Environmental Consequences of Investment Stimulus Policy

Dana C. Andersen
University of Alberta

E. Mark Curtis
Wake Forest University

Eric Ohrn
Grinnell College

January 2025

Abstract

We study the 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%. Using a pollution transport model with fine spatial resolution, we estimate overall environmental damages at between \$20 and 45 billion per year. We show that these environmental damages exceed the policy's stimulus benefits, implying that the investment tax incentive reduces aggregate welfare. The policy was also highly regressive and exacerbated racial inequalities to pollution exposure. We document that the magnitude of the aggregate damages we estimate is due primarily to bonus depreciation's unintentional targeting of the most emissions-intensive industries. We show that alternative policies can stimulate the same amount of investment and economic growth at a fraction of the environmental cost.

Keywords: Pollution, Environmental Damages, Pollution Transport Model, Environmental Justice, Corporate Taxation, Investment Stimulus Policy, Bonus Depreciation
JEL Codes: E62, H25, H32, Q53, Q58

We thank Dylan Brewer, Kat Bilicka, Keith Brouhle, Jevan Cherniwchan, Kim Clausing, Lucas Davis, Dan Garrett, Nathan Hendren, Danae Hernandez-Cortes, Stephen Holland, Wojciech Kopczuk, Patrick Kennedy, Cooper Monroe, Joshua Rauh, Max Risch, Kevin Roberts, Joe Shapiro, Juan Carlos Suárez Serrato, Vincent Thivierge, Reed Walker, Danny Yagan, Alex Yu and participants at the NBER Economic Analysis of Business Taxation Conference, NBER Summer Institute, UC Berkeley, Canadian Economic Association, Southern Economic Association, Carolina Applied Micro Conference, Georgia Tech SWEEEP, Columbia Tax Law Workshop, AERE Summer Conference, US Census Bureau, University of Alberta REES, and Grinnell College for helpful comments and suggestions. We are grateful to the Kauffman Foundation and the Brookings Institution for their support of this project.

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 countries implemented policies that decreased the cost of physical capital (Steinmüller, Thunecke, and Wamser, 2019). A prescient example is the recent US Tax Cuts and Jobs Act of 2017, which included more than $1 trillion in investment incentives (CBO, 2017).[1] 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 are the environmental costs generated by the investment these policies stimulate. Given the magnitude of these policies, their environmental consequences are potentially large and therefore critical in any systematic policy analysis of their costs and benefits.

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 a range of 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 magnitude and geographic distribution of 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. Results from the pollution transport model show that the economic damages caused by these additional emissions amount to between $20 and $45 billion per year or between 36 and 81 cents per dollar of policy benefits. The magnitude of these damages is due primarily to bonus depreciation's unintentional targeting of the most emissions-intensive industries. Moreover, we show that alternative policies that target different industries can stimulate the same amount of investment at a fraction of the environmental costs.

[1] This estimate is composed primarily of the cost of the bill's statutory corporate income tax rate cut and its accelerated depreciation incentives.

We also find that 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 efficient design of investment stimulus policies must consider their potentially large and unequal environmental costs.

The policy we study, bonus depreciation, was first implemented to combat the 2001 recession and has been in nearly continuous use ever since. Bonus depreciation is expensive; it's estimated fiscal costs were more than a quarter of a trillion dollars over the last ten years (US Treasury, 2020). The Tax Cuts and Jobs Act extended a generous version of the incentive through 2026. Bonus depreciation 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.[2] 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

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

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 on average 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 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.

This estimate represents the causal effect of bonus depreciation on emissions if the emissions of treated and control plants 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, after the policy was enacted. 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 technique effect by estimating firm-level responses in emissions-intensity to bonus depreciation. Both DD and dynamic DD specifications show that the policy did not lead firms to decrease emissions intensity. 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 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. 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.[3]

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. We use the InMAP model to translate plant-level increases in criteria air emissions due to bonus depreciation into increased pollution concentrations and environmental damages across the US. The model accounts for both atmospheric transport and chemical reactions of pollution to determine damages at a fine degree of spatial resolution. The InMAP model has been embraced by economists and environmental agencies due to this spatial granularity, which allows for more precise estimation of pollution exposure across different demographic groups (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

[3] We also reinforce these results using surface-level pollution data from the EPA's Air Quality System (AQS). We find that bonus depreciation increased particulate matter concentrations at AQS monitoring sites. Details of this analysis are provided in the Appendix J.

range between \$20 and \$45 billion USD, which corresponds to per-capita damages between \$66 and \$148 USD.[4] Economic damages are highly uneven geographically, with some sub-populations incurring damages that far exceed the average.

Economic damages are also highly unequal across racial groups, with African Americans experiencing per-capita economic damages 68% higher than the national average. Moreover, counties with greater Black population shares incurred higher economic damages, even after controlling for median income and poverty rates. Unfortunately, further analysis shows the jobs created by the policy do not proportionally accrue to the same people and as a result, the damages per job created are also concentrated among historically disadvantaged populations. Overall, these results suggest that the policy exacerbated existing racial disparities in exposure to air pollution.

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 would have been approximately 40% higher without existing environmental regulations.

Given the substantial damages we document, we explore whether the magnitude of these damages are inherent to investment stimulus policies or are a particular feature of bonus depreciation. We document that bonus depreciation unintentionally targets the most emissions intensive industries, resulting in disproportionately high environmental costs. Alternative policies designed to stimulate the same amount of investment by targeting either (i) the industries benefiting least from bonus depreciation or (ii) the cleanest industries both generate less than 5% of the environmental costs of the actual policy.

Finally, to understand the net welfare consequences of bonus depreciation, we perform a back-of-envelope empirical welfare analysis. We estimate that for every dollar of benefits generated by the policy, there was 77 cents worth of fiscal cost to the government. As such, before including environmental costs, this policy is welfare-improving. However, the environmental damages we measure result in an additional 39 to 88 cents of costs per dollar of benefits. Hence, after accounting for environmental costs, the policy becomes welfare-decreasing.

[4] This range corresponds to low and high estimates of the relationship between mortality and pollution concentration from Krewski et al. (2009) and Lepeule et al. (2012). Throughout, we assume the value of a statistical life (VSL) is 9 million 2020 USD following Goodkind et al. (2019). This is a conservative approximation of the EPA's current VSL standard (EPA, 2010).

This paper's findings represent four major contributions. First, the substantial 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 Suarez Serrato, 2020; Curtis et al., 2021).[5] We document a significant negative externality resulting from bonus depreciation, finding that the policy's true costs exceed its benefits when pollution damages are accounted for. We show that the magnitude of the economic damages we estimate is due to the fact that bonus depreciation unintentionally targeted the most emissions-intensive industries. Therefore, our findings suggest the reliance on very similar policies 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 environmental costs.

Second, our results show that investment stimulus policies can be important determinants of emissions and pollution.[6] Our findings therefore add to the large literature in environmental economics exploring the importance of various determinants of industrial emissions, including trade and outsourcing, structural transformation, productivity growth, and environmental regulations (See e.g. Levinson, 2009, 2015; Shapiro, 2020; Najjar and Cherniwchan, 2021). Shapiro and Walker (2018) demonstrates that environmental regulations are a key determinant of emissions and are primarily responsible for the decline in total pollution in the United States over the past 50 years. Expressed over a 10-year period, the environmental damages we estimate represent between 13.8 and 31.3% of the environmental benefits of the landmark 1990 Clean Air Act Amendments EPA (2011).[7] Thus, we find the environmental costs of investment stimulus policies are large even compared to the effects of major, historical environmental regulations. Furthermore, by studying the interaction between bonus depreciation and environmental regulations,

[5]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.

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

[7]According to the EPA, the Clean Air Act Amendments resulted in around 160,000 avoided deaths following passage to 2010 (EPA, 2011), or \$1.44 trillion USD using a similar VSL value as our study. We view this as a comparable period as important pieces of the 1990 amendments, such as the Acid Rain Program, were not fully implemented until a decade after its passage. Our damage estimates also represent between 74 and 125% of the annualized environmental benefits of the recently proposed change to the National Ambient Air Quality Standards for Particulate Matter (EPA, 2024).

we also directly contribute 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).

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 led to higher environmental costs for African American communities, which are not explained by differences in income. Further analysis shows similar racial disparities in environmental damages per job created by the policy. These results demonstrate that investment stimulus policies 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. In Section 7, we investigate whether the magnitude of the costs we estimate is particular to bonus depreciation or is a general feature of investment stimulus policies. Section 8 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.[8] 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 benefits 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 was first implemented as part of the Job Creation and Worker Assistance Act of 2002. The bill allowed 30% bonus depreciation for investments made after September 10, 2001.[9] In May 2003, the bonus rate was increased to 50% for 2003 and 2004. The incentive was allowed to lapse in 2005, but Congress reinstituted the policy at a 50% rate in 2008. The 50% rate was available through 2016 except for in 2011, when the bonus rate was 100% (sometimes referred to as full expensing).[10] Based on IRS expenditure estimates, Garrett, Ohrn, and Suarez Serrato (2020)

[8] 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.

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

[10] During the time period we study, the US made use of a second accelerated depreciation policy referred to as

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 reinstituted (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 Suarez 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 typically invest in capital 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)

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.

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 depreciated 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.[11]

[11] 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.

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 Suarez 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}) 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.[12] 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.[13] $\mathbf{X}_{icjt}$ 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).

Our DD estimate, β, 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 emissions 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

[12] 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 4-digit NAICS z_0 distribution at the 33rd percentile (Curtis et al., 2021). Finally, as Callaway, Goodman-Bacon, and Sant'Anna (2024) 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.

[13] 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.

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 be 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 other localized 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.[14] 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.

Finally, because our identification strategy relies on industry variation across time, we must control for other industry-level shocks that occur during our analysis period that might be correlated with our measure of bonus exposure. Of particular concern are the well-documented "China Shock" and other federal tax policies that have been shown to have differential effects across industries. To this end, we directly control for industry-level variation in trade exposure due to China's accession to the World Trade Organization using data from Autor, Dorn, and Hanson (2013). We also directly control for the Domestic Production Activities Deduction

[14]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 driven by changes in utilities relative to plants in other sectors. Appendix A provides a detailed description of how regulated utilities benefit from bonus depreciation. Although plants in the sector benefit from the investment incentive, Table A3 shows our baseline estimates after dropping utilities plants from the sample. We find very similar results.

(DPAD), a federal tax incentive which provided a tax benefit based on the percentage of income derived from manufacturing activities in the US (Ohrn, 2018).

Overall, 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 identifying assumption underlying our estimates 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 or transferred offsite.[15] 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 manufactured, processed, or used at least one toxic chemical in excess of the relevant reporting threshold. The EPA can assess civil penalties for not reporting or misreporting releases. Additionally, the data are not used to calculate emissions fees. These factors help assuage misreporting concerns.[16] Appendix B provides a more extensive and detailed discussion of the TRI dataset.

[15]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.

[16]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 (EPA, 1993). See de Marchi and Hamilton (2006) for an in-depth analysis of misreporting and accuracy of the TRI dataset.

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 air releases in the TRI that are covered under the Clean Air Act.

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 quantify 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 every year between 1996 and 2001, and every third year starting in 2002 (i.e., 2002, 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 each facility, the reporting thresholds vary over time and by county.[17]

[17] These thresholds vary due to county-level attainment status and voluntary reporting decisions (EPA, 2017). Changes in reporting thresholds are a potential concern. 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

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 use as an input in pollution-transport models and estimating aggregate economic damages from emissions. 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 per dollar of revenue or pre-tax income). 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). Our matched sample is based on 5,902 TRI plants. Appendix C provides a detailed description of the construction of this sample.

4.4 Bonus Depreciation Variation

As we note in Section 3, we rely on 4-digit NAICS-level measures 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 (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. We limit our treatment period to the 2002–2012 period because Zwick and Mahon (2017) construct z_0 using

dataset, which is not affected by these same thresholds.

data only through tax-year 2010. As discussed above, we transform the continuous z_0 measure 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, generate 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 Nonattainment according to National Ambient Air Quality Standards during the sample period. We are able to link 26% 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) presents estimates of 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. 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 international trade shocks and other federal tax policies. In particular, we control for the "China Shock" by measuring industry-level changes in Chinese import penetration between 1999 and 2007 (Autor, Dorn, and Hanson, 2016) and we control for the DPAD by measuring the value of the tax deduction at the 4-digit NAICS industry based on data from Ohrn (2018).[18]

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 plants that benefited most from the the policy increased toxic releases by approximately 30%. For context, Zwick and Mahon (2017) and Curtis et al. (2021) estimate that the same policy increased corporate capital investment by around 15% and manufacturing employment by around 10% during the same period we study. Thus, the substantial response that we document is large even relative to the capital and labor responses to the policy.

[18] 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.

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, the coefficients are positive, statistically significant, and generally increasing in magnitude. Together, these findings indicate that differences in emissions between 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.[19]

To place the magnitude of these effects in context, Panel (B) of Figure 2 maps our reduced-form estimates onto trends in 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 plants that benefited less from the policy.[20] 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

[19] 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.

[20] To construct these plots we add our coefficient estimates from Panel (A) to the average log of total chemical releases for the balanced sample of plant we observe.

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 the 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 regulated 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. Panel (A) of 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 A4 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 for this selected sample indicates total releases increase by 56% for the most-affected plants relative to the less-affected plants after the policy was introduced.

If this emissions response is due to the investment stimulus policy, then we should observe a concomitant capital investment response among the sample of firms that we match to plant-level TRI data. We test this hypothesis using firm-level data and a slightly-modified dynamic DD design. The outcome is the log of capital stock.[21] Figure 3, Panel (B) shows our baseline dynamic DD specification. Coefficient estimates indicate that in the years after implementation,

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

capital stocks for the most-treated firms show a large statistically significant increase relative to firms that benefit less from the policy. Corresponding DD estimates with alternative levels of fixed effects are presented in Panel (A) of Table 4. Specification (2), which corresponds to the dynamic DD estimates and includes firm and pre-period firm size bins interacted with year fixed shows bonus depreciation increased capital stocks by just over 30% for firms in industries that that benefited most from the policy relative to firms in industries that benefited less.[22] 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.[23]

5.5 Effects on Emissions Intensity and Energy Efficient Investments

Another benefit of the TRI-Compustat sample is that it allows us to explore the effect of bonus depreciation on emissions intensity. To do so, we use our DD approach to estimate the effect of the policy on firm-level emission intensity, measured as the log of total releases scaled by capital stock.[24] DD estimates are presented in Panel (B) of Table 4. Focusing on Specification (2), which includes firm fixed effects and pre-period firm size bins interacted with year fixed effects, our DD coefficient is 0.143 and is statistically insignificant at conventional levels. Dynamic DD estimates corresponding to this specification are presented in Panel (C) of Figure 3. The figure shows no differential trends in the pre-period and also no statistically significant effects in any years after bonus depreciation was implemented. In Specifications (1), (3), and (4) of Table 4 Panel (B), we show these null effects are stable in the presence of alternative fixed effects designed to control for other pre-period firm-level differences in capital structure. We also find null results when we explore the effect of bonus depreciation on alternative measures of emissions intensity in Appendix Table A5. Overall, we do not find any evidence that bonus depreciation decreases

[22]Specification (1) of the same panel shows this finding is not driven by the inclusion of the firm-size bins interacted with year fixed effects. Specifications (3) and (4) show this finding is also robust to the inclusion of pre-period debt ratio bins interacted with year fixed effects and pre-period capital intensity bins interacted with year fixed effects.

[23]Our results are slightly larger, but are the same order of magnitude as Zwick and Mahon (2017). The differences between them are potentially attributable to our use of capital stocks rather than investment flows as an outcome and our sample for this analysis which consists of publicly traded industrial firms.

[24]We rely primarily on emissions scaled by capital stock because bonus depreciation is designed to stimulate investment in capital assets. We also construct measures of emissions intensity as (1) total releases scaled by revenue and (2) total releases scaled by pre-tax income. Results based on these outcomes are presented in Appendix Table A5.

emissions intensity.

That bonus depreciation does not affect average emissions intensity, begs the question: did bonus depreciation lead to *any* adoption of cleaner production technologies?[25] To provide some evidence on this question, we turn to the Manufacturing Energy Consumption Survey (MECS) from the Department of Energy.[26] 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 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 green technologies.

One possible explanation for the null emissions intensity effects and the suggestive evidence that bonus stimulated some green investment is that bonus depreciation led to an increase in capital intensity. Because capital-intensive production is more emissions intensive, this adjustment may have offset any of the gains from greener technologies. To explore this hypothesis, we estimate the effect of bonus depreciation on firm-level capital intensity (the log of capital stock per unit of total assets). The results presented in Panel (D) of Figure 3 and Panel (C) of Table 4 show bonus depreciation led to an increase in capital intensity.

Overall, we find that while bonus depreciation likely stimulated some greener technology adoption, the overall technique effect did not decrease emissions intensity. A plausible explanation for these two responses is the increase in firm-level capital intensity that we document.

