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The effects of environmental investments on the economic performance of industrial plants – Evidence from Finland

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ABSTRACT

Industrial plants that invest in environmental protection are larger and more productive, but do environmental protection investments also have a causal effect on their economic performance? This study proposes a novel econometric method to analyze the economic performance effects of environmental investments. Propensity score matching and difference-in-differences estimation on matched sample are used to investigate whether Finnish industrial plants that start investing in environmental protection out- or underperform otherwise similar plants. The empirical results show that plants that invest in environmental protection increase their turnover in comparison to control plants and that their labor productivity also increases. The economic gains are stronger when environmental protection investments are combined with environmental R&D, which implies complementarities between these activities.

1. Introduction

Due to environmental problems and climate change, environmental questions are at the forefront of many national and global policy initiatives. Solving environmental problems will also require unprecedented environmental protection investments by private companies. However, private incentives for these investments crucially depend on whether investments in environmental protection conflict with other business objectives or whether environmental and economic interests are aligned. This information is not only important for managers, but it also helps to shape national environmental policies and clarify how environmental regulation impacts the costs and competitiveness of domestic industries. On the one hand, there is concern that environmental protection expenses and investments, especially if compelled by regulation, lead to additional costs, the deterioration of economic performance and the offshoring of polluting industrial activities (Brunel, 2017; Li and Zhou, 2017). On the other hand, the empirical research evidence reveals a positive correlation between the environmental and economic performances of firms, although the causal evidence remains scarcer and more ambiguous (Dechezleprêtre et al., 2019; Hang et al., 2019; Horváthová, 2010). Further empirical research that identifies causal effects is thus clearly needed. The present study contributes to this debate by proposing a novel econometric method that mitigates the endogeneity bias and estimating, how the economic performance of industrial plants changes when they start investing in environmental protection.

The empirical literature on the economic effects of environmental innovations and environmental management practices is extensive (Barbieri et al., 2016; Dechezleprêtre et al., 2019; Endrikat et al., 2014; Takalo et al., 2021). However, not only R&D and other intangible investments but also tangible investments impact the economic and environmental performance of firms. Thus, the effects of tangible environmental investments also need to be understood. Prior studies that have analyzed the effects of environmental investments on economic performance at micro-level remain scarcer, offer mixed results and some of them may be subject to the endogeneity bias.

Prior research has shown that firm characteristics explain, which firms perform environmental investments and expenditures (Banerjee et al., 2021; Bhuiyan et al., 2021; Hammar and Löfgren, 2010; Jaraite et al., 2014; Siedschlag and Yan, 2021). This implies that these investments are an endogenous decision and economic performance also influences environmental investments leading to dynamic endogeneity

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problem (Arellano and Bond, 1991; Hang et al., 2019). However, most extant studies rely on standard panel estimation methods that do not account for endogenous selection and that can be biased in the presence of dynamic endogeneity. Few studies that apply instrumental variable methods to address endogeneity concerns are Weche (2019) and Chen and Ma (2021), who focus on investment crowding-out and profitability effects.

In this context, the present study contributes to the literature by 1) suggesting a method of propensity score matching and difference-in-differences estimation on matched sample to better disentangle the causal effects of environmental investments and 2) providing novel empirical results on the economic performance effects of tangible environmental investments for which the previous findings have remained mixed. In the empirical section of the paper, propensity score matching and difference-in-differences method are applied to estimate the effect of environmental investments on plant-level turnover and labor productivity among Finnish industrial plants that start investing in environmental protection. The approach compares the economic performance of facilities that start investing in environmental protection to other facilities with similar characteristics and past performance, but whose investments do not target environmental protection. While the analysis still relies on observational data and thus falls short of randomized controlled trial, the methods consider the selection process in environmental investments and other sources of endogeneity. Furthermore, I also analyze potential complementarity between environmental investments and environmental R&D (research and development) suggested by Christmann (2000) and Garcés-Ayerbe & Cañón-de-Francia (2017) as well as industry heterogeneity in the effects. Performance effects are also analyzed for several years in order to observe the possible time lag in the effects.

Finally, studying environmental investments in the Finnish context is interesting, as Finland consistently ranks high in, e.g., the OECD's Environmental Policy Stringency index and Environmental Performance Index (Wendling et al., 2020). Thus, all Finnish industrial plants face strong environmental requirements, which are, however, comparable to many European countries (OECD, 2022). Nevertheless, the empirical investigation shows that Finnish plants that invest in environmental protection increase their turnover and labor productivity in comparison to the control plants, which indicates that environmental investments bring economic gains also in a strict environmental regulation context. The results also indicate a clear complementarity between tangible environmental investments and environmental R&D.

2. Literature review

This section discusses the theoretical arguments underlying the relationship between environmental investments and economic performance at the micro-level as well as the existing empirical studies. While vast number of studies have analyzed environmental innovations (Barbieri et al., 2016; Takalo et al., 2021) and relationship between environmental performance and economic performance in general (Dechezleprêtre et al., 2019; Endrikat et al., 2014; Hang et al., 2019; Horváthová, 2010), fewer studies have focused on tangible environmental investments.

Environmental protection investments reduce the negative environmental externalities of production. However, the economic benefits of pollution or waste reduction to the investing firm may not be easily observable and can thus be underestimated by managers (Hart, 1995; King and Lenox, 2002). Yet, environmental investments can create competitive advantage and improve economic performance. Sales may be improved due to improvement in market access, differentiation of products and sales of pollution control technologies and byproducts (Ambec and Lanoie, 2008). The production costs may decrease due to lower material and energy costs as environmental investments can lead to an improvement in the efficiency of resource use (Barbieri et al., 2016; Dechezleprêtre et al., 2019). Investments may also lower the cost of complying with regulation and help to reduce capital costs or costs of risk management (Ambec and Lanoie, 2008; Dechezleprêtre et al., 2019). The positive implications of pollution abatement on worker productivity and firm profitability are also recognized, e.g., by Pang (2018). Potential for higher sales and cost reductions also imply improvements in labor productivity due to environmental investments.

