heterogeneity across and even within regions, with the most affected county experiencing a 45-fold larger effect than the least affected county in terms of per-capita damages. Scaling by median income reveals even more extreme disparities.

Given the significant geographic heterogeneity in damages we have uncovered, we explore the extent to which low-income and racial minorities are differentially (both unconditionally and conditionally) impacted by pollution due to bonus depreciation. As a first step in this analysis, we present some visual evidence of these relationships. Figure 8 presents bin-scatter plots relating per-capita economic damages to (A) median household income, (B) poverty rate (all ages), (C) share of non-white population, and (D) share of Black population. The dots represent average damages for 30 equal-sized bins for each variable. The lines are based on regressions of county-level damages on each characteristic based on the underlying data.[33] The plots presented in Figure 8 provide strong visual evidence that economic damages from bonus

[31] The InMAP uses a variable-resolution computational grid containing grid-level data on population and racial composition. However, income and poverty measures are only estimated for larger administrative units, such as counties.

[32] Using the higher concentration-response parameter, per-capita damages per median income range from $0.35 to $2,103 per $100,000 income.

[33] Scatter plots of the underlying data are presented in Appendix Figure A5. Appendix Figure A4 presents scatter plots of the underlying data when per-capita damages are scaled by median household income.

depreciation emissions are concentrated in counties with lower median incomes, higher poverty rates, lower non-white share of the population, and higher Black population share. Appendix Figure A6 displays even tighter correlations when we scale the per-capita economic damages by median household income.

To formally analyze the relationships between socioeconomic status and race with economic damages, Table 10 presents both conditional and unconditional regressions of per-capita economic damages on median income, poverty-rate, and racial group shares.[34] Specification (1) indicates that per-capita damages are negatively related to median income, while Specification (2) indicates that per-capita damages are positively related to poverty rates, but the relationship is not statistically significant. Specifications (3)-(6) indicate that per-capita damages are positively related to the county-level share of Black residents, whereas per-capita damages are negatively related to the share of Latino, Asian, and Native American residents. Specification (7) indicates that per-capita damages are negatively related to the share of Non-White population. These findings are consistent with Table 9, which indicates that per-capita damages are highest among Black populations, and second-highest among White populations.

Of course, income and race are correlated so the results in Specifications (1) and (2) may be driven by the correlations presented in Specification (3)-(7) and vice versa. To try to disentangle the relationships, in Specifications (8) and (9), we regress damages on measures of both income and race. In both regressions, the emissions damages show strong, statistically significant relationships with racial composition, but not with income measures. We take these results to suggest that even among counties with similar median income levels and poverty rates, the economic damages of emissions generated by bonus depreciation are most concentrated in counties with larger shares of Black residents. A sizable literature documents inequalities in exposure to air pollution across income and racial-ethnic groups (Banzhaf, Ma, and Timmins, 2019). Our results suggest that bonus depreciation likely exacerbated the differences documented in these papers.

6.4 Quantifying the Role of Regulations

In Section 5.6, we showed that environmental regulation can play a key role in mitigating the emissions response to bonus depreciation. We now use analysis based on NEI data and the

[34] We weight the regressions in Table 10 by county population.

InMAP model to explore how environmental regulations may affect the level and distribution of economic damages due to the policy.

To begin, we use NEI data to estimate heterogeneous responses to bonus depreciation depending on county non-attainment status.[35] The results presented in Table 11 show that bonus depreciation has a large and statistically significant effect on all four criteria pollutants in attainment counties. The table also shows that the response of all four types of emissions to the policy was significantly smaller in non-attainment counties. These findings echo the results presented in Section 5.6 and reinforce the conclusion that environmental regulation can significantly mitigate the environmental effect of investment stimulus policies.

Next, we adapt the procedure in Section 6.1 to quantify the emissions changes associated with bonus depreciation. In particular, we allow the effect of bonus depreciation on each pollutant to vary based on whether the facility is in an attainment or non-attainment county.

Row 3 of Table 8 presents the total changes in emissions due to the bonus depreciation policy, accounting for heterogeneous emission responses according to county-level attainment status. Accounting for heterogeneity increases aggregate changes in $PM_{2.5}$, SO_2, and NO_x emissions. We also now estimate positive changes in VOCs due to the policy as the additional interaction resulted in statistically significant effects in attainment counties. To obtain hypothetical emissions changes if all counties or no counties were in non-attainment status, we use the regression estimates for either non-attainment or attainment counties, respectively. Emissions changes assuming all counties were in attainment are presented in the fourth row of Table 8 and the fifth row presents emissions changes assuming all counties were in non-attainment status.

To calculate aggregate economic damages and economic damages for different racial/ethnic groups, we use the coefficient estimates from Table 11 as inputs for the InMAP model under three scenarios, each described below. The damage estimates are presented in Table 12. The two columns entitled Actual Non-Attainment refer to economic damages under the actual Non-Attainment designations. We expect that economic damages under actual non-attainment designations should be similar to baseline economic damages presented in Table 9; however, there are a few subtle reasons there might be differences. The primary difference is that emissions changes would be relatively larger in attainment counties and smaller in non-attainment counties (compared to the average effect captured in the baseline model). Because excess mortality

[35] This heterogeneity analysis largely follows the TRI heterogeneity analysis presented in Section 5.6.

depends on the number of individuals exposed and the pollution sensitivity of the population, and these factors are plausibly related to attainment status, aggregate damages would generally be dissimilar after accounting for heterogeneous effects across attainment status. A secondary difference results form the fact that the coefficient for VOC was not statistically different from zero in the baseline estimations, implying there were no VOC emissions changes used to calculcate aggregate damages. However, after accounting for heterogeneous effects, the coefficient is statistically significant, and the aggregate damages presented in Table 12 reflect these VOC emissions changes. Table 12 demonstrates that economic damages are slightly higher after accounting for heterogeneous effects. Aggreagate damages now range from around 19 to 43 billion USD.

Table 12 also presents two counterfactual scenarios regarding attainment status. First, we estimate economic damages under the counterfactual assumption that all counties are in attainment (All Attainment). Second, we estimate economic damages under the counterfactual assumption that all counties are in non-attainment (All Non-Attainment). Comparing damages between the Actual Non-Attainment and All Attainment scenarios shows that between $7.8 and 17.6 billion USD or 40% of damages were avoided due to the extant regulatory environment. Along the same lines, the difference in damages between the Actual Non-Attainment and All Non-Attainment scenarios shows $5.4 to 12.2 billion USD or 28% in additional damages could have potentially been avoided if all counties were designated non-attainment.

Note that across the three scenarios presented in Table 12, the percentage differences in economic damages between the scenarios are generally larger than the corresponding percentage differences in emissions changes. This implies that environmental regulations not only serve to reduce the effect of bonus depreciation on emissions, but also shift the emissions generated by the policy to places with less pollution or less susceptible populations, where they create less damage.

6.5 Discussion of Economic Damages

The aim of this section is to provide some additional (back-of-the-envelope) context to facilitate comparison and interpretation of the magnitudes of our estimates. Recall that the reduced-form estimates (in our preferred specifications) of the elasticity of emissions with respect to the bonus policy was around 0.32 for total releases using the TRI dataset (Table 2), and between 0.30 and

0.35 for criteria air pollutants using the NEI dataset (Table 7). That is, bonus depreciation increased emissions by around 30% for a range of pollutants. For comparison, Zwick and Mahon (2017) estimate that the same policy increased capital investment by around 10.4% between 2001 and 2004, and 16.9% between 2008 and 2010. Similarly, Garrett, Ohrn, and Suárez Serrato (2020) estimate that policy increased employment by around 2%. Thus, in terms of reduced-form estimates, pollution emissions are more responsive to bonus depreciation than either investment and jobs. This is consistent with positive effect of bonus depreciation on emissions intensity that we show in Section 5.5.

How do economic damages associated with pollution compare to overall costs and benefits of the policy? To answer this question, we compare the pollution damages caused by the policy to the policy's fiscal cost to the government and to some of the benefits it generates. We find economically-significant economic damages resulting from bonus depreciation that range from $17.4 to 39.0 billion USD. For comparison with other studies, we calculate total damages of the policy over a 10-year period, which correspond to 174 to 390 billion USD.

To begin, Garrett, Ohrn, and Suárez Serrato (2020) estimate that the fiscal cost of the policy was $311 billion over the 2003-2012 period. Comparing this number to the economic damages we estimate, implies that pollution damages represent between 56 and 125% of the total fiscal cost of the policy.

To contextualize how incorporating the environmental damages created by the policy might affect related cost-benefit analyses, consider how these damages affect cost-per-job calculations. Garrett, Ohrn, and Suárez Serrato (2020) estimate that the policy created around 6.24 million jobs resulting in a fiscal cost per job of around $50,000. Incorporating the environmental damages associated with the policy increases the cost-per-job to between $77,000 and $112,500 per job.

How do economic damages compare to the effects of environmental regulations? The Clean Air Act Amendments (CAAAs) of 1990 were the most wide-ranging and ambitious environmental policies aimed at improving the nation's air quality in recent times.[36] According to the EPA, the benefit of the 1990 CAAAs reached approximately $2 trillion USD by 2020, and exceed the costs by a factor of more than 30 to one (EPA, 2011). Based on EPA mortality estimates, we

[36]The Clean Air Act (CAA) of 1970 and 1977 CAA Amendments were similarly ambitious, but were implemented in a dissimilar period and context. Furthermore, the benefits of the 1990 CAA Amendments have been extensively investigated as the Amendments included provisions mandating assessing benefits and costs of regulations.

estimate that during the treatment period we study (2002–2012), the CAA avoided approximately $70 billion in environmental damages per year. Based on these estimates, we conclude that the economic damages caused by bonus depreciation are between 23 and 54% of the damages avoided damages due to the 1990 CAAAs. These magnitudes are striking and speak to the potential scale of the environmental consequences of investment stimulus policies.

7 Conclusion

In this paper, we studied the environmental consequences of bonus depreciation, one of the largest investment stimulus policies in US history. The investment stimulus policy led to increases in toxic emissions and criteria air pollutants. The costs of these emissions were large, representing more than 50% of the fiscal cost of the policy. These emissions exacerbated existing racial disparities in exposure to pollution in the US. While existing environmental regulations mitigated the damages created by the policy, they potentially did so by attenuating the investment response to the policy.

These results have several important policy implications. First, policy makers should anticipate and account for interactions between fiscal policies and environmental regulations. We show fiscal policies can directly counter the goals of environmental regulation by increasing emissions and pollution. At the same time, existing environmental regulations may undercut the ability of fiscal policy to achieve its desired effects. Ignoring these important interactions may overstate the estimated impacts of either fiscal policies or environmental regulations.

Second, policy makers seeking to stimulate the economy while minimizing environmental damages should consider directed rather than generalized investment stimulus policies. Bonus depreciation, a generalized policy that decreased the cost of all capital investments, led to increased emissions and did not decrease emissions intensity. Directed stimulus policies, such as investment tax credits for solar energy production or other green technologies, are likely to generate a stimulative effect while decreasing emissions intensity. US policy makers have already put this lesson into practice; a number of directed, green investment incentives were included in the recent Inflation Reduction Act of 2022.

Ultimately, our findings represent a cautionary tale. Investment stimulus policies, which are used around the world to promote business investment and macroeconomic stability in times of crisis, can have large environmental consequences. Policy makers considering fiscal stimulus options must directly incorporate such environmental damage estimates into their decision making processes. Failing to do may result in a policy agenda with costs, environmental and otherwise, that far outpace its benefits.