[25]Unfortunately, recent data on pollution abatement investments are scarce. 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).

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

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 test whether CAA environmental regulations led to heterogeneous emissions responses to bonus depreciation. To do so, we compare emissions responses across plants in attainment and nonattainment counties. We focus primarily 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 nonattainment counties in 2004 and 2005. We use a time-invariant measure of nonattainment, defining a county as in nonattainment if was in nonattainment following the 2004 and 2005 reforms.[27]

As a prelude to the attainment status heterogeneity analysis, Figure 4, 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 3 and show bonus depreciation had a large, positive impact on the emissions regulated by the CAA.

Panel (B) shows dynamic DD estimates describing the effect of bonus depreciation on CAA emissions separately for plants in attainment and nonattainment 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 nonattainment and attainment counties, but the effects diverged at the exact same time that the new nonattainment standards went into effect. In particular, the emissions for plants in nonattainment 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 5 provides regression estimates in which we include

[27] Almost all counties in nonattainment status prior to the 2004 and 2005 reforms remained in nonattainment 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.

interactions between Bonus × Post and an indicator equal to one for plants in nonattainment counties.[28] 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 29% (0.286=0.138/0.482) in nonattainment counties.

We also test 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 nonattainment 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 nonattainment standards caused a shift from regulated to unregulated emission (Gibson, 2019).

The interaction term for On-Site Releases in Specification (2) remains negative and statistically significant. The fact that the heterogeneous effect coefficients are nearly identical for CAA releases and On-Site Releases suggests that nonattainment standards did indeed temper responses to bonus depreciation for a broader set of emissions. This result also suggests that nonattainment standards did not cause a significant shift from regulated and unregulated emissions. This is consistent with the observation that regulated and unregulated pollutants are often co-generated (Burtraw et al., 2003).

A potential explanation for the nonattainment heterogeneity results is that capital investment is also less responsive to bonus depreciation in more regulated counties. In Appendix Table A7, we compare capital investment responses to bonus depreciation for firms that have plants in nonattainment counties to responses for firms that do not using a regression specification similar to those used in Table 5.[29] All interaction coefficients are negative and economically significant in magnitude but are imprecisely estimated, likely owing to the smaller matched TRI-Compustat sample. These results suggest that environmental regulation may have the ability to temper

[28] 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 and magnitude.

[29] We define a firm as Nonattainment if at least one of its plants is located in a nonattainment county.

emissions responses to investment stimulus policies, although they may do so by undermining the ability of the policy to actually stimulate investment.

Overall, we conclude that environmental regulations played a significant role in mitigating emissions responses to bonus depreciation. In Section 6.5, we provide further evidence for this conclusion using NEI data.

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 corroborating evidence for our TRI results and allows us to quantify aggregate economic damages due to policy's environmental consequences, which we do in the following section.[30]

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.

Table 6 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 0.299 to 0.360, indicating that county-industries benefiting the most from bonus depreciation increased their emissions of these criteria air pollutants by between 30 and 36% after the policy was implemented in 2002.

[30] In Appendix J, we provide more corroborating evidence based on the EPA's Air Quality System (AQS) surface-level pollution data. We find particulate matter concentrations at AQS monitoring sites increased more in counties with higher exposure to bonus depreciation.

As with the TRI analysis, we estimate dynamic DD models for each criteria air pollutant.[31] Figure 5 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 showing that bonus depreciation had a large, positive effect on emissions of criteria air pollutants.[32] 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

Thus far we have documented that investment stimulus policies can have large effects on emissions. Ultimately, we want to know how these emissions translate into reduced environmental quality and economic damages. 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.

To estimate economic damages, we use a four-step procedure following a number of recent high-impact papers (e.g. Holland et al., 2016; Fowlie and Muller, 2019). First, we 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.[33] 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

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

[32] Across all four event study plots presented in Figure 5, coefficients in years 1996–1998 and coefficients in years 1999 and 2000 are very similar. In Appendix E, 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.

[33] Around 85% of the economic costs associated with 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.

policy.

6.1 Calculating Emissions Changes

We use the coefficient estimates from Table 6 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.[34] 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 as a result of bonus depreciation. 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 VOCs despite the large—but statistically insignificant—point estimate.

Table 7 presents baseline pollution emissions and our estimates of total pollution emissions (in metric tons) 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 102 thousand, SO_2 emissions was around 1.8 million, 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 6. The remaining rows are discussed in Section 6.5.

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.[35] We then calculate aggregate damages based on the number of additional deaths attributable to the increase in $PM_{2.5}$ pollution, which depends

[34] 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.

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

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 et al., 2009) to 14% (Lepeule et al., 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 (EPA, 2010).[36]

Table 8 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 $20 to 45 billion US, which corresponds to per capita damages between $66 and $148.[37] These damages represent between 51 and 115% of the fiscal cost of the policy. We further detail this simple calculation and provide an empirical welfare analysis to better contextualize the magnitude of our damage estimates in Section 7.3.

The results presented in Table 8 also show that the economic damages from the policy are highly disproportionate across racial groups, with Black populations incurring per-capita economic damages that are 68% higher than the national average.

6.3 Disparate Impacts of Bonus Depreciation Emissions

To more closely examine the disparate impacts of emissions generated by bonus depreciation across regions, 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

[36]The EPA recommends a VSL of 7.9 million in 2008 dollars(EPA, 2010), which we inflation-adjust to approximately 9 million in 2020 dollars.

[37]We highlight that these damages are based solely on increases in particulate matter concentrations. Bonus depreciation also likely generates damages via increased greenhouse gases. Unfortunately, no plant-level data on carbon dioxide and other greenhouse gas emission is available during our sample period.

and Poverty Estimates.[38]

Figure 6 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 $350.

Given this significant geographic heterogeneity in damages, 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 7 presents binscatter 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 (population weighted) for each variable. The lines are based on regressions of county-level damages on each characteristic based on the underlying data. The plots presented in Figure 7 provide strong visual evidence that economic damages from bonus 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.

To formally analyze the relationships between demographic characteristics and economic damages, Table 9 presents both conditional and unconditional regressions of per-capita economic damages on median income, poverty-rate, and racial group shares.[39] Specifications (1) and (2) indicate that per-capita damages are negatively related to median income and positively related to poverty rates. 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 8, which shows that per-capita damages are 68% higher for African Americans than the national average. The disparity in economic damages for Black populations reflects both differences in pollution exposure and differences in mortality sensitivity to pollution. We estimate that African Americans are exposed to 29.8% higher levels of pollution generated

[38]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.

[39]We weight the regressions in Table 9 by county population.

by the policy than the national average. This suggests that both differences in exposure and differences in mortality sensitivity to pollution are important factors in explaining the racial disparities we document.

Of course, income and race are correlated so the results in Specifications (1) and (2) (and (8)) may be driven by the correlations presented in Specification (3)-(7) and vice versa. To try to disentangle the relationships, in Specification, we regress damages on measures of both income and race. Here, 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 show that bonus depreciation likely exacerbated the differences documented in these papers.

6.4 Pollution and Jobs

While the economic damages associated with bonus depreciation are concentrated among low-income and Black populations, the economic benefits generated by the policy may also disproportionately accrue to these communities. A particularly salient benefit of the policy is the jobs that it created. To investigate the relationship between the jobs created and pollution damages from the policy, we compare our estimates of county-level damages (per-capita) to county-level job creation (per 100k population) estimates based on **?**.[40] Panel (A) of Figure 8 shows a binned scatterplot representing this comparison. Perhaps surprisingly, we find that county-level pollution damages are inversely related to the jobs created by the policy. That is, the job benefits of the policy do not disproportionately accrue to the same populations as the pollution costs. There are two reasons for this negative correlation. First, emissions generated by the policy disperse in the atmosphere and are transported downwind, often to distant counties.

Second, and perhaps more importantly, bonus depreciation created jobs in industries throughout the economy. In contrast, only a subset of industries are responsible for the majority of toxic emissions and criteria air pollutants.[41] As a result, the job benefits do not accrue to populations

[40]Using a local labor markets empirical approach, **?** estimate that during the time period we study, bonus depreciation created more than 5.5 million jobs.

[41]When we instead focus exclusively on jobs created in the industrial sector, which contains all high-emitting

that are disproportionately harmed by bonus depreciation.

We further explore the relationship between pollution damages and jobs created in Panels (B) and (C) of of Figure 8, which correlate damages per job to median household income and Black population shares. We find that damages per job, like damages themselves, are highest in counties with lower median incomes and in counties with larger Black population shares.[42,43] These comparisons reinforce our conclusion that the jobs created by bonus depreciation do not offset the pollution costs of the policy in ways that undo its disparate impact among low-income and Black populations.

6.5 Quantifying the Role of Regulations

In Section 5.6, we showed that environmental regulations can play a key role in mitigating the emissions response to bonus depreciation. We now 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 by county nonattainment status.[44] The results presented in Table 10 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 nonattainment counties. These findings echo the results presented in Section 5.6 and reinforce the conclusion that environmental regulations can significantly mitigate the emissions effects 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 nonattainment county.

Row 3 of Table 7 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

industries (see Appendix H), then we do observe a positive correlation between pollution damages and jobs generated by bonus depreciation (Figure A4).

[42] Appendix Table A8 reports regressions of pollution damages per 100 thousand jobs on county-level demographic measures. The table shows that even in a multivariate regression, damages per job are concentrated among both low-income counties and counties with high Black population shares.

[43] We also find that the relationships in Panels (B) and (C) are similar when restricting jobs to only those in the industrial sector (see Panels (B) and (C) of Appendix Figure A4).

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

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 nonattainment status, we use the regression estimates for either nonattainment or attainment counties, respectively. Emissions changes assuming all counties were in attainment are presented in the fourth row of Table 7 and the fifth row presents emissions changes assuming all counties were in nonattainment status.

To calculate aggregate economic damages and economic damages for different demographic groups, we use the coefficient estimates from Table 10 as inputs for the InMAP model under three scenarios, each described below. The damage estimates are presented in Table 11. The two columns entitled Actual Nonattainment refer to economic damages under the Actual Nonattainment designations. We expect that economic damages under Actual Nonattainment designations should be similar to baseline economic damages presented in Table 8; however, there might be a small difference due to variation in emissions levels across nonattainamnet and attainment counties.[45] Table 11 demonstrates that economic damages are slightly lower after accounting for heterogeneous effects, ranging from around 19 to 43 billion USD.

Table 11 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 nonattainment (All Nonattainment). Comparing damages between the Actual Nonattainment 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 Nonattainment and All Nonattainment scenarios shows $5.4 to 12.2 billion USD or 28% in additional damages could have potentially been avoided if all counties were designated nonattainment.

Note that across the three scenarios presented in Table 11, the percentage differences in

[45] The primary difference is that emissions changes would be relatively larger in attainment counties and smaller in nonattainment counties (compared to the average effect captured in the baseline model). Because excess mortality 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 from 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 calculate aggregate damages. However, after accounting for heterogeneous effects, the coefficient is statistically significant, and the aggregate damages presented in Table 11 reflect these VOC emissions changes.

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 existing pollution or less susceptible populations, where they create less damage.

7 Policy Analysis: Bonus Depreciation vs. Alternatives

In this section, we seek to understand why bonus depreciation resulted in substantial pollution damages and whether alternative stimulus policies might achieve similar fiscal objectives at lower environmental costs. To provide additional insight, we also provide a simple back-of-the envelope welfare analysis of bonus depreciation and these alternative policy options.

7.1 Does Bonus Target Dirty Industries?

A natural question that arises is whether the magnitude of damages we estimate are a natural feature of all fiscal stimulus policies or whether they are specific to bonus depreciation? That is, bonus depreciation may unintentionally benefit the most emissions-intensive industries, thereby resulting in disproportionately high economic costs. To explore this question, in Panel (A) of Figure 9, we compare bonus depreciation generosity to emissions intensity at the industry-level. On the horizontal axis, we measure bonus depreciation generosity as the log of $(1 - z_0)$, where z_0 is the weighted present value of depreciation allowances in the absence of bonus depreciation. Industries with higher log of $(1 - z_0)$ benefit more from the investment stimulus policy. We measure emissions intensity as the log of annual emissions damages per annual dollar of investment.[46] The size of each data point corresponds to the industry's annual investment. The figure shows a strong positive correlation between bonus depreciation generosity and emissions intensity. Industries to the right of the green dashed line are those that we classify as treated in our empirical analysis. Clearly, bonus depreciation does, in fact, favor the most emissions intensive industries. This suggests the economic damages we estimate are due to bonus depreciation, itself, rather

[46] Economic damages are the weighted sum of industry level emissions of NEI criteria air pollutants ($PM_{2.5}$, SO_x, NO_x, VOC) where the weights are average economic damages for each pollutant type. We calculate average economic damages using the InMAP model by estimating economic damages for each pollutant type divided by the change in corresponding emissions. We focus on industry emissions damages per dollar of investment as a measure of pollution costs relative to the primary benefit of increased investment under bonus depreciation. We find similar patterns using alternative measures of emissions intensity, such as capital stock or sales.

than investment stimulus policies in general.

7.2 Alternative Stimulus Policies

To better understand the extent to which the damages we estimate are due to this unintentional targeting feature of bonus depreciation, we now design two alternative investment stimulus policies and compare their damages to those from bonus depreciation. We imagine these policies can be directed at a particular set of target industries in the industrial sector and generate the same investment response as bonus depreciation, in percentage terms. An example of such a policy would be a corporate income tax cut targeted at certain industries that is sufficiently large to generate the same percent investment response as bonus depreciation. Because the investment stimulus effects of these hypothetical policies are, by definition, the same as for bonus depreciation, and because the investment bases are the same, these hypothetical policies must stimulate the same amount of total investment as bonus depreciation.

We define the two hypothetical policies by the industries they target. The first policy targets the industries that benefit the least from bonus depreciation. We refer to this policy as the "Anti-Bonus" policy. By selecting the industries that benefit the least, we can better understand how differences in the benefits of bonus deprecation across industries contributed to aggregate damages. To choose the set of industries, we start with the industries with the highest z_0 and add industries to our targeted group until their cumulative investment base matches the investment base of bonus depreciation, thereby ensuring the policy stimulated an equal amount of investment.

The industries that are targeted by this alternative Anti-bonus policy lie to the left of the blue-dashed line in Figure 9 Panel (A). Clearly, the industries treated by this Anti-bonus policy have lower emissions intensity. Figure 9 Panel (B) presents economic damages per capita for bonus depreciation (green bars) and the hypothetical Anti-Bonus depreciation policy (blue bars). Recall that bonus depreciation generated between \$20 and \$45 billion in annual damages. We estimate that the Anti-Bonus policy would produce significantly less damages, ranging between 1 and 2.3 billion annually. These damages represent around 5% of the damage of the actual bonus depreciation policy. The figure demonstrates that damages were slightly over \$145 per capita under the bonus depreciation policy, whereas damages were less than \$8 per capita under the Anti-Bonus policy. Per-capita damages were drastically lower under the Anti-Bonus policy for all racial groups.[47] Together, these comparisons show that bonus depreciation was biased towards emissions-intensive industries and therefore produced nearly 20 times more economic damages compared to an alternative policy targeting Anti-Bonus industries.

The second hypothetical policy targets the least emissions intensive industries.[48] To identify the industries targeted by this second policy, we begin by ranking industries according to emissions intensity. Our targeted group is composed of the lowest emissions-intensity industries that represent the same investment base as the industries we define as treated by bonus depreciation in our main analysis. The industries treated by this "Low Emissions Policy" lie below the black dashed line in Figure 9.

Figure 9 Panel (B) also presents economic damages per capita for this "Low Emissions-Intensity Targeting Policy" (black bars, which are barely visible). Remarkably, total economic damages under this targeted policy are less than half a percent of actual economic damages due to bonus depreciation. Under this alternative policy, economic damages were equal to or less than $1 per capita for all demographic groups.

Our analysis of these two alternative hypothetical investment stimulus policies clearly demonstrates that the scale of economic damages from bonus depreciation is not an inevitable consequence of fiscal policy in general. Instead, the large environmental damages generated by bonus depreciation are due to the fact that the most emissions-intensive industries disproportionately benefit from the policy. We conclude that alternative policies can be designed to stimulate the same amount of investment at a fraction of the environmental cost. In the following section, we examine the welfare consequences of these findings using a Marginal Value of Public Funds (MVPF) framework.

7.3 Welfare Analysis

The MVPF is used across a variety of fields as a benchmark for empirical welfare analysis (Hendren and Sprung-Keyser, 2020).[49] The MVPF is defined as the ratio of the marginal benefit to

[47] African Americans, who had the highest damages per capita under the actual policy, had the largest reduction in damages under the anti-bonus policy in absolute terms; however, the percentage reduction was less than the national average.

[48] An important related question to this second policy is the scope to stimulate investment while maintaining low or acceptable levels of pollution damages. In Appendix I, we show that a policy targeting the lowest emissions industries can be designed to stimulate around twice the amount of additional investment as the actual bonus depreciation policy with very little resultant economic damages.

