DIRECT AND INDIRECT TAXES IN POLLUTION DYNAMICS

By

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ABSTRACT

Analyzing the universe of federal environmental regulations in the U.S., we construct a measure of regulations—direct taxes on pollution. Analyzing the universe of firms' investor disclosures, we construct a measure of material environmental concerns—indirect taxes on pollution. These two empirical measures are new to the environmental regulations literature. Thirdly, we document an important new fact that the cross-sectional distribution of pollution changes is lumpy. We build a dynamic heterogeneous firm model with non-convex adjustment costs that fits the cross-sectional pollution evidence. The model explains half of the pollution decline in U.S. manufacturing over the last two decades due to direct and indirect taxes. We show that the dynamics of direct taxes (environmental regulations) and indirect taxes (environmental concerns), non-convex adjustment costs, and idiosyncratic productivity shocks are key determinants of pollution dynamics in U.S. manufacturing.

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1 Introduction

The environment-related challenges have led to stricter environmental regulations and to companies adjusting their behavior to changing societal pressures. Environmental regulations, primarily defined in the U.S. by the Environmental Protection Agency (EPA), act as direct taxes to control pollution. The growing environmental concerns, especially in the past decade, affect firms' incentives to pollute, and act as indirect taxes. The goal of this paper is to empirically measure the universe of EPA environmental regulations (direct taxes on pollution) and companies' material environmental concerns (indirect taxes on pollution), to estimate their effects on firm-level toxic releases, and to quantify their impact on the dynamics of pollution in a dynamic heterogeneous firm model with non-convex pollution adjustment costs that aligns with the cross-sectional evidence.

First, we construct a measure of the universe of direct pollution control instruments as well as a measure of indirect pollution control instruments and analyze their effects on firm-level pollution. The direct instruments comprise the universe of EPA regulations. This measure of direct taxes is new to the literature as it encompasses the entirety of active environmental regulations, rather than individual laws, and, importantly, captures the direct relevance of specifically environmental regulations to affected industries. The indirect instruments are represented by firms' material environmental concerns as reflected in disclosures and investor communications. We show that these two measures play an important role in determining the dynamics of pollution.

The measure of environmental regulations encompasses all effective EPA rules in Title 40 of the Code of Federal Regulations (CFR) over the period 2001-2020 and is based on 497,490 pages of regulatory text comprising 284 million words. Specifically, our index of environmental regulations comprises two components: the restrictiveness of each regulation and the direct relevance of specifically environmental regulations to affected industries. The restrictiveness of each regulation is based on the number of restrictive words within each document, following established practice in legal literature to measure binding obligations and prohibited activities (e.g., Danet, 1980, Trosborg, 1995). The key ingredient of our index is a measure of relevance of environmental regulations which we construct by directly assessing applicability of each individual environmental regulation to affected industries. We show that the resulting index of environmental regulations for manufacturing has increased by over 30 percent over the last two decades, and, importantly, document a significant heterogeneity of these direct taxes across NAICS 3-digit industries. For example, regulations on chemical, primary metal, and fabricated metal industries increased the most over the last 20 years, while apparel and beverage industries did not experience any pronounced increase in environmental regulations.

Our approach to measuring regulations is different from the existing literature. In contrast with, for example, Greenstone (2002), Greenstone, List and Syverson (2012), Ryan (2012) and Taylor and Druckenmiller (2022), who focus on individual rules such as the Clean Air or Clean Water Acts, we construct a measure of the universe of EPA regulations. An important paper by Shapiro and Walker (2018) can also be thought of as quantifying the effect of the totality of environmental regulations. They measure the effect of all environmental rules as a wedge implied by their model of pollution. In contrast, we directly measure the distortion induced by the universe of EPA regulations as opposed to estimating the implied wedge that exactly matches the data. The difference between our approach and that of Shapiro and Walker (2018) is what Restuccia and Rogerson (2017) describe as the difference between wedge accounting (measuring wedges that account for the data) and direct approaches (measuring the effects of policies directly) to measuring distortions.

Accounting literature has also measured environmental regulations, using an indirect measure of relevance based on all CFR regulations rather than directly focusing on EPA's environmental regulations (e.g., Fan and Wu, 2022). Their relevance score is constructed using machine learning algorithms (McLaughlin and Nelson, 2021) trained on the entire CFR, most of which is not environment-related. We show in Appendix A.1 that this algorithmic measure of relevance based on the universe of CFR regulations is substantially different from our direct measure of relevance of specifically environmental regulations. On average, our index of regulations is positively correlated with an index of regulations based on the relevance score derived from all CFR regulations; however, there is a significant number of industries within manufacturing sector for which the correlation between the two indices is small or negative. Even more importantly, for a significant fraction of regulation-industry pairs a relevance score is zero when derived using the universe of CFR regulation, even though the EPA explicitly states that the corresponding parts are directly relevant to those individual manufacturing industries. Thus, our measure of regulations incorporates the direct relevance of specifically environmental regulations rather than an indirect measure of relevance of all CFR regulations.

Second, we construct a measure of indirect pollution control distortions by creating an index of non-regulatory environmental concerns. The principal reason for including this measure is that growing environmental concerns can incentivize firms to reduce pollution not only through formal regulations but also due to awareness of the potential material impact of environment-related events on their current and future profits.[1] We construct a measure of non-regulatory environmental concerns for U.S. public firms based on two major voluntary communication channels: the 8-K filings with the Securities and Exchange Commission (SEC), and conference call transcripts. Overall, we analyzed 403,000 8-K filings and 27,000 conference call transcripts for manufacturing firms with the total of over 3.7 billion words.

In order to measure firms' exposure to environmental non-regulatory concerns, we use a list of signal word combinations, or bigrams, compiled by Sautner, van Lent, Vilkov and Zhang (2023) to capture discussions about environmental and climate concerns in 8-K filings and conference transcripts. While a variant of this measure has been used in finance to assess firms' exposure to climate risks, we introduce it to the literature on environmental regulations as it provides a measure of indirect taxes on pollution. We show that the index of environmental concerns has increased by over 200 percent over the past 20 years, with substantial heterogeneity across industries. For example, firms in the petroleum and electrical equipment industries demonstrate the largest increase in environmental concerns, while the printing and textile industries have experienced a much smaller rise in concerns.

Having constructed the measures of direct and indirect taxes, we document the negative relationship between firm-level pollution and environmental regulations and environmental concerns using data on toxic releases from the Toxics Release Inventory (TRI). This dataset,

[1]Notable examples include the BP Deepwater Horizon oil spill in 2010 and the Pacific Gas and Electric Company wildfires from 2017-2020 in California.

available on an annual basis, includes information on over 800 different toxic pollutants emitted by manufacturing facilities. We find that increased regulations and environmental concerns are associated with economically significant reductions in pollution. Specifically, a one standard deviation increase in regulations is associated with a 13 percent decline in the growth of toxic releases, while a similar increase in concerns results in a 7 percent reduction. To corroborate these findings, we use the National Emissions Inventory (NEI) data, which has a triennial frequency and covers major air pollutants. The results from the NEI data are broadly comparable to those obtained from the TRI data.