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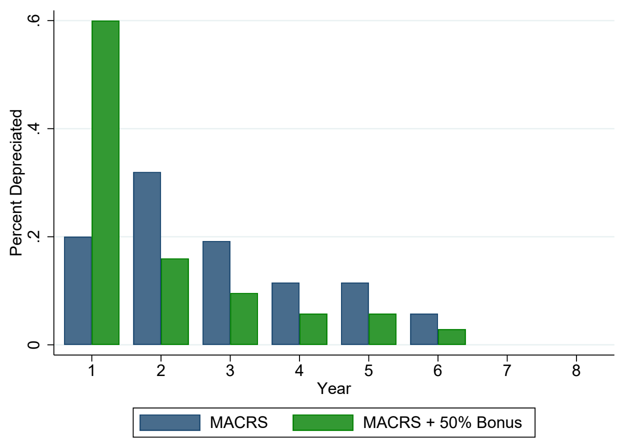
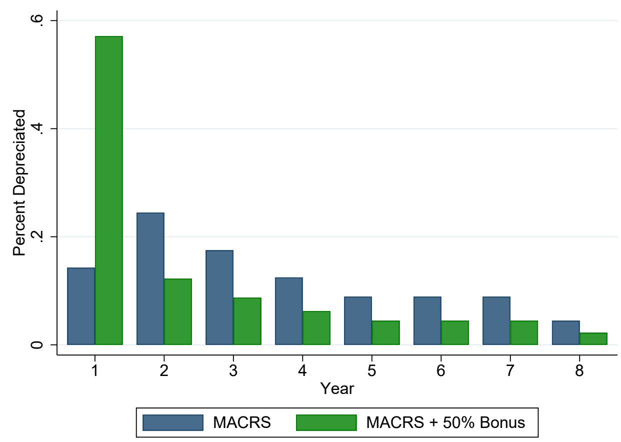
Figures

Figure 1: Bonus Depreciation Policy Details

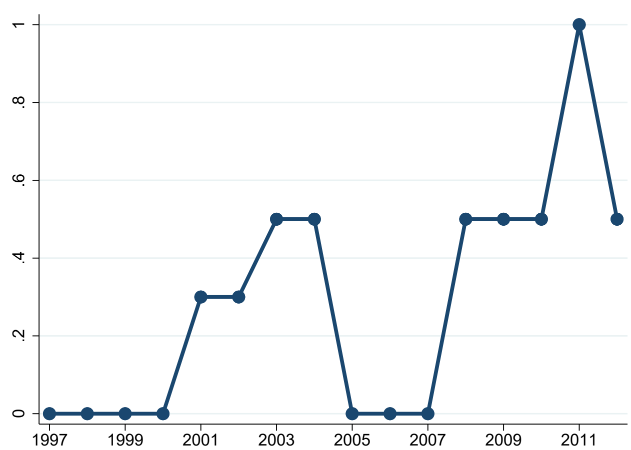
(A) Effect of 50% Bonus, 5-year MACRS



(B) Effect of 50% Bonus, 7-year MACRS



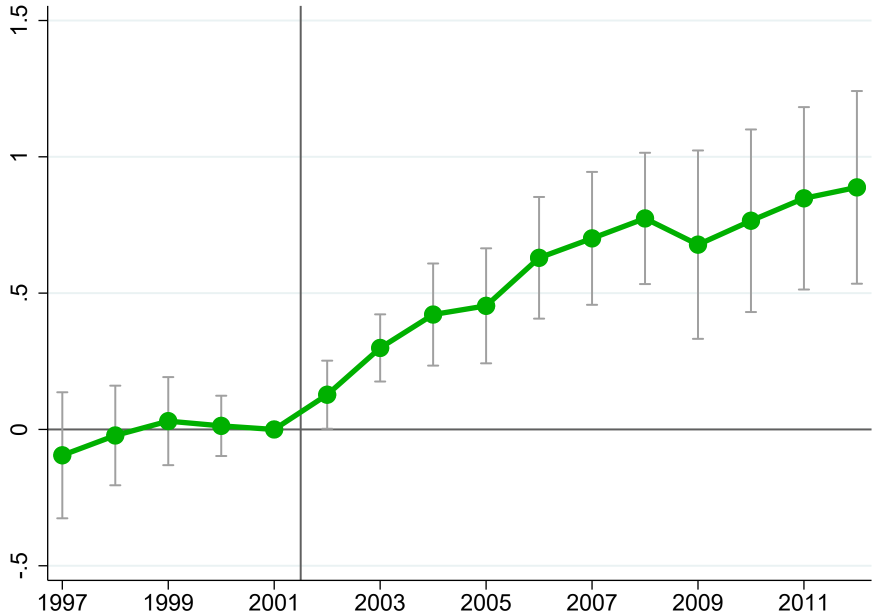
(C) Bonus Depreciation Rates During Sample Period



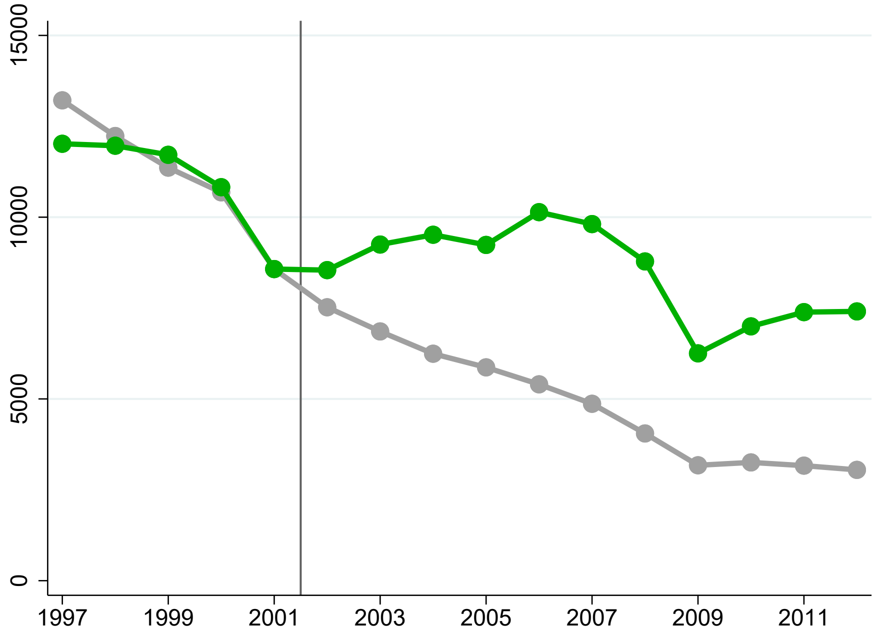
Notes: Figure 1 describes the bonus depreciation investment incentive. Panel (A) displays the effect of 50% bonus depreciation on annual tax deductions for investment in a new 5-year MACRS asset. Panel (B) shows the same series for a new 7-year MACRS asset. Panel (C) displays statutory bonus depreciation rates during the sample period. *Source:* Authors' calculations based on annual versions of IRS Publication 946.

Figure 2: Effects of Bonus Depreciation on Total Chemical Releases

(A) Dynamic DD Estimates; Preferred Specification

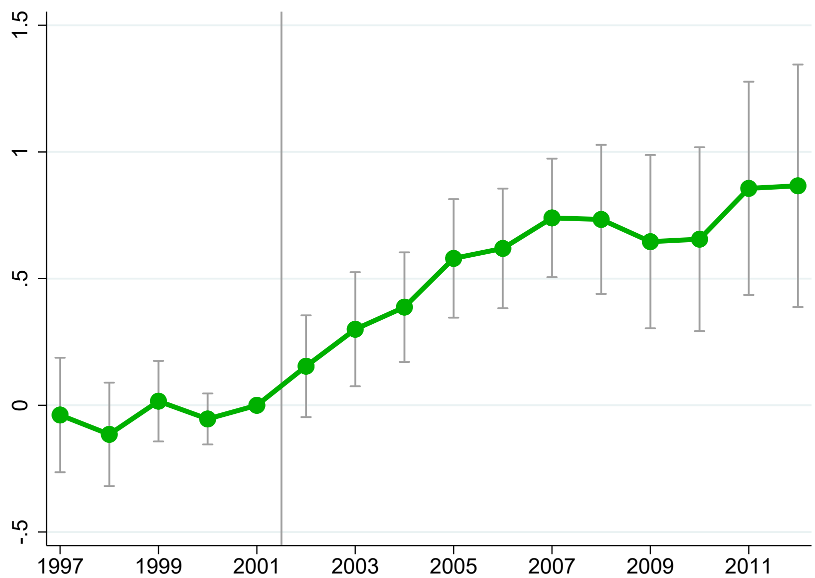


(B) Dynamic DD Estimates + Aggregate Trends



Notes: Panel (A) of Figure 2 displays Dynamic DD estimates and 95% confidence intervals describing the effect of bonus depreciation on Log(Total Chemical Releases) from Specification (2). Estimates include plant, county-year, and sector-year fixed effects. Standard errors are clustered at the NAICS 4-digit industry level. The 2001 coefficient is normalized to zero. The corresponding DD estimate is presented in Panel (A), Column (4) of Table 2. In Panel (B), the 0.5 $\times$ the DD estiamtes are added to the annual average Log(Total Chemical Releases). *Source:* Authors' calculations based on TRI and Zwick and Mahon (2017) data.

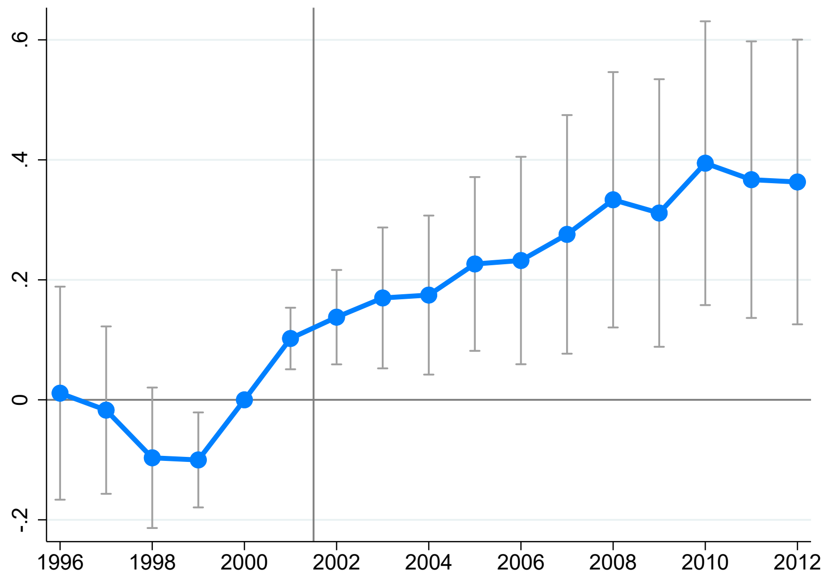
Figure 3: Effects of Bonus on Total Chemical Releases; Compustat Sample



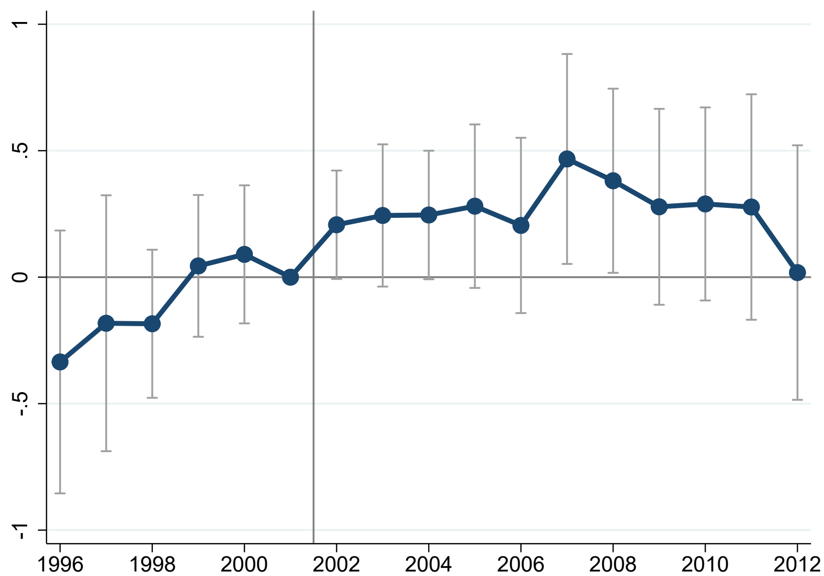
Notes: Figure 3 displays Dynamic DD estimates and 95% confidence intervals based on equation (2) describing the effect of bonus depreciation on Log(Total Chemical Releases) for the sample of plants that we match to Compustat firms. Estimates include plant, county-year, and sector-year fixed effects. Standard errors are clustered at the NAICS 4-digit industry level. The 2001 coefficients are normalized to zero. The corresponding difference-in-difference estimates are presented in Column (4) of Table A3. *Source:* Authors' calculations based on the data from TRI, COMPUSTAT and Zwick and Mahon (2017).