[49] Finkelstein and Hendren (2020) provide guidance on the implementation and interpretation of using the MVPF in empirical welfare analysis. Briefly, the MVPF can be interpreted as the social benefit (or willingness to

the marginal fiscal cost of the policy inclusive of behavioral responses impacting the government budget, such as changes in investment and output (Finkelstein and Hendren, 2020). We define the net marginal benefit as the change in after-tax private income (accruing to firm owners and workers) associated with the policy less the corresponding pollution damages.[50] More formally, the MVPF is defined as

$$\text{MVPF} = \frac{\text{dI - dE}}{\text{dT}},$$

where dI is the change in private income, dE is the change in pollution damages, and dT is the fiscal cost of the policy.

To provide additional insight into how pollution damages contribute to this measure and to quantify these effects, we can divide the MVPF into three distinct effects. Private (after tax) income, by definition, is before tax income (or output Y) less taxes paid. Changes in private income are therefore equal to the sum of the change in total output or GDP less the change in taxes paid. Because both the fiscal cost and the change in private taxes paid include behavioral responses (i.e., changes in output), the change in taxes paid is exactly equal to the inverse of the fiscal cost of the policy, implying that dI=dY+dT and:

$$\text{MVPF} = 1 + \frac{\text{dY}}{\text{dT}} - \frac{\text{dE}}{\text{dT}}.$$

The first effect, equal to 1, is the mechanical effect of cutting effective taxes on after-tax income (holding behavioral effects constant). The second effect, dY/dT, is the ratio of additional output to the fiscal cost of bonus depreciation. This ratio represents the amount of GDP stimulus generated per dollar of government tax expenditures, which we refer to as the *stimulus value of public funds* or SVPF. The sum 1+SVPF is therefore the combined effects on private income, which we refer to as the *income value of public funds* of IVPF. The third effect, dE/dT is the amount of pollution damages per dollar of government tax expenditure, which we refer to as the *environmental burden of public funds* or EBPF. Hence, the MVPF is composed of the income

pay) for $1 of government spending (or foregone tax revenue). The MVPF for a given policy therefore elucidates the tradeoffs involved in policies and facilitates comparison with other dissimilar policies. As is conventional in the literature, the empirical welfare analysis represents a partial-equilibrium analysis, and we abstract from potential general equilibrium and income effects of the policy.

[50] We use changes in private income as it is transparent, objectively measured, and comparable to other studies Kennedy et al. (2024). This measure is approximately equal to private willingness-to-pay for the policy assuming disutility effects of labor are negligible. We view this assumption as reasonable as bonus was implemented during an economic downturn and because studies find that wages are generally more responsive to corporate tax incentives than employment Kennedy et al. (2024).

value of public funds and the environmental burden of public funds:

$$\text{MVPF} = \overbrace{1 + \text{SVPF}}^{\text{IVPF}} - \text{EBPF}.$$

Abstracting from distributional considerations, a welfare-improving policy would require that the MVPF exceed the marginal cost of public funds (i.e., the cost of raising $1 of tax revenue to finance bonus depreciation). Although the marginal cost of public funds (MCPF) depends on the tax instruments used to finance bonus depreciation, a useful benchmark is to assume that the MCPF is equal to 1.[51] Using this benchmark, bonus depreciation is therefore welfare improving when the MVPF is greater than one. Analogously, the policy increases welfare when the positive stimulus externality (SVPF) exceeds the negative pollution externality (EBPF).

To calculate the MVPF, we assign values of government fiscal cost based on previous studies, and use estimates of the capital response to the policy coupled with well-established capital-output elasticities to quantify the effect of the bonus on GDP.[52] Garrett, Ohrn, and Suarez Serrato (2020) estimate that the fiscal cost of bonus depreciation inclusive of behavioral responses was $311 billion total or about $31 billion per year (or 39.5 billion in 2020 dollars) during the period we study. Zwick and Mahon (2017) estimate that bonus depreciation increased capital investment by $30.4 billion and $55.9 billion per year in the first and second rounds, respectively.[53] We use a well-established capital-output elasticity of 1/3 to translate changes in capital investment to changes in output (Vollrath, 2021).

Table 12 reports our welfare estimates for bonus depreciation and our alternative investment stimulus policies. For the actual policy, we calculate a IVPF equal to 1.41, implying that every dollar that the government spends on bonus depreciation increases private income by $1.41.[54] Thus, in the absence of any pollution externalities, we estimate bonus depreciation is welfare

[51] Assuming the MCPF = 1 is equivalent to assuming the government financed bonus depreciation via non-distortionary lump-sum taxes. More realistically, under the assumption that the government financed bonus depreciation via distortionary taxes, the MVPF would need to exceed unity plus the deadweight loss (or excess burden) from these taxes. However, specifying which additional taxes are associated with bonus depreciation is challenging. For details regarding the theoretical underpinnings of the arguments in this paragraph, we refer to the recent paper by Bastani (2024).

[52] Appendix K details our MVPF calculations and tests the sensitivity of our results to alternative parameterizations.

[53] While Zwick and Mahon (2017) present a range of estimates for various assumptions and specifications, we use these effects as they are based on a similar empirical strategy.

[54] This estimate is consistent with MVPFs for other corporate tax cuts (which do not account for pollution externalities). Based on findings from Kennedy et al. (2024), we calculate a corresponding MVPF of 1.4 for the corporate income tax cuts that were part of the Tax cuts and Jobs Act (TCJA) of 2017.

improving because the IVPF is greater than 1, with a positive stimulus externality (SVPF) of 41 cents per dollar of tax expenditure.

However, our estimates of the negative pollution externality (EBPF) from bonus depreciation range from 51 cents to $1.14, corresponding to the Low and High concentration-response parameter, respectively. As a result, after accounting for the pollution externality, our estimates of the policy's MVPF ranges between 0.26 and 0.90. These estimates are well below the necessary benchmark of unity for the policy to be welfare-improving.

There are two ways to see why incorporating pollution externalities leads us to conclude that bonus depreciation is a welfare-decreasing policy. First, the policy's negative externality in terms of the environmental burden from public funds ranges between 51 cents and $1.14, which exceeds the 41 cent positive stimulus externality. Second, we can consider the fiscal and pollution costs per dollar of private income. The inverse of the IVPF (i.e. 1/IVPF) gives us the fiscal cost per dollar of private income, which we calculate as 71 cents. That it costs only 71 cents to stimulate a dollar of benefit implies that the policy, in the absence of pollution externalities, is welfare improving. However, when we add between 36 and 81 cents of pollution damages per dollar of income (EBPF/IVPF), the social cost of the policy per dollar of benefit ranges from $1.07 and $1.52. Because it now costs more than $1 to generate a dollar in income, our estimates show the policy is welfare-decreasing when we account for its environmental damages.

This same comparison is even more striking in nominal terms. That is, we estimate that the increase in private income less the fiscal cost of bonus depreciation was $16.0 billion per year. However, subtracting our pollution damage estimates from this number suggests that the policy *decreased* welfare by between $4.0 billion and $29.1 billion per year.

We can also use the MVPF framework to evaluate the two hypothetical investment stimulus policies we introduced in Section 7.2. Given that, by design, both alternative policies (Anti-bonus and Low Emissions-Intensity Targeting) stimulate the same amount of investment and, under reasonable assumptions, have the same fiscal cost as bonus depreciation (see Appendix K), we estimate both alternative policies also have the same IVPF. However, pollution damages and corresponding MVPFs are highly dissimilar.

Focusing first on the Anti-Bonus policy, we estimate that the negative pollution externality (EBPF) is between 3 and 6 cents per dollar of tax expenditure. As a result, the MVPF ranges between 1.35 and 1.38. The low-end of this range lies well above the unity benchmark, because the 41 cent positive stimulus externality far exceeds the 3 cent to 6 cent range of the negative pollution externality.

For the Low Emissions-Intensity Targeting policy, the negative pollution externality (EBPF) is between 0.2 and 0.5 cents per dollar tax expenditures, while the pollution damages per dollar of income ranges between 0.2 and 0.3 cents. In the Low Emissions-Intensity Targeting policy, the MVPF is nearly identical to the IVPF and adding pollution damages contributes virtually zero to the total cost of the investment stimulus policy.

For both of the alternative policies, the MVPF remains above unity, suggesting both are welfare-increasing even accounting for the pollution damages they create. Overall, these results underscore that the magnitude of the economic damages we estimate is due to the fact that bonus depreciation unintentionally targets the most emissions intensive industries. Investment stimulus policies that do not favor pollution-intensive industries can be welfare-improving and yield sizable gains compared to bonus depreciation.

8 Conclusion

In this paper, we study the environmental consequences of bonus depreciation, one of the largest investment stimulus policies in US history. We find the policy increased toxic emissions and criteria air pollutants in plants that benefited the most by approximately 30%. We estimate that these emissions resulted in large environmental damages, which also exacerbated existing racial disparities in exposure to pollution in the US. We document that the magnitude and disparate effects of bonus depreciation are primarily due to the fact that the policy provided the most benefit to firms in the most emissions-intensive industries. Finally, we perform a back-of-the-envelope welfare analysis, estimating that pollution damages per dollar of policy benefits ranged between 36 and 81 cents. These additional costs tip the policy from welfare-increasing to -decreasing because its total social costs exceed its positive stimulus benefits.

These findings have important implications for policymakers designing investment stimulus policies. First, policymakers should consider the potentially large and unequal environmental costs generated by such policies. For example, to inform legislative deliberations, US congressional budget rules require all tax, spending, and regulatory policies to be "scored" for budgetary impacts. In addition to scoring the fiscal cost, our findings suggest that the environmental consequences should also play a major role in policy deliberations as they can potentially exceed fiscal costs. Second, the design of investment stimulus policies should consider the emissions-intensity of industries and types of investments targeted by the policy. Policies that intentionally target investments made by the least emissions-intensive industries can drastically reduce environmental damages. The green investment incentives that were included in the recent Inflation Reduction Act of 2022 provide examples of such targeted policies. Third, policymakers should anticipate and account for interactions between fiscal stimulus and environmental regulations, which may unintentionally sharpen or blunt the effects of either instrument.

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

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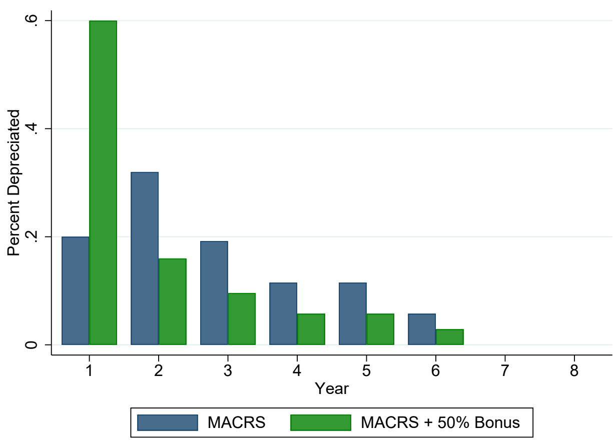
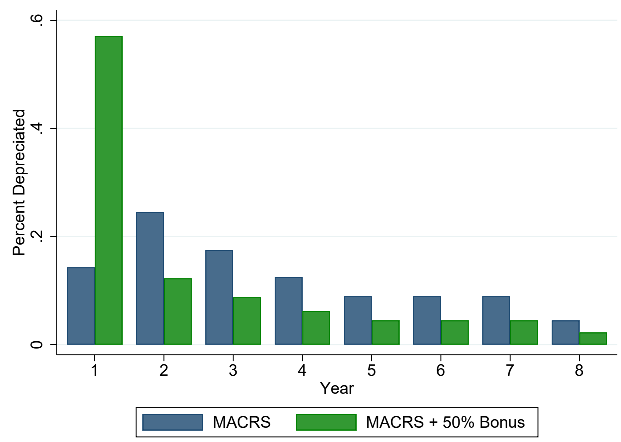
Figures

Figure 1: Bonus Depreciation Policy Details

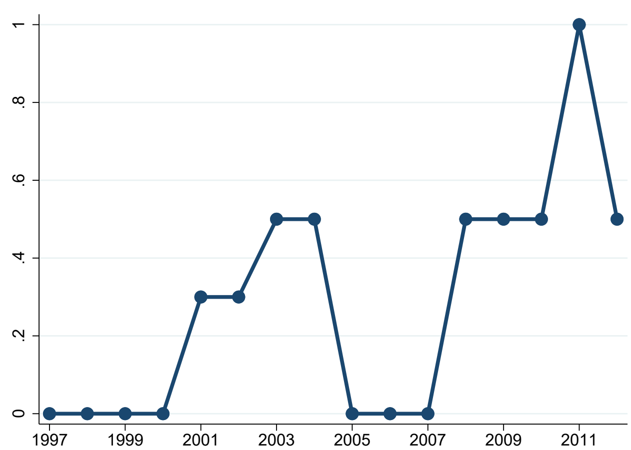
(A) Effect of 50% Bonus, 5-year MACRS



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



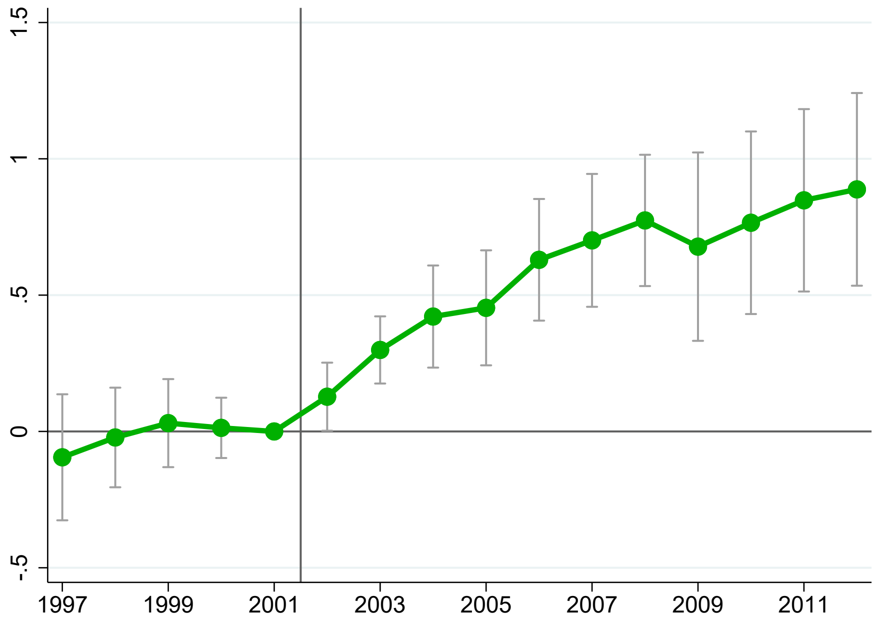
(C) Bonus Depreciation Rates During Sample Period



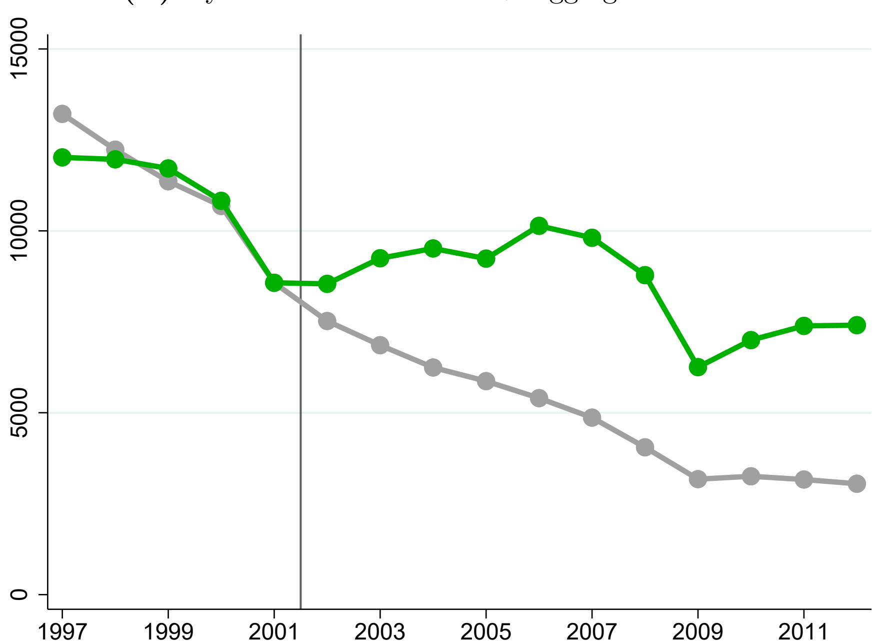
Notes: Figure 1 describes the bonus depreciation investment incentive. Panel (A) displays the effect of 50% bonus depreciation on annual tax deductions for investment in a new 5-year MACRS asset. Panel (B) shows the same series for a new 7-year MACRS asset. Panel (C) displays statutory bonus depreciation 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