Third, we document that the empirical cross-sectional distribution of pollution changes for U.S. firms is lumpy, meaning that while many firms maintain consistent levels of pollution from one period to the next (defined as the inaction rate), those that change their pollution levels tend to do so in substantial amounts (defined as the spike rate). The documentation of the lumpy behavior of pollution changes is new to the literature and, importantly, leads to the necessity for introducing a dynamic model of firms with idiosyncratic productivity shocks and non-convex adjustment costs to explain this cross-sectional evidence. We show that adjustment costs is an important determinant of pollution elasticity to direct and indirect taxes, and of pollution dynamics in the quantitative model. These costs act as expenditures that a firm incurs to modify its production process, such as installing new pollution control equipment, temporarily shutting down operations to implement pollution reduction measures, and covering legal and compliance costs to meet environmental standards.[2] We then show that another key determinant of both the cross-section of pollution changes and of the elasticity to direct and indirect taxes is the idiosyncratic productivity process for firms.

We model the price of the dirty good as a combination of time-varying direct (environmental regulations) and indirect (environmental concerns) pollution taxes. The literature on environmental regulations, particularly Shapiro and Walker (2018), provides a comprehensive quantitative analysis of the effects of environmental regulations in a static environment. Our paper builds the first dynamic model to provide an analysis of the evolution of pollution. Our framework models forward-looking firms, incorporates rich heterogeneity in the

[2]These costs have previously been found to be significant for most firms (e.g., Blundell, Gowrisankaran and Langer, 2020). Compliance costs to meet environmental targets have also been cited as a major issue for many U.S. firms (https://www.whitehouse.gov/p1).

dynamic shocks to firms and non-convex adjustment costs, and studies the transition dynamics of pollution. There are three aspects in which dynamic modeling is essential. First, the time profile of direct and indirect taxes determines firms' current and future plans to change pollution. Second, the dynamic model with non-convex adjustment costs and idiosyncratic productivity shocks explains the lumpy distribution of pollution growth rates we document in the data. Third, the time profiles of direct and indirect pollution taxes and firms' dynamic decisions to adjust pollution levels, subject to non-convex costs and stochastic productivity shocks, non-trivially interact with each other and shape the dynamics of pollution.

First, we find that EPA regulations explain a 9 percent decline in aggregate pollution over the last two decades, while a significant recent increase in environmental concerns explains an additional 11 percent decline. It is instructive to contrast our findings with an important paper by Shapiro and Walker (2018). In a static model, they construct a wedge that accounts for essentially the entire decline in U.S. manufacturing pollution over the last several decades. Our findings show that, in our dynamic model, the direct measure of pollution control instruments, comprising both direct and indirect taxes, explains about a half of the 40 percent pollution decline in the U.S. manufacturing over the last two decades, with both the direct and indirect instruments being about equally important. We then determine transition dynamics for twenty manufacturing NAICS 3-digit industries using industry-specific indices of regulations and environmental concerns. Our direct measure of regulations and concerns explains nearly the entire pollution decline in the food, petroleum, and primary metal industries.

Second, we find that the lumpy distribution of pollution changes is a central feature that shapes the dynamics of pollution. There are two empirical statistics that are important for a quantitative model of pollution dynamics to account for. The first is the inaction rate—the share of firms that do not change their pollution levels from one period to another. The second statistic is the spike rate—the share of firms that make large pollution adjustments. In our model, non-convex adjustment costs lead to both the endogenous region of inaction, where firms do not change their pollution levels despite rising contemporaneous and future direct and indirect taxes, and to discrete adjustments, where firms abruptly and significantly change their pollution levels, explaining the lumpy distribution of pollution changes in the data.[3]

We assume that firms draw adjustment cost shocks and choose to adjust pollution levels if the shock realization is low enough. In other words, the adjustment decision is characterized by an endogenous cutoff value, whereby firms undertake an adjustment if the value of a shock is below this threshold. In order to determine how adjustment costs shape the dynamics of pollution, consider a model with a lower inaction rate relative to the data. In that counterfactual setting, the cutoff value of costs triggering pollution adjustment is higher relative to the baseline parameterization. An increase in direct or indirect taxes lowers the adjustment cutoff. The elasticity of rising taxes is therefore stronger in the model with low adjustment costs since more firms get triggered to adjust as the cutoff gets reduced from an initially high level. Quantitatively, we find that a lower inaction rate in the case of low adjustment costs increases the effectiveness of regulations and leads to a 5 percentage point higher cumulative decline in pollution over the period 2001-2020. Conversely, the cumulative decline in pollution is five percentage points smaller relative to the baseline in the model with an inaction rate twice the size of what we observe in the data.

Another central element of our dynamic framework is the stochastic idiosyncratic productivity process for firms. The volatility of these productivity shocks generates ex-post heterogeneity among ex-ante identical firms; we parameterize the volatility of shocks to match the empirical distribution of pollution changes. In the limiting case where volatility is zero, the model collapses to a representative firm framework, which cannot fit the cross-sectional evidence we provide. The persistence of shocks is based on the U.S. Census microdata, and is directly related to the spike rate: the higher the persistence is, the larger the spike rate becomes.[4] Intuitively, low persistence makes productivity shocks more transient, disincentivizing firms from making costly adjustments even in the case of large productivity shocks, since they expect productivity to revert back in the next period. Consequently, they choose

[3]These discrete patterns are a central feature of the macroeconomics literature on investment dynamics, where similar observations are made for capital investments (e.g., Cooper and Haltiwanger, 2006, Bai, Li, Xue and Zhang, 2022). In particular, Cooper and Haltiwanger (2006) argue that convex adjustment costs (and the frictionless choice in the limit) cannot account for periods of inactivity in capital adjustment. Khan and Thomas (2008) explore the macroeconomic implications of lumpy investment; in turn, Smirnyagin and Tsyvinski (2022) find important asset pricing implications. Discrete patterns of investment are also pronounced for other types of capital, such as supplier capital (Liu, Smirnyagin and Tsyvinski, 2024).

[4]See, for example, Foster, Haltiwanger and Syverson (2008) and Smirnyagin (2023) for estimation details.

not to respond, resulting in a low spike rate.

We demonstrate that both the persistence and volatility of productivity shocks increase the elasticity of toxic releases to pollution taxes, thereby improving their effectiveness. On one hand, low persistence makes the firm's current idiosyncratic state less informative of its future profits. As a result, firms are less responsive to the paths of both direct and indirect taxes, leading to a lower cumulative pollution decline. On the other hand, lower volatility results in a larger fraction of firms being within the inaction region, thereby limiting the model's response to rising direct and indirect pollution taxes.

Finally, our model is set in general equilibrium, and it is important to discuss the role of endogenous price adjustments. Specifically, we find that in partial equilibrium, the decline in aggregate toxic releases is stronger, with a cumulative decline of 7 percentage points more relative to the baseline. The effect of general equilibrium is somewhat straightforward as it is commensurate with the share of the dirty factor in the production technology of firms. For instance, it would be much more pronounced in the context of carbon emissions, where the typical exponent of the (dirty) energy input is four to five times higher than what is used for toxic releases (e.g., Golosov, Hassler, Krusell and Tsyvinski, 2014, Hassler, Krusell and Olovsson, 2018).

The rest of the paper is organized as follows. In Section 2, we provide institutional background for environmental regulations in the U.S. and build indices of environmental regulations and environmental concerns. Empirical results are reported in Section 3. We then build and parameterize a dynamic heterogeneous firm model in Section 4. Section 5 provides our quantitative results, and Section 6 concludes.