Due to the environmental externalities associated with environmental investments, governments often intervene with regulation requiring firms to invest in environmental protection. According to the conventional view, such regulation limits the decision space of firms, crowds out more profitable activities and leads to weaker economic performance and productivity, as profit-maximizing firms would already conduct optimal environmental investments even without regulation (Ambec et al., 2013). However, the literature following the Porter hypothesis (Porter and Van der Linde, 1995) states that well-designed environmental regulation will induce firms to innovate, which should offset the negative effects at least in the long run. Thus, the Porter hypothesis and following studies indicate that environmental protection investments should lead to economic benefits at least when combined with complementary investment, such as innovation and R&D expenditure (Christmann, 2000; Garcés-Ayerbe & Cañón-de-Francia, 2017; Qiu et al., 2018). Also environmental management practices are often cited as a complement to environmental efforts (Hall and Wagner, 2012). Moreover, literature on the environmental innovations indicates that the effects of environmental investment may also depend on the type of investments and that process-integrated environmental investments could be more likely to bring economic gains than end-of-pipe investments[1] (Ghisetti and Rennings, 2014; Horbach and Rennings, 2013). The economic impacts may also differ across sectors due to, e.g., differences in environmental impacts, regulatory pressure or technological development. In sum, the effect of environmental investments on economic performance remains an empirical question.

In the empirical literature that studies crowding out effects, Gray and Shadbegian (1998) show that environmental investments are often made together with other investments, leading to temporal correlation. They also state that there is a crowding out of other investments among plants that invest more in environmental protection. Weche (2019) uses an instrumental variable (IV) method to study the same question and finds that end-of-pipe environmental investments and investments in renewable energy in particular crowd out other business investments in Germany.

Other empirical studies provide mixed evidence regarding other aspects of economic performance. Shadbegian and Gray (2005) find that pollution abatement capital has a positive effect on output in the paper industry but not in oil or steel. In contrast, Broberg et al. (2013) study Swedish heavy industry firms and find that environmental investments reduce the efficiency of firms, especially in pulp and paper industries. Sueyoshi and Goto (2009) find an insignificant relationship between environmental investments and return on assets among US electric utility firms, whereas Pekovic et al. (2018) find an inverted U-shaped relation between environmental investments and profitability among French firms. Positive effects are reported by Chen and Ma (2021), who use OLS and IV methods and find that environmental investment intensity improves the profitability of Chinese energy firms.

[1] Environmental protection investments can be divided into end-of-pipe-type investments that aim to reduce pollution and investments in cleaner production processes. End-of-pipe investments add, for example, filters or scrubbers to avoid the release of pollution but do not otherwise change the production processes. Investments in clean production processes, i.e., process-integrated investments, change production processes in a manner that lowers emissions and pollution, e.g., by increasing recycling or reducing the use of fossil fuels or chemicals. Environmental investments can also be further divided into investments in air, water, soil or noise pollution abatement and improved waste management.

Garcés-Ayerbe & Cañón-de-Francia (2017) use panel estimation methods and find that environmental investments improve firms' market value and that there is a complementarity with R&D investments. Finally, Stucki (2019) reports that investments in green energy technologies improve labor productivity but only in firms with high energy costs.

Another strand of literature has analyzed the determinants of environmental investments. Hammar and Löfgren (2010) find that investments in clean production processes are higher when firms also invest in environmental R&D. Forslid et al. (2018) and Banerjee et al. (2021) discuss how environmental expenditures and investments are affected by firms' export market status and Siedschlag and Yan (2021) report that the propensity to invest in environmental protection is higher for larger firms, importers and energy intensive firms. Cao et al. (2016) and Hang et al. (2019) show that current and past economic performance influence firm's current environmental performance and investments.

Most of the above-mentioned studies analyzing the economic performance effects of environmental investments have relied on standard panel estimation methods and have not considered, how firms endogenously select to invest in environmental protection, which is also documented in the prior literature. This self-selection, dynamic endogeneity and other sources of endogeneity may bias the prior empirical evidence of the economic effects of environmental investments. These shortcomings may also partly explain the ambiguity in the prior findings. Weche (2019) and Chen and Ma (2021) have applied instrumental variable methods and explored investment crowding-out and profitability effects. Further research is needed to investigate the causal effects of environmental investments on other aspects of economic performance and this study aims to fill this gap.

3. Data and descriptive statistics

Environmental protection investments can be defined as activities directly targeting the prevention, reduction and elimination of pollution or any other degradation of the environment. I use data on environmental protection investments, which come from an annual survey of plant-level environmental protection expenditures and investments in Finland. The survey covers approximately 2000 industrial plants yearly with a response rate of 80–90%. The investment data cover investments in end-of-pipe-type facilities and investments in cleaner production processes. Environmental investments include investments in machinery, buildings and land areas. Energy conservation is not counted as an environmental investment in this case. The survey also asks the plants to report their environmental expenses and R&D as well as income they receive from environmental protection.

The environmental survey data are linked to data on industrial plants from Statistics Finland, which covers facilities with over 20 employees and some smaller facilities if they have operations that correspond to a facility with 20 employees. These data can be linked to 97% of the observations with reported environmental investments and 94% of the observations with no reported environmental investments. The data cover plant employment, turnover, value added and other economic information.

Plants are classified as treated, i.e., starting to make environmental investments, when they report positive environmental investments in year t but reported zero environmental investments in years t-1 and t-2. Thus, it is possible that the treated plants have invested in environmental protection at some point before period t-2. Requiring a longer period with observations of zero investments would limit the sample size significantly, as the surveyed plants often change and some plants do not complete the survey each year that they are surveyed. The control group includes plants that have not invested in environmental protection in t-2 or t-1 and also do not invest in period t. However, they may invest after period t.[2] The robustness of results to alternative pretreatment period definitions is investigated in Appendix A.

The main outcome variables of interest are turnover and value added per employee — a measure of labor productivity. Other used variables are: number of employees, whether plant is active in exports, whether plant has bought R&D and capital stock. Capital stock includes machinery and equipment and it is calculated using perpetual inventory method. I also separate the plants based on whether they operate in high-polluting industry or low-polluting industry. Following Eurostat (2010), high-polluting industries are as follows: Mining and quarrying, paper and pulp, coke and petroleum refining, chemicals, non-metallic mineral products, basic metals and electricity and utilities. Other industrial activities are considered low-polluting industries.

The environmental survey data start in 2002, but because information from two prior years is needed to identify treated and control plants, the first treated plants are observed in 2004. The economic data is available until 2016. As changes in plant performance are analyzed from t to t+2, the last treated observations included in the analysis are from 2014. Less than half of all surveyed plants were included and responded to three consecutive surveys. The sample is further limited, as some plants have missing information for some economic variables.

