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Can Environmental Policy Encourage Technical Change? Emissions Taxes and R&D Investment in Polluting Firms

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Higher country taxes on noxious manufacturing emissions lead to substantial increases in firms' R&D spending. The R&D response is entirely driven by those high-pollution firms most affected by emissions taxes. Pollution taxes increase the marginal value of R&D spending in polluting firms, even when this spending does not lead to new innovation. Pollution taxes have the strongest effect on R&D investment in sectors in which new invention is difficult to appropriate and outside knowledge is easier to acquire, suggesting an important reason dirty firms invest in R&D is to expand their capacity to absorb external knowledge and technical know-how. (*JEL* G31, O13, O33, Q53)

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Policies that encourage firms to shift to cleaner production technologies have the potential to mitigate climate change risks and other environmental concerns without significantly slowing long-run economic growth (e.g., Acemoglu et al. 2012). This potentiality has motivated a prominent literature to study how

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environmental policy affects the development of new "clean" products and technologies (e.g., Aghion et al. 2016). But environmental policy can influence the path of technical change through another, less studied, mechanism: inducing polluting firms to make the new technology investments that enable them to fundamentally transform their production processes.[1] Although several studies highlight the key role technology spending plays in firms' efforts to re-engineer production and reduce pollution at the source (e.g., Hammar and Löfgren 2010; Xie et al. 2015), there is little systematic evidence that environmental policy can encourage polluting firms to make these investments.

We fill this gap in the literature by studying how country-level taxes on dirty manufacturing emissions affect technology spending in high-pollution firms. Our main idea is that emissions taxes make it more expensive for polluting firms to continuing using their existing production technologies. The taxes thus incentivize polluting firms to make the investments that allow them to adopt and implement cleaner production processes. In this sense, the technology investments that facilitate the transition to cleaner production have a higher marginal payoff to polluting firms when countries impose taxes on dirty emissions. The prediction of a tax-induced investment response follows directly from the theoretical literature on directed technical change: because of path dependence in technical change, policy action is needed to encourage dirty firms to invest in new technologies (e.g., Acemoglu et al. 2016).

To test this idea, we estimate how cross-country differences in taxes on sulfur oxide (SO_x) emissions affect firm investment in research and development (R&D). We focus on SO_x taxes because, in addition to SO_x being a major air pollutant, the country-level variation in SO_x taxes over time is considerable. In addition, we have sufficiently disaggregated information on SO_x emissions at the industry level, which we use to sort firms based on how heavily "treated" they are by higher pollution taxes. We focus on R&D spending because R&D is the only widely available and internationally comparable measure of technology investment that we know of. Beyond this practical consideration, extensive evidence shows that R&D plays a central role in facilitating firm efforts to overhaul production processes and reduce environmental impact (e.g., Hammar and Löfgren 2010). In particular, firms invest in R&D as a means to expand their capacity to use and absorb external knowledge about cleaner production techniques (e.g., Xie et al. 2015). Thus, R&D spending captures technology investments that determine both the speed and the path of technical change (e.g., Aghion and Howitt 1992; Acemoglu et al. 2016).

We merge OECD data on SO_x taxes by country and year with information on firm-level R&D investment from the Compustat Global and North America

[1] Studies in the environmental studies field show that dirty firms are able to lessen their environmental impact primarily through broad, integrated changes to the production process itself. In practice, these changes typically mean firms adopt production processes that rely on cleaner raw materials and/or use existing inputs more efficiently. See, for example, the evidence and discussions in Frondel, Horbach, and Rennings (2007) and Johnstone (2005).

databases. To measure cross-industry differences in pollution intensity, we use data from Levinson (2009) on SO_x emissions in U.S. manufacturing industries. We document a strong positive link between taxes on SO_x emissions and firm investment in R&D. The positive association between SO_x taxes and R&D only appears after taxes increase, a test that Bertrand and Mullainathan (2003) emphasize as crucial for establishing the causal effects of policy changes. In addition, the effects of higher SO_x taxes are concentrated in firms located in more pollution-intensive industries. These *differential* effects indicate causality because firms in pollution-intensive industries are more exposed to (or treated by) the higher pollution taxes (e.g., Rajan and Zingales 1998). We find similar differential effects when we study how R&D spending affects the market value of the company's equity; these tests show that a marginal dollar of R&D is more valuable when polluting firms face higher emissions taxes. As far as we know, this is the first study to show that country-level taxes on dirty emissions affect the level and value of new technology investment in polluting firms.

To better understand the R&D response we identify in polluting firms, we explore the "two faces" of R&D spending: firms invest in R&D not only to develop new products and innovations (the "first face" of R&D) but also to expand their capacity to understand and assimilate the external knowledge and technical know-how needed to fundamentally transform the way they produce (Cohen and Levinthal 1989, 1990).[2] Broadly, the first face of R&D corresponds more closely to studies on the development of clean products and technologies (e.g., Aghion et al. 2016), whereas the second face of R&D relates to the literature on re-engineering production and adopting cleaner production processes (e.g., Hammar and Löfgren 2010; Xie et al. 2015).[3]

For these tests, we use information from the European Patent Office's Worldwide Patent Statistical Database (PATSTAT). PATSTAT contains detailed bibliographic information on the vast majority of worldwide patents filed since the 1960s. We evaluate the new invention face of R&D by studying whether it is associated with more patentable innovative output. We find no relation between higher pollution taxes and patenting activity in all technology classes; however, pollution taxes are positively related to new patents in air pollution abatement technologies. Thus, higher pollution taxes appear to encourage the development of clean technologies, broadly consistent with the evidence in prior studies linking environmental policy with new invention (e.g., Lanjouw and Mody 1996; Popp 2002; Aghion et al. 2016). However, in sharp contrast

[2] An important literature emphasizes R&D's role in facilitating the acquisition of external knowledge and expanding the firm's technological absorptive capacity. See, for example, Jaffe (1986), Cohen and Levinthal (1989, 1990), Geroski, Machin, and Van Reenen (1993), Zahra and George (2002), and Griffith, Redding, and Van Reenen (2003, 2004).

[3] Of course, the two faces of R&D are not mutually exclusive: a given firm can invest in R&D to invent new technologies and to increase its technological absorptive capacity. As such, distinguishing between the two faces of R&D, particularly in firms actively engaged in new product innovation, can be challenging to do. Our tests exploit the idea that the second face of R&D is less likely to show up in patent-based measures of innovative output and more likely to appear when there is more external knowledge for firms to acquire.

to R&D, we find no evidence that the high-pollution firms most affected by the higher emissions taxes drive the increase in clean patenting. Thus, the typical high-pollution firm responds to pollution taxes by increasing R&D, but not new invention.[4]

Why then do polluting firms increase R&D? A plausible answer is that they invest in R&D to expand their technological absorptive capacity. We know of no proxy that directly measures output from the "second face" of R&D. We thus derive a series of cross-sectional tests to evaluate this mechanism. To start, we sort firms based on two ex ante proxies for the likelihood that any given dollar of R&D spending represents new product innovation. The R&D response to higher pollution taxes is concentrated in firms from sectors with *low* levels of new product innovation and in sectors in which R&D spending is more focused on *process* innovation rather than new product development. At a minimum, these findings are consistent with the idea that a key reason polluting firms invest in R&D is to expand absorptive capacity rather than to develop new patentable innovations.

We construct more direct heterogeneity tests from the model in Cohen and Levinthal (1989), which makes clear predictions about the conditions under which it is optimal for firms to invest in R&D for absorptive capacity reasons. Most importantly, in settings in which new knowledge is difficult to appropriate and, as such, more readily spills across firms, firms have *more* incentive to invest in R&D to expand absorptive capacity but *less* incentive to invest in R&D for new invention. This insight suggests that to the extent the R&D response in polluting firms reflects investment in absorptive capacity rather than new invention, the R&D response should be relatively stronger among firms operating in sectors where external knowledge is easier to acquire. On the other hand, if the R&D response is about new invention, the effects should be relatively stronger in settings in which new knowledge is easier to appropriate.

We find that polluting firms operating in sectors with low appropriability (high knowledge spillovers) account for essentially *all* of the R&D response we document. Moreover, higher pollution taxes are associated with an increase in the marginal value of R&D investment in the subsets of firms where R&D is most closely tied to absorptive capacity rather than new invention. Thus, it is not the case that polluting firms are simply poor innovators who are unable to convert the higher R&D into new patentable output.

Our research contributes to the empirical literature on how innovative activity responds to environmental policies and regulations. Two of the pioneering studies in this area are Jaffe and Palmer (1997), who find a positive association between environmental compliance expenditures and

4 Among the small group of high-pollution firms *with a prior history of new invention in clean technology*, there is a positive association between emissions taxes and patents related specifically to pollution abatement technologies. This is a plausible subset of polluting firms in which to find evidence of a "first face" R&D response (e.g., Aghion et al. 2016).

R&D in U.S. manufacturing industries, and Lanjouw and Mody (1996), who document a positive cross-country relation between environmental regulations and environmental patents. The evidence from this early work is consistent with the idea that more stringent environmental regulations can encourage innovation, although the nature of the data and aggregate level of analysis makes it challenging to draw any definitive conclusions, a point Jaffe and Palmer (1997) emphasize. Moreover, as Jaffe, Newell, and Stavins (2002) discuss, market-based environmental policies (such as pollution taxes) may provide stronger incentives for firms to implement cheaper and more efficient production technologies compared to the command and control approaches (such as environmental compliance regulation) that have been studied in prior work. Our evidence linking SO_x taxes with R&D in high-pollution firms is consistent with this idea.

Our study complements Aghion et al. (2016), who show that higher tax-inclusive fuel prices lead to clean energy patenting in the auto industry.[5] Whereas Aghion et al. (2016) find that price changes affecting the (dirty) products an industry produces lead to new product innovations in the sector, we find that higher taxes on dirty production technologies lead to systematic increases in firm-level R&D, even among the high-pollution firms who are not actively engaged in new product innovation. These are distinct mechanisms through which environmental policies can influence the direction of technical change.

Our findings are also relevant for evaluating and modeling the macroeconomic consequences of environmental policies (e.g., Jaffe, Peterson, and Stavins 1995; Porter and van der Linde 1995; Calel and Dechezleprêtre 2016). On the one hand, we show that taxing environmental pollutants can affect firm-level investment in new technology, which is broadly consistent with a key theoretical mechanism in the modern literature on endogenous growth under environmental constraints (e.g., Acemoglu et al. 2012, 2016). But we also emphasize the distinction between technology investments that stimulate new invention and those that allow even less innovative firms to expand their capacity to assimilate new knowledge and re-engineer production. In particular, just as ignoring R&D's role in promoting absorptive capacity can substantially understate the social returns to R&D (e.g., Griffith, Redding, and Van Reenen 2003, 2004), our results show that some key technology investments are missed if one only considers how environmental policy affects the development of (patentable) clean products and pollution abatement technologies.

More broadly, our work draws attention to the "second face" of R&D spending and illustrates why it is not always appropriate or desirable to use

5 A related literature shows that higher energy prices induce the development of energy-efficient technologies (e.g., Aghion et al. 2016; Hassler, Krusell, and Olovsson 2021; Johnstone, Hascic, and Popp 2010; Newell, Jaffe, and Stavins 1999; Jaffe and Stavins 1995; Popp 2002).

R&D and patents as substitute measures of innovative activity. This point is especially relevant given the ever-expanding literature at the intersection of finance and innovation, which often uses R&D and patenting interchangeably (e.g., Hsu, Tian, and Xu 2014; Brown and Martinsson 2019; Atanassov and Liu 2020). Our work highlights a setting where R&D investments are value enhancing, even when they do not lead to new patents.

Finally, our work is part of an emerging literature on the linkages between finance and the environment. One strand of this literature focuses on the impact of climate change and other environmental issues on firms and financial markets (e.g., Dimson, Karakaş, and Li 2015; Hong, Li, and Xu 2019; Bansal, Kiku, and Ochoa 2016; Bernstein, Gustafson, and Lewis 2019; Krueger, Sautner, and Starks 2020; Bolton and Kacperczyk 2021; Ilhan, Sautner, and Vilkov 2021; Hsu, Li, and Tsou 2021), while a separate strand focuses on the legal, institutional, and financial determinants of environmentally friendly (or costly) behaviors (e.g., De Haas and Popov 2019; Levine et al. 2019; Shive and Forster 2020; Akey and Appel 2021; Xu and Kim 2021). Our paper adds to the latter set of studies by linking environmental taxes with the real investment decisions that determine the path of technical change.

1. Data, Measurement, and Sample Characteristics

1.1 Sample construction

We build our firm-level sample from the Compustat Global and North America databases. We focus on non-U.S. firms with fully consolidated financial statements and a primary industry classification in the manufacturing sector (SIC 2000–3999).[6] To identify a within-firm response to pollution taxes we need a sample of firms that at least semiregularly reports R&D spending, so we exclude firms with fewer than three nonmissing R&D observations over the period 1990 to 2012. Our findings are similar if we set all missing R&D values to zero. We require countries to have at least 10 firms with usable R&D data because we need within-country, across-industry coverage of R&D spending for the empirical tests.

We merge the firm-level data from Compustat with information on air pollution taxes for 18 OECD countries. We collect information on the level of taxes and charges directly applied to the emission of sulfur oxides (SO_x) by the manufacturing sector from two OECD sources: the Environmental Stringency Index data set, and the Policy Instruments for the Environment (PINE) Database (see Botta and Kozluk 2014). The OECD data provides a categorical "score"

[6] We focus on firms outside of the United States for two primary reasons. First, we use information from U.S. firms to measure cross-industry differences in pollution intensity (e.g., Rajan and Zingales 1998). Second, as Shapiro and Walker (2018) discuss, the United States does not have a national pollution tax. The United States levies various taxes and enforces regulations on pollution at the local or regional level; however, neither would broadly apply to all (or most) publicly listed manufacturing firms.

for each country-year based on the presence and extent of SO_x emissions taxes. The resultant pollution tax variable (*Pollution taxes*) ranges from 0 to 6, with 0 indicating no pollution tax and larger values indicating higher taxes on SO_x emissions. By construction, the categorical scores are comparable across countries and over time.