2 Data

In this section, we describe the data and construct measures of direct and indirect pollution control instruments for individual manufacturing industries and for the overall manufacturing sector. Our direct instrument comprises the universe of regulatory texts from the Title 40 of CFR and, importantly, a direct measure of relevance from the EPA, distinguishing it from the model-based measure of Shapiro and Walker (2018). In order to construct a measure of indirect pollution control instruments, we apply the methodology of Sautner, van Lent, Vilkov and Zhang (2023) to two major voluntary communication channels of U.S. public firms: 8-K filings and conference call transcripts.

These measures capture important industry-specific regulations and material environmental concerns, as evidenced by the pronounced heterogeneity across manufacturing industries in the dynamics of these indices over the last two decades. We use these indices to discipline the quantitative model developed in Section 4 and study which fraction of the observed pollution decline can be attributed to direct and indirect taxes.

2.1 Measuring Direct Pollution Control Instruments

2.1.1 Institutional Background: EPA Environmental Regulations

The EPA is an independent executive agency of the U.S. federal government tasked with environmental protection. When Congress passes an environmental law, the new law, called an act or statute, often does not include all the details on how businesses and others might follow the law. To put the law into practice, Congress authorizes the EPA to create regulations that set specific requirements about what is legal and what is not.

In order to issue a regulation, the EPA needs to go through several steps; the details of this process are relegated to Appendix A.2. Once a regulation is finalized, the regulation text is codified in the CFR. The CFR is the official legal record of all federal government regulations. The CFR has 50 volumes, called titles. Each volume focuses on a particular area; environmental regulations are codified under Title 40.

The CFR text is organized into chapters, subchapters, parts, subparts, and so on. Each part typically addresses a set of related issues. For example, related to air pollution control, Part 60 contains standards of performance for new stationary sources, and Part 63 lists national emission standards for hazardous air pollutants. For the manufacturing industries, the EPA has issued numerous regulations appearing in different parts of the CFR Title 40 (hereafter referred to as 40 CFR) covering topics of air quality, water quality, hazardous waste management, and chemical safety.

New rules can modify the CFR text in various ways, including creating new parts or subparts, amending existing parts, and removing rescinded regulations. The CFR text is the legal content of all effective EPA regulations and includes historical versions of given regulation topics, thereby allowing for tracking changes and revisions over time.

2.1.2 Measuring Industry-Specific Regulations

Each part of the regulation text focuses on a set of related issues that have similar relevance for certain industries, and is consistently referenced in the regulatory text. Thus, we chose CFR part as the unit of our analysis. Our index construction encompasses two steps: (1) identifying industries that a given CFR part targets, and (2) quantifying the part-level regulations over time.

Identifying Industry-Part Exposure In order to identify EPA regulations at the industry level, we use information provided by the EPA's official website as the primary source. The EPA lists important regulations by sector on its website.[5] Among sectors, the manufacturing sector (NAICS 31-33) has the most granular information on important regulations. For each manufacturing NAICS 3-digit industry, the EPA lists not only important regulations by topic but also the corresponding parts in 40 CFR.

Some of the listed regulations are quite general and apply to the overall manufacturing sector. For instance, the Greenhouse Gas Reporting Program, which became effective on December 29, 2009, is included in the list of regulations for all manufacturing industries. This regulation requires manufacturing businesses to report greenhouse gas data and other relevant information, and the regulation text has been codified in 40 CFR Part 98 since 2010. At the same time, there are regulations that are specific to certain manufacturing industries. For example, for the chemical manufacturing industry (NAICS 325), there is a list of regulations under air, toxic substances, and water topics. Regulations on benzene waste operations under the National Emission Standards for Hazardous Air Pollutants (NESHAP) have been codified in 40 CFR Part 61 since 1990, and regulations on cellulose products manufacturing have been codified in 40 CFR Part 63 since 2002. Clearly, this set of regulations does not apply to other manufacturers, such as the food industry. As a result, different manufacturing

[5] https://www.epa.gov/p1.

industries have to comply with various sets of regulations. We use information from the EPA website and create a list of CFR parts that are stated by the EPA to regulate each NAICS 3-digit manufacturing industry.

We use the relevance index from the RegData database of the Mercatus Center as a supplementary data source for industry-part pairs not mentioned by the EPA website. The relevance score of each part to each 6-digit NAICS industry is constructed using machine-learning algorithms. The Center utilized the XML version of the historical FR as the training data. They searched all proposed and final rules published in the FR from 2000 to 2016 for exact matches of the full NAICS industry name, the name of a parent industry, or the name of a child industry as indicators of relevance to an industry. With this training sample, they built classification models to obtain text patterns that best identify specific industries.

Measuring Regulations In order to measure part-level regulations over time, we analyze regulation text in 40 CFR and quantify the amount of requirements imposed by each regulation. To this end, we follow the established practice in legal literature and measure the restrictions by counting the words *shall*, *must*, *may not*, *prohibited*, and *required* (e.g., Danet, 1980, Trosborg, 1995). These words create binding obligations or prohibited activities for the regulated entities, and thus a regulation with more restrictions tends to impose more compliance requirements and activities. Given that electronic CFR data is available after 1996 and the text can consistently be analyzed since 2001, our measure of environmental regulations spans the time period 2001-2020.

2.1.3 Index Construction

Our index of environmental regulations incorporates both the exposure of each industry to 40 CFR parts, and the restrictiveness of each part. We construct index at the NAICS 3-digit level; this aligns with the quantitative model developed in Section 4. We denote industry j's exposure to part p at time t as $Exposure_{j,p,t}$. As discussed above, we set $Exposure_{j,p,t}$ equal 1 if industry j is mentioned by the EPA as being directly affected by regulation p. In case a part p is not identified as directly affecting industry j in year t, then $Exposure_{j,p,t}$ is set equal to the similarity score provided by the Mercatus center to capture indirect relevance

(McLaughlin and Nelson, 2021, Fan and Wu, 2022). $Restriction_{p,t}$ denotes the part-level restriction word count in year t.

The total amount of EPA regulation restrictions that industry j is exposed to in year t is the product of the part-level restriction word count and the exposure measure of the part to the industry, summed over all parts. To account for the differences in the length of CFR regulations, we normalize this measure by the total count of words in 40 CFR in year t. Formally, the index of EPA regulations for industry j in year t is given by:

$$EPA_{j,t} = \frac{\sum_p Exposure_{j,p,t} \times Restriction_{p,t}}{\sum_p WordCount_{p,t}}. \tag{1}$$

This index is a time-varying and industry-specific measure of direct pollution control instruments that comprises the universe of active federal environmental regulations.[6] In order to facilitate the interpretation of empirical results, we standardize the index across industries and time.

2.2 Measuring Indirect Pollution Control Instruments

Over the past two decades, societal awareness and concerns about the environment and climate have surged significantly. The public is increasingly mindful of firms' impact on climate change, biodiversity loss, deterioration of ecosystems and human health.

Although there were no mandatory environment-related reporting requirements for businesses until recently, U.S. public firms have nevertheless been voluntarily reporting environment- and climate-related issues using 8-K filings and conference calls—the two major voluntary communication channels. The 8-K filings are reports that public companies must file with the SEC to announce significant, material events that shareholders should know about. These filings are meant to provide timely information to investors and the public about major corporate events.