Table 1 presents the summary statistics of plants that vary in their environmental investment status: plants that do not invest (control), plants that do not yet invest but that invest in the next year (treated) and plants that invest continuously and are thus not considered in the matching analysis. All financial variables are deflated to year 2010 prices.

Table 1 reveals that plants with repeated environmental investments have more employees, greater turnover, higher value added per employee, higher capital stock, report more often environmental expenses, sales and R&D and they operate more often in high-polluting industries. Moreover, plants that start investing in environmental protection in the next period are larger, have greater turnover and higher labor productivity already before they start investing in environmental protection. Thus, there is a selection process into environmental investment.

Table 2 shows the number of treated and control observations in each industry. The table shows that starting to make environmental investments is not equally common in all industries. It is more common, e.g., in pulp and paper plants and less frequent, e.g., in electronics.

4. Methods

The estimation approach combines propensity score matching and difference-in-differences methods. The used approach is similar to Gradzewicz (2021) and Gormley and Matsa (2011). The combination of these methods is used in order to control for self-selection into environmental investment and to more reliably identify the causal effect of environmental investments on the economic performance. In this approach, the performance effect is estimated by matching industrial plants that start investing in environmental protection in year t to otherwise similar plants that make no environmental investments. Matching on propensity score controls for differences in the observable pretreatment covariates, and exact matching within years removes the effect of time-variant common shocks such as business cycle fluctuations. Moreover, it is considered whether the industrial plants operate in high-polluting industry or not and matching is conducted within these broad sectors. The difference-in-differences approach further removes

[2] The control group is not restricted to plants that never report environmental investments, because this would lead to different selection criteria that would depend on how long the plant is included in the survey.

Table 1
Summary statistics.

	Not investing plants (Control)				Starters (Treatment)				Regularly investing plants (Excluded)			
	Mean	Median	SD	Obs	Mean	Median	SD	Obs	Mean	Median	SD	Obs
Turnover (Y)	89,714.680	23,881.730	599,737.800	2846	129,310.900	46,074.960	628,986.700	252	215,170.500	73,932.410	717,422.000	1898
Labor productivity (LPROD)	124.681	67.793	670.474	2714	140.481	77.217	215.761	240	175.617	102.030	522.648	1898
Employees (L)	194.921	100	357.358	2960	273.425	177.200	410.210	255	359.110	207.600	494.199	1898
Machinery and equipment (K)	15,067.360	4659.645	60,980.000	2960	36,512.520	11,551.800	77,084.790	255	66,142.760	22,219.150	125,223.900	1898
Has bought R&D	0.449	0	0.497	2960	0.475	0	0.500	255	0.512	1	0.500	1898
Export status	0.297	0	0.457	2960	0.369	0	0.483	255	0.331	0	0.471	1898
Environmental investments									616.726	14.471	2540.435	1898
Environmental expenses	33.849	0	441.133	2960	201.021	7.256	997.326	255	1116.495	48.541	4119.268	1898
Has environmental expenses	0.285	0	0.452	2960	0.588	1	0.493	255	0.734	1	0.442	1898
Environmental sales	95.592	0	880.001	2960	395.572	0	1880.783	255	577.022	0	2567.785	1898
Has environmental sales	0.230	0	0.421	2960	0.416	0	0.494	255	0.455	0	0.498	1898
Environmental R&D	21.132	0	502.025	2960	3.622	0	27.802	255	30.222	0	386.738	1898
Has environmental R&D	0.055	0	0.229	2960	0.145	0	0.353	255	0.249	0	0.432	1898
High-polluting industry	0.389	0	0.488	2960	0.471	0	0.500	255	0.623	1	0.485	1898

Notes. Financial variables deflated to year 2010 prices and expressed in thousands of Euros.

Table 2
Number of observations by industry.

Industry	Control	Treated	Total
Mining and quarrying	127	10	137
Food and beverages	186	27	213
Textile, leather and wearing apparel	117	11	128
Wood products	213	19	232
Paper and pulp	150	25	175
Petroleum and chemicals	123	17	140
Rubber and plastic	122	9	131
Non-metallic mineral products	166	24	190
Basic metals	380	27	407
Fabricated metal products	159	12	171
Electronics	585	26	611
Vehicles and transport equipment	84	8	92
Electricity and utilities	205	17	222
Other manufacturing	343	23	366
Total	2960	255	3215

the effect of time-invariant observables that might bias the results. Treatment in the model occurs when the plant invests in environmental protection for the first time or for the first time after a break. Some treatment group plants also continue to make environmental investments after their initial investment, but some do not.

The first step is to estimate a probit model that captures, how the start of environmental investments depends on the observable pre-treatment characteristics of the plant. The dependent variable D_{it} takes the value 1 when a plant i invests in environmental protection and 0 otherwise. The explanatory variables are either lagged by one year or constant over time. The probability model is represented as follows:

$$\Pr(D_{it} = 1) = \Phi\left(X_{i,t-1}\right), \tag{1}$$

where $\Phi(.)$ is the normal cumulative distribution function. $X_{i,t\text{-}1}$ denotes lagged explanatory variables: the number of employees, capital intensity, a dummy for whether a plant has bought R&D services, export market status, a dummy for reported environmental expenses, a dummy for reported environmental sales, a dummy for reported environmental R&D, and industry and year dummies. A log transformation is used for the continuous variables. It is worth noting that the probit estimations do not include pretreatment turnover or labor productivity, which are the outcome variables of interest. Using the pretreatment outcome variables in matching and then combining this approach with the differences-in-differences method could lead to biased estimates due to regression to the mean (Chabé-Ferret, 2017; Daw and Hatfield, 2018). Matching on time-variant covariates can also produce similar bias. Daw and Hatfield (2018) show that bias due to matching on time-variant covariate is minimal, when the serial correlation of the variable is very high or when the pretreatment difference between treated and control groups is small. The bias is also small when the correlation between the covariate and outcome is small. To avoid bias, the explanatory variables X are chosen accord to these conditions and covariates not meeting these conditions are not used.[3]

Based on the probit model, each plant's propensity to start making environmental investments, i.e., its propensity score (PS), is estimated.