A potential concern with the OECD data is whether the tax applies to a sufficiently large fraction of manufacturing firms in the country. We thus check the underlying data in the PINE database to ensure that the taxes on SO_x emissions are either levied at the national level (as in Denmark, France, Italy, and Korea) or affect a significant portion of the country (as in Australia, Canada, Spain, and Japan). If the tax only affects a small fraction of the country (which would be the case in the United States), we assume the national tax level is zero.

We also match the Compustat firms from countries with pollution tax data with patenting metrics from the Worldwide Patent Statistical Database (PATSTAT). PATSTAT is a comprehensive database on global patenting activity maintained by the European Patent Office (EPO). This database has over 100 million patent documents, covering essentially the universe of worldwide patents since the 1960s. Our matching process, which we describe in detail in Appendix B, follows the approach that Hall, Jaffe, and Trajtenberg (2001) use to map patents filed at the United States Patent and Trademark Office to U.S. firms in the Compustat North America database (also see Bena et al. 2017). Briefly, we search the PATSTAT database for matches to the company names in Compustat, then work with unique company identifiers in PATSTAT to find firm-specific information on patent counts and citations. Following Aghion et al. (2016), we focus on new triadic patents, which are patents simultaneously registered at the European, Japanese, and U.S. patent offices for the same invention by the same applicant. To measure the number of new triadic patents a given firm generates in a given year, we use the application date on ultimately granted patents. Our findings are similar if we use future citations to all patents a firm generates in a given year or citation-adjusted patent counts (e.g., Trajtenberg 1990) as alternative ways to measure new invention.

After merging data from these various sources, we work with a primary sample of around 33,500 firm-years across 18 countries over the period 1990 to 2012. Table A1 reports observation counts across the countries in the sample. Japan accounts for the most observations (by far), followed by the United Kingdom and Canada. As we will discuss below, all of our main findings are robust to excluding the most influential countries.

Finally, for some tests we incorporate daily market price data from the Compustat Global *Security Daily* file. We describe the *Security Daily* file and the matching process with our main sample in Appendix C. Table 1 defines all the variables we use in the study, and Table 2 reports the sample's summary statistics (in constant US$(2000)). Table A2 contains a correlation matrix for the main firm-level variables we use in the study.

Table 1
Description of variables

Variable name	Definition	Source
$R\&D_{i,t}$	The natural logarithm of firm-level research and development (R&D) expenditures (deflated to US$(2000) millions and winsorized at the 1% level)	Compustat Global and North America
$Sales_{i,t}$	The natural logarithm of firm level sales (deflated to US$(2000) millions and winsorized at the 1% level)	Compustat Global and North America
Cash-flow-to-assets$_{i,t}$	Cash flow divided by the beginning of year book value of total assets (winsorized at the 1% level)	Compustat Global and North America
Sales growth$_{i,t}$	First difference in Sales (winsorized at the 1% level)	Compustat Global and North America
Cash holdings-to-assets$_{i,t}$	Cash holdings divided by the beginning of year book value of total assets (winsorized at the 1% level)	Compustat Global and North America
Total debt-to-assets$_{i,t}$	Total debt divided by the book value of total assets (winsorized at the 1% level)	Compustat Global and North America
$IFRS_{i,t}$	An indicator variable taking on the value one if the firm reports using International Financial Reporting Standards (IFRS) in a given year, zero otherwise	Compustat Global and North America
Patent count$_{i,t}$	The natural logarithm of one plus the firm level count of triadic patents that are eventually granted; dated by application date (winsorized at the 1% level)	Worldwide Patent Statistical Database (PATSTAT)
Patent citations$_{i,t}$	The natural logarithm of one plus the count of future citations to patents that are eventually granted; dated by application date on the granted patent (winsorized at the 1% level)	Worldwide Patent Statistical Database (PATSTAT)
$\Delta MV_{i,t}/MV_{i,t-1}$	The percentage change in the market value of equity for firm i between year t and $t-1$ (winsorized at the 1% level)	Compustat Global and North America, Security Daily File
$R\&D_{i,t}/MV_{i,t-1}$	The ratio of R&D expenditures to the lagged market value of equity (winsorized at the 1% level)	Compustat Global and North America, Security Daily File
Pollution taxes$_{c,t}$	Taxes and charges directly applied to the pollution of sulfur oxides (SO_x). It is based on tax rate in Euros per tonne pollution by country and year. Categorized between 0 to 6, indicating low to high taxation levels	Environmental Stringency Index, PINE Databases (OECD)
Pollution tax change$_{c,t}$	Indicator variable equal to zero in the years before an increase in Pollution taxes, and one thereafter. If there are two changes in Pollution taxes, Pollution tax change starts at zero, increases to one after the first change in pollution taxes, and increases to two after the second change	Authors' calculations based on *Pollution taxes*$_{c,t}$
SO_x *emission*$_j$	Pounds of sulfur oxides (SOx) per unit of output in each three-digit SIC industry in the U.S. manufacturing sector in 1987	Levinson 2009

1.2 Pollution taxes

Figure 1 shows how country-level pollution tax values change over time. There is considerable cross- and within-country variation in *Pollution taxes*. Eight countries tax SO_x emissions, and seven of them introduced the tax during the sample period. Denmark and Korea experienced the largest changes during the time period, both reaching the highest value for *Pollution taxes*. Australia and Canada introduced a relatively low SO_x emissions tax. Spain makes multiple

Table 2
Summary statistics

	Obs.	Mean	Median	SD
$R\&D_{i,t}$	33,545	1.038	0.325	1.428
$Sales_{i,t}$	33,545	2.778	2.297	2.718
$Cash\text{-}flow\text{-}to\text{-}assets_{i,t}$	33,343	0.076	0.084	0.154
$Sales\ growth_{i,t}$	33,343	0.042	0.035	0.306
$Cash\text{-}holdings\text{-}to\text{-}assets_{i,t}$	33,343	0.209	0.132	0.289
$Total\ debt\text{-}to\text{-}assets_{i,t}$	33,343	0.218	0.189	0.190
$IFRS_{i,t}$	33,343	0.196	0.000	0.397
$Patent\ count_{i,t}$	33,545	0.442	0.000	0.948
$Patent\ citations_{i,t}$	33,545	2.788	2.639	2.520
$\Delta MV_{i,t}/MV_{i,t-1}$	30,153	0.155	0.011	0.696
$R\&D_{i,t}/MV_{i,t-1}$	30,153	0.029	0.001	0.069
$Pollution\ taxes_{c,t}$	414	0.959	0.000	1.898
$Pollution\ tax\ change_{c,t}$	414	0.478	0.000	0.738
$SO_x emission_j$	107	9.216	1.086	21.603

This table reports the summary statistics for the key variables included in this study. The firm-level data are from Compustat Global and North America and consist of R&D reporting firms with at least three nonmissing R&D observations during 1990–2012 and a primary SIC industry classification between 2000 and 3999. We convert all dollar values to constant US$(2000) using the local currency unit conversion reported in Compustat Global and the annual U.S. GDP deflator from World Bank Development Indicators. Table 1 defines the variables in detail.

changes over the sample period, and Japan has the highest value in *Pollution taxes* during the entire sample period. The 10 other countries in our sample have zero *Pollution taxes* throughout the sample's time period.

1.3 Pollution intensity

Our identification strategy focuses on the differential impact of higher pollution taxes in industries with a higher propensity to emit SO_x. To sort industries by how pollution intensive their production technologies are, we use information from Levinson (2009) on pounds of SO_x emissions per unit of output (*SO_x emissions*) in each three-digit SIC industry in the United States in 1987. Eight three-digit SIC industries have no SO_x emissions; we exclude these industries, although including them does not affect our findings. The intersection of the firm-level data on R&D and patenting and the industry-level information on pollution intensity leaves us with firms in 107 distinct three-digit SIC manufacturing industries.

Panels A and B of Table 3 list the 10 most- and least-polluting industries (with at least 50 observations) in our sample. Hydraulic cement manufacturing (SIC 324) is by far the industry with the highest pollution intensity. The 10 most-polluting industries emit on average (median) 66.701 (52.898) pounds of SO_x per unit of output compared to 0.067 (0.086) for the 10 least-polluting industries. Table 2 shows that average (median) *SO_x emissions* across all industries is 9.216 (1.086). Thus, the average (median) level of SO_x pollution is more than 6 (50) times higher in the 10 most-polluting industries relative to the sample as a whole.

An important benefit of the pollution data from Levinson (2009) is the level of disaggregation. Eight of the top-10 most pollution-intensive industries are

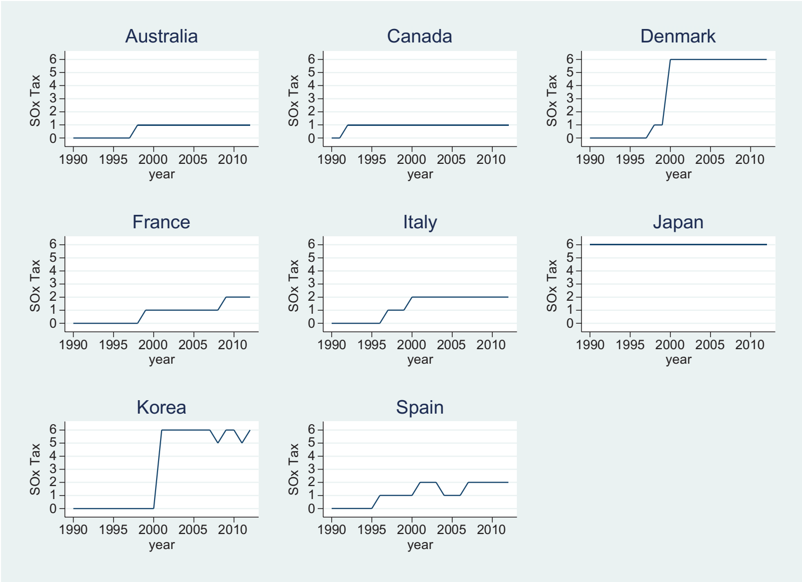

Figure 1
Taxes on SO_x emissions, 1990 to 2012
This figure reports the evolution of taxation on sulphur oxides (SO_x) by country and over time. Our sample also includes 10 countries with no SO_x tax: Austria, Belgium, Finland, Germany, Greece, Ireland, Netherlands, Norway, Sweden, and the United Kingdom. *Source*: OECD.

in three two-digit SIC codes: 28, 32, and 33. Yet, these same broad two-digit categories also contain some of the *least* pollution-intensive industries. For instance, whereas the cement and concrete industries (SIC 324 and 327) are among the highest SO_x-emitting industries, Flat glass (SIC 321), Glass Products, Made of Purchased Glass (SIC 323), and Cut Stone and Stone Products (SIC 328) are all relatively low polluters (approximately 2 pounds of SO_x per unit of output). SO_x emissions in the Cement industry are around 70 times greater than emissions in these three industries, even though they are in the same two-digit industry group.

We use pollution intensities from U.S. industries because they are, to the best of our knowledge, the only sufficiently disaggregated and comprehensive measures of cross-industry differences in the emission of major air pollutants. Another benefit of the pollution intensity data is that it is measured before our sample period begins in a country not included in the sample (e.g., Rajan and Zingales 1998). However, it is important to note that our identification does not hinge on industry pollution levels being the same across all countries. Rather, the assumption is merely that the relative *ordering* of pollution intensity is similar across countries, for example, that an industry like Cement is generally more pollution intensive (and thereby more heavily treated by pollution taxes) than an industry like Glass Products. In addition, we focus on differences across

Table 3
Pollution intensity and R&D investment in selected industries

SIC	Industry	SO_x emissions	R&D	# obs.
	A. Top-10 most-polluting industries			
324	Cement, hydraulic	140.330	1.097	92
299	Misc. products of petroleum and coal	119.471	1.343	68
281	Industrial inorganic chemicals	82.974	0.715	467
327	Concrete, gypsum, and plaster products	71.692	0.504	296
331	Steel works, blast furnaces, mills	53.392	0.681	828
333	Primary smelting and refining	52.404	0.904	242
329	Abrasive, asbestos, and misc.	42.567	0.742	289
204	Grain mill products	36.625	0.439	223
287	Agricultural chemicals	34.352	0.754	287
286	Industrial organic chemicals	32.929	0.633	316
	Mean 10 most polluting	66.701	0.781	311
	Median 10 most polluting	52.898	0.729	288
	B. Ten least-polluting industries			
382	Laboratory apparatus and instruments	0.141	0.926	1,309
275	Commercial printing	0.112	0.911	186
341	Metal cans and shipping containers	0.112	1.277	85
355	Special industry machinery, ex. metal	0.090	0.891	1,370
384	Photographic, medical, and optical goods	0.087	1.102	1,394
357	Computer and office equipment	0.085	1.054	1,016
205	Bakery products	0.024	0.143	111
394	Dolls, toys, games, and sporting	0.009	0.753	395
365	Household audio and video equipment	0.006	1.257	320
345	Screw machine products, bolts, nuts, etc.	0.001	0.248	132
	Mean 10 least polluting	0.067	0.856	632
	Median 10 least polluting	0.086	0.918	358

This table lists the 10 most (panel A) and 10 least (panel B) polluting industries (with more than 50 observations). *SO_x emissions* measures the total amount of pollution (in pounds) of sulfur oxides (SOx) per unit of output in the United States based on data from Levinson (2009). R&D is the average *R&D* by industry. Table 1 defines the variables in detail.

bins of pollution-intensity (quartiles or medians), which is even less likely to substantially differ across countries. Consistent with this idea, the evidence in Hettige, Lucas, and Wheeler (1992) suggests that cross-sector differences in pollution emissions are very stable across countries and over time. We show in Appendix D that the cross-industry differences in pollution intensity documented using U.S. data are broadly consistent with the patterns in Italy, the Netherlands, and Denmark, three other developed countries for which we have relatively detailed information on industry SO_x emissions.