Our measure of indirect pollution control instruments is represented by firms' exposure

[6] There have been several attempts to directly quantify environmental regulations, including qualitative indices of regulatory stringency, quantitative measures of enforcement effort, and measures of compliance costs, as reviewed by Brunel and Levinson (2016). Our index of direct taxes is a comprehensive quantitative measure of all environmental regulations as it reflects both their stringency and direct relevance to individual industries.

to material non-regulatory environmental concerns. To this end, we use the list of signal word combinations, or bigrams, compiled by Sautner, van Lent, Vilkov and Zhang (2023), to identify discussions about environmental and climate concerns. While Sautner, van Lent, Vilkov and Zhang (2023) analyzed conference call transcripts, we analyze both the universe of 8-K filings and conference call transcripts for U.S. public firms, counting the number of environment-related non-regulatory bigrams and the total number of bigrams in each document.[7]

The exposure of a firm to environmental and climate concerns, based on its 8-K filings or conference call transcripts, is represented by the ratio of the number of environmental (non-regulatory) concern-related bigrams to the total number of bigrams. We aggregate firm-level measures to the industry level using firms' industry affiliations. The resulting index of environmental concerns is the average of industry-specific indices based on 8-K filings and conference call transcripts. To facilitate the interpretation of empirical results, we standardize the index by pooling data across industries and time.

2.3 Other Data

Our main data source for pollution is the Toxics Release Inventory (TRI) housed by the EPA. We validate our findings using an alternative dataset, the National Emissions Inventory (NEI).

Toxics Release Inventory Our main measure of pollution is based on the data from the TRI. The TRI Program at the EPA tracks the industrial management of toxic chemicals that may cause harm to human health and the environment. The program commenced in 1987 as part of the Emergency Planning and Community Right-to-Know Act (EPCRA) to support and promote emergency planning and to provide the public with information about releases of toxic chemicals in their communities.

Not all plants are required to file with the TRI, and the coverage of plants by the TRI depends on several factors. First, the facility needs to operate in certain industries (including

[7]Some examples of non-regulatory bigrams include: "sustainability goal," "battery solar," and "air heat." The list of regulatory environment-related bigrams includes: "EPA require," "comply emission," and "pollution reduction."

the manufacturing sector), the plant must have at least 10 employees, and the release of at least one toxic chemical must be above the threshold determined by the TRI. There are currently nearly 800 different chemicals that plants report to the TRI; however, the coverage of chemicals has changed over time, reflecting varying TRI requirements.[8] In our analysis, we present findings for the chemicals consistently reported across sample years. We note that, in most cases, the results are broadly similar if we use all reported chemicals.

National Emissions Inventory NEI provides comprehensive emissions estimates of air pollutants at the plant-level. NEI is released every three years, and is based primarily on data provided by state, local, and tribal air agencies for sources in their jurisdictions, and supplemented by data developed by the EPA. Since the data has triennial frequency, we use it to conduct supplementary analyses to corroborate our results based on the TRI data.

2.4 Summary Statistics

Table 1 reports descriptive statistics. Panel (A) shows the top-ten CFR parts in Title 40 based on their average number of total words over the sample period. The largest part is Part 63, which covers the National Emission Standards for Hazardous Air Pollutants for Source Categories. This part is frequently referenced by the EPA in relation to the manufacturing sector.

Eight out of ten parts correspond to regulations under Air Programs (Parts 50-99); the two non-air related parts are Part 721 (Toxic Substances Control Act) and Part 136 (Water Programs). We find that the aforementioned parts are referenced more frequently than others by the EPA, and thus have a higher weight in our regulations index.

Panel (B) reports summary statistics for the main variables used in the empirical analysis. The EPA regulations (EPA) and the environmental concerns (EC) indices are standardized, thus having a mean of zero and a standard deviation of one. Changes in the EPA index (ΔEPA) and in the environmental concerns index (ΔEC) are also reported. The mean and

[8]The quality of the TRI data is enforced by the government. Section 1101 of Title 18 of the U.S. Code criminalizes the act of providing false information to the U.S. Government, including the intentional falsification of records kept for inspection. Section 325(c) allows for civil and administrative penalties for failing to comply with TRI reporting requirements.

Table 1: Summary Statistics

Panel A		
Part by #Word	Part Title	Program
63	National Emission Standards for Hazardous Air Pollutants for Source Categories	Air
52	Approval and Promulgation of Implementation Plans	Air
60	Standards of Performance for New Stationary Sources	Air
86	Control of Emissions from New and In-Use Highway Vehicles and Engines	Air
80	Regulation of Fuels and Fuel Additives	Air
98	Mandatory Greenhouse Gas Reporting	Air
721	Significant New Uses of Chemical Substances	Toxic Substances Control Act
51	Requirements for Preparation, Adoption, and Submittal of Implementation Plans	Air
136	Guidelines Establishing Test Procedures for the Analysis of Pollutants	Water
61	National Emission Standards for Hazardous Air Pollutants	Air

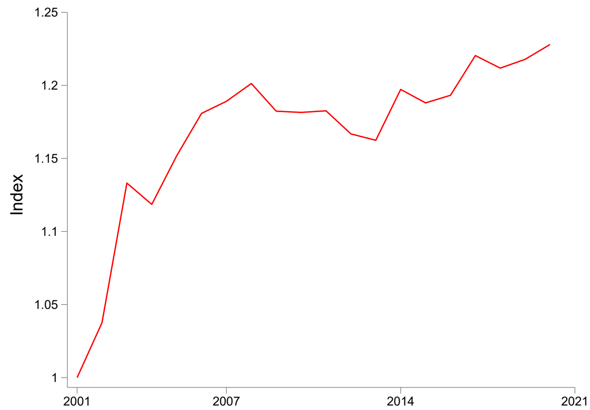
Panel B	Mean	SD	10%	25%	50%	75%	90%
EPA	0.00	1.00	-0.88	-0.80	-0.27	0.20	1.52
ΔEPA	0.01	0.04	-0.01	-0.00	0.00	0.01	0.04
EC	0.00	1.00	-0.72	-0.63	-0.34	0.17	1.06
ΔEC	0.10	0.36	-0.17	-0.06	0.03	0.18	0.55
$\log(TRI)$	5.62	4.33	0.00	0.33	6.23	9.36	11.03
$\Delta\log(TRI)$	-0.06	1.38	-0.77	-0.18	0.00	0.10	0.60

Panel C	EPA		ΔEPA		EC		ΔEC	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
311	-0.34	0.04	0.01	0.02	-0.30	0.52	0.10	0.34
312	-0.88	0.00	0.00	0.00	-0.28	0.45	0.05	0.34
313	-0.61	0.02	0.00	0.01	-0.52	0.39	0.09	0.32
314	-0.88	0.00	0.00	0.00	-0.51	0.51	0.09	0.28
315	-0.88	0.00	0.00	0.00	-0.53	0.50	0.10	0.27
321	-0.07	0.06	0.01	0.03	0.13	0.64	0.04	0.66
322	-0.07	0.06	0.01	0.03	-0.19	0.48	0.06	0.31
323	-0.48	0.03	0.01	0.01	-0.59	0.41	0.05	0.25
324	0.29	0.08	0.02	0.04	0.61	0.94	0.16	0.59
325	2.72	0.22	0.05	0.11	-0.40	0.36	0.08	0.20
326	0.14	0.07	0.01	0.03	-0.22	0.55	0.12	0.32
327	0.41	0.09	0.02	0.04	-0.13	0.49	0.12	0.33
331	1.27	0.15	0.03	0.07	0.21	0.57	0.10	0.34
332	2.26	0.22	0.04	0.10	-0.09	0.46	0.10	0.26
333	0.01	0.05	0.01	0.02	0.42	0.59	0.12	0.30
334	-0.60	0.02	0.00	0.01	-0.06	0.47	0.10	0.21
335	-0.88	0.00	0.00	0.00	3.17	1.28	0.16	0.68
336	0.13	0.07	0.01	0.03	0.67	0.85	0.18	0.40
337	-0.69	0.01	0.00	0.01	-0.45	0.49	0.10	0.27
339	-0.88	0.00	0.00	0.00	-0.54	0.38	0.08	0.20