[3] Other covariates such as the amount and intensity of past tangible investments, intermediate input use, environmental expenses, environmental sales and environmental R&D were tested. These covariates vary more over time and are correlated with the treatment and outcome variables and thus do not meet the necessary conditions. Moreover, such propensity score estimations led to larger differences in the pretreatment trends between the treated and matched control group. Nevertheless, using these covariates for matching lead to treatment effect estimates that were highly similar with respect to turnover. The labor productivity effects showed more sensitivity to the choice of covariates; however, these estimations were also more questionable due to the pretreatment trend differences.

Each treated plant is then matched with one or more control group plants with a similar PS. The matching approach rests on the assumption that selection into treatment depends only on the observable characteristics of the plant and that the important covariates are balanced after matching. I combine matching with a difference-in-differences approach, which removes any bias due to time-invariant unobservables. Thus, parallel pretreatment trends in the treated and control groups is central for the reliability of the results (Rubin, 2008). However, if there is selection on time-variant unobservables that also affects the outcome variables, the approach may lead to biased estimates of the causal effects. This assumption cannot be tested. However, the pretreatment levels and trends in the outcome variables and other covariates are investigated and robustness tests are conducted to reduce this concern.

After PS estimation, several matching methods are available. Nearest neighbor matching, radius matching and kernel matching were tested. Radius matching with a caliper of 0.01 within common support is chosen, as it performed best in terms of similarity in the pretreatment trends. A benefit of radius matching is that it uses several matches when good matches are available, which can reduce the estimates' standard errors when the number of observations is limited. Radius matching produces weights for each observation that indicate whether the observation is matched successfully and its weight in the treatment effect estimation. Appendix A reports results when other matching methods are used in the estimation.

After matching we construct a cohort of plants that start investing in environmental protection and matched control plants for each year using plant-year observations for the year of the start, two years before and two years after. The data is then pooled across cohorts. The plant does not need to have data for every year to be included in the cohort. It is also worth noting that a plant may act as a control in an earlier cohort and start environmental investments later so that it appears as a treated plant in a later cohort.

I then estimate a following generalized difference-in-differences model:

$$y_{ict} = \sum_{j\in\{-1,0,1,2\}} \beta_j D_{ic} \times \tau_j + \gamma_{tc} + \alpha_{ic} + \varepsilon_{ict} \tag{2}$$

In equation (2), y_{ict} is the outcome variable of interest, D_{ic} denotes plant i's treatment status in cohort c. τ_j denotes time period relative to the treatment. Treatment takes place in period t. The cohort data includes also data for year t-2, that is two years before the treatment. t-2 forms the base year of the estimation and therefore does not enter equation (2). The coefficients β_j provide the treatment effect estimates. β_{-1} relates to year t-1, which is the matching year. This coefficient should be close to zero if the pretreatment trends are parallel. Coefficients β_0, β_1 and β_2 provide the treatment effect estimates for the year of the treatment and two years after that.

α_{ic} denotes plant-cohort fixed effect and γ_{tc} denotes year-cohort fixed effects. Following prior literature, the fixed effects are allowed to vary by cohort (Gormley and Matsa, 2011; Gradzewicz, 2021). The matching step of the estimation is designed to remove the pretreatment differences between the treatment and control groups and exact matching within years controls for, e.g., business cycle effects. Thus, the purpose of the fixed effects is to improve the accuracy of the estimation. Moreover, fixed effect estimation appears preferable to OLS when an unbalanced panel is used in the estimation (Lechner et al., 2016).

Equation (2) does not include any other time-varying control variables, because these variables could be affected by the treatment, and including them would confound estimates of β_j. Equation (2) is estimated using the matching weights for each observation. Finally, the standard errors are clustered at plant level.

5. Empirical results

5.1. Propensity score estimation results

The results from the estimation of propensity scores are presented in Table 3. The dependent variable is a binary variable indicating, whether the plant starts investing in environmental protection. The results show that plant size in terms of employees and capital intensity are important explanatory factors for starting to make environmental investments. Export market status also explains, which plants conduct environmental investments as also indicated by earlier literature. However, R&D dummy does not predict environmental investments. However, reported environmental expenses, environmental sales and environmental R&D are associated with increased probability of environmental investments.

Next, the covariate balance tests are presented. Table 4 shows that there are large and statistically significant differences before matching but they are substantially reduced after matching and only regarding the amount of environmental expenses and sales there are notable differences left. Furthermore, the difference-in-differences approach removes any remaining time-invariant differences. The similarity of pretreatment trends is central for the validity of the difference-in-differences approach. That is, the levels of the pretreatment outcomes could vary between the treated and control groups, but they should show similar time trends before treatment. Figs. 1 and 2[4] presents the trends in the outcome variables for the treatment and control groups before and after the treatment. The graphs show similar developments in turnover and labor productivity in t-2 and t-1. Figures also gives a first impression of the treatment effects from year t onwards. These effects are further investigated in the next section.

5.2. Matching results

Table 5 presents the average treatment effect estimates based on the estimation of equation (2) using matched sample. The outcome variables are turnover and value added per employee, i.e., labor productivity. The results in Table 5 show that plants that start making environmental investments increase their turnover in comparison to control plants that have similar characteristics but whose investments do not target

Table 3
Propensity score estimation.

Ln(L)	0.189***
	(0.034)
Ln(K/L)	0.181***
	(0.042)
Has bought R&D	0.007
	(0.078)
Export status	0.461***
	(0.164)
Has environmental expenses	0.470***
	(0.075)
Has environmental sales	0.278***
	(0.085)
Has environmental R&D	0.314**
	(0.128)
Observations	3215
Pseudo R2	0.142

Notes. Probit estimation. *p < 0.1, **p < 0.05, ***p < 0.01. Standard errors are clustered at plant level. All estimations include industry and year dummies.

[4] The downward trends observable in Fig. 1 may seem surprising. However, the analyzed data are strongly influenced by the financial crisis period. Moreover, economic growth in Finland during the period analyzed was stronger in the service sector and more stagnant in the industrial sector.

Table 4
Covariate balance.