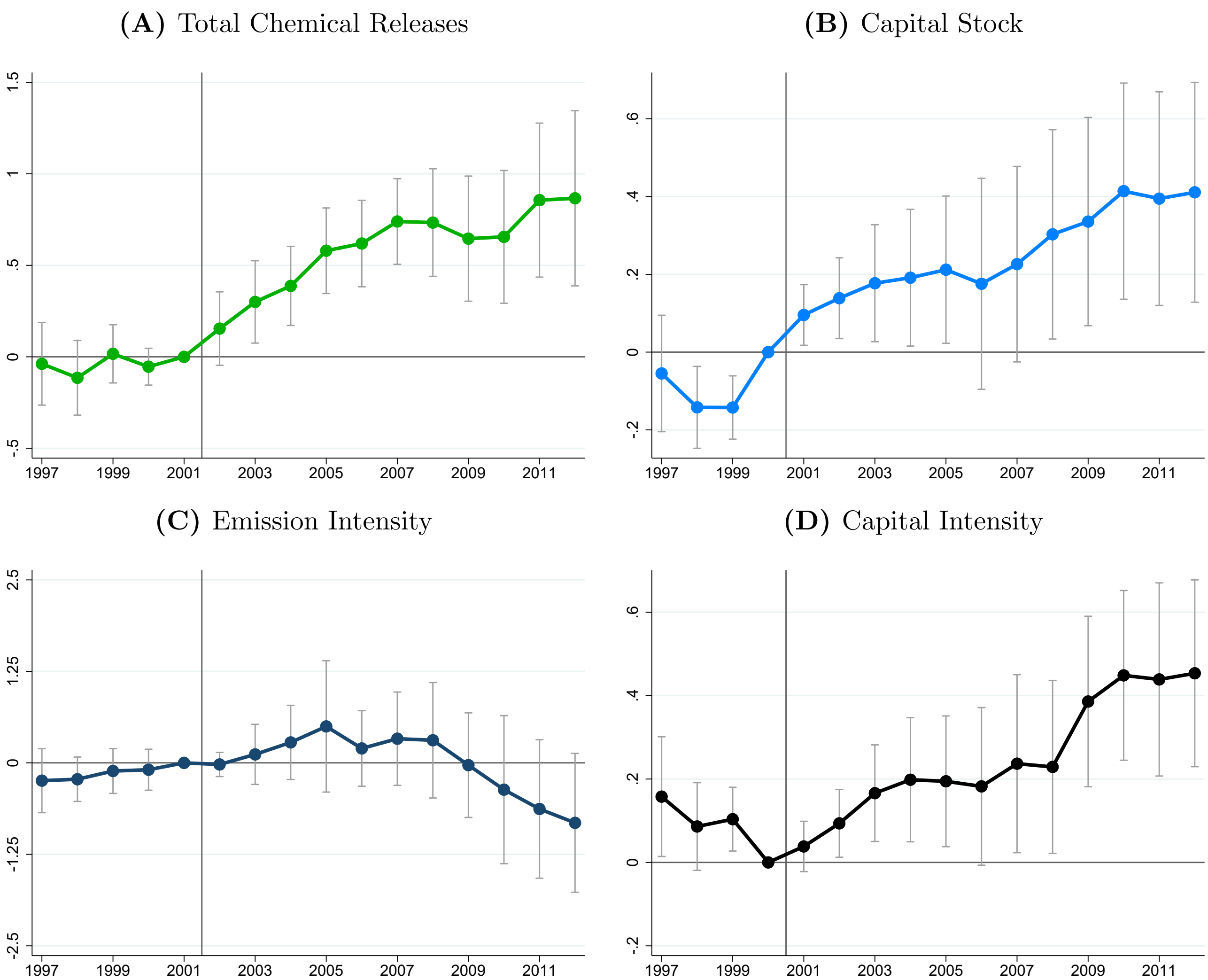


(B) Dynamic DD Estimates + Aggregate Trends



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 × 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.

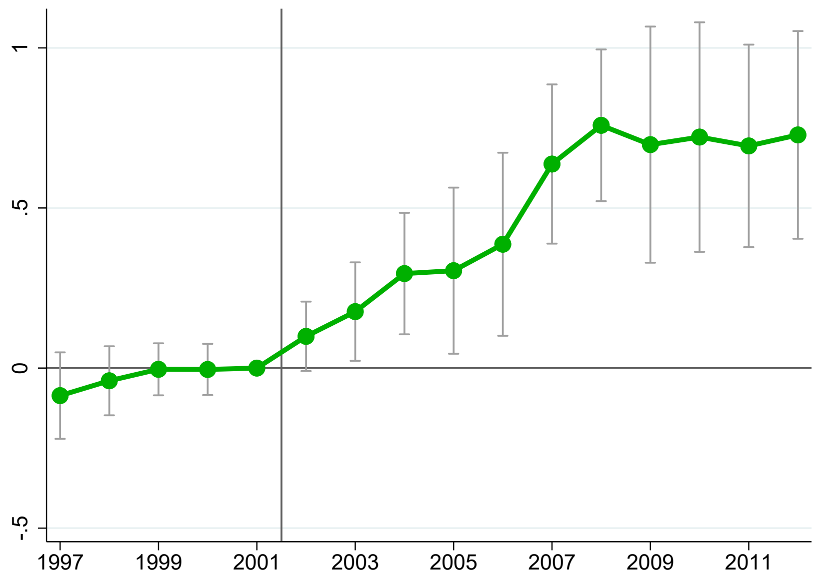
Figure 3: Effects of Bonus Depreciation; Compustat Matched Sample



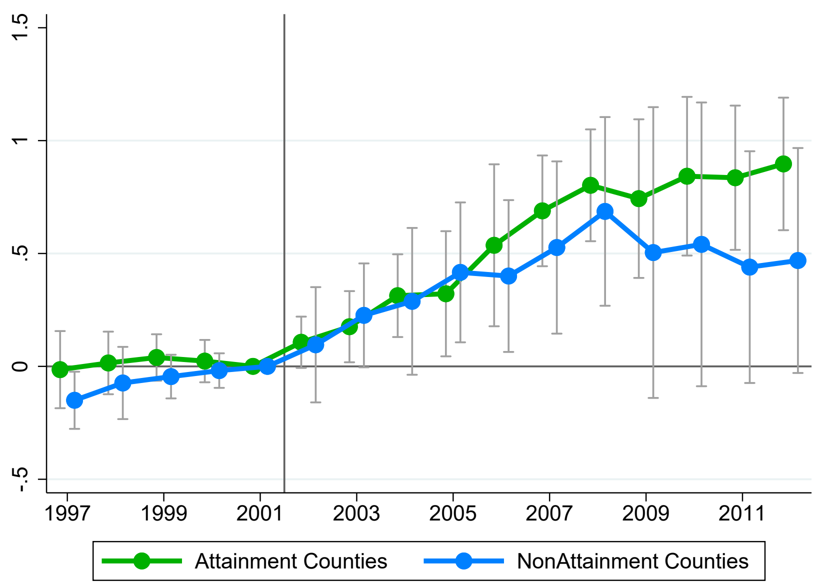
Notes: Figure 3 displays Dynamic DD estimates and 95% confidence intervals based on equation (2) describing the effect of bonus depreciation on outcomes for the sample of TRI plants that we match to Compustat firms. Standard errors are clustered at the 4-digit industry level. The outcome in Panel (A) is the Log of Total Chemical Releases. Panel (A) estimates include plant, county-year, and sector-year fixed effects. DD estimates corresponding to Panel (A) are presented in Column (4) of Table A4. The outcome variables in Panels (B), (C), and (D) are log capital stock, log emissions intensity (total emissions per unit of capital), and log capital intensity (capital per unit of total assets). Panel (B), (C), and (D) estimates include firm fixed effects and pre-period firm-size bins interacted with year fixed effects. Regressions in Panels (B), (C), and (D) are weighted by pre-period capital stock. DD estimates corresponding to Panels (B), (C), and (D) are presented in Specification (2) of Table 4. Consistent with the timing of capital investment responses documented in Zwick and Mahon (2017), we normalize differences in outcomes in the year 2000 in the analyses presented in Panels (B) and (D). *Source:* Authors' calculations based on the data from TRI, COMPUSTAT and Zwick and Mahon (2017).

Figure 4: Effects of Bonus Depreciation on CAA Releases

(A) Log(CAA Releases)

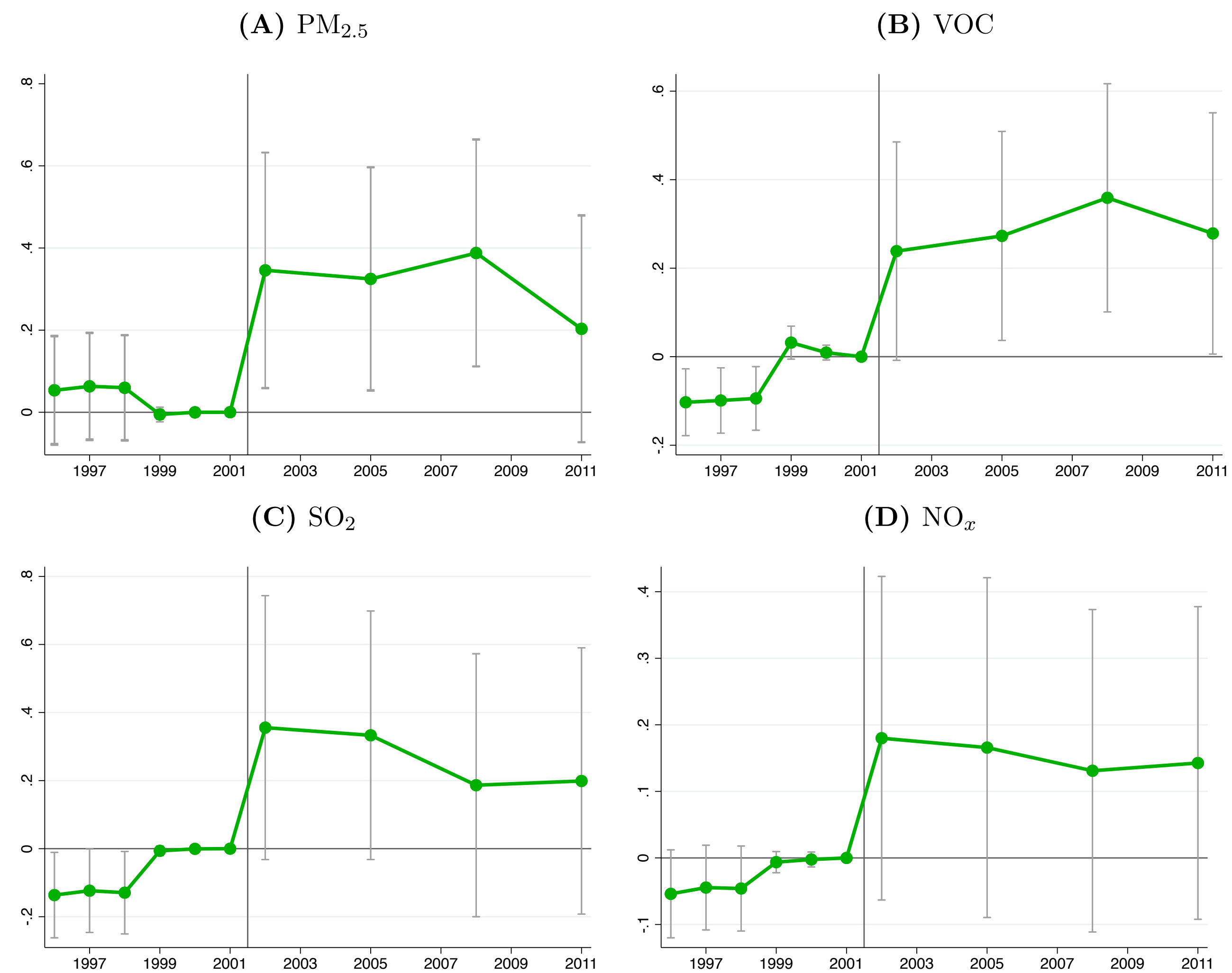


(B) Log(CAA Releases) by Attainment Status



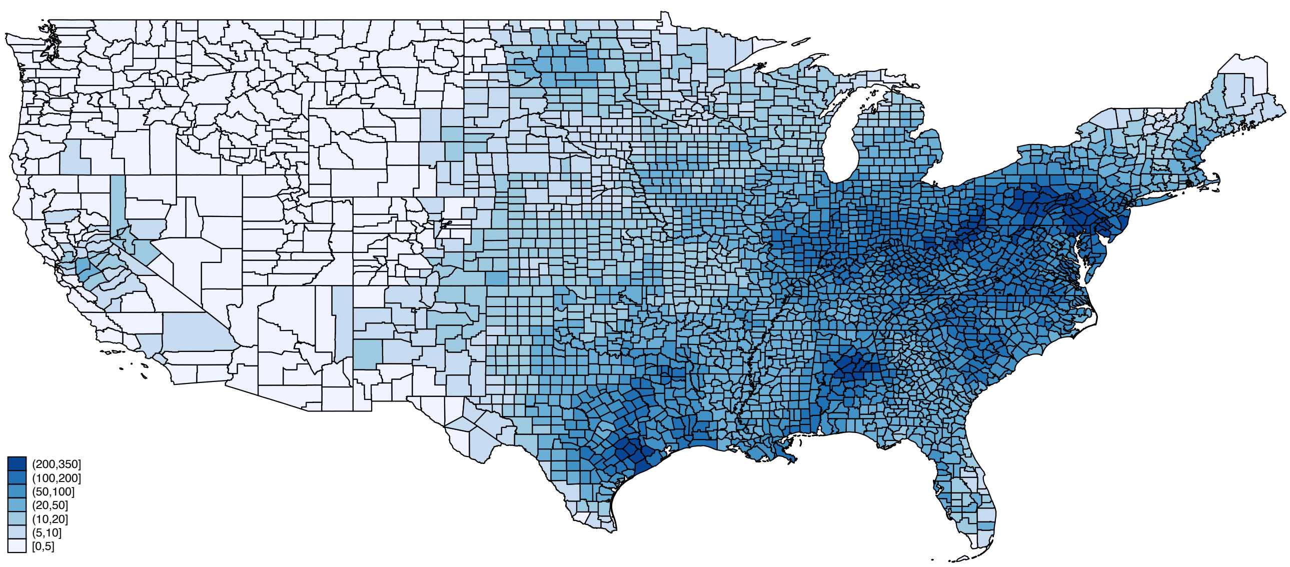
Notes: Figure 4 displays dynamic DD estimates and 95% confidence intervals describing the effect of bonus depreciation on Log(CAA Releases) in Panel (A) and on Log(CAA Releases) separately for plants in counties in nonattainment status or not following CAA reforms in 2004 and 2005 in Panel (B). All specifications 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 5: Effect of Bonus Depreciation on NEI Criteria Air-Pollution Emissions



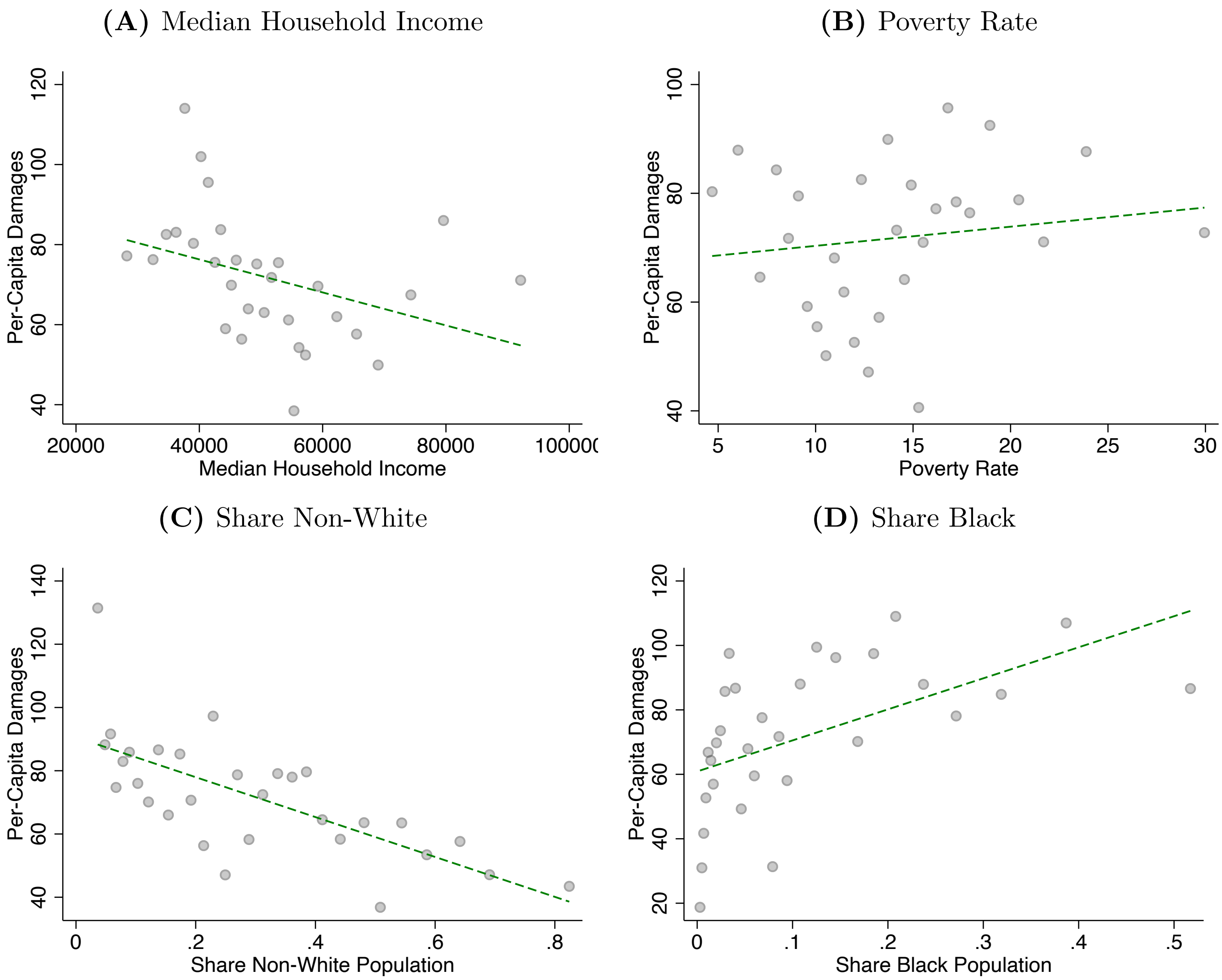
Notes: Figure 5 displays dynamic DD estimates and 95% confidence intervals describing the effect of bonus depreciation on county-industry criteria air pollutants from the NEI. All specifications include fixed effects by industry, county by year, and sector by year. *Source:* Authors' calculations based on NEI and Zwick and Mahon (2017) data.