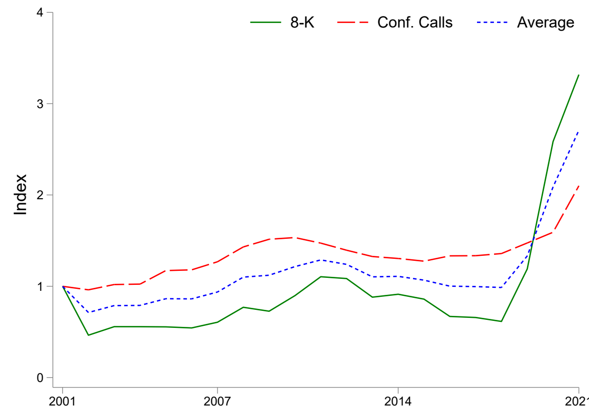
Notes: Table 1 provides summary statistics. Part (A) reports the largest CFR parts. Panel (B) provides summary statistics for the U.S. manufacturing sector, while Panel (B) reports summary statistics by NAICS 3-digit industry.

standard deviation of ΔEC are much higher than those of ΔEPA, highlighting the dramatic increase in material environmental concerns during the sample period. The average (median)

Figure 1: Indices of Environmental Regulations and Environmental Concern: Manufacturing Sector



(A) Environmental regulations



(B) Environmental concerns

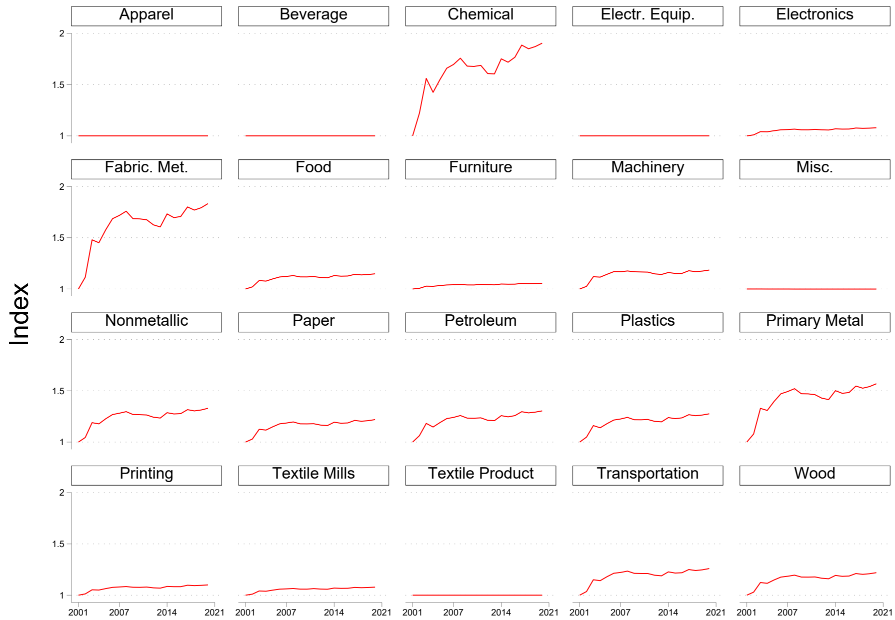
Notes: Figure 1 plots indices of environmental regulations and environmental concerns for the manufacturing sector (NAICS 31-33). See Section 2 for details.

log value of total toxic releases $\log(TRI)$ is 5.62 (6.23). The average change in toxic releases is negative; this reflects the decline in pollution over the sample time period.

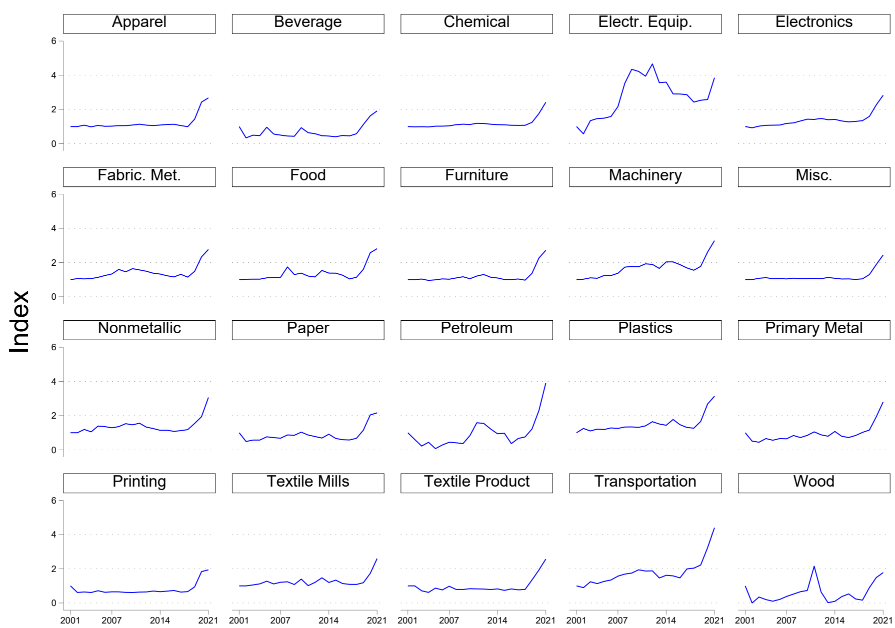
Figure 1 plots indices of environmental regulations and environmental concerns for the U.S. manufacturing sector. To facilitate visual inspection, levels of the indices at the start of the sample period have been set to 1. Panel (A) demonstrates a significant increase in environmental regulations over the last two decades, with the most pronounced increase occurring in the first half of the sample period. In contrast, Panel (B) shows that environmental concerns experienced a swift increase in the last five years.

Figure 2 illustrates the substantial heterogeneity in the dynamics of regulations and concerns across manufacturing NAICS 3-digit industries. Panel (A) indicates that EPA regulations have increased most notably in the chemical, fabricated metal, and primary metal industries. In contrast, some industries, such as apparel, beverage, and electrical equipment, have experienced minimal changes in regulations over the past two decades. Panel (B) shows pronounced heterogeneity in the dynamics of environmental concerns. While nearly all industries experienced a rise in the index in recent years, certain industries, such as electrical equipment, petroleum and wood, saw significant increases in the middle of the sample period.

Figure 2: Indices of Environmental Regulations and Environmental Concern by NAICS 3-digit Industry



(A) Environmental regulations



(B) Environmental concerns

Notes: Figure 2 plots indices of environmental regulations and environmental concerns by NAICS 3-digit manufacturing industry. See Section 2 for details.