Variable	Treated	Control	p-value	Matched treated	Matched control	p-value	Bias reduction
Ln(Y)	17.368	16.543	0.000	17.265	17.218	0.782	94.3%
Ln(LPROD)	11.328	11.178	0.008	11.249	11.221	0.752	81.0%
Ln(L)	4.990	4.293	0.000	4.945	4.882	0.597	90.9%
Ln(K/L)	11.209	10.725	0.000	11.051	11.028	0.830	95.3%
Has bought R&D	0.498	0.434	0.034	0.462	0.429	0.481	48.1%
Export status	0.326	0.243	0.002	0.350	0.347	0.956	97.0%
Has environmental expenses	0.595	0.262	0.000	0.534	0.576	0.363	87.1%
Ln(Environmental expenses)	2.355	0.761	0.000	2.065	1.729	0.096	78.9%
Has environmental sales	0.412	0.205	0.000	0.404	0.392	0.806	94.5%
Ln(Environmental sales)	4.359	3.866	0.023	4.428	3.732	0.054	−41.3%
Has environmental R&D	0.134	0.050	0.000	0.121	0.078	0.129	48.9%
Ln(Environmental R&D)	0.320	0.145	0.000	0.299	0.226	0.365	48.9%

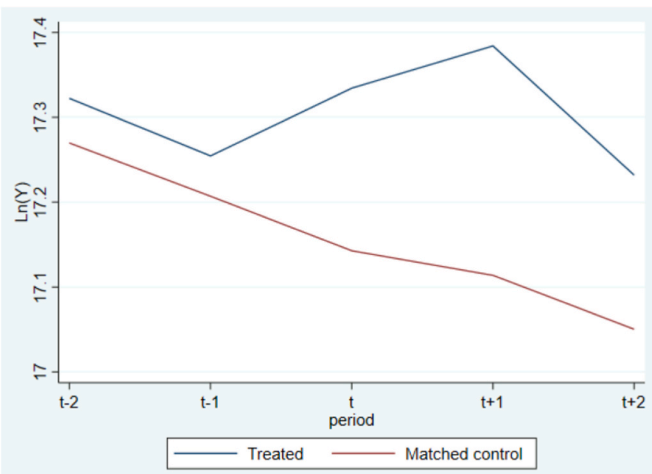

Fig. 1. Development of ln(Y) in matched treated and control groups.

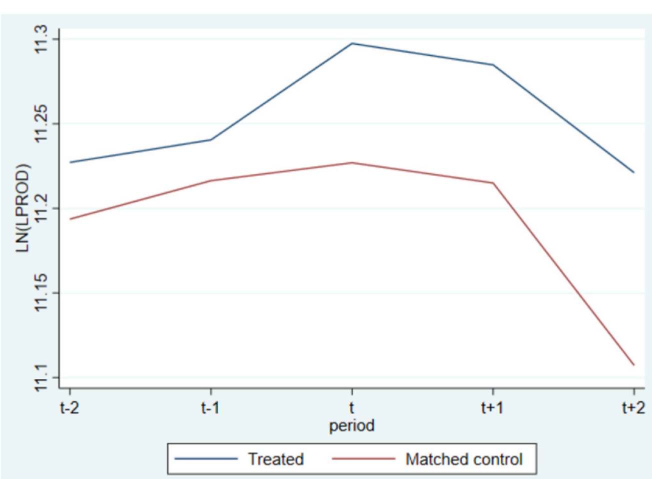

Fig. 2. Development of ln (LPROD) in matched treated and control groups.

environmental protection. The treatment effect is 0.131 for the first year. This suggests a 13% increase in turnover for the treated plants in comparison to the matched control plants. The estimate for year t+1 is 0.190 and significant, but the estimate for t+2 is not statistically significant. Overall, environmental investments appear to have an immediate effect on turnover that further increases in the next year, after which the effect partly fades. Turning to the labor productivity results, the table shows no significant change in labor productivity in the first two years, although the estimates are positive. For year t+2 after

Table 5
Matching results.

	ln(Y)	ln (LPROD)
t-1	0.010	0.009
	(0.036)	(0.058)
t	0.131**	0.069
	(0.058)	(0.052)
t+1	0.190***	0.048
	(0.069)	(0.062)
t+2	0.126	0.135**
	(0.081)	(0.061)
Observations	8590	8143
Adj. R-squared	0.034	0.045

Notes. *p < 0.1, **p < 0.05, ***p < 0.01. Standard errors are clustered at plant level. Estimations include plant-cohort and year-cohort fixed effects.

starting environmental investments, the estimate is positive and significant indicating 13.5% increase in labor productivity in comparison to the control group. Thus, environmental investments are found to be beneficial both in terms of turnover and labor productivity.

The results of Table 5 are in line with Chen and Ma (2021) but do not indicate that profitable investment are crowded out as shown by Weche (2019). As discussed in section 2, the effects of process-integrated and end-of-pipe environmental investment may differ and Weche (2019) shows that investment crowding out is especially related to the later type. In contrast to the German sample analyzed by Weche, the majority of investments analyzed in this study is process-integrated or simultaneous investments in both types. Unfortunately, a separate estimation of the effects of end-of-pipe investments is not possible due to the low number of observations.[5] Overall, the results of Table 5 should be interpreted as economic impacts of mainly process-integrated environmental investments, which according to the literature review can be more positive than the effects of end-of-pipe investments.

The causal interpretation of Table 5 relies on the assumption that selection into environmental investing is not driven by time-variant unobservables. E.g., facilities where environmental investments have higher expected benefits can be more likely to invest than other apparently similar facilities. Unfortunately, this cannot be tested. If such factors were to bias the results, the factors should be uncorrelated with the plants' past performance as well as the other observable covariates analyzed in Table 4.

5.3. *Heterogeneity of results*

As discussed in sections 1 and 2, the benefits of environmental

[5] Pre-treatment trend and covariate similarity are not achieved making the estimation unreliable. However, excluding end-of-pipe investments from the baseline estimation is observed to have only limited impact on the results of Table 5.

investment may depend on whether the industrial plants possess complementary assets such as environmental management practices or R&D. Information on plant level management practices is unavailable, but the information on environmental R&D investments allows testing for complementarity between tangible environmental investments and environmental R&D. Thus, the treated plants are divided into two groups based on whether the plant also invests in environmental R&D in period t. The control group includes both plants with R&D and those without.[6] The separate analyses for these two groups are presented in Table 6.