Figure 6: Geographic Distribution of Economic Damages Per Capita



Notes: Figure 6 displays county-level per-capita economic damages. 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. To calculate county-level damages, we sum InMAP damages across all computational grids within a given county. *Source:* Authors' calculations based on NEI and Zwick and Mahon (2017) data using InMAP.

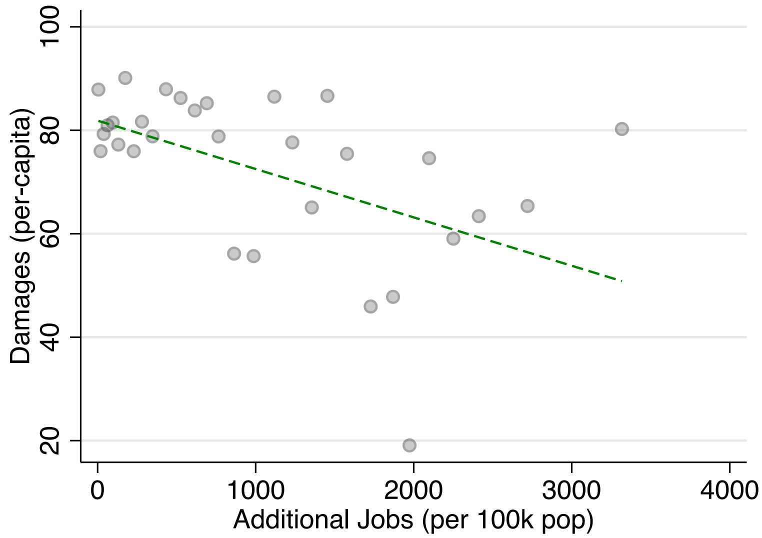
Figure 7: Per-Capita Economic Damages by Socioeconomic Status and Racial Group



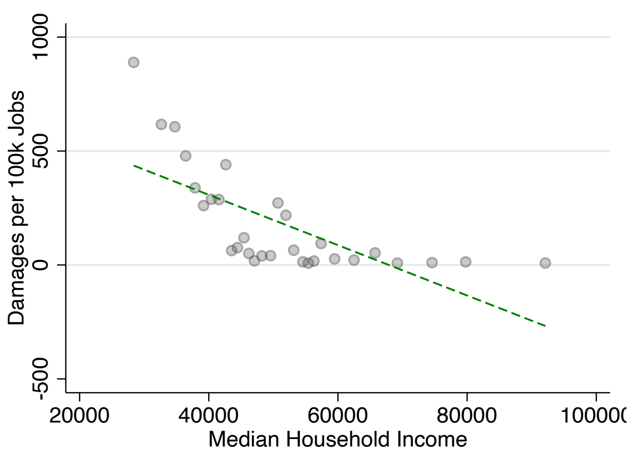
Notes: Figure 7 presents binscatter plots relating county-level per-capita economic damages to county-level median household income, poverty rate, share non-white and share Black in Panels (A), (B), (C) and (D), respectively. Economic damages assume a concentration-response parameter of 4% and a VSL of 9 million USD. *Source:* Authors' calculations based on NEI, SAIPE, and Zwick and Mahon (2017) data using InMAP.

Figure 8: Economic Damages and Job Creation

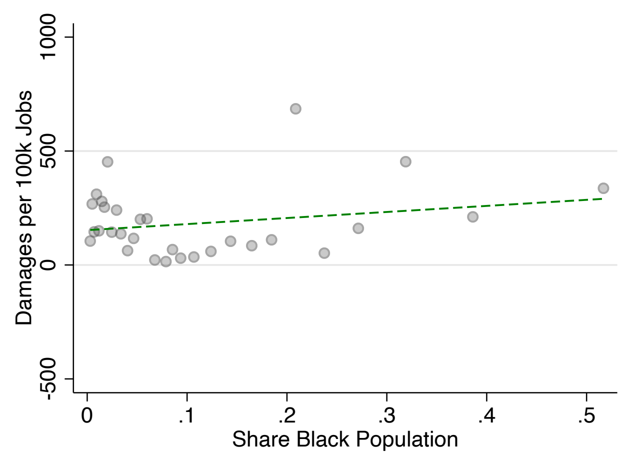
(A) Panel A



(B) Panel B



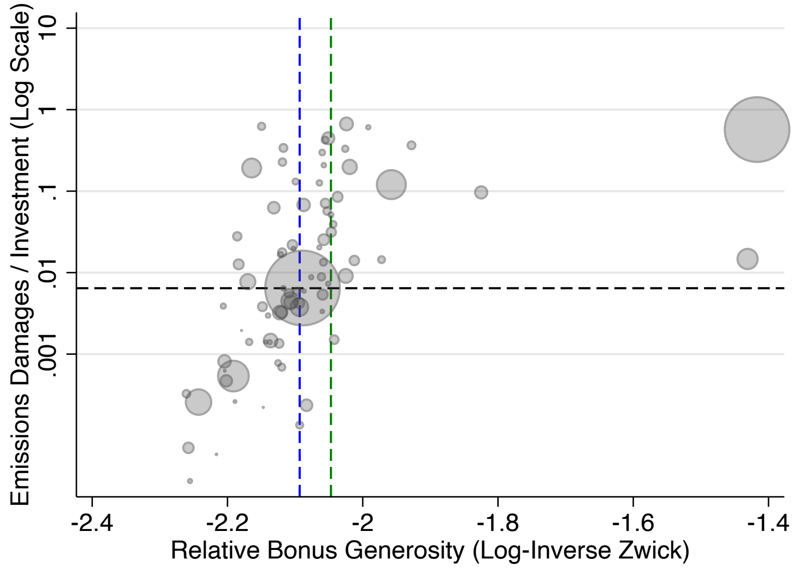
(C) Panel C



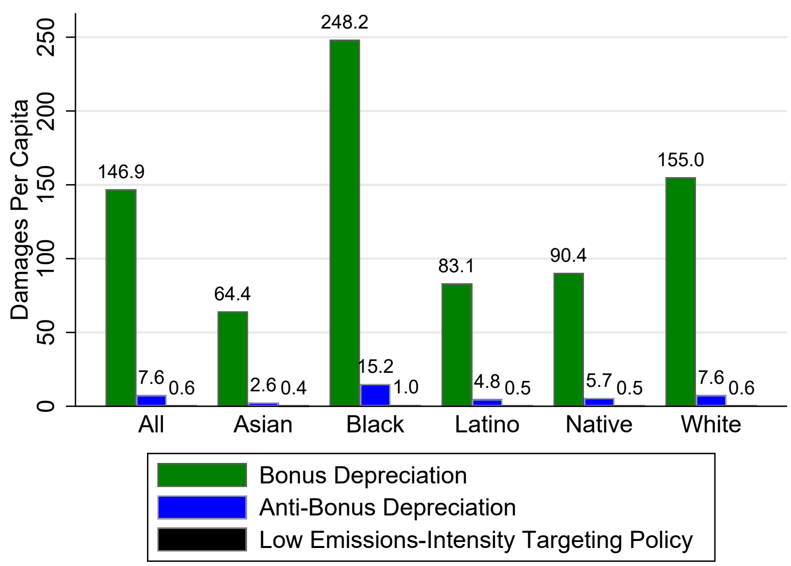
Notes: Panel A of Figure 8 presents binscatter plots relating county-level per-capita economic damages to county-level per-capita employment gains from Garrett, Ohrn, and Suarez Serrato (2020). Panels B and C provide binscatters showing the relationship between damages per 100k industrial jobs created, median household income, and Share Black respectively. Because bonus generates benefits and costs, damages per 100k jobs generated provides a measure of the relative net costs a county incurs from bonus. Economic damages assume a concentration-response parameter of 4% and a VSL of 9 million USD. *Source:* Authors' calculations based on NEI, SAIPE, Garrett, Ohrn, and Suarez Serrato (2020) and Zwick and Mahon (2017) data using InMAP.

Figure 9: Environmental Costs of Alternative Investment Stimulus Policies

(A) Emissions Intensity and Bonus Depreciation Generosity



(B) Economics Damages from Alternative Policies



Notes: Panel (A) displays the relative bonus depreciation benefit, measured as the $log(1 - z_0)$, and emissions damages per dollar of investment for each industrial sector NAICS 4-digit industry. z_0 is the present of depreciation allowances per dollar of investment in the absence of bonus depreciation. We define industries to the right of the green dashed line as treated in our emissions analysis. Industries to the left of the blue dashed line are treated under the hypothetical "anti-bonus depreciation" policy that generates the same amount of investment as bonus depreciation, but targets the industries that benefit least from bonus. Industries below the black dashed line are treated under an alternative "low emissions intensity targeting" policy that stimulates the same amount of investment, but targets the least emissions intensive industries. Panel (B) displays the economic damages per capita for each of these three alternative investment stimulus polices on average and for different demographic groups. The green bars correspond to bonus depreciation. The blue bars correspond to the anti-bonus policy. The black bars (which are not visible due to their tiny magnitude) correspond to damages from the policy that targets the least emissions intensive industries. *Source:* Authors' calculations based on NEI, NBER-CES, BEA, 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. Nonattainment 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: Effects of Bonus Depreciation; Compustat Matched Sample

	(A): Capital Stock			
	(1)	(2)	(3)	(4)
Bonus × Post	0.310***	0.308***	0.347***	0.305***
	(0.109)	(0.109)	(0.0952)	(0.0918)
	(B): Emissions Intensity			
	(1)	(2)	(3)	(4)
Bonus × Post	0.132	0.143	0.258	0.0947
	(0.312)	(0.320)	(0.324)	(0.345)
	(C): Capital Intensity			
	(1)	(2)	(3)	(4)
Bonus × Post	0.195**	0.192**	0.206***	0.203**
	(0.0752)	(0.0738)	(0.0570)	(0.0912)
Firm FE	✓	✓	✓	✓
Year FE	✓			
Firm Size × Year FE		✓	✓	✓
Debt Ratio × Year FE			✓	✓
Cap. Intensity × Year FE				✓
Obs.	6,181	6,181	6,181	6,181

Notes: Table 4 displays difference-in-differences estimates describing the effect of bonus depreciation on log capital stock, log emissions intensity (total emissions per unit of capital), and log capital intensity (capital per unit of total assets). for the TRI-Compustat matched sample of firms. Column (1) estimates include firm and year fixed effects. Column (2) estimates include firm and pre-period firm-size bins interacted with year fixed effects. Columns (3) and (4) progressively add pre-period debt ratio bins interacted with fixed effects and pre-period capital intensity bins interacted with year fixed effects. All regressions are weighted by pre-period capital stock. Column (2) estimates correspond to the events dynamic difference-in-differences plaots presented in Figure 3. 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 the data from TRI, COMPUSTAT and Zwick and Mahon (2017).

Table 5: 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 5 presents specifications similar to Equation (1) that also include an interaction between the DD term and an indicator for counties in nonattainment 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 6: 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 6 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 7: Baseline Emissions Levels and Estimated Changes due to Bonus Depreciation

	$PM_{2.5}$	SO_2	NO_x	VOC
Total Emissions	101,817	1,769,140	896,019	180,396
Δ Emissions (Average)	20,205	583,708	229,784	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 7 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 6), 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 10), 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 8: Economic Damages from Bonus Depreciation

	Million $		$/pop	
Demographic	Low	High	Low	High
All	20,164	45,393	66	148
White	13,583	30,578	69	156
Black	4,188	9,428	111	250
Latino	1,880	4,232	37	84
Asian	408	918	29	65
Native	79	178	41	91

Notes: Table 8 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 9: Determinants of Per-Capita Economic Damages

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Median Income (log)	-0.864***							-0.323	-0.124
	(0.0914)							(0.215)	(0.206)
Poverty Percent, All Ages		0.0218***						0.0238**	0.00206
		(0.00448)						(0.0108)	(0.00960)
Share Black			3.334***						2.783***
			(0.188)						(0.199)
Share Latino				-3.748***					-3.092***
				(0.152)					(0.171)
Share Asian					-7.949***				-4.017***
					(0.520)				(0.631)
Share Native American						-8.121***			-8.184***
						(0.833)			(0.743)
Share Non-White							-1.383***	-1.506***	
							(0.117)	(0.156)	
Obs.	3,107	3,107	3,108	3,108	3,108	3,108	3,108	3,107	3,107

Notes: Table 9 presents county-level cross-sectional regressions, where the dependent variable is log 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 10: 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 10 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 11: 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	27,076	60,976	13,850	31,168
White	13,059	29,395	18,263	41,130	9,282	20,888
Black	3,929	8,844	5,605	12,624	2,907	6,543
Latino	1,798	4,046	2,518	5,672	1,308	2,943
Asian	363	816	545	1,227	285	641
Native	87	196	107	242	53	118

Notes: Table 11 presents economic damages using the InMAP model. Economic damages are expressed in million USD. The two columns under the Actual Nonattainment header are aggregate economic damages under Actual Nonattainment 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 Nonattainment header are aggregate economic damages under the assumption that all counties are in Nonattainment. 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.

Table 12: Welfare Analysis: Marginal Value of Public Funds

	IVPF	EBPF		EBPF/IVPF		MVPF	
Scenario		Low	High	Low	High	Low	High
Bonus	1.41	0.51	1.14	0.36	0.81	0.90	0.26
Anti-Bonus	1.41	0.03	0.06	0.02	0.04	1.38	1.35
Low Emissions-Intensity Targeting	1.41	0.002	0.005	0.002	0.003	1.40	1.40

Notes: Table 12 presents estimates of the marginal value of public funds (MVPF). See Section K for details regarding the calculation of MVPF. The Bonus scenario refers to incorporating pollution damgages from the actual Bonus Depreciation Policy, whereas the Anti-Bonus and Low Emissions-Intensity Targeting scenarios incorporate pollution damages from various hypothetical policy scenarios described in Section 7. The Low columns assume the low end of the damage estimates, using a concentration-response parameter of 4% from Kewski et al. (2009), while the High columns assume the high end of the damage estimates, using a concentration-response parameter of 14% from Lepuele et al. (2012). *Source:* 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 provides details on how regulated utilities benefit from bonus depreciation. Appendix B provides additional details on the TRI and data quality robustness checks. Appendix C gives information on the TRI - Compustat matched sample. Appendix D presents analysis of heterogenous capital investment responses by CAA nonattainment status. Appendix E shows that potentially correlated data in the NEI does not have significant effects on our results. Appendix F gives details on the MECS sample and regression results. Appendix G presents additional details on the InMAP model. Appendix H provides information on our estimates of industrial job creation. Appendix I discusses the scope for alternate stimulus policies that would target different industries. Appendix J provides detail on the county-level pollution analysis we perform using the EPA's AQS data. Appendix K provides discusses details and sensitivity checks of our welfare analysis.

A Bonus and Regulated Utilities

This section provides evidence that regulated utilities benefit from bonus depreciation. First, we reference the relevant tax code pertaining to capital investment for regulated firms, describing how bonus depreciation lowers capital costs. Second, we describe our communication with senior management at a major regulated electric utility confirming that regulated firms take advantage of bonus depreciation and that it bears on their capital investment decisions. Third, we empirically investigate whether bonus influences pollution emissions among regulated utilities. Because all utilities are defined as treated, we explore this question by excluding all (i) utilities and all (ii) regulated utilities, demonstrating that the results are nearly identical.