3 Regulations, Concerns, and Pollution

In this section, we establish the link between EPA regulations and environmental concerns with pollution reduction. First, in Section 3.1 we examine the effect of EPA regulations on toxic chemical releases. We study the impact of environmental concerns on toxic chemical releases in Section 3.2. In Section 3.3, we explore the link between pollution intensity, regulations and concerns in a sample of public firms. Section 3.4 documents a lumpy distribution of pollution changes in the cross-section of firms.

3.1 EPA Environmental Regulations

We study the effect of industry EPA regulations on plant-level toxic releases by regressing the logarithm of current and future toxic releases on changes in industry-level EPA regulations:

$$\log\left(TRI_{i,t+k}\right) \text{ or } \Delta_{t-1}^{t+k}\log\left(TRI_i\right) = \beta\Delta EPA_{j(i),t} + \lambda\mathbf{X}_{i,t} + \epsilon_{i,t}, \tag{2}$$

where i denotes plant, t denotes time, j denotes NAICS 3-digit industry, and $k \in \{0, 1\}$. ΔEPA is the change in the industry-level EPA regulation index from $t-1$ to t. The dependent variable $\log\left(TRI_{i,t}\right)$ is the natural logarithm of the total amount of toxic chemicals released by facility i in year t. The vector of controls $\mathbf{X}_{i,t}$ includes an intercept, industry and time fixed effects. In our analysis, we also control for lagged $\log\left(TRI\right)$ to account for any auto-correlation or mean-reversion of toxic releases. We cluster standard errors at the industry and time level.

Table 2 reports the results. The coefficient estimates of ΔEPA are negative and statistically significant at the 5 percent level across all specifications. The link between regulations and pollution is economically significant since a one standard deviation increase in the ΔEPA is associated with a 13 percent decrease in the mean of $\Delta_{t-1}^{t+1}\log\left(TRI\right)$.

3.2 Environmental Concerns

We next study the effect of environmental concerns on facility-level toxic releases. We estimate a model similar to Equation (2) with ΔEC as the key independent variable; ΔEC

Table 2: EPA Regulations and Pollution

	$\log(TRI_t)$	$\log(TRI_{t+1})$	$\Delta_{t-1}^{t}\log(TRI)$	$\Delta_{t-1}^{t+1}\log(TRI)$
ΔEPA	-0.0821**	-0.1567***	-0.0903**	-0.1615***
	(0.0366)	(0.0109)	(0.0381)	(0.0152)
$\log(TRI_{t-1})$	0.9246***	0.8898***	-0.0713***	-0.1069***
	(0.0058)	(0.0081)	(0.0054)	(0.0078)
Cons	0.3833***	0.5692***	0.3588***	0.5487***
	(0.0326)	(0.0465)	(0.0300)	(0.0448)
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Obs	346,334	314,010	346,334	314,010
Adj. R^2	0.8775	0.8249	0.0404	0.0600

Notes: Table 2 reports the results of regressing logarithms of current and future plant-level toxic releases $\log(TRI)$ on changes in EPA regulations (ΔEPA) over the period 2001-2021. Only chemicals that are present throughout the sample period are included. The industry EPA regulation index EPA is normalized to have a mean of zero and a standard deviation of one. Toxic releases are measured as the logarithm of total toxic releases plus one. Industry and time fixed effects are included, and standard errors are double-clustered at the industry and time level. The sample is restricted to the manufacturing sector (NAICS 31-33). *, **, *** denote significance at the 10%, 5%, and 1% level, respectively.

denotes the change in the index of industry-level environmental concerns from $t-1$ to t. As before, we include industry and time fixed effects, and cluster standard errors at the industry and time level.

Table 3 reports the results. The coefficient of interest β is negative and statistically significant at the 5 percent level for the contemporaneous period. The point estimate using one-period ahead toxic releases is similar in magnitude but insignificant, suggesting that the effect of environmental concerns is more transitory than that of EPA regulations. In terms of economic magnitude, a one standard deviation increase in the ΔEC is associated with a 7 percent decrease in the mean of $\Delta_{t-1}^{t+1}\log(TRI_i)$.

Robustness Although in our construction of the environmental concerns index we did not include bigrams that are directly related to regulations (see Section 2), it is still plausible that non-regulatory concerns may at least partially be driven by regulations. To address this issue, we orthogonalize ΔEC by regressing ΔEC on ΔEPA, and repeat the analysis using the orthogonalized ΔEC. The results, reported in Appendix Table C3, show that the

Table 3: Environmental Concerns and Pollution

	$\log(TRI_t)$	$\log(TRI_{t+1})$	$\Delta_{t-1}^{t}\log(TRI)$	$\Delta_{t-1}^{t+1}\log(TRI)$
ΔEC	-0.0270**	-0.0209	-0.0257**	-0.0203
	(0.0098)	(0.0227)	(0.0090)	(0.0224)
$\log(TRI_{t-1})$	0.9245***	0.8898***	-0.0714***	-0.1069***
	(0.0058)	(0.0081)	(0.0054)	(0.0078)
Cons	0.3838***	0.5659***	0.3589***	0.5453***
	(0.0329)	(0.0460)	(0.0304)	(0.0442)
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Obs	345,193	312,916	345,193	312,916
Adj. R^2	0.8782	0.8259	0.0409	0.0602

Notes: Table 3 reports the results of regressing logarithms of current and future plant-level toxic releases $\log(TRI)$ on changes in environmental concerns (ΔEC) over the period 2001-2021. Only chemicals that are present throughout the sample period are included. The industry environmental concerns index (EC) is normalized to have a mean of zero and a standard deviation of one. The toxic releases are measured as the logarithm of total toxic releases plus one. Industry and time fixed effects are included, and standard errors are double-clustered at the industry and time level. The sample is restricted to the manufacturing sector (NAICS 31-33). *, **, *** denote significance at the 10%, 5%, and 1% level, respectively.

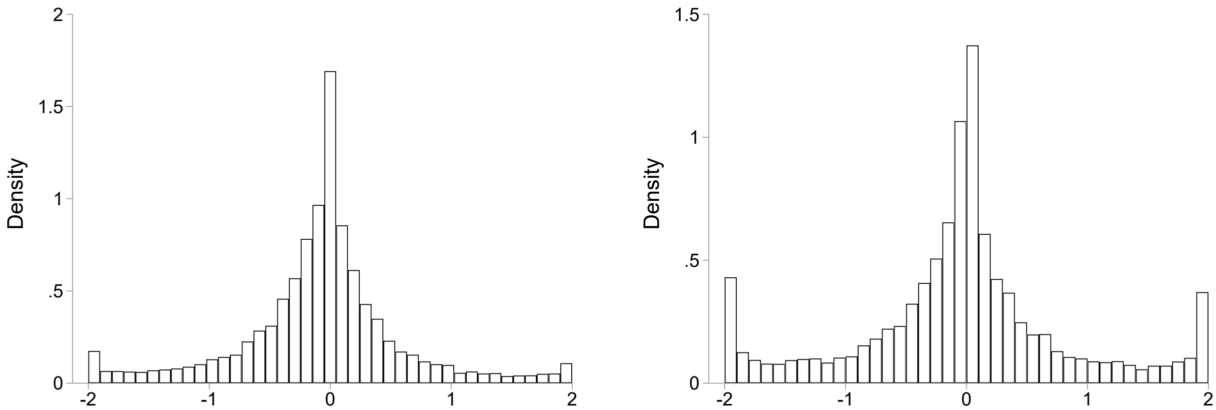
findings are broadly similar to those reported in this section.