As shown in Table 6, industrial plants that conduct environmental investments and invest in environmental R&D experience strong increase in their turnover and labor productivity in comparison to control plants. The treatment effects are twice as high as in Table 5 and they are statistically significant in every year for both turnover and productivity. The effects on turnover and labor productivity are also positive in the investing plants that do not invest environmental R&D; however, the effects are considerably lower and only marginally significant. Thus, the results indicate that there is a complementarity between tangible environmental investments and environmental R&D, which is in line with the Porter hypothesis and earlier studies.

Furthermore, the economic gains of environmental investments may differ by industry and, thus, separate analyses are conducted for low-polluting and high-polluting industry groups. The results of Table 7 indicate that there are statistically significant results only in the low-polluting industries, where there is an increase both in turnover and labor productivity. In high-polluting industries, none of the effects are statistically significant, although most estimates have similar magnitude. The number of observations is lower in high-polluting industry, which may explain why the estimates are not statistically significant. Thus, we cannot make clear conclusions about differences between sectors.

5.4. Further economic outcomes

Next, the channels behind the labor productivity effect are investigated in more detail and the changes in total value added, intermediate costs and employment are analyzed. The matching results for these outcomes are presented in Table 8. The results indicate a significant increase in total value added, but no significant change in intermediate costs or employment, although the estimates are positive for employment. Moreover, when alternative matching methods and different sample restrictions were used, the treatment effect estimates for employment received also positive and significant values (results not reported). Thus, the increase in turnover is not associated with increase in intermediate input use but may be reflected in employment. This is also reflected as an increase in the value added and a somewhat weaker improvement labor productivity.

The results of Tables 5 and 8 indicate that the improvement in sales is the main channel of economic gains. However, efficiency gains also appear to be reached, when the labor productivity improves as the costs of production do not increase. Furthermore, Table 6 indicates that the largest sales improvements are achieved, when environmental investments are complemented with environmental R&D investments.

Table 6
Complementarity between environmental investments and environmental R&D.

	Ln(Y)		Ln (LPROD)	
	R&D	No R&D	R&D	No R&D
t-1	−0.019	0.022	0.018	0.004
	(0.087)	(0.036)	(0.135)	(0.059)
t	0.298**	0.085	0.272**	0.008
	(0.139)	(0.058)	(0.122)	(0.051)
t+1	0.368***	0.135*	0.269***	−0.034
	(0.152)	(0.071)	(0.117)	(0.066)
t+2	0.380***	0.048	0.246*	0.107*
	(0.173)	(0.085)	(0.128)	(0.063)
Observations	7771	8330	7359	7890
Adj. R-squared	0.062	0.054	0.047	0.058

Notes. *p < 0.1, **p < 0.05, ***p < 0.01. Standard errors clustered at plant level. Estimations include plant-cohort and year-cohort fixed effects.

Table 7
Matching results for low-polluting and high-polluting industries.

	Ln(Y)		Ln (LPROD)	
	Low-polluting industries	High-polluting industries	Low-polluting industries	High-polluting industries
t-1	0.048	−0.038	−0.030	0.059
	(0.041)	(0.061)	(0.080)	(0.084)
t	0.123*	0.140	0.090	0.048
	(0.074)	(0.090)	(0.070)	(0.077)
t+1	0.230**	0.141	0.060	0.052
	(0.093)	(0.100)	(0.091)	(0.080)
t+2	0.133	0.122	0.149*	0.122
	(0.108)	(0.124)	(0.079)	(0.093)
Observations	5581	3009	5322	2821
Adj. R-squared	0.056	0.029	0.064	0.024

Notes. *p < 0.1, **p < 0.05, ***p < 0.01. Standard errors clustered at plant level. Estimations include plant-cohort and year-cohort fixed effects.

Table 8
Matching results for alternative economic outcomes.

	Ln (Value added)	Ln (Intermediate costs)	Ln(L)
t-1	0.018	−0.010	0.012
	(0.056)	(0.027)	(0.012)
t	0.092*	−0.009	0.030
	(0.054)	(0.031)	(0.020)
t+1	0.059	0.035	0.018
	(0.062)	(0.033)	(0.025)
t+2	0.142**	−0.010	0.007
	(0.065)	(0.051)	(0.032)
Observations	8217	8911	8885
Adj. R-squared	0.058	0.054	0.100

Notes. *p < 0.1, **p < 0.05, ***p < 0.01. Standard errors clustered at plant level. Estimations include plant-cohort and year-cohort fixed effects.

5.5. Robustness tests

Various tests are conducted to analyze the robustness of baseline results. The results from these robustness tests are presented in Appendices A and B and summarized here. In Appendix A, 1) other matching methods besides the baseline radius matching are used, 2) the robustness of results to different sample restrictions is tested and, finally, 3) a placebo test is conducted. Overall, the turnover results remain robust to different matching methods and sample restrictions. The labor productivity results show more heterogeneity both with respect to the matching method and sample restriction. The labor productivity estimates remain, nevertheless, positive, but in many cases statistically insignificant. However, the results regarding the complementarity of environmental R&D remain robust for both variables, when alternative matching methods or different sample restrictions are used (not reported in Appendix). Finally, the placebo treatment has insignificant effect in all estimations, which lends support to the validity of the estimations.

[6] If the control group is restricted to plants with identical environmental R&D status, the results are very similar. This is expected, because the propensity score matching already considers the environmental R&D investment status.

The novelty of this study is to use matching and difference-in-differences methods to estimate the effect of environmental investments. I also estimated panel fixed effect models used in many prior studies. These results are presented and discussed in Appendix B. Overall, the panel results show considerable heterogeneity depending on the industry and handling of time lags. This finding aligns with the mixed results reported in the prior literature.

6. Conclusions

This study investigates how the economic performance of industrial plants changes, when they start investing in environmental protection. The study applies a novel method of propensity score matching and difference-in-differences estimation on matched sample to address the limitations of the prior research that has typically relied on standard panel methods. The analysis shows that plants with and without environmental investments differ and that plants with environmental investments exhibit significantly better economic performance across many metrics. This finding is in accordance with the prior literature that has found a positive correlation between environmental and economic performance.

Moreover, the matching analysis reveals that industrial plants that start investing in environmental protection increase their turnover in comparison to control plants that have similar characteristics and economic performance in the prior years. Thus, not only are environmental and economic performance correlated, but environmental investments also have a robust positive impact on turnover. In addition, labor productivity of plants also improves, although the magnitude and significance of the improvement are more sensitive to methodological choices. Furthermore, the results indicate that the economic gains appear especially strong when industrial plants complement environmental investments with environmental R&D investments. Thus, the complementarity of environmental protection and R&D investments is confirmed among the Finnish industrial plants.