2. Pollution Taxes and R&D Investment

2.1 Baseline specification

To evaluate the effects of pollution taxes we follow Jaffe and Palmer (1997) and model R&D as a function of output (sales), starting with the following specification:

$$R\&D_{i,t} = \beta Pollution\ \ taxes_{c,t-1} + \gamma Sales_{i,t} + \eta_i + \eta_t + \varepsilon_{i,t}. \quad (1)$$

In Equation (1), $R\&D_{i,t}$ is the natural logarithm of R&D investment, and *Sales* is the natural logarithm of net sales, in firm i, in year t. The key explanatory

Table 4
Pollution taxes and R&D investment

	(1)	(2)	(3)	(4)	(5)	(6)
Pollution taxes$_{c,t-1}$	0.062	0.055				
	(0.020)***	(0.018)***				
Sales$_{i,t}$	0.312	0.353	0.311	0.352	0.311	0.352
	(0.036)***	(0.038)***	(0.035)***	(0.037)***	(0.035)***	(0.037)***
Pollution tax change$_{c,t}$			0.149	0.133		
			(0.053)**	(0.052)**		
Pollution tax change$^{(-1)}$					0.006	−0.007
					(0.011)	(0.012)
Pollution tax change$^{(0)}$					0.038	0.036
					(0.025)	(0.026)
Pollution tax change$^{(\geq 1)}$					0.156	0.136
					(0.056)**	(0.053)**
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm control set	No	Yes	No	Yes	No	Yes
Observations	33,545	33,343	33,545	33,343	33,545	33,343
Adjusted R^2	.954	.957	.955	.957	.955	.957

This table reports the OLS estimates for Equation (1). *R&D*$_{i,t}$ is the dependent variable. The firm-level data are from Compustat Global and North America and consist of non-U.S. firms with at least three nonmissing R&D observations during 1990–2012 and a primary SIC industry classification between 2000 and 3999. All regressions include firm and year fixed effects. Columns 2, 4, and 6 also include the following firm-level control variables: *Cash-flow-to-assets*, *Sales growth*, *Cash-holdings-to-assets*, *Total debt-to-assets*, and *IFRS*. Table 1 defines the variables in detail. Standard errors are clustered at the country level. *$p < .1$; **$p < .05$; ***$p < .01$.

variable is *Pollution taxes*$_{c,t-1}$, which is the level of SO_x taxation in country c at the beginning of year t. The specification includes both firm and year fixed effects (η_i and η_t). Firm fixed effects account for any unobserved, time-invariant firm characteristics that may affect R&D, including any stable characteristics of the country in which the firm operates, such as culture, institutional quality, and accounting conventions. Year fixed effects control for aggregate time-varying shocks common to all firms in all countries. We cluster standard errors at the country level.[7]

We also estimate augmented versions of Equation (1), where we focus on differences in the response to *Pollution taxes*$_{c,t-1}$ across firms with differing exposures to the tax. To implement these tests, we sort firms into quartiles based on SO_x emissions intensity in the firm's three-digit SIC industry. We then interact this pollution intensity indicator variable (Q_k *of* SO_x *polluters*) with the time-varying measure of country *Pollution taxes*. If *Pollution taxes* have a causal impact on firm investment in R&D, the effects should be relatively stronger in firms who are more heavily exposed to the tax.

2.2 Baseline results

Columns 1 and 2 in Table 4 report the estimates for Equation (1). The ordinary least squares (OLS) estimate of β reported in column 1 is positive and highly

[7] All of our inferences for statistical significance are similar if we replace the country clustering with bootstrapped standard errors (with 50, 100, 200, 400, 1,000, and 2,000 repetitions). These results are available on request.

statistically significant, showing that increases in country-level pollution taxes are associated with more firm-level investment in R&D. The estimate (0.062) indicates that a one standard deviation increase in *Pollution taxes* is, on average, associated with an increase in R&D of around 0.12, or approximately 11%, of the sample average *R&D*. Column 2 shows that the estimate on the *Pollution taxes* term is almost identical if we control for a standard set of time-varying firm-level characteristics (*Cash-flow-to-assets*, *Sales growth*, *Cash-holdings-to-assets*, and *Total debt-to-assets*, as well as an indicator variable for whether the firm-year reporting follows the International Financial Reporting Standards (*IFRS*)).[8]

In columns 3–6, we explore whether the estimated effects of pollution taxes show up before the tax is introduced (or increased). We start by constructing the variable *Pollution tax change*, which equals zero in the years before an increase in pollution taxes, and one thereafter. For a country with no changes in pollution taxes, the *Pollution tax change* variable is always equal to zero. For countries with two changes in pollution taxes, *Pollution tax change* starts at zero, increases to one after the first increase in pollution taxes, and increases to two after the second increase.[9] The results in columns 3 and 4 show that *Pollution tax change* is positively and significantly related to firm investment in R&D. The coefficient estimate indicates that, on average, the introduction of a new (higher) pollution tax is associated with an increase in R&D of around 0.13–0.15, or 13%–14%, of the sample average level of R&D spending.

Clearly, if the relationship between pollution taxes and R&D is causal, R&D should not respond until *after* pollution taxes increase. We thus decompose the *Pollution tax change* variable into three separate periods: *Pollution tax change*$^{(-1)}$, which equals the forward value of *Pollution tax change* in the year before a pollution tax increase, and zero otherwise; *Pollution tax change*$^{(0)}$, which equals *Pollution tax change* in the year of the pollution tax change, and zero otherwise; and *Pollution tax change*$^{(\geq 1)}$, which equals the lagged value of *Pollution tax change* in all years after a pollution tax increase, and zero otherwise. Notably, whether or not we include the firm-level control variables, the coefficient estimate on *Pollution tax change*$^{(-1)}$ is near zero and statistically insignificant, showing that R&D is not already trending higher prior to an increase in pollution taxes. The coefficient estimate on *Pollution tax change*$^{(0)}$ is positive and larger in magnitude, but not statistically significant. In sharp

8 Compustat data item "ACCTSTD" equals "DI" if the firm's financial statements follow IFRS. We control for IFRS adoption to address potential concerns that our findings are biased by cross-country differences in the accounting treatment of R&D. Given that we control for firm fixed effects and primarily focus on within-country, across-industry differences, potential differences in R&D comparability across countries should be a concern only to the extent that some subsets of firms in a given country change how they report R&D in a way that is correlated with changes in pollution taxes. The most important accounting change during our sample period is the adoption of IFRS.

9 We ignore any changes in pollution taxes that are reversed within three years, as occurs in Korea in 2008 and 2011 and Spain in 2004. Broadly, our construction of the *Pollution tax change* variable follows the approach used by Acharya and Subramanian (2009) to study how changes in creditor rights affect innovation.

Table 5
Pollution taxes and R&D investment: Differential effects in high-pollution industries

	(1)	(2)	(3)	(4)	(5)
Pollution taxes$_{c,t-1}$	0.000	−0.006			
	(0.013)	(0.011)			
Sales$_{i,t}$	0.311	0.352	0.259	0.304	0.297
	(0.035)***	(0.038)***	(0.032)***	(0.036)***	(0.034)***
Pollution taxes$_{c,t-1}$x	0.050	0.042	0.042	0.033	0.012
Q_2 *of* SO_x *polluters*	(0.016)***	(0.014)***	(0.016)**	(0.017)*	(0.036)
Pollution taxes$_{c,t-1}$x	0.087	0.089	0.083	0.086	0.103
Q_3 *of* SO_x *polluters*	(0.042)*	(0.039)**	(0.022)***	(0.022)***	(0.033)***
Pollution taxes$_{c,t-1}$x	0.097	0.097	0.103	0.103	0.092
Q_4 *of* SO_x *polluters*	(0.014)***	(0.011)***	(0.015)***	(0.013)***	(0.023)***
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	No	No	No
Firm control set	No	Yes	No	Yes	Yes
Country-year fixed effects	No	No	Yes	Yes	Yes
Industry-year fixed effects	No	No	No	No	Yes
Observations	33,545	33,343	33,529	33,327	33,003
Adjusted R^2	.955	.957	.959	.961	.961

This table reports the OLS estimates for Equation (1) augmented with interactions between country *Pollution taxes* and indicators for the industry pollution intensity quartiles. $R\&D_{i,t}$ is the dependent variable. The firm-level data are from Compustat Global and North America and consist of non-U.S. firms with at least three nonmissing R&D observations during 1990–2012 and a primary SIC industry classification between 2000 and 3999. All regressions include firm fixed effects; columns 1 and 2 (3–5) include year (country-year) fixed effects; and column 5 includes industry-year fixed effects. Q_k *of* SO_x *polluters* is an indicator variable taking on the value one if the firm is located in the kth quartile in SO_x *emission*. Columns 2, 4, and 5 include the following firm-level control variables: *Cash-flow-to-assets*, *Sales growth*, *Cash-holdings-to-assets*, *Total debt-to-assets*, and *IFRS*. Table 1 defines the variables in detail. Standard errors are clustered at the country level. $^{*}p<.1$; $^{**}p<.05$; $^{***}p<.01$.

contrast, the coefficient for *Pollution tax change*$^{(\geq 1)}$ is large in magnitude and statistically significant, showing that the effects of higher pollution taxes are entirely concentrated in the years after the taxes increase. Using the most conservative point estimate, the results suggest that, on average, a given firm's R&D spending is around 0.13 higher (12.5% of the sample average R&D) in the years following a pollution tax increase compared to the R&D level two years before the increase. This evidence addresses the potential concern that policy makers only impose higher taxes on dirty production technologies after firms have already started to increase new technology spending.

2.3 Differential effects

Table 5 reports the estimates for Equation (1) augmented with interactions between country *Pollution taxes* and the indicators for the industry pollution intensity quartiles. The first two columns report results with aggregate year dummies (as in Equation (1)). One advantage of starting with this specification is that we can include the uninteracted *Pollution taxes* variable, which directly shows the relation between pollution taxes and R&D in the least pollution-intensive industries. Another advantage is showing that the inclusion of more refined sets of fixed effects has very little impact on the coefficient estimates.

In column 1 of Table 5, the coefficient estimate on the uninteracted *Pollution taxes* term is zero, while the coefficients for the interaction terms are positive and statistically significant. That is, while low-pollution firms do not increase R&D in response to higher *Pollution taxes*, the higher pollution firms with more exposure to the tax significantly increase R&D. Moreover, the magnitude of the R&D response is largest among firms in the top two quartiles of pollution intensity, as expected if the effects are causal rather than spurious. Column 2 shows that including the additional firm control variables has little impact on the coefficient estimates.

In the remainder of Table 5, we include country-year fixed effects, which absorb the uninteracted *Pollution taxes* term and broadly account for any time varying country-level factors that affect innovative activity across all firms (such as changes in a given country's economic opportunities or R&D incentive policies). Columns 3 and 4 show that we draw similar inferences with the country-year fixed effects, and, again, including the set of firm control variables does not materially affect the coefficient estimates. In the final column, we also include a full set of industry-year fixed effects, which flexibly controls for any time-varying industry shocks that may affect R&D activity. Consistent with the other specifications, *Pollution taxes* shares a differentially stronger positive relation with R&D in industries with a higher ex ante pollution intensity.

The results in Table 5 consistently show that the coefficients for the *Pollution taxes* x Q_k *of* SO_x *polluters* interactions are positive and statistically significant for the two most pollution-intensive quartiles. These coefficients are around 0.08–0.10, indicating that, for every one standard deviation increase in *Pollution taxes*, firms located in industries with above-median pollution intensity increase *R&D* by approximately 0.15–0.19 *more than* firms in industries with the lowest pollution intensity. This differential effect is around 14%–18% of the sample average level of *R&D*.[10]

One potential concern with the results in Table 5 is that a country's pollution tax level is correlated with some other time-varying country characteristic, and that it is actually this alternative characteristic that drives the positive (differential) association between pollution taxes and R&D. For such a characteristic to explain our findings, it must be positively correlated with pollution taxes and disproportionately important for R&D in higher pollution industries. We consider three characteristics that could potentially satisfy both conditions: (a) the level of economic development, measured by gross domestic product (GDP) per capita (*Development*), (b) the level of public funding for environmental innovation, measured by public sector spending on environmental R&D (*Env. R&D*), and (c) the user cost of R&D (*User cost*), which captures any changes in a country's R&D tax credits.[11] We interact

[10] We find similar-sized differential effects if we focus on *R&D-to-assets* rather than *R&D*. Specifically, in the baseline difference-in-difference regression, a one-standard-deviation increase in *Pollution taxes* is associated with a differential increase in *R&D-to-assets* in the highest quartile of polluters of approximately 15% of the sample average R&D-to-assets ratio.