In the United States, many electric utilities operate in regulated markets where the retail rates (the prices customers pay) are set by a government body and based on the regulated rate of return on investments. Retail rates are established based on a regulated rate of return on investments, designed to mitigate potential exploitation of market power by utilities while at the same time guaranteeing them a predetermined rate of return. This arrangement accounts for all associated expenses, including operating costs, depreciation, and taxes. Importantly, depreciation expenses used in calculating retail rates are distinct from depreciation deductions used for tax purposes. These rules are determined by the Federal Energy Regulatory Commission (FERC). This pricing system begs the question whether regulated electric utilities will benefit from bonus depreciation or whether the tax advantages will simply be passed directly to consumers in the form of lower electricity prices. In the latter scenario, bonus depreciation would fail to serve as an incentive for further investment.

Recognizing this issue, and wanting to ensure that bonus depreciation would incentivize electric utility investment, the IRS established a number of rules to ensure that the benefits of bonus would not "flow through" to customers. In particular, the Internal Revenue Code contains so-called "normalization provisions" for "public utility property" which ensure that regulated utilities benefit from the policy (Internal Revenue Service, 2007). These normalization provisions explicitly prevent regulators from using the benefits of bonus depreciation to benefit ratepayers (referred to as "flow through"), which would undermine the efficacy of the tax incentive. Normalization in particular entails that income tax expenses for the purpose of setting retail rates will be determined as if deprecation were based on GAAP straight-line depreciation. The immediate income tax deductions from bonus depreciation would therefore not be offset by corresponding reductions in retail rates. These rules were originally set out in the Tax Reform Act of 1986 (Section 203e) which limited the rate at which excess tax reserves may flow through to utilities' customers in setting rates. As such, electric utilities are required by FERC to take Bonus Depreciation and provisions are in place to ensure that bonus reduces the effective cost of capital to regulated utilities. See Federal Energy Regulatory Commission (2016) for a recent ruling on this matter.

To better understand the implications of these rules, we also rely on tax guidance from an accounting firm PwC (one of the Big Four accounting firms) as well as interviews with the Vice President of Taxation at a major electric utility. PwC provides a summary of the implications of normalization on stimulating investment among regulated entities[55]:

> "Normalization is a method of ensuring that regulated utilities benefit from the various tax law provisions that were designed to encourage capital expenditures. For example, accelerated depreciation

[55] The passage is from PwC "Utilities and Power Companies Guide" which provides accounting guidance for reporting entities when preparing financial statements. More information can be found at https://viewpoint.pwc.com/dt/us/en/pwc/accounting_guides/utilities_and_power_/utilities_and_power__US/upfm.html#pwc_topic.

and ITCs are intended to encourage capital expenditures, not to subsidize customers' utility costs. However, because these deductions and credits reduce cash income taxes, the tax component of the cost of providing services would be lower, and thus, the rates charged to customers would be lower if these benefits were immediately provided to customers. This lowers the regulated utility's revenues in the short term. Normalization protects revenues from the effects of lower rates, and allows regulated utilities and customers to share the benefits of accelerated depreciation and investment tax credits."

Next, to confirm that regulated utilities are aware of the tax benefit of bonus depreciation, we corresponded with the Vice President of Taxation at a large regulated electric utility. Regarding the question of whether bonus depreciation would in fact incentivize capital investment at a regulated electric utility, we received the following response:

> "The answer is 'yes'. It's effectively an interest-free loan in the form of deferred taxes. In fact, it's specifically characterized as such by certain utility commissions. For example, in Indiana, accumulated deferred income taxes are included in a utility's capital structure as a zero-cost source of capital. This has the effect of reducing the utility's weighted average cost of capital."

Finally, we demonstrate that the effect of bonus depreciation on pollution emissions is similar among utilities. To this end, we replicate our baseline results from Table 2 (specifications 1-3) excluding (i) utilities and all (ii) regulated utilities. Table A3 reports the results when dropping all electric utilities (specifications 1-3) and dropping all regulated electric utilities. Comparing the results from Table A3 with our baseline results from Table 2 demonstrates that the results are nearly identical, suggesting that the effect of bonus is similar for electric utilities and regulated electric utilities.

Based on existing IRS tax provisions and expert advice from industry, as well empirical corroboration, we conclude that there is ample evidence that bonus depreciation has similar effects on utilities as the rest of the industrial sector, and we therefore include this sector in our baseline empirical analysis.

B TRI

In this appendix we provide additional details on the Toxic Release Inventory, discuss the data cleaning process, and test whether results hold for a balanced sample of plants. The TRI is a public database managed by the United States Environmental Protection Agency (EPA). While it is the most comprehensive annual emissions data set available for stationary source emitters, it contains important, documented drawbacks which we discuss here. Established under the Emergency Planning and Community Right-to-Know Act (EPCRA) of 1986, the TRI program mandates that facilities in various sectors report annually on the amount of toxic chemicals released into the environment. Facilities are required by law to report emissions of approximately 650 chemicals and may face fines and punishments for failure to report (EPA, 2022). Concerns over the self-reported nature of the data and the reporting requirement thresholds have resulted in a number of papers exploring the reliability of the TRI. (de Marchi and Hamilton, 2006; Koehler and Spengler, 2007; Bennear, 2008).

Misreporting and under-reporting is found to have occurred particularly when the program began in the early 1990's during the take-up stage. Reported aggregate emissions jumped between 1990 and 1992 as the number of firms that complied with the reporting requirements increased. Additionally, de Marchi and Hamilton (2006) found evidence of rounding errors and only a loose correlation between reported TRI emissions and nearby air monitor readings for some chemicals. Additionally, chemical release data is generally based on emissions factors developed by engineering models and not on direct readings from smoke stacks. These models estimate chemical releases based on the fuel inputs, production process technology and abatement capital used at the facility.

While not perfect, the TRI contains considerable upsides as well and the EPA has taken a number of steps to ensure accurate reporting. First, as mentioned above, firms are required by law to report. Under the Emergency Planning and Community Right-to-Know Act (EPCRA), the Environmental Protection Agency (EPA) has the authority to impose fines of up to $25,000 for each instance of reporting non-compliance. In 2001, the total amount of these fines reached roughly $3.5 million. Between 1990 and 1999, the EPA initiated 2,309 administrative proceedings against facilities for violations related to EPCRA (de Marchi and Hamilton, 2006).

Second, they perform a number of quality checks designed to identify misreporting. These checks include: comparing reported data to information submitted under other EPA programs; evaluating reported stocks against the releases; and reviewing facilities whose emissions estimates significantly differ relative to prior years (U.S. Environmental Protection Agency, 2017).

As such, a number of recent papers have used the TRI data as both outcome and explanatory variables (Banzhaf and Walsh, 2008; Cherniwchan, 2017; Gibson, 2019; Jacqz, 2022). We follow (Gibson, 2019) in many of the cleaning steps.

The TRI does contain reporting thresholds, which are higher than those of the NEI. Thresholds vary by chemical but facilities are typically required to report if: they have greater than 10 employees and manufacture 25,000 lb/year, processes 25,000 lb/year, or uses 10,000 lb/year of a TRI-listed chemical. As such, these tend to be larger facilities. Reporting thresholds could bias our treatment effect estimates if falling above or below the threshold is correlated with our Bonus exposure variable. To ensure that are results are not driven by entry into and exit out of the sample, we re-run our model on a balanced sample of plants. These results, reported in Table A10, do not qualitatively differ from our baseline results. Given these thresholds, Gibson (2019) also provides analysis of the TRI coverage across industries finding higher coverage for more emissions-intensive industries but no meaningful changes in coverage over our sample period. The coverage and data reporting should be considered when interpreting our baseline TRI results. These results may not represent the smallest emitters but the do represent the most important emitters regardless of industry. Concerns over coverage and reporting are further alleviated by the fact that our TRI estimates align closely with estimates using National Emissions Inventory (NEI) emissions data as the outcome variable. As discussed later, the NEI is an entirely separate program with separate reporting threshold and an entirely different data collection process.

C TRI-Compustat Matched Sample

To construct our TRI-Compustat sample, we rely on the concordance between TRI facility IDs and Compustat firm identifiers from Andersen (2017). We then aggregate the total releases variable from the TRI at the Compustat firm-level. We then drop any firms that have missing or negative values of capital stock, emissions per unit of capital (capital intensity), capital stock per total assets (capital intensity), and debt pre total assets (debt ratio). To mitigate issues related to TRI sampling and corporate acquisitions, we also trim the sample to exclude firms that experience a more than 500% increase total releases, capital stock, or total revenue in a given year. Our analysis sample consists or emissions data for 5,902 TRI plants that we match to 531 Compustat firms.

D 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 investment 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 nonattainment status following the 2004 and 2005 CAA amendments. Results are presented in Table A7. The four 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.

Focusing on the triple-differences findings, across all four specifications, 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 A7 could explain why we see smaller emissions response to the policy in nonattainment 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 nonattainment country may have been between 25 and 50% smaller than the response of firms with no plants in nonattainment counties.

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

E 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 5 shows that (1) coefficient estimates for 1996-1998 are nearly identical for all pollutants and that (2) the 1999 and 2000 coefficients are nearly identical to the omitted year (2001). 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 1999-2001. 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 1999-2001 periods. In particular, we use 1997 and 2000 (excluding 1996, 1998, 1999, and 2001), 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 A9. 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 A3 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.

F 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.

G InMAP

In this appendix we provide additional description of the InMAP model and our implementation of it. 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.

H Bonus and Industrial Jobs

In this appendix we describe the process for estimating the county-level employment effects of bonus specifically for the industrial sector. Figure 8 demonstrates the relationship between the jobs benefits provided by bonus and the environmental damages. It shows that counties experiencing the largest environmental damages did not have the largest job benefits. That figure uses job estimates from Garrett, Ohrn, and Suarez Serrato (2020) which estimate the total increase in jobs by comparing total employment in counties with high shares of bonus exposed industries to those with low shares of bonus exposed industries. We use job estimates from these models because they are inclusive of all sectors in the economy as well as spillover effects from treated to untreated sectors.

However, one might separately ask whether there is a correlation between county-level pollution damages and the number of industrial jobs created in a county. Here we define industrial sectors to include the manufacturing and utility industries that are present in our emissions data. To calculate the direct industrial employment effect we follow a very similar strategy to our baseline emissions specification. Rather than facility level data, we use county-4-digit NAICS industry data from the County Business Patterns. These regressions are very similar to QWI employment regressions found in Curtis et al. (2021) with two important exceptions. First, because we are particularly interested in the county-level job effects, we employ county-industry rather than state-industry level data. Second, to be consistent with our emissions estimates we include both manufacturing and utilities industries. We continue to define treatment industries as the third of industries that benefit most from bonus.

Table A11 presents results of these regressions. Regression models progressively add fixed effects with column 3 including both county-industry and county-year fixed effects. The coefficient on Bonus x Post in this column is 0.0884 which corresponds to an 8.8% increase in employment in treated, relative to untreated, industries. To calculate the implied county-level increases in industrial employment we simply multiply 2001 levels of treated industry employment levels for each county by 1.088. Using these county-level jobs numbers we continue to find that counties with the highest pollution damages were not the counties that experienced the largest employment gains. Section 6.4 demonstrates that the job benefits of bonus were less likely to accrue to counties with high environmental damages. We suggested two reasons why counties may suffer high damages while seeing limited employment effects. First, bonus creates jobs in many non-industrial industries due to spillovers and the fact that non-industrial firms also benefit from the policy. The Garrett, Ohrn, and Suarez Serrato (2020) paper measures county bonus exposure based on all industries in the county and be using total county employment as the outcome variable, their job creation measure is inclusive of within county spillovers to other industries.

The second reason concerns the nature of pollution transport, whereby a facility's emissions often incur damages on counties that are far from their original source. If pollution is blown far distances, then downwind counties may suffer economic damages from bonus while experiencing little to no economic benefits in the form of more jobs.

Our industrial level employment results provide support for the second hypothesis by showing that even if we isolate the jobs growth occurring in the industrial sector, it is still the case that the communities with the largest damages do not experience the largest job benefits.

I The Scope for Clean Investment Stimulus

Given the potential to reduce environmental damages for a given amount of stimulus, an important question is the scope to stimulate investment while maintaining low or acceptable levels of pollution damages. To this end, we rank all industries according to emissions intensity (pollution damages per investment) and then calculate the implied effect of treatment in terms of additional pollution damages per additional investment generated. Figure A5 displays this ranking for all industries based on ascending emissions damages per investment (vertical height of each block) and the amount of investment generated (horizontal distance of each block). The green shaded blocks correspond to bonus industries, while the blue blocks correspond to non-bonus (all other) industries. For a given amount of total investment stimulus, minimizing pollution damages would entail targeting industries to the left of a given amount of total additional investment. Intuitively, we can think of the curve as a supply of investment stimulus available where the relative cost is represented by pollution damages per dollar of investment. Thus, the horizontal distance represents the total amount of additional investment while the area under the curve represents total pollution damages. The dashed green line corresponds to the total additional investment generated by bonus depreciation, and the set of industries to the left of the line corresponds to those industries in the Low Emissions-Intensity Policy that we introduced in Section 7. Recall this policy alternative entails a similar amount of additional investment. As we see from Figure A5, industries targeted by bonus depreciation were among the most costly in terms of pollution damages per investment, including industries where the amount of additional pollution damages exceed the amount of additional investment created (i.e., additional pollution damages per investment exceeded 1). Moreover, the total green area exceeds the total blue area despite the blue area representing the majority of total investment. Consistent with our observations from Section 7, pollution damages are minimal under the targeted policy which are represented by the area under the curve to the left of the green dashed line.

Figure A5 also demonstrates that potential scope of a targeted policy to stimulate a significant amount of investment with almost zero corresponding pollution damages. Indeed, compared to the amount of investment created by bonus depreciation (around \$17 billion), a targeted policy could potentially stimulate twice that amount with very little resultant economic damages. However, significant economic damages are unavoidable even under a targeted policy when the amount of total investment exceeds \$45-55 billion as pollution damages per investment increase significantly around this range. Figure A5 therefore reinforces our previous conclusions that bonus depreciation led to substantial economic damages because it inadvertently targeted the highest emissions industries. Further, intentionally targeted policies could potentially lower economic damages while stimulating even more additional investment.

J County-Level Bonus Depreciation and Pollution Concentration

This section explores the role of bonus depreciation on ambient pollution concentrations using surface-level pollution data from EPA's Air Quality System (AQS) data. The data are public use and can be downloaded from the EPA's AQS website (https://aqs.epa.gov/aqsweb/airdata/download_files.html). For consistency with the aggregate damages estimated from the pollution transport model, we focus on fine particulate matter ($PM_{2.5}$). In particular, we estimate the effect of variation in county-level bonus depreciation on annual (mean) $PM_{2.5}$ at a pollution monitoring site. For consistency in measurement, we use $PM_{2.5}$ readings that comply with the 2006 Annual $PM_{2.5}$ National Ambient Air Quality Standards.

We construct a county-level indicator variable for counties with the highest share of treated emissions based on NEI emissions of $PM_{2.5}$ using our definition of Bonus treatment baseline NEI analysis. For each county, we define the share of treated emissions as the ratio of the sum of $PM_{2.5}$ emissions among treated plants to the sum of $PM_{2.5}$ NEI emissions from all plants in the county. We find that the share of treated emissions follows a bimodal distribution with peaks around 0 and 1 (i.e., 0 and 100 percent treated emissions, respectively). Consequently, we use a indicator variable for the top 25% of the treated-emissions distribution, which captures the peak around 1. The results are very similar using both a continuous measure of treatment, as well as other treatment cutoffs.

As a preliminary investigation, we construct a binscatter plot with the change in $PM_{2.5}$ between the pre and post-period over the share of treated emissions (Figure A6). The change in $PM_{2.5}$ is defined as the log difference between average $PM_{2.5}$ concentrations in 1995 to 2000 and the same average between 2002 and 2012. The clustering of points around 0 and 1 (smaller spacing) reflects the fact that the share of treated emissions follows a bimodal distribution (as previously mentioned). Based on this preliminary investigation, there appears to be a positive relationship between the change in $PM_{2.5}$ concentrations and the share of treated emissions. Because $PM_{2.5}$ concentrations generally declined between the pre and post period, the figure demonstrates that pollution concentrations declined the least in counties that received the most bonus depreciation.