It is worth noting that the stringency of environmental policy is considerably high in Finland, which could suggest that easy economic gains by improving environmental performance might already have been exhausted. Nevertheless, environmental investments lead to economic benefits. While this suggests that industrial plants should conduct environmental investments for purely economic grounds, further environmental policies can provide additional signal of growth potential and resource use inefficiencies. This could encourage more environmental investments with both environmental and economic benefits. This applies especially to smaller industrial actors, who normally do not or only rarely invest in environmental protection. Regularly investing plants were not analyzed in this study and thus the benefits of environmental investments and related policies cannot be evaluated based on the present study.

Different institutional, regulatory and other country-specific factors could influence the connection between environmental investments and subsequent economic performance. Nevertheless, a previous meta-analysis on the link between environmental performance in general and economic performance did not find systematic differences due to geography (Hang et al., 2019). The overall level of environmental policy stringency in Finland is also comparable to many European countries (OECD, 2022). However, there may be other country-specific factors that cause differences in the composition of environmental investments and related economic benefits. The majority of investments in the analyzed sample are process-integrated investments, whereas Weche (2019) reports an opposite situation in Germany. While Frondel et al. (2007) suggest that Germany may be an exception and process-integrated investments are generally more common, it should be kept in mind that the results of this study may not properly reflect the impacts of end-of-pipe investments, which may be important in some countries. With this caveat, the above facts nevertheless imply that the findings of this study are not limited only to the Finnish context.

However, some other limitations of the analysis should be stated. While matching and difference-in-differences address several problems present in standard panel analysis, the approach may still be biased due to selection on unobservables, which cannot be tested. Another limitation is that the data include only investments in Finland. It could be argued that the firms that would be most negatively affected by environmental regulation and whose economic performance would suffer most greatly from mandatory environmental investments would choose to invest in other locations and, thus, such facilities are missing from the data altogether. Finally, the analyzed Finnish industrial facilities are subject to the same laws and regulations. Thus, the effects identified here cannot be interpreted as the effects of regulation, but instead, the effects should be interpreted as reflecting voluntary environmental investments or plant's choices regarding how to respond to regulation.

Credit author statement

Jaana Rahko: Conceptualization; Data curation; Methodology; Formal analysis; Writing, Writing – original draft, Writing – review & editing

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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Appendix A

Various robustness tests for the baseline estimates were conducted. The results from robustness tests are presented in Tables A.1-A.3.

First, alternatives to the baseline radius matching are tested. Table A.1 presents results for radius matching with calipers 0.005 and 0.02, nearest neighbor matching and kernel matching. Kernel matching is done with epanechnikov kernel and bandwidth 0.06. The results with respect to turnover are robust or even stronger when using the alternative matching methods; however, the results for labor productivity depend on the choice of method and caliper 0.02 and nearest neighbor matching do not yield statistically significant estimates. Caliper 0.005 and kernel matching show an increase in labor productivity in period t+2 similar to Table 5 and kernel results also show a significant effect in period t. The magnitude of the estimates remains similar in all estimations except for labor productivity estimates using nearest neighbor matching, which are clearly lower.

Table A.1
Alternative matching methods

	Ln(Y)				Ln (LPROD)			
	r = 0.005	r = 0.02	nn	kernel	r = 0.005	r = 0.02	Nn	kernel
t-1	0.014	0.009	0.011	0.016	−0.007	0.024	−0.035	0.028
	(0.040)	(0.033)	(0.035)	(0.028)	(0.065)	(0.053)	(0.066)	(0.052)
t	0.163**	0.136**	0.126**	0.156***	0.054	0.085	0.038	0.110**
	(0.064)	(0.060)	(0.060)	(0.059)	(0.059)	(0.053)	(0.065)	(0.050)
t+1	0.223***	0.198***	0.192***	0.232***	0.046	0.038	−0.026	0.077
	(0.075)	(0.075)	(0.073)	(0.073)	(0.071)	(0.059)	(0.073)	(0.054)
t+2	0.131	0.154*	0.151*	0.191**	0.123*	0.095	0.030	0.095*
	(0.088)	(0.087)	(0.083)	(0.082)	(0.070)	(0.058)	(0.077)	(0.056)
Observations	5645	11,911	2265	14,735	5355	11,262	2158	13,931
Adj. R-squared	0.037	0.031	0.031	0.036	0.048	0.037	0.036	0.036

Notes. *p < 0.1, **p < 0.05, ***p < 0.01. Standard errors clustered at plant level. Estimations include plant-cohort and year-cohort fixed effects.

The second robustness test relates to the sample restriction. The baseline estimates limit the estimation sample to industrial plants that reported zero environmental investments in t-2 and t-1. However, some sample plants may have reported positive investments before that. Furthermore, plants that report zero investments also often have gap years with missing reports, and it appears likely that they did not invest in those years either. Next, I test the robustness of results to different sample restrictions. First, I use the same two-year period as in baseline but interpret also missing environmental investments in t-2 as zeros. Then, I extend the period to three years and redo the analysis both by interpreting missing investments in t-3 as zeros and by excluding plants with missing investment figures. Finally, I extend the period to four years and repeat the estimations.

The results in Table A.2 show that the different sample restrictions do not drive the turnover effects. With four-year period, the sample size is much smaller and the results are no longer significant; however, the coefficients for t and t+1 remain in line with the other columns. Results with respect to labor productivity show more heterogeneity as in Table A.1 as well. With three-year period that includes missing investments in t-3, there is a positive and significant effect in period t. Otherwise, the labor productivity effect estimates are positive but not statistically significant. Thus, we may conclude that the positive effects on turnover are robust to the choice of matching method and sample restrictions, but the results with respect to labor productivity show sensitivity to the choice of methods and sample restrictions.