To further corroborate our main empirical findings, in Appendix A.3 we consider two additional robustness checks. First, we consider an alternative dataset (NEI). Second, we account for differences in toxicity across chemicals by repeating the analysis (1) at the facility-chemical level, and (2) by aggregating chemicals using their toxicity scores as weights. In both cases, we find results consistent with those reported in Sections 3.1 and 3.2.

3.3 Impact on Pollution Intensity

So far, we have shown that increases in EPA regulations and environmental concerns are negatively related to pollution. We now examine the relationship between increases in EPA regulations or environmental concerns and changes in the sales-to-pollution ratio. If increases in environmental indices lead to a larger decline in sales relative to toxic releases, we would expect to find a negative relationship between changes in EPA regulations or environmental concerns and changes in companies' sales-to-pollution ratio, and vice versa. Since the TRI

Figure 3: Distribution of Pollution Growth Rates: TRI Data



(A) Unweighted (B) Weighted

Notes: Figure 3 plots the distribution of annual arc-growth rates of toxic releases $\tilde{\Delta} d$ $\left(\tilde{\Delta} d = 2\frac{d_{t+1}-d_t}{d_{t+1}+d_t}\right)$. Panel (A): toxic releases of various chemicals treated equally. Panel (B): toxic releases of various chemicals weighted by toxicity level.

data does not provide information on sales, we fuzzy-match TRI facilities to Compustat firms, and aggregate pollution across plants that are affiliated with a given U.S. public firm.[9]

Table C6 in the Appendix reports the results. Overall, we find a positive relationship between changes in companies' sales-to-pollution ratio and ΔEPA or ΔEC. In other words, environmental regulations and concerns are associated with a larger decline in pollution relative to sales among U.S. public firms. We use the resulting estimates to put discipline on time profiles of direct and indirect pollution taxes in the quantitative model developed in Section 4.

3.4 Distribution of Pollution Changes in Cross-Section of Firms

In this section, we demonstrate that the distribution of pollution changes in the cross-section of firms is lumpy: while most firms maintain a consistent level of pollution from year to year, a considerable fraction of firms change it by a substantial amount. Figure 3 plots the distribution of annual arc-growth rates (Davis, Haltiwanger and Schuh, 1996) of toxic releases in the TRI data. The arc-growth measure is bounded between -2 and 2; this feature reduces

[9]We first fuzzy-match based on companies' names and, subsequently, manually check for accuracy.

the impact of outliers without arbitrary winsorization of extreme observations.[10] Panel (A) shows the distribution of toxic releases where various chemicals are treated equally, while Panel (B) displays the distribution when toxic releases are weighted by toxicity levels.[11] In both cases, the distribution exhibits a spike around zero and heavy tails.

Table 4 reports various concentration measures for pollution changes across NAICS 2-digit sectors. There are two important statistics. The first is the inaction rate—the share of firms that change their pollution levels from one period to another by less than one percent. The second statistic is the spike rate—the share of firms that make pollution adjustments of over 20 percent in absolute value. Overall, the inaction rate is 11 percent, and the spike rate is 55 percent. The data reveal pronounced heterogeneity across sectors; for instance, the share of observations with growth rates less than 1 percent is about 5 percent in the utilities (NAICS 22) and transportation and warehousing (NAICS 48) sectors, whereas this share exceeds 15 percent in the food (NAICS 11) and manufacturing (NAICS 31) sectors. Table C1 in the Appendix demonstrates that there is a sizable heterogeneity in patterns of pollution changes across NAICS 3-digit manufacturing industries.

In order to account for lumpiness of pollution changes in the data, in Section 4 we develop a model of firm dynamics with non-convex adjustment costs.

4 Model

We develop a model of industry dynamics with heterogeneous firms which operate subject to distortions induced by environmental regulations and concerns. Time in the model is discrete and the horizon is infinite $t = 0, 1, \ldots$. The economy is populated by heterogeneous firms and a representative household. Firms produce a homogeneous final good. Households own shares in firms, supply labor, and consume the final good.

[10] Technically, this measure is a second-order approximation of the log-difference growth rate around 0.

[11] The toxicity level of various chemicals is based on the Risk-Screening Environmental Indicators (RSEI) table housed by the EPA. Specifically, the toxicity weight we use is the maximum value taken from either inhalation or oral toxicity metrics. Each metric represents the inverse of the "exposure to the human population (including sensitive subgroups) that is likely to be without appreciable risk of deleterious health effects during a lifetime." Data are available at https://www.epa.gov/rsei.

Table 4: Summary Statistics: Distribution of Pollution Growth Rates by NAICS 2-digit Sector

Industry	Obs.	$\lvert\tilde{\Delta}\rvert < 0.01$	$\lvert\tilde{\Delta}\rvert < 0.1$	$\lvert\tilde{\Delta}\rvert > 0.2$	Mean ($\tilde{\Delta}$)	Std. ($\tilde{\Delta}$)	P10 ($\tilde{\Delta}$)	P50 ($\tilde{\Delta}$)	P90 ($\tilde{\Delta}$)
11	426	0.242	0.408	0.486	-0.064	0.697	-0.918	0.000	0.614
21	3847	0.068	0.258	0.608	-0.041	0.756	-0.987	-0.002	0.840
22	11773	0.041	0.301	0.506	-0.084	0.551	-0.707	-0.033	0.428
31	31205	0.156	0.324	0.541	-0.032	0.683	-0.824	0.000	0.683
32	210486	0.100	0.315	0.527	-0.038	0.645	-0.762	0.000	0.644
33	252967	0.119	0.286	0.574	-0.062	0.723	-0.956	0.000	0.713
42	15565	0.103	0.320	0.528	-0.028	0.641	-0.780	0.000	0.667
48	234	0.060	0.265	0.615	-0.026	0.776	-0.997	-0.006	0.974
49	158	0.177	0.291	0.601	-0.054	0.803	-1.057	0.000	0.866
54	361	0.050	0.158	0.745	-0.053	0.913	-1.353	0.000	1.210
56	4439	0.083	0.217	0.662	-0.001	0.766	-0.933	0.000	0.961
81	256	0.133	0.297	0.578	-0.015	0.639	-0.710	0.000	0.661
92	5839	0.049	0.204	0.658	-0.014	0.799	-1.024	-0.001	1.000
Total	537556	0.110	0.299	0.553	-0.049	0.687	-0.859	0.000	0.670

Notes: Table 4 reports summary statistics for distributions of (annual) growth rats in toxic releases by NAICS 2-digit sector. The growth rates are arc-growth rates (Davis, Haltiwanger and Schuh, 1996). Underlying data: TRI.

4.1 Environment

Technology Every firm produces a homogeneous output y by combining labor n and a dirty factor d with corresponding shares $1-\gamma$ and γ, respectively:

$$y(d, z, n) = e^{z}\left(d^{\gamma} n^{1-\gamma}\right)^{\kappa},$$

where parameter κ captures returns to scale, $\gamma, \kappa \in (0,1)$. The idiosyncratic productivity z follows an AR(1) process with the persistence parameter $\rho_z \in (0,1)$:

$$z_{t+1} = \rho_z z_t + \varepsilon^z_{t+1}, \quad \varepsilon^z_{t+1} \sim \mathcal{N}(0, \sigma_z). \tag{3}$$

Innovations ε^z_{t+1} are i.i.d. across time and space.