Next, to more rigorously investigate the role of bonus depreciation in pollution concentrations, we use a difference-in-differences estimation strategy to estimate the effect of county-level bonus depreciation on annual mean $PM_{2.5}$ pollution at monitoring sites. Specifically, we interact a dummy variable equal to 1 if the site is in a treated county and a dummy variable for the post-treatment period (2002-2012). To account for common national-level trends in pollution, we include year fixed effects, and to account for unobserved differences in pollution across counties, we include county fixed effects. Additional specifications control for site fixed effects to control for differences in pollution within counties. For example, some sites might be relatively closer or downwind from pollution sources compared to other sites within the same county. Finally, we also create dummy variables for Nonattainment with the two relevant NAAQS amendments during the period (Ozone and Particulate Matter following reforms implemented in 2004 and 2005, respectively). We interact these two dummy variables with year dummies, which allows us to control for both the effect of Nonattainment designations after their implementation, as well as differential pre-trends among sites in Attainment and Nonattainment counties prior to the NAAQS amendments.

Table A12 presents our DD estimates, which represents the change in $PM_{2.5}$ concentrations in the most affected by bonus depreciation relative to counties less affected by bonus depreciation. We find that pollution concentrations are around 5-6 percent higher in counties treated by bonus depreciation, with DD coefficients that become slightly larger and more precisely estimated when including additional fixed effects. That the county-level pollution concentration estimates are smaller in magnitude compared to the plant-level emissions estimates is exactly as expected for two primary reasons. First, our NEI plant-level emissions estimates are only among emissions point sources, whereas pollution concentrations reflect all emissions sources, including sources that we would not expect to be affected by bonus depreciation, such as emissions from non-point sources (e.g., automobiles). Second, only a fraction of emissions generated remain within the county in which they are generated, implying that we would expected a relatively smaller increase in concentrations compared to emissions. These estimates are subject to a number of concerns, but the investigation of county-level effects are highly consistent with our plant-level estimations, at least qualitatively.

Table 6 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.

K Welfare Analysis: Details and Sensitivity

In this section, we provide additional details pertaining to the welfare analysis presented in Section 7.3 and conduct sensitivity analysis with respect to the assumed rate of capital depreciation. For consistency with our pollution damage estimates, we convert all nominal dollars to constant 2020 USD.

K.1 Fiscal Cost

A key component of the welfare analysis is the estimation of the fiscal cost of bonus depreciation and the alternative policies. Recall that we rely on estimates of the fiscal cost of bonus depreciation from Garrett, Ohrn, and Suarez Serrato (2020). Estimating the fiscal cost of our alternative policies is challenging as these scenarios are hypothetical and depend on a myriad of factors specific to the actual policy. To fix ideas, we suppose these alternative policies are in the form of targeted (by industry) corporate tax reductions that generate an equivalent investment response (in percentage terms) as bonus depreciation. While the government utilizes a range of instruments to promote business investment, specifying the alternative polices as corporate income tax cuts is helpful as recent research demonstrates that one present value dollar of tax breaks generated by bonus depreciation results in the same amount of investment as one dollar of tax breaks generated by corporate income tax cuts (Ohrn, 2018). Because the hypothetical policies are defined to stimulate an equivalent amount of investment, they would have an equivalent fiscal cost. Of course, governments use a range of instruments to stimulate investment, including some policies that might have potentially higher cost than bonus depreciation. Our emphasis is that the government *could*, in practice, stimulate a similar amount of investment at a similar cost using targeted corporate tax cuts.

We also note that we calculate a pollution-exclusive MVPF for bonus depreciation of 1.3. This is very similar to the implied MVPF we calculate from Kennedy et al. (2024), which focuses on the TCJA corporate income tax cuts estimated. Thus, the ratio of investment stimulus to government expenditures is very similar across these two types of investment stimulus policies. This provides additional, albeit indirect, evidence that corporate tax cuts, for a given amount of investment stimulus, would have similar fiscal cost to the government.

K.2 GDP effects of bonus

To estimate the effect of bonus depreciation on additional GDP, we start with estimates of the effect of bonus depreciation on capital investment from Zwick and Mahon (2017). Recall that Zwick and Mahon (2017) estimate that bonus depreciation increased capital investment by \$73.6 billion in the first round (2001-2004) and \$135 billion in the second round (2005-2010).

The second step is to translate these changes in investment to changes in aggregate physical capital. We define additional physical capital in year t (dK_t) as the sum of investment in year t (due to bonus) and additional physical capital in year $t-1$ (net of depreciation in year t). That is,

$$dK_t = I_t + (1-\delta)dK_{t-1}$$

where I_t is investment from bonus estimated by Zwick and Mahon (2017), and δ is the depreciation rate. Intuitively, additional capital in year t is equal to additional capital form year $t-1$ plus investment from bonus minus additional depreciation. We use a baseline depreciation rate equal to 0.10 (10%). To assess the sensitivity of the results to the depreciation rate, we perform a sensitivity analysis where we use 6% and 15% depreciation rates.

Finally, to translate changes in physical capital to changes in GDP, we use a constant capital-output elasticity equal to 1/3. Specifically, additional output dY_t is given by:

$$dY_t = (1/3)Y_t \frac{dK_t}{K_t}$$

where Y_t is GDP in year t and K_t is the physical capital stock, which we obtain from the U.S. Bureau of Economic Analysis and Penn World Tables, respectively.

Vollrath (2021) contends that this one-third elasticity is one of the most common assumptions within economics. One key assumption is zero-profits (or no markups). However, incorporating markups would slightly decrease the capital-output elasticity, implying the marginal benefit of bonus depreciation, in terms of additional output, would be slightly smaller. We use the larger 1/3 value to ensure we are more likely overstating the benefit of the policy vis-à-vis pollution damages.

We calculate average annual additional output by summing over the 2001 to 2010 period and dividing by the number of years in the period. We find that additional annual output due to bonus depreciation was around 51.3 billion (2020 $). Put another way, GDP was around 0.5% higher at the end of period as a consequence of the policy. While our back-of-the-envelope calculate is highly stylized, our estimates are consistent with studies estimating GDP effects of comparable policies. For example, Barro and Furman (2018) estimate that including permanent bonus depreciation (at 50%) to the 2017 TCJA would increase GDP by around 0.3% after 10 years. Our estimate is similar in magnitude (0.5%), albeit slightly larger, potentially due to a number of differences between the 2017 Act and the policy we study. For example, the 2002 Act was passed during an economic downturn and in the context of relatively higher corporate income tax rates, both of which might contribute to slightly larger effects of bonus depreciation. If our estimate of GDP is slightly overstated then we would be understating the importance of pollution damages relative to the policy's benefits.

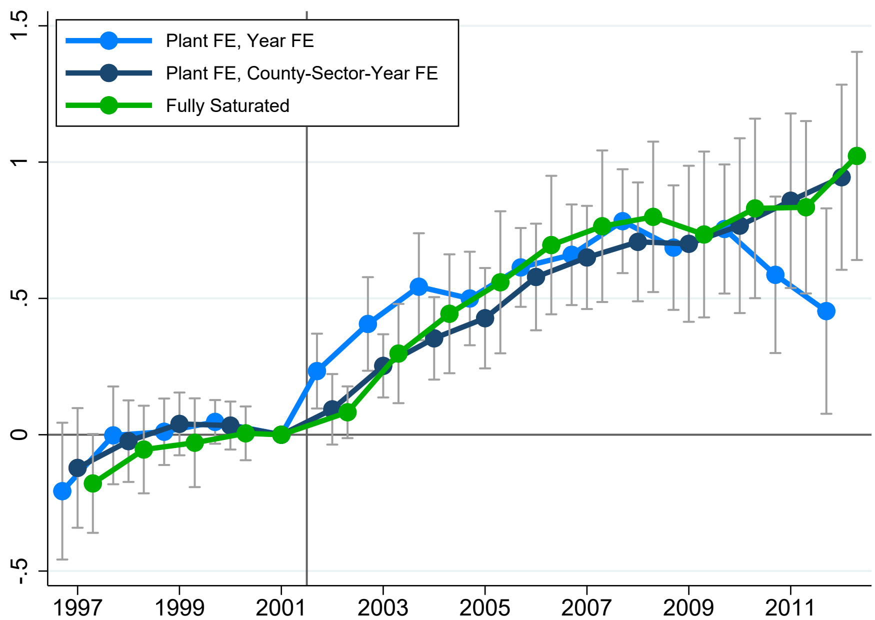
K.3 Sensitivity Analysis: Depreciation Rate

To assess the sensitivity of the estimates to changes in the depreciation rates, we calculate additional output and the corresponding MVPF using a range of depreciation rates. In particular, we use a low-end depreciation rate of 6% and a high-end depreciation rate of 15%.

Table A13 reports our MVPF estimates based on a 6% depreciation rate (Panel A) and a 15% depreciation rate (Panel B). Using a low depreciation rate increases the IVPF from 1.4 to 1.45, while the high depreciation rate decreases the IVPF to 1.36. Incorporating pollution damages from Bonus significantly reduces the MVPF under both low and high depreciation rates, ranging between 0.31 to 0.94 under low depreciation and between 0.22 and 0.85 under high depreciation rates. Similar to our baseline depreciation rate, the MVPF under the Anti-Bonus and Emissions Intensity Targeting polices are very similar to the IVPF. This section demonstrates that while changes in the depreciation rate shifts the IVPF values, the conclusion that bonus depreciation significantly reduces the MVPF remains unchanged.

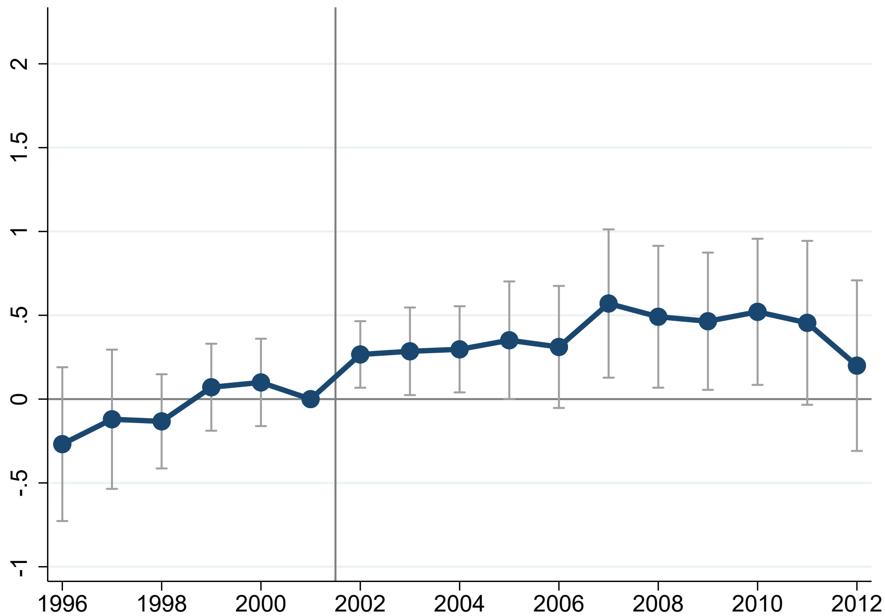
Appendix Figures

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



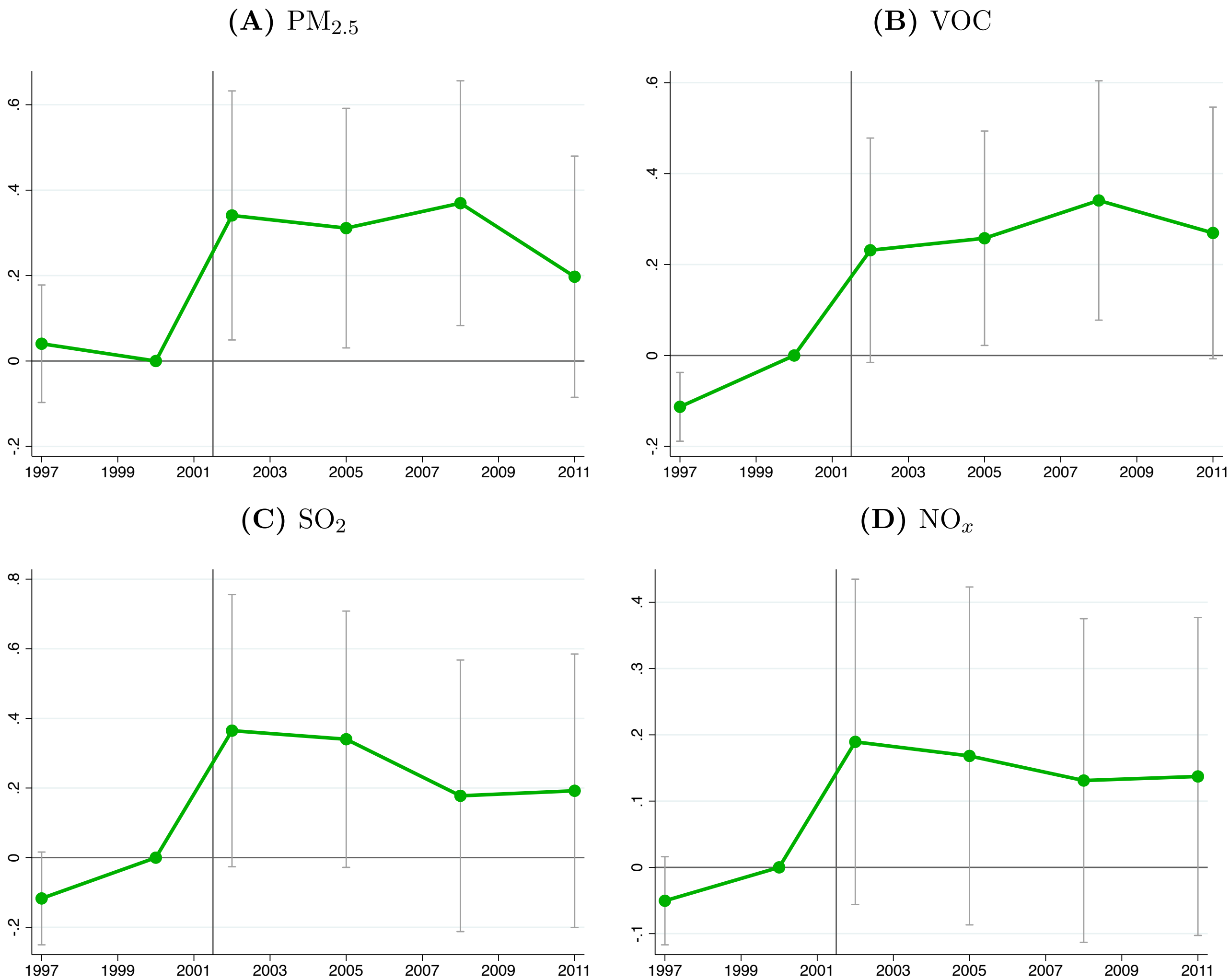
Notes: Figure A1 displays dynamic DD estimates and 95% confidence intervals based on equation (2) describing the effect of bonus depreciation on Log(Total Chemical Releases) with alternate levels of fixed effects. The first specification includes only plant and year fixed effects. The second specification 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: Effect 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.