Table A.2
Alternative sample restrictions

	Ln(Y)					Ln (LPROD)				
	2 years incl. missing	3 year, incl. missing	3 years excl. missing	4 years incl. missing	4 years excl. missing	2 years incl. missing	3 years incl. missing	3 years excl. missing	4 years incl. missing	4 years excl. missing
t-1	0.004	0.039	0.013	−0.015	−0.07	−0.024	0.045	0.068	−0.013	0.044
	(0.033)	(0.035)	(0.039)	(0.046)	(0.048)	(0.051)	(0.064)	(0.061)	(0.071)	(0.081)
t	0.164**	0.114**	0.142*	0.081	0.112	0.089	0.124**	0.020	0.033	0.087
	(0.071)	(0.054)	(0.084)	(0.087)	(0.140)	(0.058)	(0.056)	(0.064)	(0.080)	(0.100)
t+1	0.250***	0.167***	0.274**	0.153	0.226	0.031	0.080	0.002	0.035	0.099
	(0.091)	(0.063)	(0.127)	(0.109)	(0.196)	(0.058)	(0.067)	(0.070)	(0.085)	(0.112)
t+2	0.167**	0.082	0.141	0.005	0.022	0.036	0.089	0.005	0.057	0.192
	(0.074)	(0.081)	(0.142)	(0.126)	(0.123)	(0.061)	(0.071)	(0.082)	(0.126)	(0.138)
Observations	12,763	6631	4496	4075	2873	12,086	6289	4246	3841	2716
Adj. R-squared	0.035	0.064	0.066	0.052	0.059	0.024	0.047	0.046	0.047	0.042

Notes. *p < 0.1, **p < 0.05, ***p < 0.01. Standard errors clustered at plant level. Estimations include plant-cohort and year-cohort fixed effects.

The final method used to test the robustness of results is a placebo test. I do this by falsely assuming that the treatment took place in t-1 and matching treated and control plants using t-2 data.[7] I then estimate difference-in-differences equation that compares the development of outcome variables from t-3 to t-1. The placebo treatment in t-1 has insignificant effect in both estimations of Table A.3, which lends support to the validity of the estimations.

Table A.3
Plasebo test

	Ln(Y)	ln (LPROD)
t-2	−0.046	0.026
	(0.049)	(0.055)
t-1	−0.025	0.035
	(0.064)	(0.066)
Observations	4565	4343
Adj. R-squared	0.015	0.013

Notes. *p < 0.1, **p < 0.05, ***p < 0.01. Standard errors clustered at plant level. Estimations include plant-cohort and year-cohort fixed effects.

[7] Conducting the matching on t-2 data and re-estimating equation (2) produces similar results as the baseline estimates in Table 5 but weaker similarity in the pretreatment trends.

Appendix B

Most prior studies analyzing environmental investments rely on panel regression models. To compare how the choice of estimation method influences the results, simple fixed effect models are estimated and presented in Tables B.1 and B.2. Following prior studies, these regressions include also plants with regular investments in environmental protection and consider both whether plant invests in environmental protection and the intensity of these investments, i.e., Ln ((Environmental investments+1)/L).

Using fixed effect regression and current environmental investments, the results in Table B.1 show that overall environmental investments do not have a significant effect on turnover or labor productivity. However, analyzing low-polluting and high-polluting industries separately reveals significant results and differences. Plants with environmental investments have a higher turnover in low-polluting industries but not otherwise. The intensity of investments has no effect on turnover. In contrast, in high-polluting industries plants with environmental investments have higher labor productivity, but the intensity of investments has no impact on productivity.

In Table B.2, I consider whether plants have environmental investments in the current and two past years and the average amount of these investments. This changes the results and reveals that the average intensity of environmental investments has a negative effect on turnover in high-polluting industries. In low-polluting industries the estimate is positive but not significant. Regarding labor productivity, the results again reveal that having environmental investments is correlated with higher productivity overall and especially in high-polluting industries. The results for low-polluting industries are positive but not significant.

Overall, Tables B.1 and B.2 show that standard panel methods can produce positive, insignificant or negative economic performance effects depending on the choice of industry and the time lags considered. These findings align with the mixed evidence provided by the prior studies as discussed in Section 2.

Table B.1
Fixed effect panel estimation with current environmental investments

	Ln(Y)			Ln (LPROD)		
	Overall	Low-polluting industries	High-polluting industries	Overall	Low-polluting industries	High-polluting industries
Has env. investment	0.020	0.058*	0.008	0.035	0.012	0.070*
	(0.026)	(0.033)	(0.040)	(0.028)	(0.041)	(0.038)
Ln((Env. investment+1)/L)	−0.004	0.014	−0.019	0.008	0.006	0.002
	(0.008)	(0.011)	(0.012)	(0.009)	(0.012)	(0.014)
Ln(L)	0.761***	0.779***	0.728***	−0.239***	−0.211***	−0.292***
	(0.094)	(0.065)	(0.160)	(0.079)	(0.079)	(0.111)
Ln(K/L)	0.084	0.040	0.120	0.023	−0.055	0.092
	(0.064)	(0.057)	(0.101)	(0.048)	(0.056)	(0.064)
Observations	8086	5053	3033	7779	4861	2918
Adj. R-squared	0.163	0.17	0.167	0.034	0.022	0.068

Notes. Fixed effect panel estimation. *p < 0.1, **p < 0.05, ***p < 0.01. Standard errors clustered at plant level. Estimations include plant and year fixed effects.

Table B.2
Fixed effect panel estimation with three year average environmental investments

	Ln(Y)			Ln (LPROD)		
	Overall	Low-polluting industries	High-polluting industries	Overall	Low-polluting industries	High-polluting industries
Has env. investments	0.035	0.049	−0.017	0.058*	0.033	0.105*
	(0.028)	(0.041)	(0.035)	(0.030)	(0.039)	(0.059)
Ln((Avg. env. investments+1)/L)	−0.243***	0.567	−0.256***	−0.063	0.667	−0.107
	(0.047)	(0.414)	(0.070)	(0.145)	(0.826)	(0.146)
Ln(L)	0.734***	0.760***	0.713***	−0.221***	−0.165	−0.275**
	(0.094)	(0.069)	(0.167)	(0.082)	(0.134)	(0.108)
Ln(K/L)	0.066	0.005	0.121	0.031	−0.015	0.090*
	(0.064)	(0.078)	(0.090)	(0.049)	(0.100)	(0.047)
Observations	4689	2705	1984	4506	2601	1905
Adj. R-squared	0.161	0.164	0.177	0.032	0.022	0.068

Notes. Fixed effect panel estimation. *p < 0.1, **p < 0.05, ***p < 0.01. Standard errors clustered at plant level. Estimations include plant and year fixed effects.

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