Figure 4: Effects on Capital Stock and Emissions Intensity

(A) Log Capital Stock



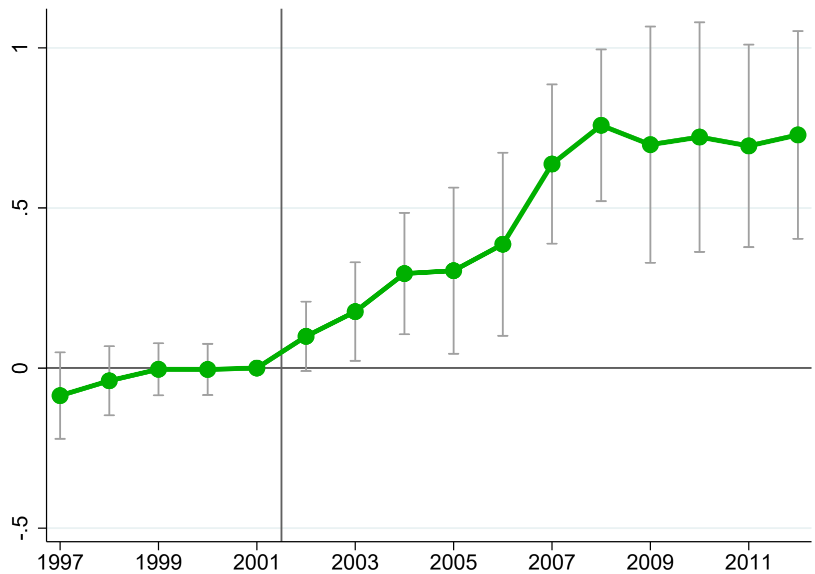
(B) Log Releases per unit of Capital



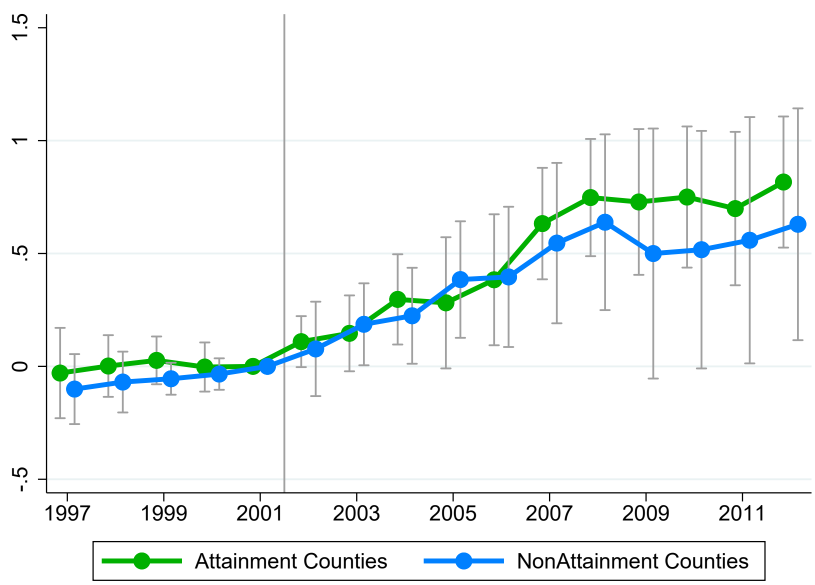
Notes: Panel (A) displays dynamic DD estimates and 95% confidence intervals describing the effect of bonus depreciation on Log(Capital Stock) for the sample of Compustat firms that have plants in the TRI. Panel (B) displays similar estimates for the Log(Total Releases per unit of Capital Stock). Estimates include firm and firm-size bins-by-year fixed effects. Standard errors are clustered at the NAICS 4-digit industry level. Corresponding DD estimates are presented in Specifications (2) of Table and in Specification (2) of Table 5. *Source:* Authors' calculations based on the data from TRI, Compustat, and Zwick and Mahon (2017).

Figure 5: Effects of Bonus Depreciation on CAA Releases

(A) Log(CAA Releases)

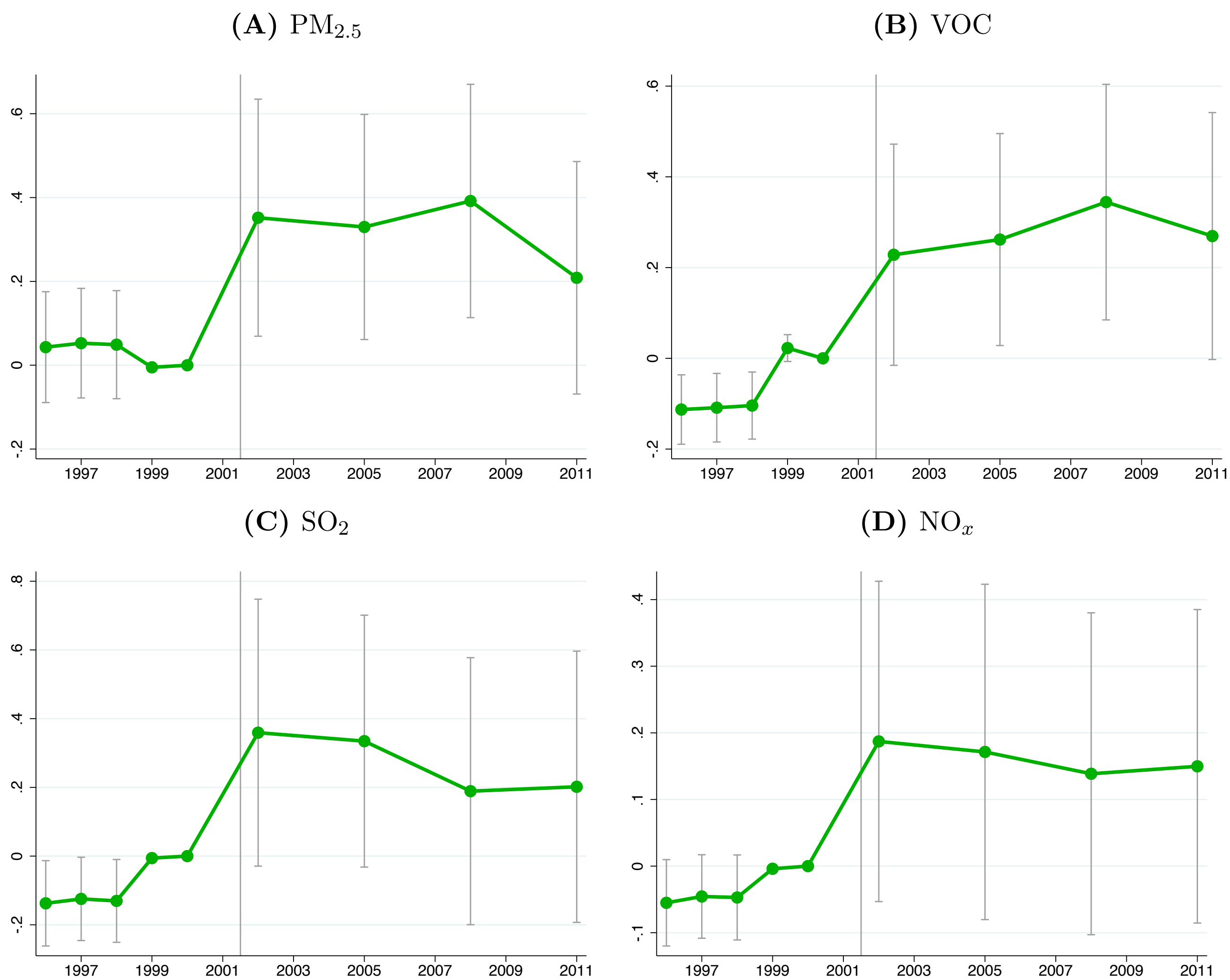


(B) Log(CAA Releases) by Attainment Status



Notes: Figure 5 displays dynamic DD estimates and 95% confidence intervals describing the effect of bonus depreciation on Log(CAA Releases) in Panel (A) and on Log(CAA Releases) separately for plants in counties in non-attainment status or not following CAA reforms in 2004 and 2005 in Panel (B). All specifications include plant, county-by-year, and sector-by-year fixed effects. Standard errors are presented in parentheses and clustered at the 4-digit NAICS level. *, **, and *** denote statistical significance at the 10, 5, and 1% level. *Source:* Authors' calculations based on TRI and Zwick and Mahon (2017) data.

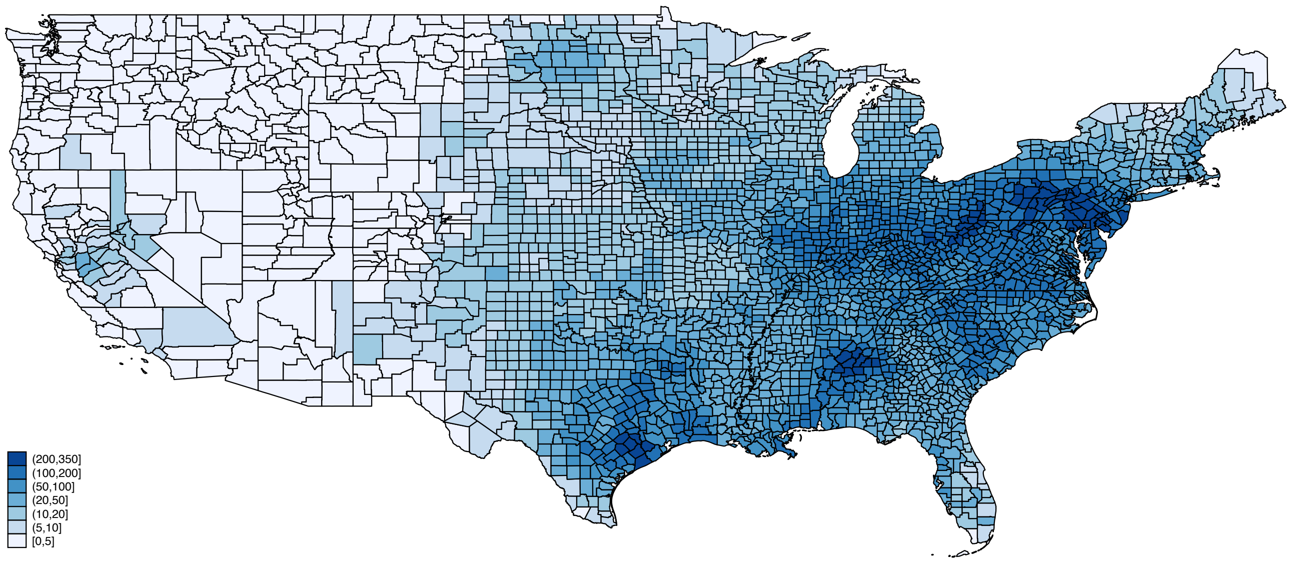
Figure 6: Effect of Bonus Depreciation NEI Criteria Air-Pollution Emissions



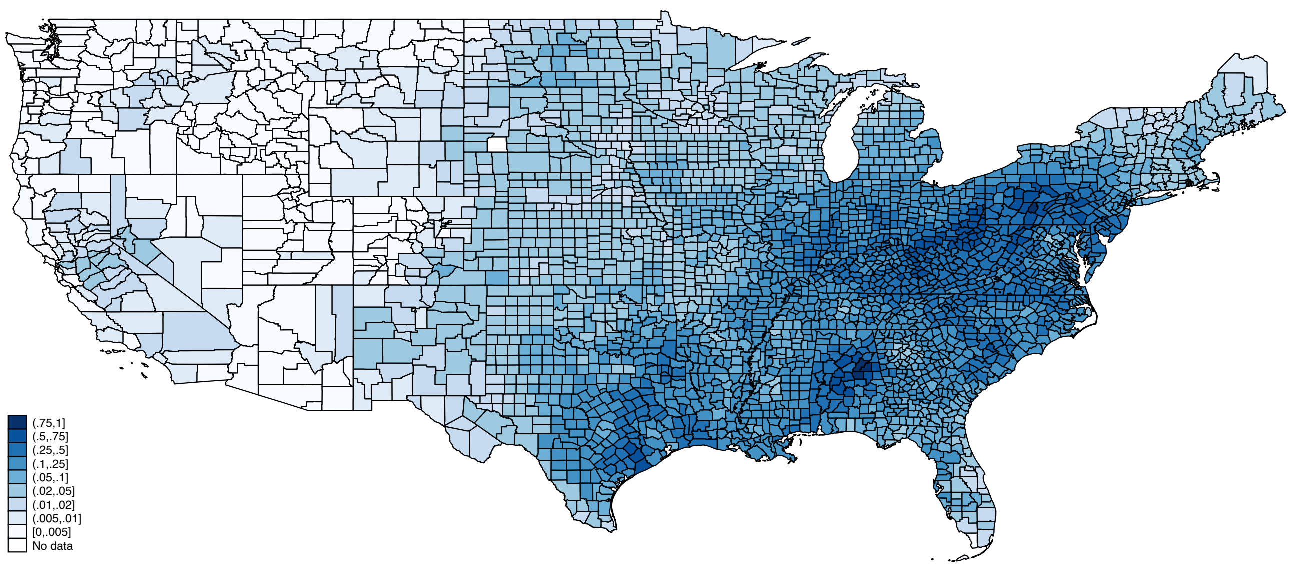
Notes: Figure 6 displays dynamic DD estimates and 95% confidence intervals describing the effect of bonus depreciation on county-industry criteria air pollutants from the NEI. All specifications include fixed effects by industry, county by year, and sector by year. *Source:* Authors' calculations based on NEI and Zwick and Mahon (2017) data.