[11] Table A3 shows that these three country characteristics are unrelated to pollution taxes. The correlation between *Pollution taxes* and *Development*, *Env. R&D*, and *User cost* is −0.303, −0.008, and 0.123, respectively. We collect

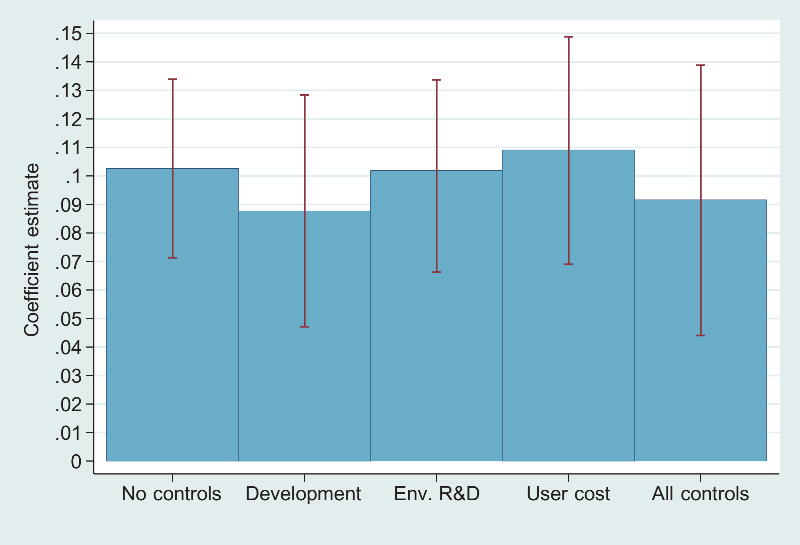

Figure 2
Robustness of the estimated relation between pollution taxes and R&D to alternative country-level mechanisms
This figure summarizes how adding a series of alternative country-level control variables to the augmented version of Equation (1) affects the coefficient for *Pollution taxes* x Q_4 of SO_x *polluters* with *R&D* as dependent variable. The additional country-level variables are GDP per capita (*Development*), public environmental R&D to GDP (*Env. R&D*), and the user cost of R&D (*User cost*). The additional country-level variables are interacted with Q_k of SO_x *polluters* and added to the regression alongside the firm and country-year fixed effects. Table 1 defines the variables in detail. Standard errors are clustered at the country level. The columns in the figure indicate the coefficient estimate on *Pollution taxes* x Q_4 of SO_x *polluters*, while the bands represent 95% confidence intervals.

each of these time-varying country characteristics with the industry pollution intensity indicators (Q_k *of* SO_x *polluters*) and include the interactions in the augmented version of Equation (1). Figure 2 summarizes how the coefficient for the interaction between *Pollution taxes* and Q_4 *of* SO_x *polluters* changes when these additional interactions are also included in the regression. The results show that regardless of whether we include the additional interactions separately or all together in the same regression, the coefficient for the *Pollution taxes x* Q_4 *of* SO_x *polluters* is similar in sign and significance to the estimates in Table 5.

2.4 Alternative approaches and robustness checks

The positive association between pollution taxes and R&D is robust to numerous sampling and modeling choices. We compile some of the most important robustness checks in Tables A4–A6 in the appendix.

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the variables *Development* and *Env. R&D* from the OECD's data portal, and we build the *User cost* variable from Thomson (2009).

2.4.1 Sample composition. Table A4 shows that our findings are not driven only by a particular country or set of countries. Panel A of Table A4 reports the estimates for the baseline regression (Equation (1)), while panel B reports the estimates for the difference-in-differences specification. Columns 1–4 show that excluding the three countries with the most observations in our sample (Canada, Japan, and the United Kingdom) has little effect on the coefficient estimates and none on our inferences, whether we drop the countries one by one or exclude all of them simultaneously.

Perhaps most notably, despite the sharp decline in sample size (from 33,545 to 9,114 observations) that occurs when we drop all three of the largest countries, we continue to find a positive and significant differential effect of higher pollution taxes on R&D in the most pollution-intensive industries. Column 5 shows that we also find similar results if we drop the countries without any variation in SO_x *emissions* taxes.

2.4.2 Omitted shocks. The pollution tax changes are staggered across countries, but several of the changes occur in the 1997–2001 period, a time of strong global economic activity. A potential concern is that this strong economic period had a *particularly* important impact on R&D in high-pollution firms, thereby generating a spurious (differential) association between pollution taxes and firm R&D. We address this possibility in columns 1 and 2 in Table A5 by including interactions between the industry pollution intensity indicators and a dummy variable taking on the value one in 1997–2001, the years where pollution tax increases are most common in our sample. The results in column 1 reveal no systematic relation between the 1997–2001 time period and R&D investment in more pollution-intensive industries; that is, regardless of the pollution tax level, more pollution-intensive industries were not disproportionately increasing R&D from 1997 to 2001. The results in column 2 show that the differential association between pollution taxes and R&D in high-pollution industries is robust to including the additional interaction terms.

Columns 3–6 in Table A5 present results addressing the potential concern that cross-country and firm-level differences in the accounting treatment of R&D biases our inferences. In particular, the introduction of IFRS during our sample period changes how R&D is accounted for in many of our sampled countries (e.g., Healy, Myers, and Howe 2002; Soderstrom and Sun 2007; Daske et al. 2013). This change could affect our inferences if IFRS adoption was correlated with increases in pollution taxes and had a differential effect on the way firms in more pollution-intensive industries report R&D.

We have already shown that the results are robust to controlling for firm-specific adoption of IFRS, but to rule out the possibility that country adoption is correlated with pollution taxes and R&D in a way that would bias our inferences, we create an indicator variable taking on the value of one in the year a country adopts IFRS, and zero otherwise. We then interact this dummy variable with the pollution intensity quartile indicator variables. The results in column 3 show that IFRS adoption did not have any differential effects on the level of reported R&D across industries with different pollution intensity. The results in column 4 show that adding the IFRS interactions has no effect on our main inferences on the association between pollution taxes and R&D.[12] Finally, in columns 5 and 6 we test whether IFRS adoption at the firm level intersects with country pollution taxes in a way that might affect our inferences. For these tests we build an indicator variable, *Not IFRS*, which equals one in firm-years that do not follow IFRS standards, and zero otherwise. The estimate on the interaction between *Not IFRS* and *Pollution taxes* is small and statistically insignificant, further indicating that IFRS adoption does not materially affect the relation between pollution taxes and R&D.

2.4.3 Industry growth opportunities. In Table A6, we address potential concerns about time-series changes in industry growth opportunities by controlling for time-series changes in the industry's share of total R&D and total employment in the country. Perhaps countries systematically introduce higher pollution taxes at precisely the time that the high-pollution industries located in the country encounter more innovation opportunities or growth prospects. The evidence in Table A6 shows that although each of these industry share measures relate positively to R&D (and significantly so in the case of industry share of employment), adding them as controls has little effect on our estimates, particularly our finding of a relatively stronger association between pollution taxes and R&D in the most pollution-intensive industries.

3. Pollution Taxes and New Invention

The most widely studied reason firms invest in R&D is to generate new products and technologies. To the extent the R&D response in high-pollution firms is focused on new invention, we should also observe an increase in the number of new patents that these firms generate. We explore this potentiality in Table 6, which estimates the relation between country pollution taxes and firm-specific counts of new triadic patents (*Patent count*). Table A7 shows that all of our inferences are similar if we use future citations to all new patents a firm produces in a given year as an alternative way to measure new invention. The patent regressions mirror those we estimate for R&D, although in some specifications

[12] Beyond establishing that IFRS adoption does not bias our inferences on the relation between pollution taxes and R&D, these results also address more general concerns about bias from cross-country differences in the accounting treatment of R&D. Namely, these results show that a major accounting reform does not affect R&D across firms in different pollution intensity quartiles. If cross-country differences in the accounting treatment of R&D were an important factor behind our results, we would expect to see some movement in R&D when those accounting rules were standardized by IFRS.

Table 6
Pollution taxes and new invention

	(1)	(2)	(3)	(4)	(5)	(6)
	All technology classes			Air pollution abatement technologies		
Pollution taxes$_{c,t-1}$	−0.028	−0.008	−0.007	0.076	0.090	0.087
	(0.031)	(0.017)	(0.012)	(0.024)***	(0.031)***	(0.028)***
Stock of triadic patents$_{i,t-1}$		0.437	0.437		0.311	0.311
		(0.018)***	(0.018)***		(0.057)***	(0.057)***
Pollution taxes$_{c,t-1}$x Q_2 *of* SO_x *polluters*			0.002			−0.016
			(0.018)			(0.018)
Pollution taxes$_{c,t-1}$x Q_3 *of* SO_x *polluters*			0.025			0.003
			(0.022)			(0.040)
Pollution taxes$_{c,t-1}$x Q_4 *of* SO_x *polluters*			−0.016			0.010
			(0.011)			(0.014)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	33,442	33,442	33,442	33,442	33,442	33,442
Adjusted R^2	.802	.846	.846	.198	.198	.198

This table reports the OLS estimates for Equation (1) (columns 1–2 and 4–5), and Equation (1) augmented with interactions between country *Pollution taxes* and the indicators for the industry pollution intensity quartiles (columns 3 and 6). *Patent count*$_{i,t}$ is the dependent variable. The firm-level data are from Compustat Global and North America and consist of non-U.S. firms with at least three nonmissing R&D observations during 1990–2012 and a primary SIC industry classification between 2000 and 3999. Patents from technology classes classified as air pollution abatement technologies (based on Hascic and Migotto 2015; reported in Table B1) are reported in columns 4–6. Q_k *of* SO_x *polluters* is an indicator variable taking on the value one if the firm is located in the kth quartile in SO_x *emission*. All regressions include firm and year fixed effects, *Sales* and the following country-level control variables: *Public environmental R&D to GDP* and *GDP per capita*. Table 1 defines the variables in detail. Standard errors are clustered at the country level. $^{*}p<.1$; $^{**}p<.05$; $^{***}p<.01$.

we also control for a given firm's prior innovative activity by including a time-varying measure of their stock of patents (*Stock of patents*$_{i,t-1}$).[13] This approach follows that of Aghion et al. (2016), who show that prior innovative activity is a strong predictor of current patenting outcomes.

In the first three columns of Table 6, the dependent variable *Patent count* includes new triadic patents from all technology classes. The estimate in column 1 shows no systematic relation between pollution taxes and overall rates of firm patenting activity. Column 2 shows that, as expected, the *Stock of patents*$_{i,t-1}$ is positively associated with *Patent count*, but controlling for prior patenting does not affect the (non)relation between *Pollution taxes* and new patents. The difference-in-differences estimates in column 3 show that the high-pollution firms who substantially increase R&D spending in response to higher emission taxes do not also (disproportionately) increase patenting.

The last three columns in Table 6 specifically focus on the relation between pollution taxes and new patents for pollution emission abatement technologies. To identify these particular technologies, we follow the OECD's ENV-TECH classifications (see Hascic and Migotto 2015). As Table B1 shows, these clean air inventions focus on purifying and removing noxious gases and chemicals

[13] To construct a patent stock for each firm, we begin in the year 1985 (the starting year of the matched patent data), apply the perpetual inventory method, and assume a deprecation rate of 20%. This approach follows the literature on the depreciation rate of R&D capital and is the rate used in Aghion et al. (2016).

from waste emissions. The baseline estimate in column 4 shows that, across all firms, pollution taxes are positively associated with the development of new air pollution abatement technologies. In column 5, we control for a firm's existing stock of patents. These estimates show that a firm's prior innovative activity is positively associated with new patents in air pollution abatement products; we continue to find a positive association between pollution taxes and new air pollution abatement patents after controlling for the firm's patent stock. These results are consistent with the positive link between environmental policy and new invention documented in prior studies (e.g., Lanjouw and Mody 1996; Aghion et al. 2016).

In column 6 of Table 6, we include the interactions between *Pollution taxes* and the pollution intensity quartiles. The coefficients for the interaction terms are around zero and statistically insignificant, showing no differential relation between pollution taxes and pollution abatement patents in high-pollution firms.[14]

4. Pollution Taxes and the Marginal Value of R&D Investment

Our primary interest is the connection between pollution taxes and real investment in new technology. But a supplemental test for the plausibility and economic importance of this connection is evidence that the pollution taxes affect how the market values R&D spending in high-pollution firms. This test is particularly important given the evidence above that high-pollution firms increase R&D, but not new invention; perhaps these firms are just not good innovators.

To explore the value implications of R&D investment, we estimate the following specification:

$$\Delta MV_{i,t}/MV_{i,t-1} = \alpha_1 R\&D_{i,t}/MV_{i,t-1} + \alpha_2(\textit{Pollution taxes}_{c,t} \times R\&D_{i,t}/MV_{i,t-1}) + X_{i,t} + \eta_i + \eta_{c,t} + \varepsilon_{i,t}. \quad (2)$$

In Equation (2), the dependent variable is the percentage change in the market value of equity for firm i between year t and $t-1$.[15] $R\&D_{i,t}/MV_{i,t-1}$ is firm i's R&D spending in year t scaled by the market value of the firm's equity in year $t-1$. With this standardization, α_1 captures the incremental value of an additional dollar of R&D on the market value of the company's equity (e.g., Faulkender and Wang 2006). To explore how the country pollution tax level affects this value, we include the interaction between $R\&D_{i,t}/MV_{i,t-1}$

[14] A longer lag between polluting firm investment in R&D and the creation of new pollution abatement technologies is possible. To explore this potential, we reestimate the specification in column 6 of Table 6 with patents in new pollution abatement technologies measured over forward periods dated $t+1$ to $t+8$. All of our inferences are similar with the longer forward patenting measures. We are grateful to an anonymous referee for suggesting this test.

[15] The results are similar if we use the firm's "excess" return relative to the country-year average.