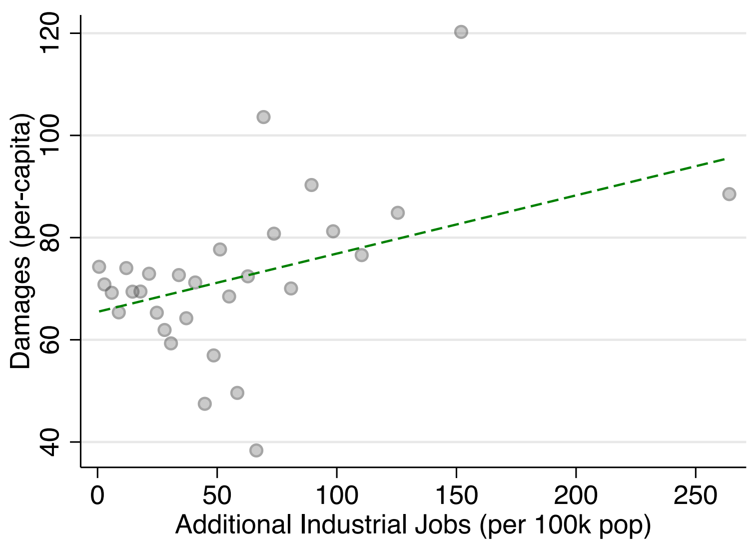
Figure A3: Effect of Bonus Depreciation on County-Industry Level NEI Criteria Air-Pollution Emissions (Restricted Sample)



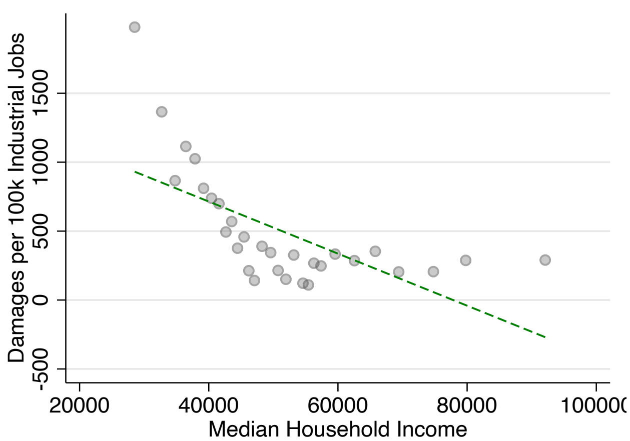
Notes: Figure A3 displays dynamic DD estimates and 95% confidence intervals describing the effect of bonus depreciation on county-industry criteria air pollutants. The 2000 coefficients are normalized to zero. We restrict the sample by excluding the years 1996, 1998, and 2000. The outcomes include air 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: Economic Damages and Industrial Job Creation

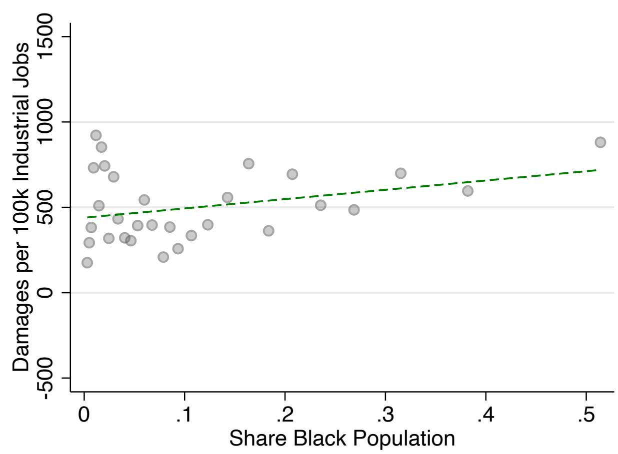
(A) Panel A



(B) Panel B

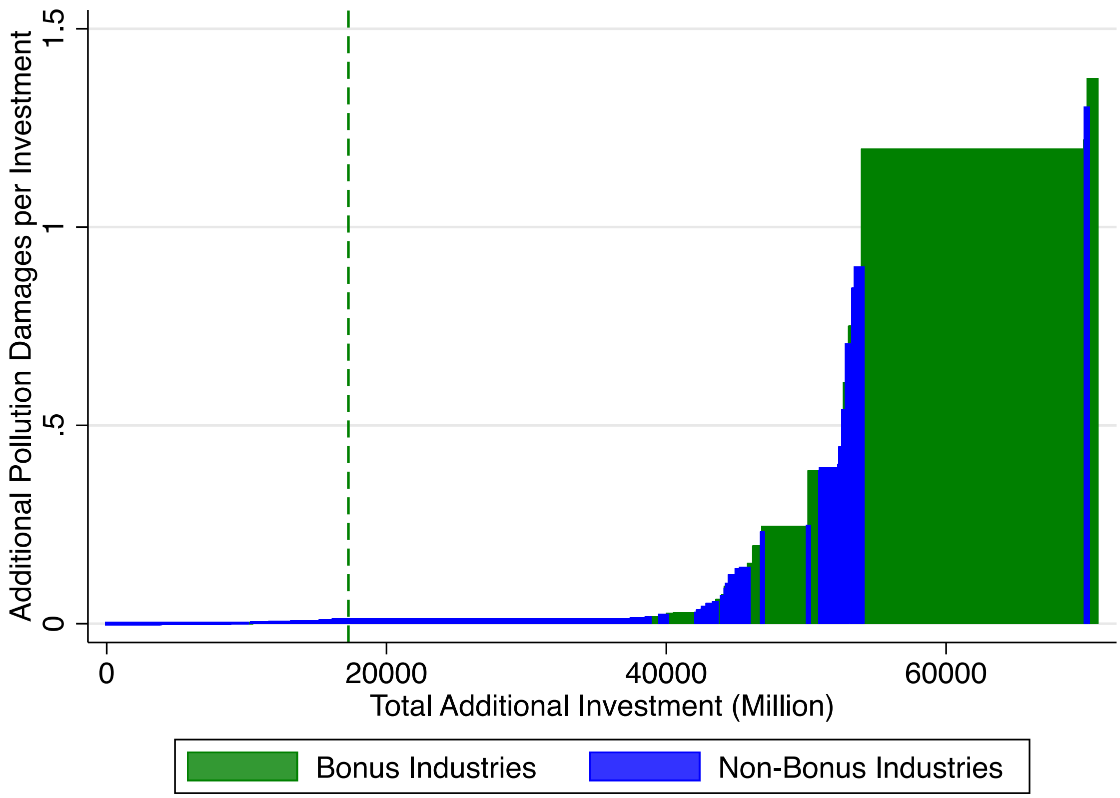


(C) Panel C



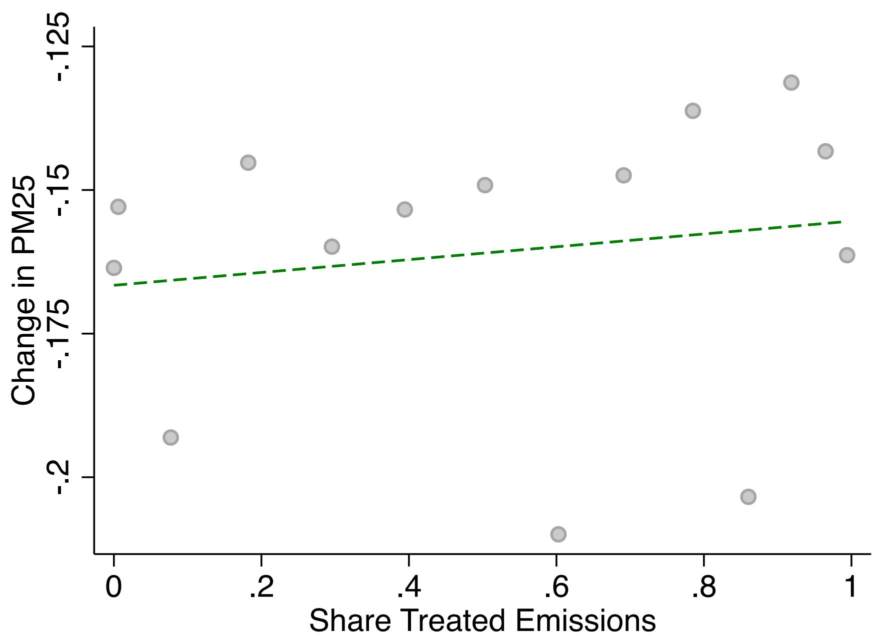
Notes: Panel A of Figure A4 presents binscatter plots relating county-level per-capita economic damages to county-level per-capita industrial employment gains. See Appendix H for details regarding estimation of county-level industrial employment gains. Panels B and C provide binscatters showing the relationship between damages per 100k industrial jobs created and median household income and Share Black respectively. Because bonus generates benefits and costs, damages per 100k industrial jobs generated provides a measure of the net costs a county incurs from bonus. Economic damages assume a concentration-response parameter of 4% and a VSL of 9 million USD. *Source:* Authors' calculations based on NEI, SAIPE, County Business Patterns and Zwick and Mahon (2017) data using InMAP.

Figure A5: Ranking Industry-Level Investment Stimulus by Emissions Intensity



Notes: Figure A5 displays the industry-level additional investment stimulated by a given policy with the same percentage effects as bonus depreciation. Industries are ranked from lowest to highest in terms of their emissions intensity (their pollution damages per dollar of investment). This ranking produces a graph akin to a "merit-order" curve that is common in the electricity literature (e.g. Cicala, 2022). The industries to the left of the black dashed line represent those that are stimulated under the alternative "Low Emissions Targeting Policy." *Sources:* Authors' calculations based on NEI, NBER-CES, BEA, and Zwick and Mahon (2017) data.

Figure A6: County-Level Bonus Depreciation and Change in Surface $PM_{2.5}$ Pollution



Notes: Figure A6 presents bin scatter plots relating changes in $PM_{2.5}$ concentrations between the pre and post-period and the share of county-level treated emissions. The change in $PM_{2.5}$ is the log difference between average $PM_{2.5}$ concentrations in 1995 to 2000 and the same average between 2002 and 2012. *Source:* Authors' calculations based on the EPA's AQS data, NEI, and Zwick and Mahon (2017) data.

Appendix Tables

Table A1: 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 on-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.
Nonattainment County	A time-invariant indicator equal to one for counties that were in nonattainment 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.
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

Continued on next page

Table A1 – *Continued from previous page*

Variable	**Description**
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

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: Dropping Electric Utilities

	Dropping All Elec Utilities			Dropping Regulated Elec Utilities		
	(1)	(2)	(3)	(4)	(5)	(6)
Bonus × Post	0.331***	0.342***	0.349***	0.311***	0.321***	0.349***
	(0.0751)	(0.0730)	(0.0677)	(0.0743)	(0.0722)	(0.0678)
Plant FE	✓	✓	✓	✓	✓	✓
Year FE	✓			✓		
County × Year FE		✓	✓		✓	✓
Sector × Year FE			✓			✓
Obs.	203,953	203,891	203,891	207,401	207,400	207,400

Notes: Table A3 mirrors Table 2 using two different samples. Columns 1, 2 and 3 drop all electric utilities from the sample and run specifications from columns 1, 2 and 4 of Table 2. Columns 4, 5 and 6 do the same after dropping regulated electric utilities from the sample. Columns 3 and 6 include sector-by-year fixed effects. As such, the results in 3 and 6 are identical and the same as column 4 of Table 2. When controlling for sector-by-year fixed effects, the identifying variation comes from within 2-digit NAICS, so dropping all electric utilities (NAICS 22) does not change the results. The outcome variable in all specifications is Log(Total Chemical Releases). Column (1) and (4) include plant and year fixed effects. Column (2) and (5) include plant and county-by-year fixed effects. Column (3) and (6) includes plant, 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 at the 10, 5 and 1 percent level. *Sources:* Authors' calculations based on TRI, and Zwick and Mahon (2017) data.

Table A4: 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 A4 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 A5: Effect of Bonus Depreciation on Alternative Measures of Emissions Intensity

	(A): Emissions / Capital			
	(1)	(2)	(3)	(4)
Bonus × Post	0.132	0.143	0.258	0.0947
	(0.312)	(0.320)	(0.324)	(0.345)
Obs.	6,181	6,181	6,181	6,181
	(B): Emissions / Revenue			
	(1)	(2)	(3)	(4)
Bonus × Post	0.334	0.335	0.460	0.408
	(0.345)	(0.353)	(0.326)	(0.387)
Obs.	6,177	6,177	6,177	6,177
	(C): Emissions / Pretax Income			
	(1)	(2)	(3)	(4)
Bonus × Post	0.115	0.125	0.258	0.246
	(0.401)	(0.412)	(0.371)	(0.399)
Obs.	5,012	5,012	5,012	5,012
Firm FE	✓	✓	✓	✓
Year FE	✓			
Firm Size × Year FE		✓	✓	✓
Debt Ratio × Year FE			✓	✓
Cap. Intensity × Year FE				✓

Notes: Table A5 displays difference-in-differences estimates describing the effect of bonus depreciation on alternative measures of emissions intensity. Emissions intensity in Panel (A) is calculated as the log of total releases per unit capital stock. Emissions intensity in Panel (B) is calculated as the log of total releases per unit revenue. Emissions intensity in Panel (C) is calculated as the log of total releases per unit pre-tax income. Column (1) estimates include firm and year fixed effects. Column (2) estimates include firm and pre-period firm-size bins interacted with year fixed effects. Columns (3) and (4) progressively add pre-period debt ratio bins interacted with fixed effects and pre-period capital intensity bins interacted with year fixed effects. All regressions are weighted by pre-period capital stock. 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 the data from TRI, Compustat and Zwick and Mahon (2017).

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 on Capital Investment; Heterogeneity by Attainment Status

	Log(Capital Investment)			
	(1)	(2)	(3)	(4)
Bonus × Post	0.441***	0.439***	0.488***	0.375***
	(0.115)	(0.117)	(0.107)	(0.121)
Bonus × Post × 1(NA)	-0.146	-0.147	-0.178*	-0.183*
	(0.102)	(0.104)	(0.0964)	(0.0978)
Firm FE	✓	✓	✓	✓
Year FE	✓			
Firm Size Bins × Year FE		✓	✓	✓
Debt Ratio Bins × Year FE			✓	✓
Cap. Intensity Bins × Year FE				✓
Obs.	6,135	6,135	6,135	6,135

Notes: Table A7 displays DD estimates describing heterogeneous capital investment responses to bonus depreciation due to county-level nonattainment status. The outcome variable in all specifications is Log(Capital Investment). The Bonus × (Year=2011) coefficient describes the 10-year capital response to bonus depreciation. The Bonus × (Year=2011) × 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 nonattainment county following the 2004 and 2005 CAA Amendments. Column (1) estimates include firm and year fixed effects. Column (2) estimates include firm and pre-period firm-size bins interacted with year fixed effects. Columns (3) and (4) progressively add pre-period debt ratio bins interacted with year fixed effects and pre-period capital intensity bins interacted with 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 A8: Determinants of Economic Damages per Job Created

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Median Income (log)	-3.828***							-3.889***	-3.521***
	(0.144)							(0.335)	(0.337)
Poverty Percent, All Ages		0.107***						-0.0203	-0.0438***
		(0.00758)						(0.0168)	(0.0159)
Share Black			3.128***						1.895***
			(0.336)						(0.323)
Share Latino				-7.291***					-5.149***
				(0.263)					(0.291)
Share Asian					-22.55***				-6.482***
					(0.829)				(1.016)
Share Native American						-3.058**			-7.135***
						(1.500)			(1.220)
Share Non-White							-3.931***	-3.183***	
							(0.197)	(0.246)	
Obs.	2,940	2,940	2,940	2,940	2,940	2,940	2,940	2,940	2,940

Notes: Table A8 presents county-level cross-sectional regressions, where the dependent variable is log 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 A9: 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 A9 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.

Table A10: Effect of Bonus Depreciation on Balanced TRI Sample

	Total Releases					
	(1)	(2)	(3)	(4)	(5)	(6)
Bonus × Post	0.320***	0.331***	0.324***	0.326***	0.319***	0.356***
	(0.0833)	(0.0804)	(0.0726)	(0.0697)	(0.0694)	(0.0648)
Plant FE	✓	✓	✓	✓	✓	✓
Year FE	✓					
County × Year FE		✓		✓		✓
Sector × Year FE			✓	✓		✓
County × Sector × Year FE					✓	
Additional Controls						✓
Obs.	112,043	111,762	112,043	111,762	110,755	106,443

Notes: Table A10 presents estimates of the effect of bonus depreciation on emissions from a balanced TRI panel. 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 A11: Effect of Bonus Depreciation on Employment

	Log(Total Employment)		
	(1)	(2)	(3)
Bonus × Post	0.117***	0.115***	0.0884***
	(0.0187)	(0.0187)	(0.0195)
Cnty-Ind FE	✓	✓	✓
Year FE	✓		
State × Year FE		✓	
County × Year FE			✓
Obs.	1,174,889	1,174,889	1,174,889

Notes: Table A11 presents estimates of the effect of bonus depreciation on industrial employment using county-industry data from the County Business Patterns. Standard errors are presented in parentheses and are clustered at the county-industry level. *, **, and *** denote statistical significance at the 10, 5, and 1% level. *Source:* Authors' calculations based on CBP and Zwick and Mahon (2017) data.

Table A12: Effect of County-level Bonus Depreciation on Surface-Level $PM_{2.5}$ Pollution

	1	2	3
Bonus County × Post	0.0483*	0.0528**	0.0592***
	(0.0260)	(0.0235)	(0.0209)
Year FE	✓	✓	✓
County FE	✓		
Site ID FE		✓	✓
NonAttainment × Year FE			✓
Obs.	13,976	13,894	13,787

Notes: Table A12 presents estimates of the effect of county-level bonus depreciation on $PM_{2.5}$ pollution concentrations using surface-level pollution data from EPA's Air Quality System (AQS) data. Standard errors are presented in parentheses and are clustered at the county level. *, **, and *** denote statistical significance at the 10, 5, and 1% level. *Source:* Authors' calculations based on the EPA's AQS data, NEI, and Zwick and Mahon (2017) data.

Table A13: Welfare Analysis: Marginal Value of Public Funds

Scenario	IVPF	MVPF Low Damages	MVPF High Damages
Panel A (6% depreciation):			
Bonus	1.45	0.94	0.31
Anti-Bonus	1.45	1.42	1.39
Low Emissions-Intensity Targeting	1.45	1.44	1.44
Panel B (15% depreciation):			
Bonus	1.36	0.85	0.22
Anti-Bonus	1.36	1.33	1.30
Low Emissions-Intensity Targeting	1.36	1.36	1.36

Notes: Table A13 presents estimates of the marginal value of public funds (MVPF). See Appendix K for details regarding the calculation of MVPF. Panel A uses a 6% depreciation rate in calculating additional GDP, while Panel B uses a 15% depreciation rate. The Bonus scenario refers to incorporating pollution damgages from the actual Bonus Depreciation Policy, whereas the Anti-Bonus and Low Emissions-Intensity Targeting scenarios incorporate pollution damages from various hypothetical policy scenarios described in Section 7. 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). *Source:* Authors' calculations based on NEI and Zwick and Mahon (2017) data using the InMAP model.