Figure 7: Geographic Distribution of Economic Damages

(A) County-Level Economic Damages Per Capita

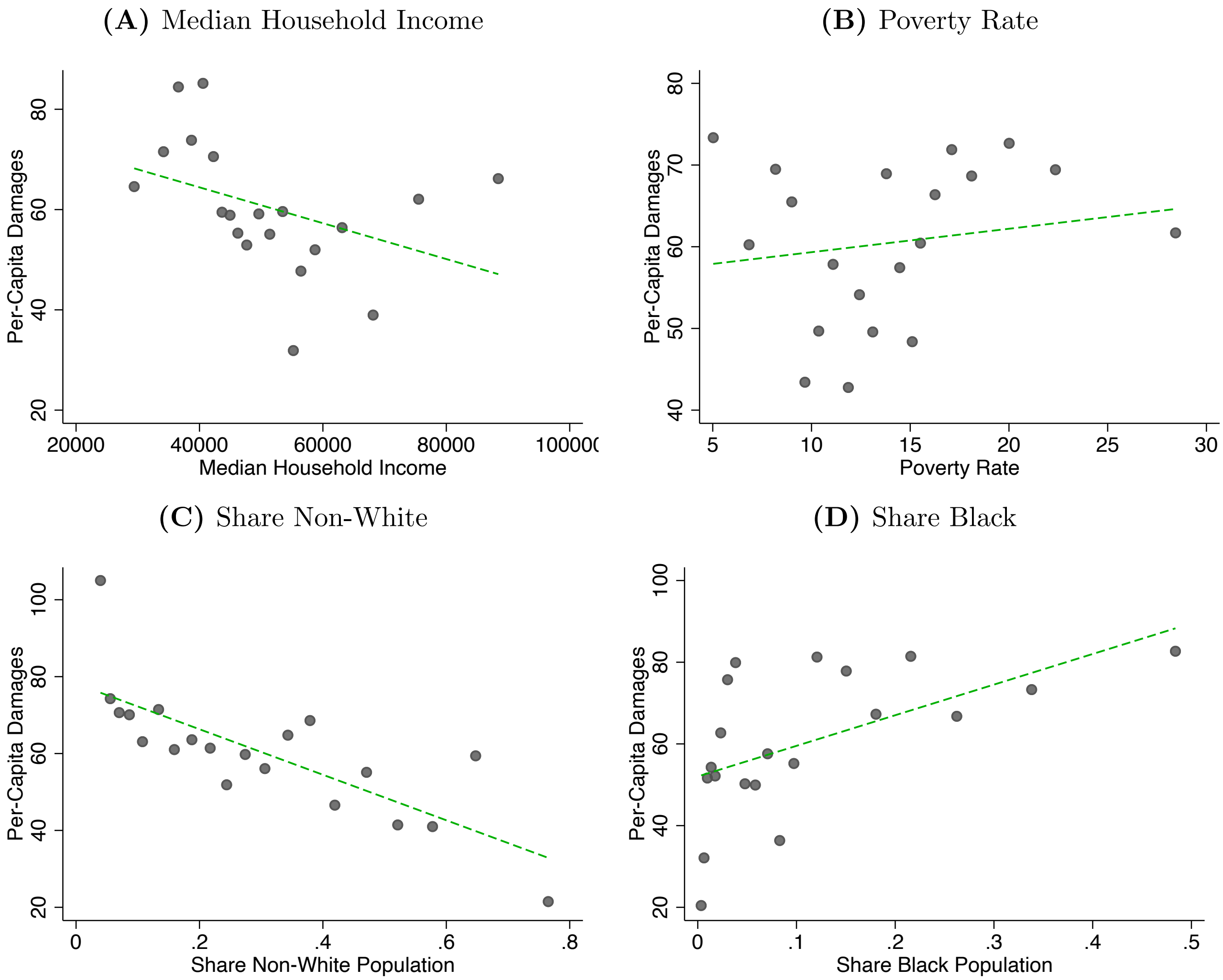


(B) County-Level Per-Capita Economic Damages as Percent of Median Income



Notes: Panel (A) displays county-level per-capita economic damages. Panel (B) displays county-level per-capita economic damages as a percentage of median income. Median Income is from the U.S. Census Bureau Small Area Income and Poverty Estimates (SAIPE). Economic damages are calculated using the lower concentration-response parameter of 4% from Kewski et al. (2009), and a Value of Statistical Life (VSL) of 9 million USD. County-level damages are calculated by summing InMap damages across all computational grids within a given county. *Source:* Authors' calculations based on NEI and Zwick and Mahon (2017) data using InMAP.

Figure 8: Per-Capita Economic Damages by Socioeocnomic Status and Racial Group



Notes: Figure 8 presents bin-scatter plots relating county-level per-capita economic damages to county-level median household income, poverty rate, share non-white and share Black in Panels (A), (B), (C) and (D), respectively. Economic damages assume a concentration-response parameter of 4% and a VSL of 9 million USD. *Source:* Authors' calculations based on NEI, SAIPE, and Zwick and Mahon (2017) data using InMAP.

Tables

Table 1: Descriptive Statistics

	Treated Plants			Controls Plants		
	Mean	Std.Dev.	Obs	Mean	Std.Dev.	Obs
Outcomes						
Total Releases	250.76	690.22	5795	71.56	325.67	12190
Total On-Site Releases	218.55	622.04	5416	65.93	303.47	10977
Air Releases	129.32	360.68	5231	42.27	154.25	10676
Water Releases	62.35	212.58	1587	25.18	122.45	1534
Land Releases	34.75	146.02	5795	5.20	58.38	12190
Clean Air Act (CAA) Releases	119.03	331.55	4352	32.57	122.27	9316
Other						
Non-attainment County	0.39	0.49	5795	0.40	0.49	12190
In Compustat Sample	0.26	0.44	5795	0.24	0.43	12190
Compustat Variables						
Capital Stock	6.63	11.36	1283	4.38	13.28	2621

Notes: Table 1 presents descriptive statistics separately for treated and non-treated plants for both the TRI analysis sample and Compustat-matched subsample of plants in 2001. Total Chemicals is the total unweighted sum of all on- and off-site releases. Total On-Site Chemicals is the unweighted sum of all on-site releases. Air Releases is the total unweighted sum of all on-site releases to air. Water Releases is the weighted sum of all on- and off-site releases to water. Land Releases is the unweighted sum of all on- and off-site releases to land. Clean Air Act (CAA) Releases is the unweighted sum of all on-site releases of chemicals covered under the Clean Air Act and present in the TRI data. Non-attainment county is a time invariant indicator equal to one for plants located in counties that went into nonattainment for the presence of particulate matter and/or sulfur dioxide in 2004 or 2005. In Compustat Sample is an indicator equal to one for plants we can connect to a COMPUSTAT firm. Capital Stock is the capital stock of a plant's Compustat firm owner. TRI outcomes are measures in 1,000s. Capital stock is measured in millions of dollars. *Sources:* Authors' calculations based on TRI, Compustat, and Zwick and Mahon (2017) data.

Table 2: Effect of Bonus Depreciation on Total Chemical Releases

	Total Releases					
	(1)	(2)	(3)	(4)	(5)	(6)
Bonus × Post	0.314***	0.323***	0.345***	0.349***	0.329***	0.316***
	(0.0703)	(0.0683)	(0.0692)	(0.0678)	(0.0678)	(0.0583)
Plant FE	✓	✓	✓	✓	✓	✓
Year FE	✓					
County × Year FE		✓		✓		✓
Sector × Year FE			✓	✓		✓
County × Sector × Year FE					✓	
Additional Controls						✓
Obs.	212,368	212,368	212,368	212,368	210,620	192,981

Notes: Table 2 presents estimates of the effect of bonus depreciation on total chemical releases based on Equation (1). The outcome variables in all specifications is Log(Total Releases). Specification (1) includes plant and year fixed effects. Specification (2) includes plant and county-by-year fixed effects. Specification (3) includes plant and sector-by-year fixed effects. Specification (4) includes plant, county-by-year and sector-by-year fixed effects. Specification (5) includes plant and county-by-sector-by-year fixed effects. Specification (6) includes county-by-year and sector-by-year fixed effects as well as controls for import competition from China and the Domestic Production Activities Deduction federal tax policy. Standard errors are presented in parentheses and are clustered at the four-digit-NAICS industry level. *, **, and *** denote statistical significance at the 10, 5, and 1% level. *Source:* Authors' calculations based on TRI and Zwick and Mahon (2017) data.

Table 3: Effect of Bonus Depreciation on Different Toxic Release Categories

	(1) On-Site Releases	(2) Air Releases	(3) Water Releases	(4) Land Releases	(5) Air CAA
Bonus × Post	0.366***	0.342***	0.362***	0.165	0.239***
	(0.0728)	(0.0706)	(0.0760)	(0.157)	(0.0724)
Plant FE	✓	✓	✓	✓	✓
County × Year FE	✓	✓	✓	✓	✓
Sector × Year FE	✓	✓	✓	✓	✓
Obs.	192,332	186,555	35,807	18,053	157,597

Notes: Table 3 presents DD estimates based on Equation (1). The outcome variable in Column (1) is Log(On-Site Releases). The outcome variable in Column (2) is Log(Air Releases). The outcome variable in Column (3) is Log(Water Releases). The outcome variable in Column (4) is Log(Land Releases). The outcome variable in Column (5) is Log(CAA Releases). Standard errors are clustered at the 4-digit NAICS level and are presented in parentheses. *, **, and *** denote statistical significance at the 10, 5, and 1% level. *Source:* Authors' calculations based on TRI and Zwick and Mahon (2017) data.

Table 4: Effect of Bonus Depreciation on Capital Stock

	Log(Investment)				
	(1)	(2)	(3)	(4)	(5)
Bonus × Post	0.286***	0.288***	0.299***	0.214**	0.295***
	(0.101)	(0.0963)	(0.0950)	(0.0847)	(0.0939)
Firm FE	✓	✓	✓	✓	✓
Year FE	✓				
Firm Size Bins × Year FE		✓	✓	✓	
Debt Ratio Bins × Year FE			✓	✓	
Cap. Intensity Bins × Year FE				✓	
Pre-Growth Bins × Year FE					✓
Obs.	9,988	9,735	9,735	9,735	9,268

Notes: Table 4 displays DD estimates describing the effect of bonus depreciation on capital stock for the Compustat sample of firms. The outcome variable in all specifications is Log(Capital Stock). Column (1) estimates include firm and year fixed effects. Column (2) estimates include firm and firm-size bins-by year fixed effects. Columns (3) and (4) progressively add to Column (2) Debt Ratio Bins-by-year fixed effects and Capital Intensity Bins-by-year fixed effects. Column (5) includes firm and pre-period capital growth bins-by-year fixed effects. Standard errors are presented in parentheses and clustered at the 4-digit NAICS level. *, **, and *** denote statistical significance at the 10, 5, and 1% level. Authors' calculations based on TRI, Compustat, and Zwick and Mahon (2017) data.

Table 5: Effect of Bonus Depreciation on Emissions Intensity

	Total Chemicals per Unit Capital Stock				
	(1)	(2)	(3)	(4)	(5)
Bonus × Post	0.255**	0.280**	0.255*	0.152	0.308**
	(0.129)	(0.131)	(0.132)	(0.172)	(0.129)
Firm FE	✓	✓	✓	✓	✓
Year FE	✓				
Firm Size Bins × Year FE		✓	✓	✓	
Debt Ratio Bins × Year FE			✓	✓	
Cap. Intensity Bins × Year FE				✓	
Pre-Growth Bins × Year FE					✓
Obs.	9,434	8,165	8,165	8,165	7,673

Notes: Table 5 presents estimates of the effect of bonus depreciation on Log(Total Chemical Relases per Capital Stock). Column (1) estimates include firm and year fixed effects. Column (2) estimates include firm and firm-size bins-by year fixed effects. Columns (3) and (4) progressively add to Column (2) Debt Ratio Bins-by-year fixed effects and Capital Intensity Bins-by-year fixed effects. Column (5) includes firm and pre-period emissions intensity growth bins-by-year fixed effects. Standard errors are presented in parentheses and are clustered at the four-digit-NAICS industry level. *, **, and *** denote statistical at the 10, 5 and 1 percent level. *Sources:* Authors' calculations based on TRI, Compustat, and Zwick and Mahon (2017) data.