Table 7
Pollution taxes and the marginal value of R&D

	(1)	(2)	(3)	(4)
	Industry pollution intensity:			
	High	High	High	Low
$R\&D_{i,t}/MV_{i,t-1}$	1.558	0.749	1.132	1.562
	(0.322)***	(0.427)*	(0.353)***	(0.270)***
Pollution taxes$_{c,t}$ x		1.431	0.685	−0.451
$R\&D_{i,t}/MV_{i,t-1}$		(0.306)***	(0.220)***	(0.554)
Firm fixed effects	Yes	Yes	Yes	Yes
Firm control set	Yes	Yes	Yes	Yes
Country year fixed effects	Yes	Yes	Yes	Yes
Firm control set x *Pollution taxes*	No	No	Yes	Yes
Observations	14,439	14,439	14,439	15,576
Adjusted R^2	.374	.378	.388	.370

This table reports the OLS estimates for Equation (2). $\Delta MV_{i,t}/MV_{i,t-1}$ is the dependent variable. The firm-level data are from Compustat Global and North America and consist of non-U.S. firms with at least three nonmissing R&D observations during 1990–2012 and a primary SIC industry classification between 2000 and 3999. High (low) polluting industries in columns 1–3 (4) are industries above (below) the median in SO_x *emission*. All regressions include firm and country-year fixed effects. All columns include the following firm control variables (all scaled by lagged market value of equity): net assets, annual change in net income, dividends, cash holdings, net financing (net stock plus debt issuance), and total debt. Regressions in columns 3 and 4 include all firm control variables interacted with *Pollution taxes*. Standard errors are clustered at the country level. $^{*}p<.1$; $^{**}p<.05$; $^{***}p<.01$.

and the country's pollution tax level (*Pollution taxes*$_{c,t}$). $X_{i,t}$ is a set of firm-year characteristics that may affect market values and be correlated with R&D spending, including earnings, dividends, cash holdings, net assets, net financing activities, and leverage. As with R&D, we scale these variables by the lagged market value of equity. The specification also includes firm fixed effects (η_i), which isolates the within-firm relation between R&D investment and changes in equity market values and flexibly controls for any time-invariant characteristics that may affect equity returns, such as firm-specific risk factors. Finally, the country-year fixed effects ($\eta_{c,t}$) control for shocks common to all firms in a given country and year, including overall equity market performance.

Table 7 reports the OLS estimates for Equation (2). In the first three columns, we focus on the subsample of firms from industries with above-median SO_x emissions. In the first column, we drop the interaction term to establish a baseline relation between R&D investment and changes in firm equity values. R&D shares a strong positive relation with changes in the market value of equity, consistent with the evidence in several studies documenting a positive link between R&D investment and firm value (e.g., Hall 1993; Hall and Oriani 2006; Chan, Lakonishok, and Sougiannis 2001; Faulkender and Wang 2006; Hou et al. forthcoming). In the next two columns, we add the interaction between country *Pollution taxes* and firm R&D. In column 2, we only interact R&D with *Pollution taxes*, whereas in column 3 we also interact the full set of firm control variables with *Pollution taxes*. In either case, the coefficient for the key interaction term (α_2) is positive and statistically significant, indicating that, among firms more exposed to pollution taxes, the marginal value of R&D

spending increases with the country pollution tax level. In contrast, the results in column 4 show that changes in country pollution taxes do not significantly affect how the market values R&D spending in firms from low-pollution industries.

In terms of economic magnitudes, consider the estimates in columns 3 and 4. In a country with zero pollution taxes, the marginal value of R&D spending is slightly higher in firms from low-pollution industries: all else equal, a one standard deviation increase in R&D is associated with a 7.8% increase in the market value of equity in high-pollution firms, and a 10.8% increase in low-pollution firms. However, at the mean pollution tax value in our sample (approximately one), the marginal effect of the same (one standard deviation) change in R&D increases substantially for the high-pollution subsample (to 12.54%), but does not change for the low-pollution firms. Thus, the country pollution tax level has a material (positive) impact on the marginal value of R&D investment in polluting firms.

5. Pollution Taxes and the Different Faces of R&D

The strong positive link between country SO_x taxes and R&D spending in high-pollution firms shows that environmental policy can affect the investments that drive technical change. The market appears to recognize the value of R&D in high-pollution firms, yet, on average, these investments do not generate new patentable invention. So why are polluting firms increasing R&D? This section develops several cross-sectional tests to distinguish the two roles of R&D investment: generating new innovation, and enhancing the firm's ability to assimilate and exploit outside knowledge.

5.1 R&D in low invention firms

In sharp contrast to the first face of R&D, firm investments to expand technological absorptive capacity will generally not result in new invention. Thus, one indication that the R&D response we identify is distinct from new product innovation is more direct evidence that higher pollution taxes lead to more R&D even in firms not engaged in new product innovation. We explore this idea in Table 8 by estimating the R&D response to pollution taxes among subsets of firms with low to no new invention output during our sample period.

In the first three columns, we focus on firms from industries with below-median patent stocks. The first column shows that higher pollution taxes are positively and significantly associated with R&D investment in firms from these "Low invention" sectors. In column 2 we add the interaction between *Pollution taxes* and an indicator variable equal to one if the firm is from an industry with above-median pollution intensity. The estimates in column 2 are consistent with our main results: within the subsample of low-invention firms, higher pollution taxes have a relatively stronger effect on R&D among more heavily treated (high-pollution) firms. Column 3 shows similar results when we replace the aggregate year dummies with country-year fixed effects.

Table 8
Pollution taxes and R&D in low invention sectors

	(1)	(2)	(3)	(4)	(5)	(6)
	Low invention industry sort based on:					
	All triadic patent stock			Air pollution abatement patents		
Pollution taxes$_{c,t-1}$	0.061	0.010		0.059	0.019	
	(0.016)***	(0.022)		(0.017)***	(0.019)	
Sales$_{i,t}$	0.329	0.329	0.277	0.333	0.332	0.276
	(0.026)***	(0.026)***	(0.025)***	(0.034)***	(0.033)***	(0.027)***
Pollution taxes$_{c,t-1}$x		0.078	0.082		0.068	0.076
Above-median SO_x *polluters*		(0.014)***	(0.012)***		(0.015)***	(0.016)***
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	No	Yes	Yes	No
Firm control set	Yes	Yes	Yes	Yes	Yes	Yes
Country-year fixed effects	No	No	Yes	No	No	Yes
Observations	16,106	16,106	16,069	25,872	25,872	25,856
R^2	.945	.945	.951	.953	.953	.958

This table reports the OLS estimates for Equation (1) (columns 1 and 4) and Equation (1) augmented with interactions between country *Pollution taxes* and the indicator for the industry pollution intensity variable (columns 2–3 and 5–6). $R\&D_{i,t}$ is the dependent variable. The firm-level data are from Compustat Global and North America and consist of non-U.S. firms with at least three nonmissing R&D observations during 1990–2012 and a primary SIC industry classification between 2000 and 3999. Columns 1-3 (4-6) define low invention industries as the firms located in industries below the median in the stock of triadic patents (define low invention industries in air pollution abatement patents as not belonging to any of the high air pollution abatement patenting industries (which together make up about 80% of all patents in air pollution abatement patents during our sample period): Industrial inorganic chemicals (281), Motor vehicles and equipment (371), Pottery and related products (326), Computer and office equipment (357), General industrial machinery equipment (356), Flat glass (321), Refrigeration and service industry machinery (358), Industrial organic chemicals (286), and Fabricated rubber products, n.e.c. (306)). *Above-median* SO_x *polluters* is an indicator variable taking on the value one (zero) if the industry is above (below) the median in SO_x *emission*. All regressions include firm fixed effects, and columns 1–2 and 4–5 (3 and 6) include year (country-year) fixed effects. All columns include the following firm control variables: *Cash-flow-to-assets*, *Sales growth*, *Cash-holdings-to-assets*, *Total debt-to-assets*, and *IFRS*. Table 1 defines the variables in detail. Standard errors are clustered at the country level. $^*p<.1$; $^{**}p<.05$; $^{***}p<.01$.

In the last three columns of Table 8 we exclude the small number of sectors that account for the vast majority of new innovations in air pollution abatement technologies during our sample period.[16] In columns 4–6, we continue to find a positive and significant differential relation between pollution taxes and R&D after dropping the high-invention firms. Overall, the results in Table 8 are consistent with the idea that one important way pollution taxes affect the nature of technical change is by encouraging low-invention firms from pollution-intensive sectors to make new investments in R&D.

16 Nine three-digit SIC industries account for around 80% of all air pollution abatement patents. These industries (SIC code in parentheses) are Industrial inorganic chemicals (281), Motor vehicles and equipment (371), Pottery and related products (326), Computer and office equipment (357), General industrial machinery equipment (356), Flat glass (321), Refrigeration and service industry machinery (358), Industrial organic chemicals (286), and Fabricated rubber products, n.e.c. (306). Industries 281 and 371 account for one-third of all triadic patents in air pollution abatement technologies. Only two of the high patenting sectors in air pollution abatement technologies (281 and 286) are among the top-10 most-polluting sectors. The other high invention sectors are around the median in terms of pollution intensity, and one (357) is among the least-polluting sectors (see Table 3).

5.2 Process R&D

Process R&D shares a close conceptual relation with investment in absorptive capacity. Multiple studies link incremental investment in process R&D with the importance of absorptive capacity in a given sector (e.g., Kim 1998; Lim 2009), and some research uses spending on process R&D as a direct proxy for investment in absorptive capacity (e.g., Leahy and Neary 2007). We do not have cross-country data on process R&D *per se*, but we can identify the sectors in which any given dollar of R&D spending is more likely to reflect process (rather than product) R&D. Specifically, Cohen and Klepper (1996) show substantial cross-industry variation in the importance of process R&D as a share of total industry R&D. Using the information in Cohen and Klepper (1996), we divide our sample into “High process R&D” and “Low process R&D” groups. To the extent that *any* R&D spending in high process R&D industries is more likely to reflect absorptive capacity, evidence of an R&D response to pollution taxes in the high process R&D subsample is at least consistent with the idea that higher pollution taxes lead to more of the “second face” of R&D.[17]

The first three columns in Table 9 report results for firms in the “High process R&D” sample. Among these firms, there is a strong positive differential association between pollution taxes and R&D in high-pollution firms; the magnitude of this differential effect is considerably larger than in the baseline (full sample) result. In sharp contrast, the final three columns show that pollution taxes are completely unrelated to R&D spending in the “Low process R&D” firms. These results are consistent with polluting firms responding to pollution taxes by making technological investments that allow them to improve their production processes.

5.3 R&D to acquire external knowledge

Cohen and Levinthal (1989) show that firms have more incentive to invest in R&D to expand absorptive capacity if they operate in environments where external knowledge is easier to acquire. This insight provides a relatively clean way to distinguish the first and second faces of R&D because, all else equal, knowledge spillovers *deter* new product innovation (e.g., Nelson 1959; Arrow 1962). In short, the incentive to invest in R&D for absorptive capacity reasons is relatively stronger in environments with more knowledge spillovers, whereas the incentive to invest in R&D for new invention reasons is relatively weaker in

[17] Cohen and Klepper (1996, their Table 1) report the share of process R&D in total R&D for nine different U.S. two-digit SIC sectors. We put firms from sectors with an above average share of process R&D in the “High process R&D” group. The sectors in this group are Food products (SIC 20), Paper products (SIC 26), Chemicals (SIC 28), Petroleum refining (SIC 29), Rubber and plastic products (SIC 30), and Primary metal industries (SIC 33). The fraction of process R&D ranges from 0.36 to 0.62 in the high process R&D sectors. In the remaining (low process R&D) sectors, the share of process R&D ranges from 0.01 to 0.15. The sectors in this group are Fabricated metal products (SIC 34), Machinery equipment except electrical (SIC 35), Electrical and electronic equipment (SIC 36), Transportation equipment (SIC 37), and Measuring, analyzing, and controlling instruments (SIC 38). An important caveat is that firms also transform their production processes by developing new patentable innovations (see the evidence and discussion in Bena, Ortiz-Molina, and Simintzi 2021). In this way, sorting by spending on process R&D is only a rough proxy for cross-sector differences in investment in absorptive capacity.

Table 9
Pollution taxes and process R&D

	(1)	(2)	(3)	(4)	(5)	(6)
		High process R&D sectors			Low process R&D sectors	
Pollution taxes$_{c,t-1}$	0.097 (0.019)***	−0.167 (0.112)		0.019 (0.024)	0.019 (0.019)	
Sales$_{i,t}$	0.306 (0.040)***	0.306 (0.041)***	0.215 (0.025)***	0.411 (0.050)***	0.411 (0.050)***	0.381 (0.055)***
Pollution taxes$_{c,t-1}x$ *Above-median* SO_x *polluters*		0.269 (0.106)**	0.313 (0.090)***		−0.001 (0.098)	−0.019 (0.075)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	No	Yes	Yes	No
Firm control set	Yes	Yes	Yes	Yes	Yes	Yes
Country-year fixed effects	No	No	Yes	No	No	Yes
Observations	12,060	12,060	12,037	18,328	18,328	18,306
Adjusted R^2	.952	.952	.960	.960	.960	.964

This table reports the OLS estimates for Equation (1) (columns 1 and 4) and Equation (1) augmented with interactions between country *Pollution taxes* and the indicator for the industry pollution intensity variable (columns 2–3 and 5–6). $R\&D_{i,t}$ is the dependent variable. The firm-level data are from Compustat Global and North America and consist of non-U.S. firms with at least three nonmissing R&D observations during 1990–2012 and a primary SIC industry classification between 2000 and 3999. Columns 1–3 (4–6) define high (low) process R&D sectors as the firms located in industries above (below) the median in process R&D as measured in Cohen and Klepper (1996). *Above-median* SO_x *polluters* is an indicator variable taking on the value one (zero) if the industry is above (below) the median in SO_x *emission*. All regressions include firm fixed effects, and columns 1–2 and 4–5 (3 and 6) include year (country-year) fixed effects. All columns include the following firm control variables: *Cash-flow-to-assets*, *Sales growth*, *Cash -holdings-to-assets*, *Total debt-to-assets*, and *IFRS*. Table 1 defines the variables in detail. Standard errors are clustered at the country level. *$p<.1$; **$p<.05$; ***$p<.01$.

these environments. As a consequence, evidence of a relatively stronger R&D response in polluting firms in high (external) knowledge environments is strong support for the absorptive capacity mechanism.