Table 6: Heterogeneous Effects of Bonus Depreciation by County-Level Attainment Status

	(1) CAA Releases	(2) On-Site Releases
Bonus × Post	0.482***	0.631***
	(0.0786)	(0.0872)
Bonus × Post × NonAttainment	-0.138**	-0.144**
	(0.0592)	(0.0551)
Plant FE	✓	✓
County × Year FE	✓	✓
Sector × Year FE	✓	✓
Obs.	157,597	192,332

Notes: Table 6 presents specifications similar to Equation (1) that also include an interaction between the DD term and an indicator for counties in non-attainment status following CAA reforms in 2004 and 2005. The outcome variables across the two specifications are Log(CAA Releases) and Log(Total On-Site Chemical Releases). All specifications include plant, county-by-year, and sector-by-year fixed effects. Standard errors are presented in parentheses and clustered at the 4-digit NAICS level. *, **, and *** denote statistical significance at the 10, 5, and 1% level. *Source:* Authors' calculations based on TRI and Zwick and Mahon (2017) data.

Table 7: Effect of Bonus Depreciation on NEI Criteria Air-Pollution Emissions

	$PM_{2.5}$	SO_2	NO_x	VOC
Bonus × Post	0.299**	0.360***	0.347*	0.195
	(0.138)	(0.135)	(0.210)	(0.128)
County × Industry FE	✓	✓	✓	✓
County × Year FE	✓	✓	✓	✓
Sector × Year FE	✓	✓	✓	✓
Obs.	148,398	173,338	111,522	137,307

Notes: Table 7 presents estimates of the effect of bonus depreciation on county-industry criteria air pollutant emissions. The outcomes include are particulate matter 2.5 (particles less than 2.5 microns in width), sulfur dioxide (SO2), nitrogen oxides (NOx), and volatile organic compounds (VOC). All specifications include county-by-industry, county-by-year, and sector-by-year fixed effects. Standard errors are presented in parentheses and are clustered at the four-digit-NAICS industry level. *, **, and *** denote statistical significance at the 10, 5, and 1% level. *Source:* Authors' calculations based on NEI and Zwick and Mahon (2017) data.

Table 8: Baseline Emissions Levels and Estimated Changed due to Bonus Depreciation

	$PM_{2.5}$	SO_2	NO_x	VOC
Total Emissions	101,817	1,769,139	896,019	180,396
Δ Emissions (Average)	20,340	518,852	230,446	0
Δ Emissions (Actual Nonattainment)	21,145	589,909	259,009	28,951
Δ Emissions (All Attainment)	25,881	768,549	344,344	19,641
Δ Emissions (All Nonattainment)	13,245	426,431	94,032	7,086

Notes: Table 8 presents total pollution emissions (in metric tonnes) of criteria air pollutants from the 2008 NEI data used for calculating aggregate economic damages. Δ Emissions (Average) is emissions changes due to bonus depreciation (see Table 7), calculated by multiplying baseline emissions (i) by a dummy for BONUS (ii) by the coefficients for Bonus × Post (0.299, 0.360, 0.347, and 0, for $PM_{2.5}$, SO2, NOx, and VOC, respectively). Δ Emissions (Actual Nonattainment) is emissions changes associated due to bonus depreciation accounting for heterogeneous effects by attainment status (see Table 11), calculated by multiplying baseline emissions (i) by a dummy for BONUS (ii) by the coefficients for Bonus × Post (0.383, 0.474, 0.520 and 0.316, for $PM_{2.5}$, SO2, NOx, and VOC, respectively) (iii) by a dummy for NonAttainment (iv) by the cofficients for Bonus × Post × NonAttainment (-0.187, -0.211, -0.378 and -0.202, for $PM_{2.5}$, SO2, NOx, and VOC, respectively). Δ Emissions (Actual Nonattainment) is emissions changes due to bonus depreciation accounting for heterogeneous effects by attainment status, calculated by multiplying baseline emissions (i) by a dummy for BONUS (ii) by the coefficients for Bonus × Post (iii) by a dummy for NonAttainment (iv) by the cofficients for Bonus × Post × NonAttainment. Δ Emissions (All Attainment) is emissions changes associated due to bonus depreciation assuming that all plants are subject to Attainment, calculated by multiplying baseline emissions (i) by a dummy for BONUS (ii) by the coefficients for Bonus × Post. Δ Emissions (All Nonattainment) is emissions changes associated with the BONUS assuming that all plants are subject to NonAttainment, calculated by multiplying baseline emissions (i) by a dummy for BONUS (ii) by the coefficients for Bonus × Post (iii) by the cofficients for Bonus × Post × NonAttainment. *Source:* Authors' calculations based on NEI and Zwick and Mahon (2017) data.

Table 9: Economic Damages from Bonus Depreciation

	Million $		$/pop	
Demographic	Low	High	Low	High
All	17,353	39,062	56	127
White	11,517	25,924	58	132
Black	3,711	8,354	98	221
Latino	1,680	3,782	33	75
Asian	365	823	25	58
Native	62	141	32	72

Notes: Table 9 presents economic damages using the InMAP model. The two columns on the left-hand-side present aggregate total economic damages for the United States, expressed in million USD. The two columns on the right-hand-side present total economic damages per capita, expressed in USD divided by corresponding population. The Low columns use a concentration-response parameter of 4% from Kewski et al. (2009) and the High columns use a concentration-response parameter of 14% from Lepuele et al. (2012). Economic damages are calculated by multiplying number of deaths by the VSL value of 9 million USD. *Source:* Authors' calculations based on NEI and Zwick and Mahon (2017) data using the InMAP model.

Table 10: Determinants of Per-Capita Economic Damages

	(1)	(2)	(3)	(4)	(6)	(6)	(7)	(8)	(9)
Median Income	-23.12***							-6.024	-7.129
	(3.904)							(9.169)	(9.485)
Poverty Rate		0.287						0.676	-0.0845
		(0.190)						(0.459)	(0.443)
Share Black			74.96***						56.95***
			(8.233)						(9.164)
Share Latino				-126.6***					-110.5***
				(6.663)					(7.886)
Share Asian					-240.7***				-95.46***
					(22.43)				(29.12)
Share Native American						-270.9***			-283.0***
						(35.48)			(34.28)
Share Non-White							-59.20***	-63.14***	
							(4.952)	(6.664)	
Obs.	3,107	3,107	3,108	3,108	3,108	3,108	3,108	3,107	3,107
R^2	0.011	0.001	0.026	0.104	0.036	0.018	0.044	0.052	0.147

Notes: Table 10 presents county-level cross-sectional regressions, where the dependent variable is county-level economic damages. The Median Income and Poverty Rate (all ages) are from the US Census Bureau's Small Area Income and Poverty Estimates (SAIPE) program. The population shares are calculated using the InMAP model population data by aggregating the computational grid to the county-level. All specifications are weighted by county population, and include a constant term (omitted from table) *, **, and *** denote statistical significance at the 10, 5, and 1% level. *Source:* Authors' calculations based on NEI, SAIPE, and Zwick and Mahon (2017) data using the InMAP model.

Table 11: Heterogeneous Effects of Bonus Depreciation on Criteria Air-Pollution Emissions by County-Level Attainment Status

	$PM_{2.5}$	SO_2	NO_x	VOC
Bonus × Post	0.383***	0.474***	0.520**	0.316**
	(0.146)	(0.146)	(0.233)	(0.140)
Bonus × Post × NonAttainment	-0.187*	-0.211**	-0.378**	-0.202*
	(0.103)	(0.102)	(0.170)	(0.107)
County × Industry FE	✓	✓	✓	✓
Sector × Year FE	✓	✓	✓	✓
Obs.	149,421	174,318	112,547	138,343

Notes: Table 11 presents estimates of the effect of bonus depreciation on county-industry emissions of criteria air pollutants. The outcomes are particulate matter 2.5 (particles less than 2.5 microns in width), sulfur dioxide (SO2), nitrogen oxides (NOx), and volatile organic compounds (VOC). All specifications include county-by-industry, county-by-year, and sector-by-year fixed effects. Standard errors are presented in parentheses and are clustered at the four-digit-NAICS industry level. *, **, and *** denote statistical significance at the 10, 5, and 1% level. *Source:* Authors' calculations based on NEI and Zwick and Mahon (2017) data.

Table 12: Economic Damages under Actual and Hypothetical Environmental Regulation

	Actual Non-Attainment		All Attainment		All Non-Attainment	
Demographic	Low	High	Low	High	Low	High
All	19,257	43,345	27,075	60,975	13,849	31,168
White	13,059	29,394	18,263	41,129	9,281	20,887
Black	3,928	8,843	5,605	12,623	2,907	6,542
Latino	1,797	4,046	2,518	5,671	1,307	2,943
Asian	362	815	544	1226	284	640
Native	86	195	107	241	52	118

Notes: Table 12 presents economic damages using the InMAP model. Economic damages are expressed in million USD. The two columns under the Actual Non-Attainment header are aggregate economic damages under actual Non-Attainment designations. The two columns under the All Attainment header are aggregate economic damages under the assumption that all counties are in Attainment. The two columns under the All Non-Attainment header are aggregate economic damages under the assumption that all counties are in Non-Attainment. The Low columns use a concentration-response parameter of 4% from Kewski et al. (2009) and the High columns use a concentration-response parameter of 14% from Lepuele et al. (2012). Economic damages are calculated by multiplying number of deaths by the VSL value of 9 million USD. textitSource: Authors' calculations based on NEI and Zwick and Mahon (2017) data using the InMAP model.

Online Appendix: Not for Publication

This appendix includes several sections of supplemental information. Appendix A presents definitions of all the variables used in the paper. Appendix B presents analysis of heterogeneous capital investment responses by CAA nonattainment status. Appendix C shows that potentially correlated data in the NEI survey does not have significant effects on our results. Appendix D further describes our MECS analysis. Appendix E presents some additional details on the InMAP model.

A Variable Definitions

Variable Name	**Description**
Bonus	Indicator equal to one for plants in the bottom tercile of the NPV of MACRS tax depreciation allowances. *Source:* Authors' calculations based on TRI and Zwick and Mahon (2017) data.
Post	Indicator equal to one in years after 2001, after bonus depreciation was implemented.
Total Releases	Natural logarithm of the sum of all on-site and off-site chemical releases to all disposal media (air, water, land). *Source:* TRI.
On-Site Releases	Natural logarithm of the sum of all off-site chemical releases to all disposal media (air, water, land). *Source:* TRI.
Air Releases	Natural logarithm of the sum of all on-site and off-site chemical releases to air. *Source:* TRI.
Water Releases	Natural logarithm of the sum of all on-site and off-site chemical releases to water. *Source:* TRI.
Land Releases	Natural logarithm of the sum of all on-site and off-site chemical releases to land. *Source:* TRI.
Air CAA	Natural logarithm of the sum of all on-site and off-site chemical releases covered under the Clean Air Act that were released to air. *Source:* TRI.
Non-attainment County	A time-invariant indicator equal to one for counties that were in non-attainment status following the CAA reforms on 2004 and 2005. *Source:* EPA Greenbook
Capital Stock	The log of firm-level net property, plant, and equipment. *Source:* Compustat
Log Releases per unit of Capital	The log of firm-level aggregate emissions divided by firm-level net property, plant, and equipment. *Source:* TRI and Compustat
Log Releases per unit of Revenue	The log of firm-level aggregate emissions divided by firm-level sales. *Source:* TRI and Compustat
$PM_{2.5}$	Log of county-industry aggregate particulate matter 2.5 releases. *Source:* NEI
VOC	Log of county-industry aggregate volatile organic compound releases. *Source:* NEI
SO_2	Log of county-industry aggregate sulfur dioxide releases.*Source:* NEI
NO_x	Log of county-industry aggregate nitrous oxide releases.*Source:* NEI
Economic Damages Per Capita	Dollar value of economics damages caused by bonus depreciation. *Source:* Author's calculations using the InMAP model based on NEI and Zwick and Mahon (2017) data.
Median Household Income	County-level median household income. *Source:* Census Small Area Income and Poverty Estimates.
Median Household Income	County-level percentage of households with incomes below the poverty line. *Source:* Census Small Area Income and Poverty Estimates.
Share Non-White	County-level percentage of non-white residents. *Source:* Census Small Area Income and Poverty Estimates.

Continued on next page

Table A1 – *Continued from previous page*

Variable	**Description**
Share Black	County-level percentage of Black residents. *Source:* Census Small Area Income and Poverty Estimates.
Compr. Air System	Percent (0-100) of establishments in an industry that installed or retrofitted their Compressed Air Systems. *Source:* MECS
Lighting System	Percent (0-100) of establishments in an industry that installed or retrofitted their Lighting System.*Source:* MECS
HVAC System	Percent (0-100) of establishments in an industry that installed or retrofitted their HVAC System. *Source:* MECS
Machine Drive Syst	Percent (0-100) of establishments in an industry that installed or retrofitted their Machine Drive System.*Source:* MECS
Proc. Cooling System	Percent (0-100) of establishments in an industry that installed or retrofitted their Process Cooling System. *Source:* MECS
Dir/Indir Heat Syst	Percent (0-100) of establishments in an industry that installed or retrofitted their Direct / Indirect Heating System.*Source:* MECS
Steam Prod. System	Percent (0-100) of establishments in an industry that installed or retrofitted their Steam Production System. *Source:* MECS
Energy Audit	Percent (0-100) of establishments in an industry that undertook an energy audit. *Source:* MECS
Install/Retro New Energy Source	Percent (0-100) of establishments in an industry that installed a new energy source or retrofitted an existing energy source. *Source:* MECS

B Heterogeneous Capital Investment Responses by CAA Exposure

In this appendix we explore whether environmental regulations that were part of the CAA tempered the capital investment response to bonus depreciation. To do so, we rely on our matched TRI-Compustat sample of firms. We regress firm-level log of capital stock on Bonus×(Year=2011) and Bonus× (Year=2011) interacted with an indicator equal to one for firms that had a plant in a county that was in non-attainment status following the 2004 and 2005 CAA amendments. Results are presented in Table A5. The five specifications differ in the fixed effects that are included in the regression. Specification (1) includes just firm and year fixed effects. Specifications (2)–(4) progressively add pre-period firm-size bins interacted with year FE, pre-period debt-ratio bins interacted with year FE, pre-period capital intensity bins interacted with year FE. Specification (5) directly controls for pre-period differences in capital investment across firms by including bins of pre-period capital growth interacted with fixed effects.

Focusing on the triple-differences findings, across all five specification the coefficient estimates are negative and fairly stable indicating that the CAA environmental regulations may have tempered the investment response to bonus depreciation. However, no coefficients are statistically significant at the 5% level and only two coefficient are statistically significant at the 10% level.

Despite this statistical imprecision, the results presented in Table A5 could explain why we see smaller emissions response to the policy in non-attainment counties: the CAA regulations tempered the investment response to the policy. Comparing the DDD to the DD coefficients suggests that the capital response for firms with a plant in a non-attainment country may have been between 25 and 50% smaller than the response of firms with no plants in non-attainment counties.

Overall, we take the results presented in this Appendix as suggestive evidence that that environmental regulations influenced the investment response to bonus depreciation.

C Accounting for Correlated Data in the NEI

In this appendix, we test whether our NEI reduced-form estimates are sensitive to potentially correlated data in the NEI. Careful examination of the dynamic difference-in-differences estimates in Figure 6 shows that (1) coefficient estimates for 1996-1998 are nearly identical for all pollutants and that (2) the 1999 coefficient is nearly identical to the omitted year (2000). A possible explanation for these very similar coefficient estimates is that there is a high degree of correlation in the underlying pollution data between 1996-1998 and 1999-2000. Upon inspection of the underlying data, we find that plant-level and /or county-level pollution is generally not identical within the two periods. Nonetheless, we remain concerned that correlated data that are not independent may bias our results in ways that hamper our analysis.

To combat this concern, we restrict our NEI sample to include only one year from each of the 1996-1998 and 1999-2000 periods. In particular, we use 1997 and 2000 (excluding 1996, 1998, and 1999), although the results are similar using any one year from each of the two periods. DD estimates using this restricted sample are presented in Table A7. The DD coefficients are nearly identical to our baseline estimates. We continue to find that bonus depreciation led to statistically significant increases in $PM_{2.5}$, SO_2, and NO_x. Our point estimates suggests the policy has a large, positive effect on VOCs, but the estimate is not statistically significant. Figure A7 shows the dynamic DD analysis using the restricted sample. All four panels of the figure show large positive jumps in criteria emissions for treated units relative to controls units after the policy was implemented in 2001.

In sum, eliminating potentially correlated data from our NEI sample yields very similar estimates describing the effect of bonus depreciation of criteria air pollutants. Based on this analysis, we conclude the potentially correlated data in the NEI does not affect our analysis in a meaningful way.

D MECS

In this appendix, we further describe our analysis using the Manufacturing Energy Consumption Survey (MECS). The MECS is sponsored by the Department of Energy and administered quadrennially by the US Census Bureau. MECS is the only data source which reports investments in assets that improve the environmental performance of the plant. It surveys approximately 15,000 establishments and represents 97%–98% of manufacturing energy consumption. Establishments are asked whether they installed or retrofitted seven types of equipment for the purpose of improving energy efficiency. The seven categories are Compressed Air System, Facility Lighting, Facility HVAC System, Direct Machine Drive, Direct Process Cooling, Refrigeration, Direct/Indirect Heating System and Steam Production/System. Publicly available MECS reports data at the industry level for approximately 70 industry categories. The regressions we report in Table A6 are run at the industry-year level for years 1994, 1998, 2002, 2006 and 2010. The outcome variable is the percent of establishments in the industry that install or retrofit these equipment categories. We also report results examining the effect of bonus on the percent of establishments in an industry that undergo an energy audit and the percent of establishments in an industry that install or retrofit a new energy source. MECS data can be found at https://www.eia.gov/consumption/manufacturing/.

While the investments measured here are specific to energy, they likely are closely tied to the establishment's emissions and represent a form of clean investment that cannot be picked up in other datasets. The Pollution Abatement Cost and Expenditure Survey was performed in 1994, 1999 and 2005 but the survey methodology changed over time and has not been administered since 2005 (Gallaher, Morgan, and Shadbegian, 2008). The MECS results suggest that, while bonus led establishments to increase their overall emissions through scale and technique effect, there is at least partial evidence that it induced some clean capital investments.

E InMAP

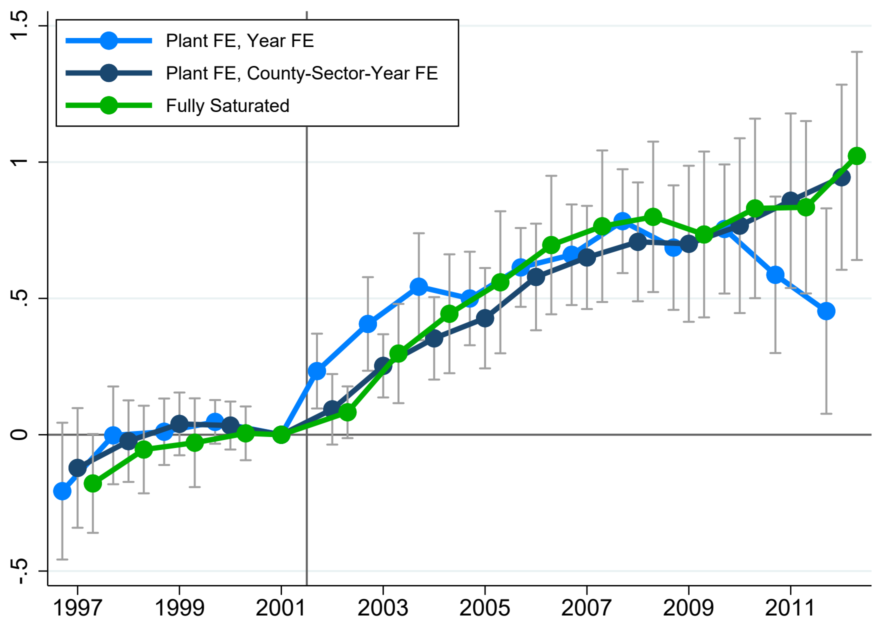
In this Appendix we provide some additional description about the InMAP model and our immplementation of the model. The InMap model uses the Python programming language with the GeoPandas shapefile library to process spatial data. General information about the model can be found here: https://www.inmap.run. Information regarding the use of source-receptor matrices to estimate health impacts can be found here: https://www.inmap.run/blog/2019/04/20/sr/.

The primary input data required is emissions data including information on the location, amount of emissions, and stack parameters. Specifically, the InMap model uses information on location of the emissions sources (coordinates with a spatial references), the short tons per year of emissions ($PM_{2.5}$, NOx, VOC, SO_x, and NH_3,), and relevant stack parameters, including stack height, velocity, diameter, and temperature of the release. This information is contained in the full-detail data of the National Emissions Inventory (NEI), and we use the 2008 NEI database, which can be found here: https://www.epa.gov/air-emissions-inventories/2008-national-emissions-inventory-nei-data.

We use GeoPandas to convert the NEI data into a GeoPandas dataframe, which can then be used to run the InMap model.