Cohen, Nelson, and Walsh (2000) show substantial cross-industry differences in the extent to which external knowledge is available and accessible to firms. As with pollution intensity, we assume these differences arise from the technological structure and nature of the industry, making it *relatively* easier for firms in some sectors to acquire outside knowledge. It is in these sectors that the incentive to invest in R&D for absorptive capacity reasons should be strongest.

Using the scores on knowledge appropriability from Cohen, Nelson, and Walsh (2000), we sort firms into “High spillover” and “Low spillover” subsamples.[18] The first three columns in Table 10 report the estimates for Equation (1) for the “High spillover” subsample; columns 4–6 do the same for firms in “Low spillover” environments. For firms in high spillover sectors, there is a strong positive association between *Pollution taxes* and firm R&D spending

18 Erkens (2011) also uses the Cohen, Nelson, and Walsh (2000) data to sort industries based on information spillovers. We take the maximum value across the five appropriability dimensions from Cohen, Nelson, and Walsh (2000, their Table 1) and assign firms to the “High spillover” (“Low spillover”) sample if they are in an industry with a below- (above-) median appropriability score.

Table 10
Pollution taxes and R&D: Splits based on knowledge spillovers

	(1)	(2)	(3)	(4)	(5)	(6)
	High spillovers			Low spillovers		
Pollution taxes$_{c,t-1}$	0.068	0.016		0.034	0.025	
	(0.017)***	(0.016)		(0.024)	(0.037)	
Sales$_{i,t}$	0.335	0.334	0.269	0.399	0.399	0.362
	(0.030)***	(0.029)***	(0.024)***	(0.063)***	(0.063)***	(0.068)***
Pollution taxes$_{c,t-1}$*x*		0.090	0.094		0.019	0.011
Above-median SO_X *polluters*		(0.007)***	(0.014)***		(0.061)	(0.075)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	No	Yes	Yes	No
Firm control set	Yes	Yes	Yes	Yes	Yes	Yes
Country-year fixed effects	No	No	Yes	No	No	Yes
Observations	15,348	15,348	15,312	13,204	13,204	13,181
Adjusted R^2	.951	.951	.957	.965	.965	.969

This table reports the OLS estimates for Equation (1) (columns 1 and 4) and Equation (1) augmented with interactions between country *Pollution taxes* and the indicator for the industry pollution intensity variable (columns 2–3 and 5–6). $R\&D_{i,t}$ is the dependent variable. The firm-level data are from Compustat Global and North America and consist of non-U.S. firms with at least three nonmissing R&D observations during 1990–2012 and a primary SIC industry classification between 2000 and 3999. Columns 1-3 (4-6) define high (low) spillover sectors as the industries below (above) the median in appropriability as measured in Cohen, Nelson, and Walsh (2000). *Above-median* SO_X *polluters* is an indicator variable taking on the value one (zero) if the industry is above (below) the median in SO_X *emission*. All regressions include firm fixed effects, and columns 1–2 and 4–5 (3 and 6) include year (country-year) fixed effects. All columns include the following firm control variables: *Cash-flow-to-assets*, *Sales growth*, *Cash- holdings-to-assets*, *Total debt-to-assets*, and *IFRS*. Table 1 defines the variables in detail. Standard errors are clustered at the country level. $*p<.1$; $**p<.05$; $***p<.01$.

(column 1). In addition, within the high spillover subsample, the link between *Pollution taxes* and R&D is relatively stronger in high-pollution firms (columns 2 and 3). However, the story in “Low spillover” environments is much different: we find *no* evidence of a significant R&D response to higher emission taxes among firms located in industries with fewer knowledge spillovers (columns 4–6).

Table A8 reports similar results using two alternative ways to identify the firms with the strongest incentive to invest in R&D to expand absorptive capacity. In the Cohen and Levinthal (1989) model, the need for a firm to increase its own R&D in order to absorb external knowledge is higher if the industry the firm operates in has more “outside” or “extra-industry” knowledge. One key measure of an industry’s extra-industry knowledge is the extent to which research is basic (rather than applied). The results in columns 1-4 in Table A8 show a stronger (differential) response to emissions taxes among polluting firms in industries where R&D is more heavily geared toward basic scientific development. Alternatively, Bloom, Schankerman, and Van Reenen (2013) estimate cross-sector differences in technology spillovers across firms. If polluting firms increase R&D to acquire outside knowledge, we expect stronger effects in the sectors with more technology spillovers. The estimates in columns 5-8 in Table A8 are consistent with this idea: we find a larger (and more significant) positive relation between pollution taxes and R&D spending

Table 11
Pollution taxes and the market value of the second face of R&D

	(1)	(2)	(3)	(4)	(5)	(6)
	Low invention sectors		High process R&D sectors		High spillover sectors	
$R\&D_{i,t}/MV_{i,t-1}$	0.667	0.992	0.856	1.314	0.664	1.017
	(0.373)*	(0.399)**	(0.395)**	(0.415)***	(0.339)*	(0.338)***
Pollution taxes$_{c,t}$ x	1.375	0.717	1.321	0.352	1.411	0.651
$R\&D_{i,t}/MV_{i,t-1}$	(0.297)***	(0.228)***	(0.298)***	(0.287)	(0.300)***	(0.234)**
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm control set	Yes	Yes	Yes	Yes	Yes	Yes
Country year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm control set x *Pollution taxes*	No	Yes	No	Yes	No	Yes
Observations	7,913	7,913	9,541	9,541	8,271	8,271
Adjusted R^2	.378	.385	.384	.398	.396	.406

This table reports the OLS estimates for Equation (2). $\Delta MV_{i,t}/MV_{i,t-1}$ is the dependent variable. The firm-level data are from Compustat Global and North America and consist of non-U.S. firms with at least three nonmissing R&D observations during 1990–2012 and a primary SIC industry classification between 2000 and 3999. All firms are located in high polluting sectors, defined as industries above the median in SO_x *emission*. Columns 1 and 2 define low invention sectors as the firms located in sectors below the median in the stock of triadic patents. Columns 3 and 4 define high process R&D sectors as the industries above the median in process R&D as measured in Cohen and Klepper (1996). Columns 5 and 6 define high spillover sectors as the industries below the median in appropriability as measured in Cohen, Nelson, and Walsh (2000). All regressions include firm and country-year fixed effects and the following firm control variables (all scaled by lagged market value of equity): net assets, annual change in net income, dividends, cash holdings, net financing (net stock plus debt issuance), and total debt. Regressions in even-numbered columns include all firm control variables interacted with *Pollution taxes*. Standard errors are clustered at the country level. $*p<.1$; $**p<.05$; $***p<.01$.

among the high-pollution firms located in industries with the highest technology spillovers.[19]

5.4 Market value and the second face of R&D

The R&D response to higher pollution taxes is concentrated in firms that generally do less new product innovation and have more incentive to invest in R&D to acquire outside knowledge. It is difficult to rationalize this full set of results without appealing to the "second face" of R&D spending. One possibility, however, is that the R&D by affected firms actually does not add value, perhaps because the responsive firms are poor innovators, or perhaps because we have stumbled on a spurious R&D response in precisely the subsets of firms with the most incentive to invest in R&D for absorptive capacity reasons.

To evaluate this potential, we return to the market-value specification we studied in Section 5. Table 11 reports the estimates for Equation (2) for subsamples of firms that are both (a) most affected by the pollution tax (from industries with above-median pollution intensity), and (b) most likely to invest in R&D for absorptive capacity reasons. Specifically, in the first two columns of

19 We put a given firm in the high (low) "Basic research" group if it is located in an industry above (below) the median in terms of the maximum value of the importance of basic versus applied sciences in Cohen, Nelson, and Walsh (2000). We put a firm in the high (low) "Technology spillovers" group if it is located in an industry above (below) the median in terms of average technology spillover during the 1980s by three-digit SIC sector in the United States from Bloom, Schankerman, and Van Reenen (2013).

Table 11 we focus on high-pollution firms from industries with below-median patent stocks (the "Low invention" industries we studied in columns 1–3 of Table 8); in columns 3 and 4 we focus on high-pollution firms from industries with above-median process R&D (the "High process R&D" industries we studied in columns 1-3 of Table 9); and in columns 5 and 6 we focus on high-pollution firms from industries with below-median appropriability (the "High spillover" industries we reported in columns 1–3 of Table 10).

We are interested in whether the country pollution tax level affects the marginal value of R&D spending in these subsets of firms. For each sort, we report a specification where R&D is the only firm-level variable interacted with *Pollution taxes* (first column), as well as a specification where all firm-level controls are interacted with *Pollution taxes* (second column). In five of the six regressions in Table 11, the coefficient estimate on the interaction between firm R&D spending and country *Pollution taxes* is positive, statistically significant, and similar in magnitude to the estimates in Table 7. The only exception is the second specification in the "High process R&D" sample (column 4), where the interaction term is positive, but smaller in magnitude and not statistically significant. Thus, pollution taxes are associated with an increase in the marginal value of R&D for high-pollution firms in "Low invention", "High process R&D", and "High spillover" industries, suggesting these firms are not investing in R&D for irrational or spurious reasons.

5.5 Do any high-pollution firms innovate?

We conclude with a final set of results that speak to the plausibility of our findings and the various ways environmental policy can encourage technical change. Some high-pollution firms have a history of developing clean technologies, and, as such, it is more likely to see evidence of the first face of R&D for these firms. For the results in Table 12, we start by focusing on firms from industries above the median in pollution intensity (the industries we have already shown drive the positive relation between pollution taxes and R&D). We then subdivide this sample of polluting firms based on whether or not they are in an industry with a history of invention in air pollution abatement technologies. We identify the "new invention" sectors based on whether they have a positive stock of patents in the emission abatement technology classes (Table B1) at the start of our sample period (1990). Note that there are roughly twice the number of observations in the subsample of polluting firms *without* a history of new invention in these technologies.

In the first two columns of Table 12, we estimate the baseline regression with R&D as the outcome variable. There is a positive and almost identical coefficient for the pollution tax variable in both subsamples, indicating that polluting firms in both high- and low-invention industries increase R&D when pollution taxes increase (the estimate is noisier in the high-pollution, high-invention subsample, and it just misses statistical significance at conventional levels). In contrast, the estimates in the last two columns show that pollution

Table 12
Pollution taxes and clean invention in high-pollution firms

	(1)	(2)	(3)	(4)
	Industry air pollution abatement patenting in 1990:			
	High	Low	High	Low
	R&D		Patent count	
Pollution taxes$_{c,t-1}$	0.092	0.093	0.445	0.005
	(0.068)	(0.020)***	(0.208)**	(0.003)
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	5,593	10,627	5,581	10,596
Adjusted R^2	.965	.944	.257	.000

This table reports the OLS estimates for Equation (1). $R\&D_{i,t}$ is the dependent variable in columns 1 and 2 and *Patent count*$_{i,t}$ is the dependent variable in columns 3 and 4. The firm-level data are from Compustat Global and North America and consist of non-U.S. firms with at least three nonmissing R&D observations during 1990–2012 and a primary SIC industry classification between 2000 and 3999. Only firms from industries above the median in SO_x *emission* are included. Patent count based on technology classes classified as air pollution abatement technologies (based on Hascic and Migotto 2015; reported in Table B1) are reported in columns 3 and 4. All regressions include firm and year fixed effects and *Sales*. Regressions in columns 3 and 4 include *Stock of triadic patents*$_{i,t-1}$ and the following country-level control variables: *Public environmental R&D to GDP* and *GDP per capita*. Table 1 defines the variables in detail. Standard errors are clustered at the country level. *$p<.1$; **$p<.05$; ***$p<.01$.

taxes are associated with new inventions in pollution abatement technologies *only* in the subset of high-pollution firms from industries with a prior history of innovating in this space. These results are consistent with a broader emphasis in the literature on path dependence in technical change: to the extent higher emissions taxes encourage new invention in polluting firms, it is in the firms with a prior history of invention in pollution mitigation technologies. It is also consistent with the evidence of a new invention response in studies that focus on the effects of environmental taxes in particular industries with a history of new product innovation (e.g., Aghion et al. 2016).

6. Conclusion

Higher taxes on SO_x emissions are associated with a substantial increase in firm-level R&D spending. The pollution taxes have relatively stronger effects on R&D in sectors with dirtier production technologies, as expected if the relation between pollution taxes and R&D is causal. In contrast to R&D, pollution taxes do not lead to more patenting in high-pollution firms, suggesting that firms increase R&D to improve their ability to use and assimilate external knowledge rather than to develop new innovations. Consistent with this idea, the R&D response to pollution taxes is concentrated in sectors where external knowledge is easier to acquire. Overall, our findings suggest that investment in technological absorptive capacity is a first-order response when noninnovative firms with dirty production technologies face higher emissions taxes.

This evidence is particularly relevant for the theoretical literature on endogenous growth under environmental constraints (e.g., Acemoglu et al. 2012, 2016). An important insight from this work is the role of policy in encouraging the development and adoption of cleaner technologies. Prior studies show that taxes on the dirty products an industry produces can encourage new invention in the affected sector (Aghion et al. 2016); our work shows tax policy can also encourage the technology investments that allow firms to broadly overhaul the way they produce, in order to reduce pollution at the source (e.g., Hammar and Löfgren 2010; Xie et al. 2015). In this way, we provide novel evidence on the micro-level linkages through which market-based environmental policies can influence technical change.