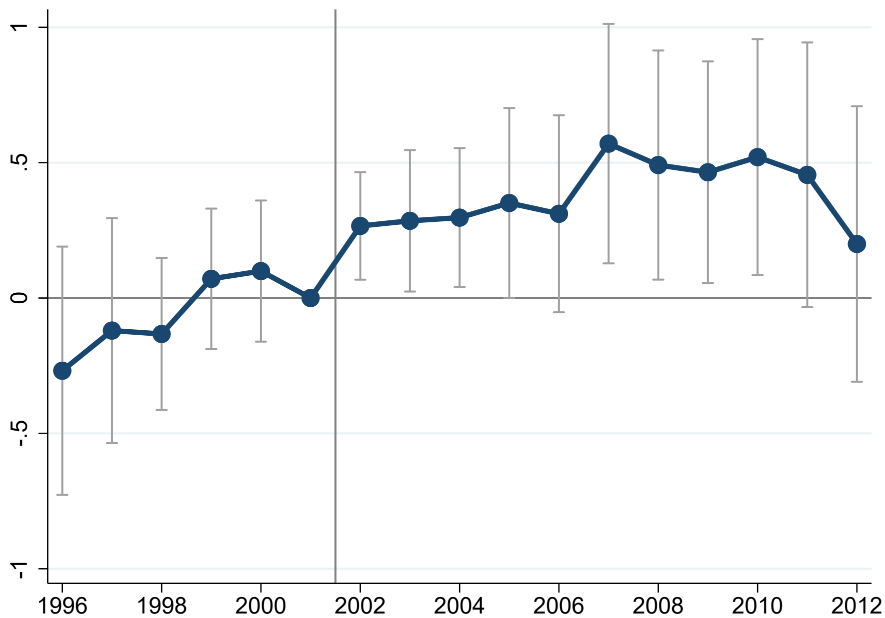
Appendix Figures

Figure A1: Effects of Bonus on Total Releases; Alternative Specifications



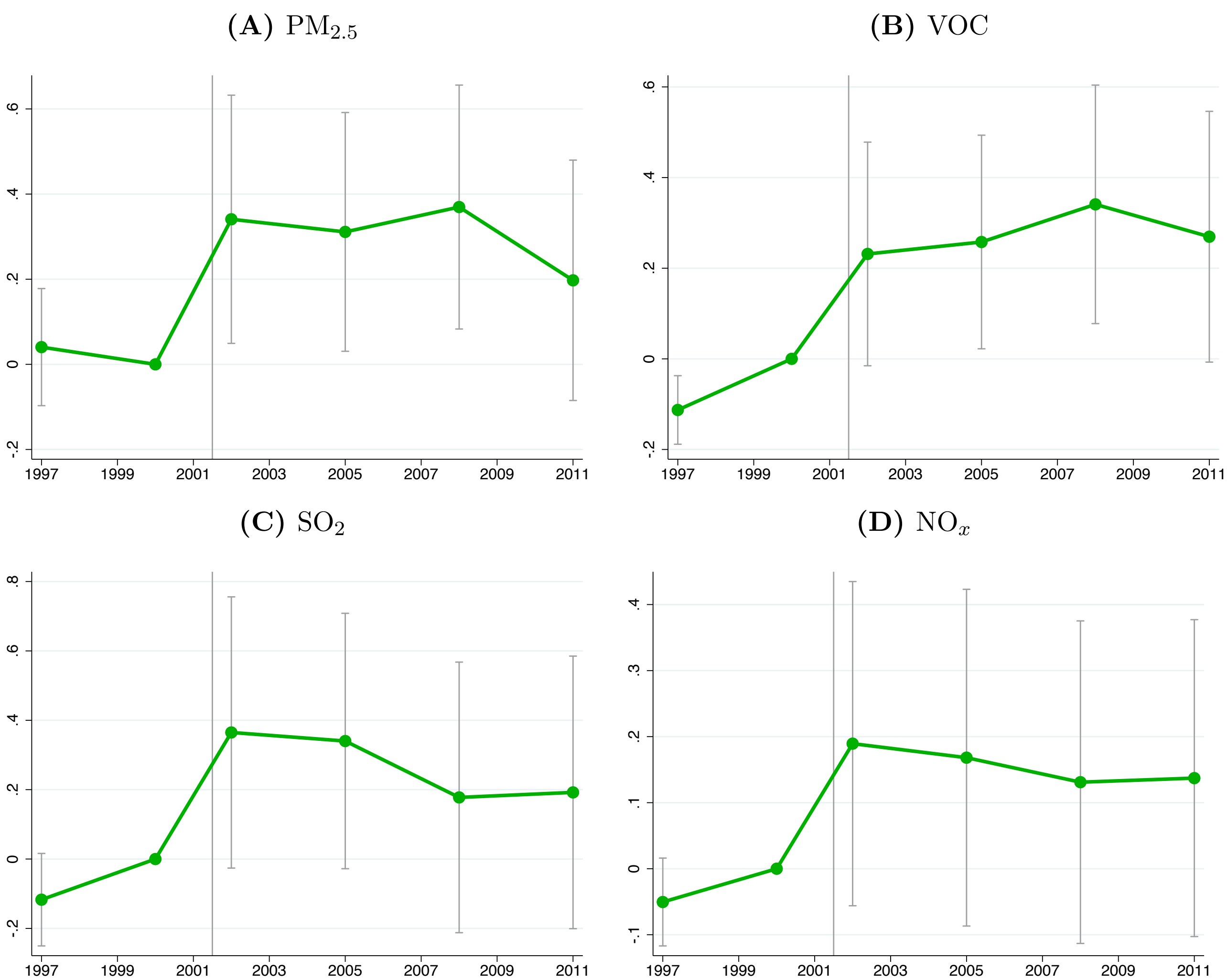
Notes: Figure A1 displays dynamic DD estimates and 95% confidence intervals based on equation (2) describing the effect of bonus depreciation on Log(Total Chemical Releases) with alternate levels of fixed effects. The first specification includes only plant and year fixed effects. The second specification includes plant, and county-by-sector-by-year fixed effects. The third specifications includes plant, county-year, and sector-year fixed effects as well as fixed effects controls for Chinese import competition, the domestic production activities deduction, and use of information and communication technology. Standard errors are clustered at the NAICS 4-digit industry level. The 2001 coefficient is normalized to zero. The corresponding DD estimates are presented in Columns (1), (5), and (6), of Panel (A), Table 2. *Source:* Authors' calculations based on TRI and Zwick and Mahon (2017) data.

Figure A2: Effects of Bonus Depreciation on Log Releases per Unit of Revenue



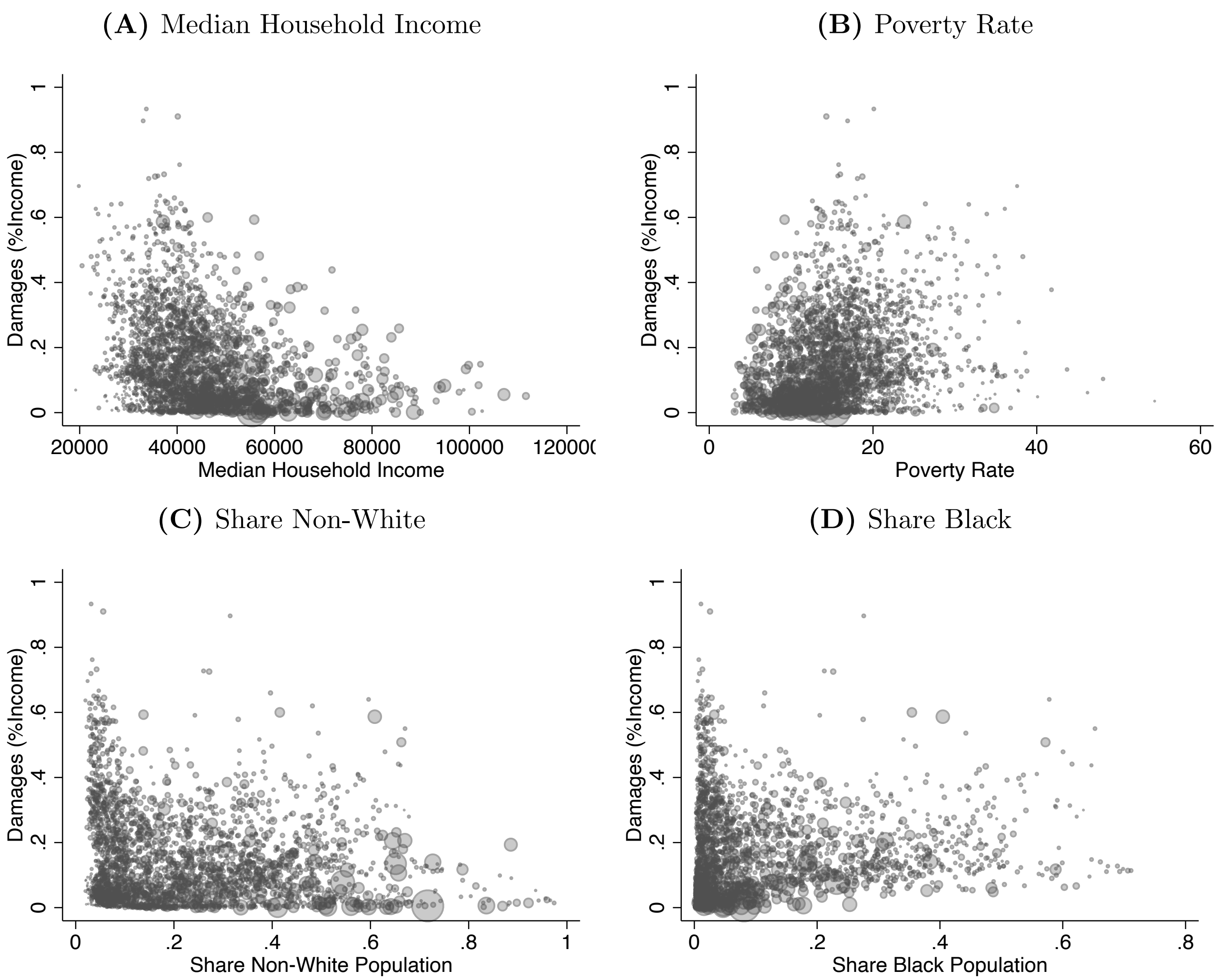
Notes: Figure A2 displays dynamic DD estimates and 95% confidence intervals describing the effect of bonus depreciation on Log(Capital Stock per Unit Revenue) for the sample of Compustat firms that have plants in the TRI. Estimates include firm and firm-size bins-by-year fixed effects. Standard errors are clustered at the NAICS 4-digit industry level. *Source:* Authors' calculations based on TRI, Compustat, and Zwick and Mahon (2017) data.

Figure A3: Effect of Bonus Depreciation County-Industry-level NEI Criteria Air-Pollution Emissions (Restricted Sample)



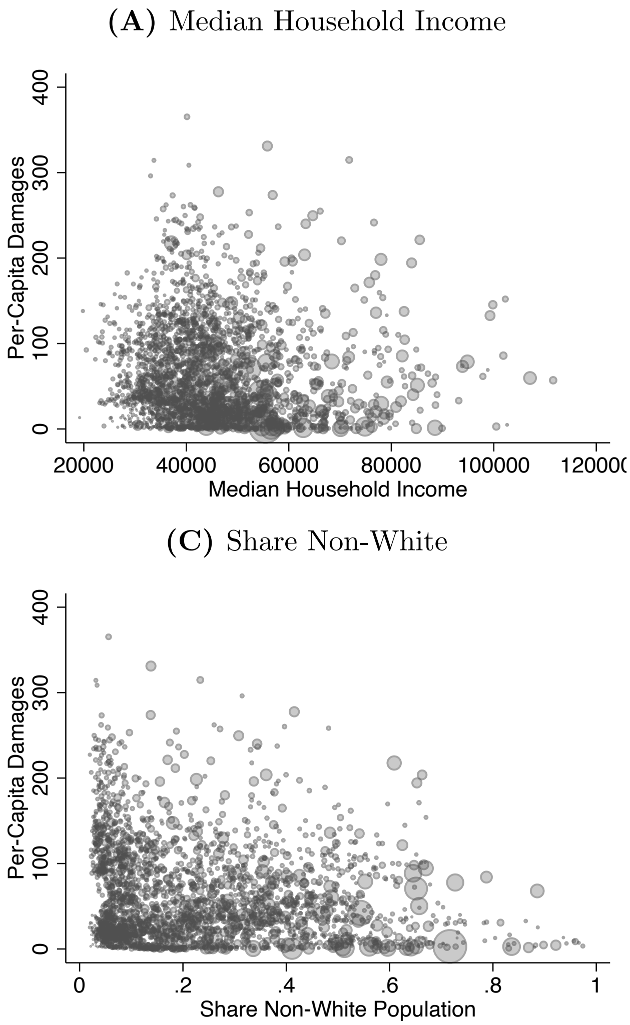
Notes: Figure A3 displays dynamic DD estimates and 95% confidence intervals describing the effect of bonus depreciation on county-industry criteria air pollutants. The 2000 coefficients are normalized to zero. We restrict the sample by excluding the years 1996, 1998, and 2000. The outcomes include air emissions of the following criteria air pollution: particulate matter 2.5 (particles less than 2.5 microns in width), sulfur dioxide (SO2), nitrogen oxides (NOx), and volatile organic compounds (VOC). All specifications include county-by-industry, county-by-year, and sector-by-year fixed effects. *Source:* Authors' calculations based on NEI and Zwick and Mahon (2017) data.

Figure A4: Per-Capita Economic Damages as Percentage of Median Income



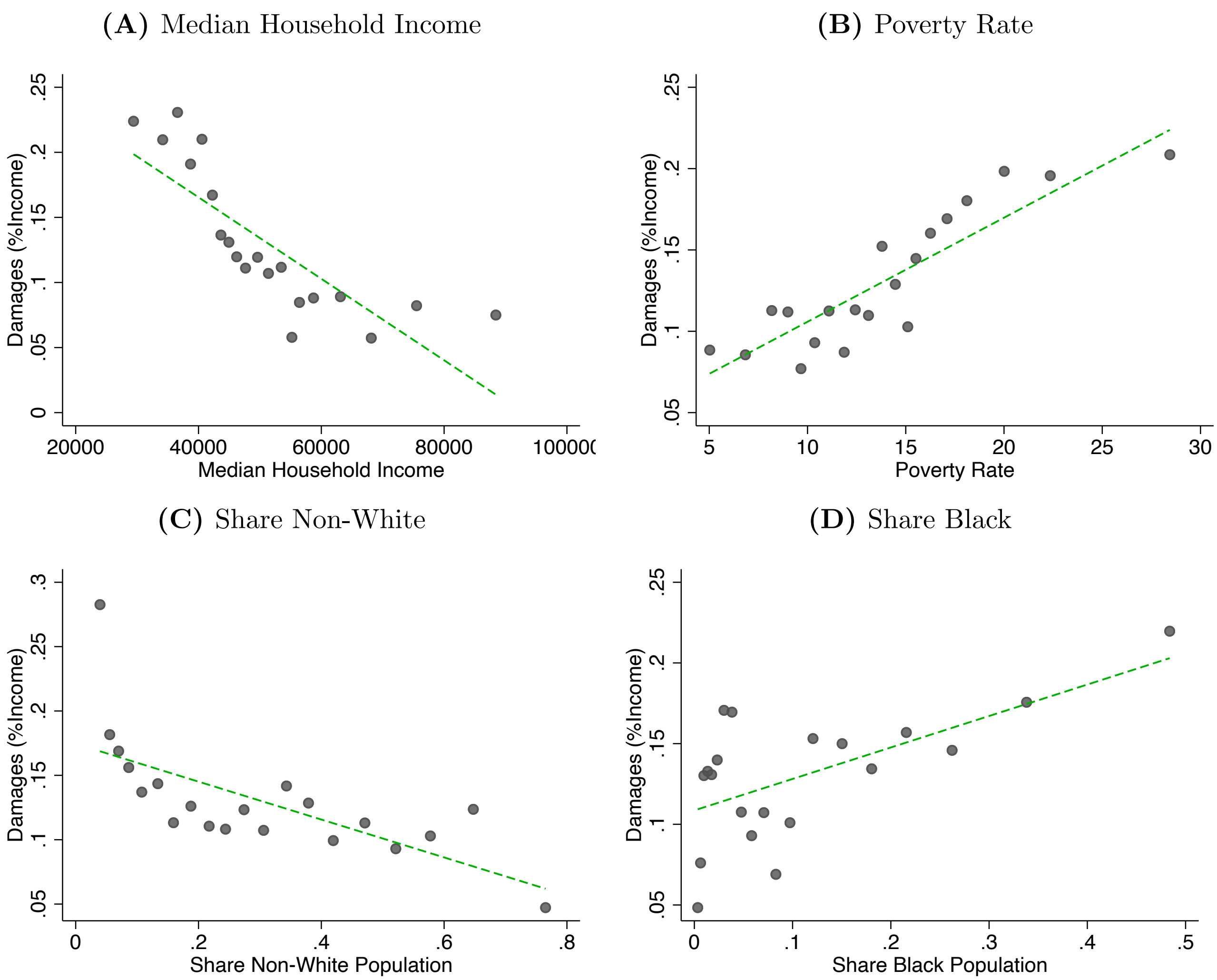
Notes: Figure A4 presents county-level per-capita economic damages using the InMAP model. Damages are calculated using the lower concentration-response parameter of 4% from Kewski et al. (2009), and a Value of Statistical Life (VSL) of 9 million USD. The relative size of points reflect the county population. *Source:* Authors' calculations based on NEI, SAIPE, and Zwick and Mahon (2017) data using the InMAP model.

Figure A5: Per-Capita Economic Damages



Notes: Figure A5 presents county-level per-capita economic damages using the InMAP model. Damages are calculated using the lower concentration-response parameter of 4% from Kewski et al. (2009), and a Value of Statistical Life (VSL) of 9 million USD. The relative size of points reflect the county population. *Source:* Authors' calculations based on NEI, SAIPE, and Zwick and Mahon (2017) data using the InMAP model.

Figure A6: Per-Capita Economic Damages as Percentage of Median Income (Bin Scatter)



Notes: Figure A4 presents county-level per-capita economic damages using the InMAP model. Damages are calculated using the lower concentration-response parameter of 4% from Kewski et al. (2009), and a Value of Statistical Life (VSL) of 9 million USD. The relative size of points reflect the county population. *Source:* Authors' calculations based on NEI, SAIPE, and Zwick and Mahon (2017) data using the InMAP model.

Appendix Tables

Table A2: Effect of Bonus Depreciation using Alternative Treatment Definitions

	Log(Total Chemical Releases)			
	(1)	(2)	(3)	(4)
Bonus × Post (33rd percentile)	0.349***			
	(0.0678)			
Bonus × Post (25th pctle percentile)		0.387***		
		(0.0701)		
Bonus × Post (40th pctle percentile)			0.311***	
			(0.0676)	
Bonus × Post (Continuous)				0.809***
				(0.267)
Plant FE	✓	✓	✓	✓
County × Year FE	✓	✓	✓	✓
Sector × Year FE	✓	✓	✓	✓
Obs.	212,368	212,368	212,368	212,368

Notes: Table A2 presents estimates of the effect of bonus depreciation on total chemical releases using alternative treatment definitions. All specifications follow the Equation (1) framework. The outcome variables in all specifications is Log(Total Releases) and all specifications include plant, county-by-year, and sector-by-year fixed effects. Treatment in Specification (1) follows our standard definition. In Specification (2), treatment is defined as plants in the bottom quartile of the z_0 distribution. In Specification (3), treatment is defined as plants in the bottom four declies of the z_0 distribution. Treatment in Specification (4) uses the continuous measure of z_0 interacted with the Post dummy. The Specification (4) treatment definition is scaled so the coefficient represents the effect of 100% bonus depreciation / 100% expensing. Standard errors are presented in parentheses and are clustered at the four-digit-NAICS industry level. *, **, and *** denote statistical significance at the 10, 5, and 1% level. *Source:* Authors' calculations based on TRI and Zwick and Mahon (2017) data.

Table A3: Effect of Bonus on Total Chemical Releases: Compustat Sample

	Log(Total Chemical Releases)					
	(1)	(2)	(3)	(4)	(5)	(6)
Bonus × Post	0.428***	0.472***	0.524***	0.555***	0.499***	0.706***
	(0.0797)	(0.0808)	(0.0981)	(0.0792)	(0.107)	(0.118)
Plant FE	✓	✓	✓	✓	✓	✓
Year FE	✓					
County × Year FE		✓		✓		✓
Sector × Year FE			✓	✓		
County × Sector × Year FE					✓	
Additional Controls						✓
Obs.	49,142	48,751	49,142	48,751	47,115	42,076

Notes: Table A3 presents estimates of the effect of bonus depreciation on chemicals releases based on Equation (1) for the sample of plants that we match to Compustat firms. The outcome variable in all specifications is Log(Total Chemical Releases). Column (1) includes plant and year fixed effects. Column (2) includes plant and county-by-year fixed effects. Column (3) includes plant and sector-by-year fixed effects. Column (4) includes plant, county-by-year, and sector-by-year fixed effects. Column (5) specifications include plant and county-by-sector-by-year fixed effects. Column (6) specifications include county-by-year and sector-by-year fixed effects as well as controls for import competition from China, the Domestic Production Activities Deduction, and use of Information and Communications Technologies. Standard errors are presented in parentheses and are clustered at the four-digit-NAICS industry level. *, **, and *** denote statistical at the 10, 5 and 1 percent level. *Sources:* Authors' calculations based on TRI, Compustat, and Zwick and Mahon (2017) data.

Table A4: Effect of Bonus Depreciation on Releases per Unit of Revenue

	Total Chemicals per Unit Capital Stock				
	(1)	(2)	(3)	(4)	(5)
Bonus × Post	0.255**	0.280**	0.255*	0.152	0.308**
	(0.129)	(0.131)	(0.132)	(0.172)	(0.129)
Firm FE	✓	✓	✓	✓	✓
Year FE	✓				
Firm Size Bins × Year FE		✓	✓	✓	
Debt Ratio Bins × Year FE			✓	✓	
Cap. Intensity Bins × Year FE				✓	
Pre-Growth Bins × Year FE					✓
Obs.	9,434	8,165	8,165	8,165	7,673

Notes: Table A4 presents estimates of the effect of bonus depreciation on Log(Total Chemical Releases per Dollar Revenue). Column (1) includes plant and year fixed effects. Column (2) includes plant and county-by-year fixed effects. Column (3) includes plant and sector-by-year fixed effects. Column (4) includes plant, county-by-year, and sector-by-year fixed effects. Column (5) specifications include plant and county-by-sector-by-year fixed effects. Column (6) specifications include county-by-year and sector-by-year fixed effects as well as controls for import competition from China, the Domestic Production Activities Deduction and use of Information and Communications Technologies. Standard errors are presented in parentheses and are clustered at the four-digit-NAICS industry level. *, **, and *** denote statistical at the 10, 5 and 1 percent level. *Sources:* Authors' calculations based on TRI, COMPUSTAT, and Zwick and Mahon (2017) data.

Table A5: Effect of Bonus on Capital Stock; Heterogeneity by Attainment Status

	Log(Capital Stock)				
	(1)	(2)	(3)	(4)	(5)
Bonus $\times$ 1(Year = 2011)	0.383***	0.382***	0.405***	0.309**	0.396***
	(0.119)	(0.119)	(0.123)	(0.136)	(0.119)
Bonus $\times$ 1(Year = 2011) $\times$ 1(NA)	-0.187*	-0.172	-0.151	-0.131	-0.194*
	(0.113)	(0.112)	(0.0940)	(0.0937)	(0.106)
Firm FE	✓	✓	✓	✓	✓
Year FE	✓				
Firm Size Bins $\times$ Year FE		✓	✓	✓	
Debt Ratio Bins $\times$ Year FE			✓	✓	
Cap. Intensity Bins $\times$ Year FE				✓	
Pre-Growth Bins $\times$ Year FE					✓
Obs.	10,119	9,866	9,866	9,866	9,744

Notes: Table A5 displays long-difference estimates describing heterogeneous responses to bonus depreciation due to county-level non-attainment status. The outcome variable in all specifications is Log(Capital Stock). The Bonus $\times$ (Year=2011) coefficient describes the 10-year capital response to bonus depreciation. The Bonus $\times$ (Year=2011) $\times$ 1(NA) coefficient describes how much larger/smaller is the 10-year capital response to bonus depreciation for firms in the TRI-Compustat sample that had a plant located in a non-attainment county following the 2004 and 2005 CAA Amendments. Column (1) estimates include firm and year fixed effects. Column (2) estimates include firm and firm-size bins-by year fixed effects. Columns (3) and (4) progressively add to Column (2) Debt Ratio Bins-by-year fixed effects and Capital Intensity Bins-by-year fixed effects. Column (5) includes firm and pre-period capital growth bins-by-year fixed effects. Standard errors are presented in parentheses and clustered at the 4-digit NAICS level. *, **, and *** denote statistical significance at the 10, 5, and 1% level. Authors' calculations based on TRI and Zwick and Mahon (2017) data.

Table A6: Effect of Bonus Depreciation on Energy-Efficient Capital Investment from MECS

	(1) Compr. Air System	(2) Lighting System	(3) HVAC System	(4) Machine Drive Syst	(5) Proc. Cooling System	(6) Dir/Indir Heat Syst	(7) Steam Prod. System	(8) Energy Audit	(9) Install/Retro New Energy Source
Bonus x Post	4.042**	-4.970	5.369**	5.094***	11.656***	-4.180	-1.201	6.089***	9.390**
	(1.940)	(3.027)	(2.606)	(1.865)	(3.902)	(3.568)	(4.286)	(2.080)	(4.496)
Ind FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Obs.	209	281	311	320	319	293	305	312	282
Avg Ind % Uptake	8.333	9.159	17.979	19.910	47.222	18.680	25.411	15.911	15.343

Notes: Table A6 presents estimates of the effect of bonus depreciation on industry-level variables from the MECS. MECS reports the number of establishments in approximately 70 industries that "install or retrofit" particular systems for the primary purpose of improving energy efficiency. The outcome variables in the regressions range from 0-100 and represent the percent of establishments in an industry that install or retrofit a given system. The MECS is collected every four years. Regressions are run on years 1994, 1998, 2002, 2006 and 2010. The outcome variables are the share of establishments installing or retrofitting Compressed Air Systems, Facility Lighting Systems, HVAC Systems, Direct Machine Drive Systems, Process Cooling Systems, Direct/Indirect Heating Systems. We also estimate the effect on the share of establishments that undergo an energy audit and the share of establishments install or retrofit an energy source. All specifications include industry and year fixed effects. Standard errors are presented in parentheses and clustered at the four-digit-NAICS industry level. *, **, and *** denote statistical significance at the 10, 5, and 1% level. *Source:* Authors' calculations based on MECS and Zwick and Mahon (2017) data.

Table A7: Effect of Bonus Depreciation on NEI Criteria Air-Pollution Emissions; Restricted Sample

	$PM_{2.5}$	SO_2	NO_x	VOC
Bonus × Post	0.292**	0.317**	0.332*	0.182
	(0.137)	(0.126)	(0.192)	(0.123)
County × Industry FE	✓	✓	✓	✓
County × Year FE	✓	✓	✓	✓
Sector × Year FE	✓	✓	✓	✓
Obs.	76,803	91,637	60,273	72,434

Notes: Table A7 presents estimates of the effect of bonus depreciation on county-Industry-level air-pollution emissions for criteria air pollutants from the National Emissions Inventory (NEI). We restrict the sample by excluding the years 1996, 1998, and 2000. The outcomes include air emissions of the following criteria air pollution: particulate matter 2.5 (particles less than 2.5 microns in width), particulate matter 10 (particles less than 10 microns in width), sulfur dioxide (SO2), nitrogen oxides (NOx), and volatile organic compounds (VOC). The outcomes are aggregated across all plants within a given count-industry (4-digit NAICS code). All specifications include county-by-industry, county-by-year, and sector-by-year fixed effects. Standard errors are presented in parentheses and are clustered at the four-digit-NAICS industry level. *, **, and *** denote statistical significance at the 10, 5, and 1% level. *Source:* Authors' calculations based on NEI and Zwick and Mahon (2017) data.