Our work raises several interesting questions for future research. First, several studies explore how firm R&D spending responds to tax incentives (e.g., Berger 1993; Bloom, Griffith, and Van Reenen 2002; Wilson 2009; Brown, Martinsson, and Petersen 2017), and much of the theoretical literature on directed technical change analyzes the role of both emissions taxes and research subsidies. We focus on emissions taxes, primarily because of the nature of our sample: there is significant country-level variation in SO_x emissions taxes in our sample period, but little variation in R&D tax credits. Nonetheless, an important question for future empirical research would be how the intersection of pollution taxes and research subsidies affects firm-level technology investment decisions.

Beyond research subsidies, other legal and institutional determinants of R&D investment exist, so it also would be interesting to know how these factors influence the effectiveness of environmental policies at encouraging the development and use of clean technologies. In particular, Brown, Martinsson, and Petersen (2013) find that cross-country differences in stock market development affect firms' R&D spending; De Haas and Popov (2019) link stock market development with innovation in clean technologies; and Levine et al. (2019) show that tighter credit conditions increase the firm's emissions of toxic pollutants. This research suggests that financial market conditions may play an important role in determining how much new technology investment polluting firms are able to make when confronted with higher emissions taxes.

Finally, we have focused on the way high-pollution firms change their R&D investments when countries increase taxes on SO_x emissions. It would be interesting to explore whether firms respond in a similar way to other types of environmental policies, including taxes on different types of emissions (e.g., carbon and nitrogen), and command-and-control regulations (e.g., pollution standards). In addition, our work leaves open the question of whether and how the R&D investments that firms make ultimately affect the firm's emissions. Although countries are increasingly interested in mandating climate-related disclosures (e.g., Jouvenot and Krueger 2019), we are not aware of any cross-country data on firm-level emissions during our sample period that would allow us to trace out the linkages between SO_x taxes, R&D investments, and SO_x emissions. Nonetheless, a systematic study of how policy-induced investments in new technology affect the extent of noxious manufacturing emissions in high-pollution firms would be a valuable next step.

Appendix A

Table A1
Observation counts and country-level rates of pollution taxes

	Number of observations	Number of firms	Pollution tax mean (1990–2012)
Australia	1,463	188	0.88
Austria	266	30	0.00
Belgium	291	34	0.00
Canada	2,652	308	0.96
Denmark	436	44	4.30
Finland	673	57	0.00
France	1,239	155	0.98
Germany	1,854	222	0.00
Greece	163	22	0.00
Ireland	225	17	0.00
Italy	361	59	1.76
Japan	18,308	1,370	6.00
Korea	269	87	4.73
Netherlands	349	40	0.00
Norway	275	40	0.00
Spain	107	21	1.34
Sweden	1,146	120	0.00
United Kingdom	3,479	382	0.00
Total	33,556	3,196	–

This table reports the number of observations (column 1) and unique firms (column 2) by country in the full sample and average *Pollution taxes* by country (column 3). Table 1 defines the variables in detail.

Table A2
Correlation matrix: Firm variables

	R&D	*Sales*	*Cash-flow-to-assets*	*Sales growth*	*Cash-to-assets*	*Total debt-to-assets*	*IFRS*	*Patent count*	*Patent citations*
R&D	1.000								
Sales	0.763	1.000							
	(.000)								
Cash-flow-to-assets	0.213	0.348	1.000						
	(.000)	(.000)							
Sales growth	0.033	0.047	0.130	1.000					
	(.000)	(.000)	(.000)						
Cash-to-assets	0.026	−0.226	−0.169	0.215	1.000				
	(.000)	(.000)	(.000)	(.000)					
Total debt-to-assets	−0.027	0.082	−0.082	0.048	−0.182	1.000			
	(.000)	(.000)	(.000)	(.000)	(.000)				
IFRS	0.321	0.301	0.022	0.002	0.014	−0.013	1.000		
	(.000)	(.000)	(.000)	(.724)	(.008)	(.018)			
Patent count	0.087	0.129	0.107	−0.017	−0.053	0.003	−0.140	1.000	
	(.000)	(.000)	(.000)	(.002)	(.000)	(.641)	(.000)		
Patent citations	0.213	0.197	0.139	−0.008	−0.042	0.011	−0.145	0.674	1.000
	(.000)	(.000)	(.000)	(.151)	(.000)	(.050)	(.000)	(.000)	

p-values are in parentheses.

Table A3
Correlation matrix: Country variables

	Pollution taxes	*GDP per capita*	*Public env. R&D -to-GDP*	*User cost of R&D*
Pollution taxes	1.000			
GDP per capita	−0.303	1.000		
	(.237)			
Public env. R&D-to-GDP	−0.008	−0.034	1.000	
	(.977)	(.896)		
User cost of R&D	0.123	−0.117	0.378	1.000
	(.638)	(.654)	(.135)	

p-values are in parentheses.

Table A4
Pollution taxes and R&D investment: Alternative samples

	(1)	(2)	(3)	(4)	(5)
	Drop Japan	Drop United Kingdom	Drop Canada	Drop three largest	Drop no change SO_x tax
			A. Baseline estimates		
Pollution taxes$_{c,t-1}$	0.033	0.065	0.065	0.025	0.032
	(0.015)**	(0.020)***	(0.020)***	(0.018)	(0.016)*
Sales$_{i,t}$	0.323	0.313	0.329	0.360	0.264
	(0.040)***	(0.042)***	(0.045)***	(0.060)***	(0.049)***
			B. Differential effects		
Pollution taxes$_{c,t-1}$	−0.025	0.002	0.003	−0.029	−0.029
	(0.010)**	(0.012)	(0.013)	(0.015)*	(0.012)**
Sales$_{i,t}$	0.322	0.312	0.328	0.358	0.263
	(0.040)***	(0.042)***	(0.045)***	(0.060)***	(0.048)***
Pollution taxes$_{c,t-1}x$	0.035	0.052	0.048	0.029	0.038
Q_2 *of* SO_x *polluters*	(0.020)*	(0.016)***	(0.017)**	(0.025)	(0.024)
Pollution taxes$_{c,t-1}x$	0.080	0.088	0.080	0.071	0.079
Q_3 *of* SO_x *polluters*	(0.030)**	(0.043)*	(0.041)*	(0.022)***	(0.038)*
Pollution taxes$_{c,t-1}x$	0.094	0.097	0.100	0.094	0.102
Q_4 *of* SO_x *polluters*	(0.015)***	(0.014)***	(0.013)***	(0.016)***	(0.014)***
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	15,237	30,068	30,899	9,114	6,520

This table reports the OLS estimates for Equation (1) (panel A) and Equation (1) augmented with interactions between country *Pollution taxes* and the indicators for the industry pollution intensity quartiles (panel B). $R\&D_{i,t}$ is the dependent variable. The firm-level data are from Compustat Global and North America and consist of non-U.S. firms with at least three nonmissing R&D observations during 1990–2012 and a primary SIC industry classification between 2000 and 3999. A large country is defined as one with more than 2,500 observations (Japan, the United Kingdom, and Canada). *No change* SO_x *tax* refers to a country without any change in the pollution tax during the sample period (see Table A1). Q_k *of* SO_x *polluters* is an indicator variable taking on the value one if the firm is located in the kth quartile in SO_x *emission*. All regressions include firm and year fixed effects. Table 1 defines the variables in detail. Standard errors are clustered at the country level. $^{*}p<.1$; $^{**}p<.05$; $^{***}p<.01$.

Table A5
Pollution taxes and R&D investment: Other channels

	(1)	(2)	(3)	(4)	(5)	(6)
	1997–2001				IFRS reform	
Sales$_{i,t}$	0.259	0.259	0.260	0.259	0.312	0.352
	(0.032)***	(0.032)***	(0.032)***	(0.032)***	(0.036)***	(0.038)***
Other channel x	−0.018	−0.012	−0.022	−0.026		
Q_2 *of* SO_x *polluters*	(0.038)	(0.037)	(0.099)	(0.101)		
Other channel x	0.001	0.008	−0.011	−0.019		
Q_3 *of* SO_x *polluters*	(0.016)	(0.015)	(0.047)	(0.045)		
Other channel x	−0.012	−0.004	−0.038	−0.051		
Q_4 *of* SO_x *polluters*	(0.027)	(0.027)	(0.038)	(0.039)		
Pollution taxes$_{c,t-1}$*x*		0.041		0.045		
Q_2 *of* SO_x *polluters*		(0.016)***		(0.023)*		
Pollution taxes$_{c,t-1}$*x*		0.084		0.086		
Q_3 *of* SO_x *polluters*		(0.021)**		(0.021)***		
Pollution taxes$_{c,t-1}$*x*		0.102		0.108		
Q_4 *of* SO_x *polluters*		(0.015)***		(0.015)***		
Pollution taxes$_{c,t-1}$					0.070	0.066
					(0.017)***	(0.018)***
Not IFRS$_{i,t}$					−0.033	−0.028
					(0.044)	(0.039)
Pollution taxes$_{c,t-1}$*x*					−0.027	−0.025
Not IFRS$_{i,t}$					(0.019)	(0.018)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-year fixed effects	Yes	Yes	Yes	Yes	No	No
Year fixed effects	No	No	No	No	Yes	Yes
Observations	33,529	33,529	33,529	33,529	33,545	33,343
Adjusted R^2	.959	.959	.959	.959	.955	.957

This table reports the OLS estimates for Equation (1) augmented with interactions between country *Pollution taxes* and the indicators for the industry pollution intensity quartiles. *R&D*$_{i,t}$ is the dependent variable. The firm-level data are from Compustat Global and North America and consist of non-U.S. firms with at least three nonmissing R&D observations during 1990–2012 and a primary SIC industry classification between 2000 and 3999. *Other channel* is either *(1997–2001)* or *IFRS reform*. *(1997–2001)* is an indicator variable taking on the value one for all countries and firm-years (zero) during 1997–2001 (1990–1996 and 2002–2012). *IFRS reform* reports the year a country implements IFRS accounting standards. Q_k *of* SO_x *polluters* is an indicator variable taking on the value one if the firm is located in the kth quartile in SO_x *emission*. *Not IFRS* in an indicator variable taking on the value one (zero) if the firm follows IFRS (or not). All regressions include firm fixed effects: columns 1–4 include country-year, and columns 5 and 6 include year fixed effects. Column 6 include the following firm-level control variables: *Cash-flow-to-assets*, *Sales growth*, *Cash-holdings-to-assets*, and *Total debt-to-assets*. Table 1 defines the variables in detail. Standard errors are clustered at the country level. *$p<.1$; **$p<.05$; ***$p<.01$.

Table A6
Pollution taxes and R&D investment: Industry share in economy

	(1)	(2)	(3)	(4)
$Sales_{i,t}$	0.313	0.320	0.312	0.319
	(0.036)***	(0.044)***	(0.036)***	(0.044)***
Industry share R&D$_{cj,t}$	0.440		0.436	
	(0.349)		(0.341)	
Industry share Employment$_{cj,t}$		0.568		0.545
		(0.186)***		(0.187)***
Pollution taxes$_{c,t-1}$	0.064	0.041	0.003	−0.017
	(0.020)***	(0.017)**	(0.013)	(0.011)
Pollution taxes$_{c,t-1}x$			0.049	0.040
Q_2 *of* SO_x *polluters*			(0.015)***	(0.021)*
Pollution taxes$_{c,t-1}x$			0.093	0.071
Q_3 *of* SO_x *polluters*			(0.040)**	(0.038)*
Pollution taxes$_{c,t-1}x$			0.092	0.097
Q_4 *of* SO_x *polluters*			(0.016)***	(0.016)***
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	33,545	27,866	33,545	27,866
Adjusted R^2	.955	.961	.955	.961

This table reports the OLS estimates for Equation (1) (columns 1 and 2) and Equation (1) augmented with interactions between country *Pollution taxes* and the indicators for the industry pollution intensity quartiles (columns 3 and 4). $R\&D_{i,t}$ is the dependent variable. The firm-level data are from Compustat Global and North America and consist of non-U.S. firms with at least three nonmissing R&D observations during 1990–2012 and a primary SIC industry classification between 2000 and 3999. Q_k *of* SO_x *polluters* is an indicator variable taking on the value one if the firm is located in the kth quartile in SO_x *emission*. All regressions include firm and year fixed effects. Table 1 defines the variables in detail. Standard errors are clustered at the country level. $^*p<.1$; $^{**}p<.05$; $^{***}p<.01$.

Table A7
Pollution taxes and future patent citations

	(1)	(2)	(3)	(4)	(5)	(6)
Pollution taxes$_{c,t-1}$	0.009	0.027	−0.034	0.196	0.247	0.232
	(0.026)	(0.034)	(0.021)	(0.084)**	(0.111)**	(0.100)**
Stock of triadic		0.398	0.397		0.011	0.011
patents$_{i,t-1}$		(0.020)***	(0.019)***		(0.002)***	(0.002)***
Pollution taxes$_{c,t-1}x$			0.284			−0.065
Q_2 *of* SO_x *polluters*			(0.221)			(0.067)
Pollution taxes$_{c,t-1}x$			0.095			0.024
Q_3 *of* SO_x *polluters*			(0.047)*			(0.142)
Pollution taxes$_{c,t-1}x$			0.026			0.044
Q_4 *of* SO_x *polluters*			(0.034)			(0.062)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	33,442	33,442	33,442	33,442	33,442	33,442
Adjusted R^2	.836	.841	.841	.237	.238	.238

This table reports the OLS estimates for Equation (1) (columns 1–2 and 4–5) and Equation (1) augmented with interactions between country *Pollution taxes* and the indicators for the industry pollution intensity quartiles (columns 3 and 6). *Patent citations*$_{i,t}$ is the dependent variable. The firm-level data are from Compustat Global and North America and consist of non-U.S. firms with at least three nonmissing R&D observations during 1990–2012 and a primary SIC industry classification between 2000 and 3999. Patents from technology classes classified as air pollution abatement technologies (based on Hascic and Migotto 2015; reported in Table B1) are reported in columns 4–6. Q_k *of* SO_x *polluters* is an indicator variable taking on the value one if the firm is located in the kth quartile in SO_x *emission*. All regressions include *Sales* and the following country-level control variables: *Public environmental R&D to GDP* and *GDP per capita*. Table 1 defines the variables in detail. Standard errors are clustered at the country level. $^*p<.1$; $^{**}p<.05$; $^{***}p<.01$.

Table A8
Pollution taxes and R&D: Splits based on extra-industry knowledge and technology spillovers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	High basic research		Low basic research		High-tech spillovers		Low-tech spillovers	
Pollution taxes$_{c,t-1}$	0.005		0.043		0.030		0.021	
	(0.026)		(0.015)**		(0.019)		(0.037)	
Sales$_{i,t}$	0.331	0.276	0.428	0.378	0.369	0.310	0.288	0.269
	(0.038)***	(0.035)***	(0.055)***	(0.069)***	(0.039)***	(0.037)***	(0.055)***	(0.045)***
Pollution taxes$_{c,t-1}$x *Above-median* SO_x *polluters*	0.090	0.093	−0.013	−0.023	0.079	0.116	0.020	0.031
	(0.023)***	(0.026)***	(0.045)	(0.040)	(0.018)***	(0.030)***	(0.027)	(0.017)*
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	No	Yes	No	Yes	No	Yes	No
Firm control set	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-year fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Observations	18,472	18,443	10,469	10,440	24,902	24,884	8,234	8,206
Adjusted R^2	.957	.962	.958	.962	.959	.963	.940	.949

This table reports the OLS estimates for Equation (1) (columns 1 and 4) and Equation (1) augmented with interactions between country *Pollution taxes* and the indicator for the industry pollution intensity variable (columns 2–3 and 5–6). $R\&D_{i,t}$ is the dependent variable. The firm-level data are from Compustat Global and North America and consist of non-U.S. firms with at least three nonmissing R&D observations during 1990–2012 and a primary SIC industry classification between 2000 and 3999. Columns 1–2 (3–4) define high (low) basic research sectors as the industries above (below) the median in terms of the maximum value of the importance of basic versus applied sciences in Cohen, Nelson, and Walsh (2002). Columns 5–6 (7–8) define high (low) technology spillover sectors as the industries above (below) the median in terms of average technology spillover during the 1980s by three digit SIC sector in the United States from Bloom, Schankerman, and Van Reenen (2013). *Above-median* SO_x *polluters* is an indicator variable taking on the value one (zero) if the industry is above (below) the median in SO_x *emission*. All regressions include firm fixed effects, and odd (even) numbered columns include year (country-year) fixed effects. All columns include the following firm control variables: *Cash-flow-to-assets*, *Sales growth*, *Cash-holdings-to-assets*, *Total debt-to-assets*, and *IFRS*. Table 1 defines the variables in detail. Standard errors are clustered at the country level. $^{*}p<.1$; $^{**}p<.05$; $^{***}p<.01$.

B. Matching between PATSTAT and Compustat

Here, we describe how we match patent assignees of the patents in Worldwide Patent Statistical Database (PATSTAT) maintained by the European Patent Office (EPO) to firms in the Compustat Global and North America database for the January 1985 to December 2012 period. Our methodology draws on those of Hall, Jaffe, and Trajtenberg (2001) and Bena et al. (2017).

PATSTAT contains bibliographical data relating to more than 100 million patent documents from leading industrialized and developing countries. It also includes the legal status data from more than 40 patent authorities contained in the EPO worldwide legal status database (INPADOC). We use the following basic outline to construct our sample and matching on patents.

1. We begin with firms from Compustat Global and include Canadian firms from Compustat North America. For a firm to enter the sample it has to have fully consolidated financial statements, a primary industry classification in the manufacturing sector, and at least three nonmissing R&D observations over the period 1990 to 2012. Next, we require countries to have at least 10 firms. We also drop firms from industries without any SO_x emissions based on data from Levinson (2009). Finally, we merge the firm-level data from Compustat with information on time-series changes in air pollution taxes for 18 OECD countries. This gives us the "Compustat sample." These sample selection criteria leave us with 3,594 unique firms.
2. We need to create meaningful names based on the company names in the Compustat sample. We do this to be able to use the firms' names in an SQL query to PATSTAT. We capitalize all firm name strings. We then ensure that firm name strings (Compustat field: conm) only contain A–Z, and 0–9 characters. We then remove approximately 300 regular expressions for firms from (among others) the United Kingdom, France, Spain, Italy, Sweden, Belgium, Denmark, Norway, the Netherlands, Poland, Greece, Germany, Czech Republic, Bulgaria, Belgium, and Japan. Examples of words and suffixes that we remove are HOLDINGS, LTD, COMPANY, SARL, and AKTIENGESELLSCHAFT. The goal with these removals is to ensure that our SQL query does not miss patent filings due to inclusion or exclusion of regular expressions. We remove countries' names from the firms' names. For borderline cases we shorten the firms' names to increase the number of "matches" in our SQL query.
3. We use these shortened firm names in an SQL query to PATSTAT. In this SQL query, we retrieve patent filings where a part of doc standard name is—as mentioned above—the same as the shortened name from the Compustat file. This query returns data on 2.2 million semi unique firms/individuals filing patents. Semiuniqueness is established by PATSTAT's unique identifier doc std id. However, a single firm may show up having a number of doc std id's because of the way the firm's name is written on the patent application form.
4. We remove firms without patents filed after 1984 and we clean and shorten the names that we obtain from PATSTAT (doc std name). Again, we capitalize all letters, and we remove regular expressions like HOLDINGS, etc. In addition, we shorten common firm names.
5. To reduce the number of false positive matches, we append the file containing the names of our Compustat firms to include even such Compustat firms that are not in "our" sample. We also clean the firm names in this stage as described above.
6. We use a matching algorithm provided by Raffo (2015) and Raffo and Lhuillery (2009) (Stata's MATCHIT) to match the shortened Compustat names (whole names, can consist of several words) and the shortened PATSTAT names (whole names, can consist of several words). Using Stata's MATCHIT command we obtain a similarity score between two different text strings by performing different string-based matching techniques. It returns a new numeric variable (similscore) containing the similarity score, which ranges from 0 to 1. A similscore of 1 implies a perfect similarity according to the string-matching technique chosen and decreases when the match is less similar. We remove matches where similscore is below 0.5.

Table B1
Definition of IPC classes for patents in emissions abatement from stationary sources

Description	IPC codes
Postcombustion technologies	
Chemical or biological purification of waste gases (e.g., engine exhaust gases, smoke, fumes, flue gases or aerosols; removing sulfur oxides, nitrogen oxides)	B01D53/34-72
Incinerators or other apparatus specially adapted for consuming waste gases or noxious gases	F23G7/06
Arrangements of devices for treating smoke or fumes of purifiers, for example, for removing noxious material	F23J15
Shaft or like vertical or substantially vertical furnaces; arrangements of dust collectors	F27B1/18
Integrated technologies	
Blast furnaces; dust arresters	C21B7/22
Combustion apparatus characterized by means for returning flue gases to the combustion chamber or to the combustion zone	F23B80
Combustion apparatus characterized by arrangements for returning combustion products or flue gases to the combustion chamber	F23C9
Apparatus in which combustion takes place in a fluidized bed of fuel or other particles	F23C10

The descriptions and IPC classes come from Hascic and Migotto (2015).

7. We measure the success of this match with what we achieved in step 6. To do this, we divide firm names into separate words. We do this both for the PATSTAT name and the Compustat name. We then generate a similscore for each word of our matches. This means that a similscore is generated for the first word in the PATSTAT name and the first word in the Compustat name and (if relevant) the same for second and third words. We do this for second and third words when both names have the same number of words. We then multiply the similscores of the matches to arrive at the final similscore. We only keep similscores that are equal to one.
8. We then delete instances where one firm's PATSTAT identifier (doc standard name id) is matched to several Compustat firms (GVKEY).
9. We then drop all firms (along with the matched patents) that are not in the original sample of the 3,594 Compustat firms.

This gives us a final sample of 3,196 unique Compustat firms (identified by GVKEY) which are matched to around 75,000 semi unique firms filing patents (identified by doc std name id). Using the information on the doc std name from PATSTAT we then retrieve the patent information from PATSTAT. We count for each firm the number of triadic patents using the INPADOC data set.[20] We also compile the sum of all patents that are not defined as a triadic patent (and call them nontriadic). We also separate patents between air pollution abatement patents and non-air-pollution abatement patents based on Hascic and Migotto (2015). See Table B1 for the different technology classes and descriptions. We also count the citations from each of the triadic and nontriadic patents.

C. Security Daily

Here, we describe how we merged daily market price data from *Security Daily* to our sample. Security Daily comprises data on publicly listed companies around the world dating back to 1985. This data set includes a GVKEY identifier and can be merged with Compustat Global. We follow

[20] For more details on the definition of triadic patents, see Dernis and Khan (2004) and Martinez (2004).

the literature (e.g., Faulkender and Wang 2006) and use the closing price on the final trading day of the fiscal year (*prcc_f*) and the number of outstanding common shares (*csho*) to measure firm market value of equity. In the instances in which more than one security is tied to the same firm-year (less than 5% of the observations), we use the first security (the variable *iid* is equal to one), which corresponds to the first security issued and corresponds to the stock listed in the domestic stock market in domestic prices. We convert and deflate all prices in to US$(2000) as we do in our main sample with the accounting variables.

We measure market value of equity as the product of the closing price on the final trading day and the number of outstanding common shares (*MV*). Our main dependent variable is equal to $MV_{i,t} - MV_{i,t-1}$ divided by $MV_{i,t-1}$. The vector of firm controls, **X**, in Equation (2) comprises the following control variables: net assets (defined as book value of total assets minus cash holdings divided by the lagged market value of the firm's equity) change in net income (defined as the annual change in income before extraordinary items divided by the lagged market value of the firm's equity), annual dividend payment (divided by the lagged market value of the firm's equity), firm cash holdings (divided by the lagged market value of the firm's equity), net financing raised (measured as net stock issues plus net debt issues divided by the lagged market value of the firm's equity), and leverage (measured as stock of long-term debt divided by the lagged market value of the firm's equity).

D. Evaluating Stability of Emission Intensity Measure

The OECD reports relatively disaggregated data on *SO_x emission* for three of our sampled countries: Italy, the Netherlands, and Denmark (see the *Air Emission Accounts*). Table D1 reports SO_x emission intensity (measured as tonnes of SO_x per million of sales in local currency) for these three countries. The data cover 12 of our sample years (2000–2012) and are reported for 17 two-digit and three-digit ISIC industry classes. Four industries—Coke and refined petroleum products, Other nonmetallic mineral products, Basic metals and Chemicals and chemical products—are consistently the most SO_x-polluting industries.[21] These four ISIC industries include 9 of the 10 most SO_x-emitting industries in Table 3. The eighth most SO_x-emitting U.S. industry in Table 3, Grain mill products (SIC 204), is part of Food manufacturing, a broadly aggregated sector for the non-U.S. countries in Table D1. Overall, the comparative evidence in Table D1 suggests that cross-industry differences in pollution intensity are very similar within the type of developed economy that we study.

[21] Denmark's fourth most-polluting industry is instead Food products, beverages, and tobacco products. This is because Denmark reports essentially no economic activity in Basic metals.

Table D1
Evaluating stability of SO_x emission measure

		Italy		Netherlands		Denmark		Pollution rank	
ISIC	Industry	SO_x emission	Rank	SO_x emission	Rank	SO_x emission	Rank	Most	Least
19	Coke and refined petroleum products	1.608	1	1.022	1	0.041	2	2	
23	Other nonmetallic mineral products	1.107	2	0.452	3	0.122	1	1, 4, 7	
24	Basic metals	0.379	3	0.855	2	0.002	8	5, 6	
20	Chemicals and chemical products	0.268	4	0.087	4	0.029	3	3, 9, 10	
17	Paper and paper products	0.087	5	0.015	6	0.006	7		
16	Wood and of products of wood and cork	0.045	6	0.005	9	0.010	5		
22	Rubber and plastic products	0.043	7	0.001	16	0.001	12		
21	Basic pharmaceutical products	0.040	8	0.005	10	0.003	6		
10-12	Food prod., beverages and tobacco prod.	0.032	9	0.012	7	0.029	4	8	7
31-33	Furniture	0.023	10	0.002	12	0.001	9		
13-15	Textiles	0.016	11	0.004	11	0.001	13		
28	Machinery and equipment n.e.c.	0.005	12	0.008	8	0.001	11		
29-30	Motor vehicles and other transport equip.	0.002	13	0.001	15	0.000	14		
26	Computer, electronic and optical products	0.000	14	0.002	14	0.000	16		1, 4, 5, 6
18	Printing and media	0.000	15	0.001	17	0.000	15		2
27	Electrical equipment	0.000	16	0.023	5	0.000	17		9
25	Fabricated metal products	0.000	17	0.002	13	0.001	10		3, 10

Table D1 lists 17 ISIC industries from OECD's data portal with information on the average tonnes of SO_x emission per one million local currency of output during 2000–2012 (in columns named "SO_x **emission**") for Italy, the Netherlands, and Denmark respectively. The columns "**Rank**" lists the industries ranked in order of SO_x emission for Italy, the Netherlands, and Denmark respectively. The final two columns display the rank of SIC three-digit industries (using U.S. industries from our baseline sample) in terms of most (least) polluting industry from Table 3.

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