Pollution Firms enter period t with a predetermined idiosyncratic level of pollution d. The amount of pollution in period $t+1$ is determined in period t. Changing the pollution level is costly, and firms which would like to adjust it for period $t+1$ have to pay a cost $\eta \geq 0$ denominated in units of labor. These adjustment costs represent expenditures that a firm incurs to modify its production process, such as installing new pollution control equipment, temporarily shutting down operations to implement pollution reduction measures, and covering legal and compliance costs to meet environmental standards. Firms draw η from the distribution F^{η} independently across time and space.

Firms operate subject to distortions induced by environmental regulations and concerns; these distortions manifest themselves as direct and indirect taxes, correspondingly. Each firm has to pay τ_t units in terms of the final good for each unit of d it emits. Throughout the paper we refer to τ_t as a pollution tax. The evolution of this tax $\{\tau_t\}_{t=0}^{\infty}$ is exogenous to the model. We assume that aggregate tax revenue is lost.

Labor Labor market is frictionless with the wage rate W_t.

Financing There is a representative household which owns all firms; the proceeds from production net of adjustment costs and pollution tax are paid out to the household as dividends. We assume no frictions on financial markets, and, thus, place no constraints on the value of dividends.

Households The economy is populated by a unit mass of identical households. Each household consumes, inelastically supplies labor, and saves into firms' shares.

4.2 Firm Optimization

Firm Value The aggregate state at time t consists of the distribution of firms over idiosyncratic states $\mu = \mu(d, z)$, as well as the value of the tax rate on toxic emissions τ_t. We index value functions by time t to reflect their dependence on the aggregate state.

The firm enters the period with a pre-determined level of pollution d. Idiosyncratic productivity z is realized at the beginning of the period. Let $v_t(d, z)$ denote the value of the firm at the start of the period t given the idiosyncratic state (d, z).

Before the production stage takes place, firms learn the pollution adjustment cost $\eta \sim F^{\eta}$. Thus, the value of the firm at the start of the period is:

$$v_t(d, z) = \int \max\{v_t^{\text{adj}}(d, z) - \eta W_t, v_t^{\text{no adj}}(d, z)\} \mathrm{d}F^{\eta}. \tag{4}$$

The values the firm attains in case of unconstrained and constrained pollution choices are v^{adj} and $v^{\text{no adj}}$, respectively.

We assume that the cost of a pollution adjustment is distributed uniformly: $\eta \sim U[0, \bar{\eta}]$. The firm will choose to undertake an unconstrained pollution adjustment (conditional on the realization of the cost shock η) if and only if

$$v_t^{\text{adj}}(d, z) - W_t \eta \geq v_t^{\text{no adj}}(d, z).$$

For each firm indexed by its state (d, z), there is a threshold value of $\eta_t^*(d, z)$ such that the firm chooses to make an unconstrained adjustment if $\eta < \eta_t^*(d, z)$, and prefers to make a marginal (constrained) adjustment if $\eta \geq \eta_t^*(k, z)$. It follows that the threshold is given by

$$\eta_t^*(d, z) = \frac{v_t^{\text{adj}}(d, z) - v_t^{\text{no adj}}(d, z)}{W_t}. \tag{5}$$

Provided that η has bounded support, we reformulate the definition of the threshold to force it lie within the interval $[0, \bar{\eta}]$:

$$\widehat{\eta}_t(d, z) = \min\{\bar{\eta}, \max\{0, \eta_t^*(d, z)\}\}. \tag{6}$$

Thus, we can rewrite the value of a firm at the start of the period (4) as follows:

$$v_t(d, z) = \left(\frac{\widehat{\eta}_t(d, z)}{\bar{\eta}}\right) \left[v_t^{\text{adj}}(d, z) - W_t \frac{\widehat{\eta}_t(d, z)}{2}\right] + \left(1 - \frac{\widehat{\eta}_t(d, z)}{\bar{\eta}}\right) v_t^{\text{no adj}}(d, z). \tag{7}$$

Value of Adjusting If the firm chooses to make an unconstrained pollution adjustment, then it solves the following programming problem

$$v_t^{\text{adj}}(d, z) = \max_{d' \geq 0} \pi_t(d, z) + \mathbb{E}_t[M_{t+1} v_{t+1}(d', z')], \tag{8}$$

where M_{t+1} is an endogenous stochastic discount factor, and firm profits $\pi_t(d, z)$ are defined as:

$$\pi_t(d, z) = \max_{n \geq 0} e^z \left(d^\gamma n^{1-\gamma}\right)^\kappa - W_t n - \tau_t d. \tag{9}$$

That is, the profit maximization problem (9) represents the static choice of the labor input.

Value of Not Adjusting The value of not adjusting $v_t^{\text{no adj}}$ solves a similar to (8) programming problem with the difference that the firm's adjustment rate is bounded by the interval $\left|\frac{d'-d}{d}\right| < b$, where b is some small positive number.

4.3 Household Optimization

The representative household maximizes the discounted stream of utilities subject to the budget constraint. We assume that labor is supplied inelastically, $\overline{N} = 1$. The wealth is held in one-period firm shares, $\xi_t(d, z)$. The price of current shares is ω_0, and the purchase price of new shares is ω_1. The household discounts future at a rate $\beta \in (0, 1)$, and its dynamic programming problem is:

$$H_t = \max_{c,\xi'} \left[U(c) + \beta \mathbb{E}_t H_{t+1}\right] \tag{10}$$

subject to

$$c + \int \omega_{1,t}(d', z') \mathrm{d}\xi_{t+1} \leq W_t + \int \omega_{0,t}(d, z) \mathrm{d}\xi_t. \tag{11}$$

The right-hand side of (11) represents the resources available to the household; it consists of firm shares coming from the previous period, as well as labor income. Part of these resources is consumed, and the rest is reinvested into firm shares.

Utility We assume log-preferences of the household over consumption:

$$U(C_t) = \log(C_t). \tag{12}$$

Let C_t be the household's consumption policy function. Also, let $\Xi_{t+1}(d', z')$ be a number of shares purchased in firms which start next period with pollution level d' and idiosyncratic productivity component z'. The detailed definition of equilibrium is relegated to Appendix B.1.

Table 5: Parameter Values

Parameter	Description	Value	Target/Source	Data	Model
β	Discount factor	0.96			
γ	Share of pollution	0.011	Shapiro and Walker (2018)		
κ	Returns to scale	0.85			
ρ_z	Persistence of idiosyncratic AR(1)	0.81	Foster et al. (2008)		
σ_z	Std of idiosyncratic AR(1)	0.08	$P\left[\left\|\tilde{\Delta} d\right\| > 0.2\right]$	0.53	0.43
b	Adj. region	0.01	Khan and Thomas (2008)		
$\bar{\eta}$	Upper bound non-convex	0.0005	$P\left[\left\|\tilde{\Delta} d\right\| < 0.01\right]$	0.11	0.12
ζ_0	Parameter of the price schedule	$\frac{\tau_0}{e^{\zeta_1}}$	See text		
ζ_1	Parameter of the price schedule	See text	See text		

Notes: Table 5 reports parameter values. $\tilde{\Delta} d$ denotes the arc-growth of pollution (Davis, Haltiwanger and Schuh, 1996).

4.4 Parameterization and Model Fit

There are three groups of model parameters: preferences, technology, and pollution taxes.

Preferences We set the model period to be one year; this aligns with the frequency of our data. We, therefore, set the discount factor $\beta = 0.96$.

Technology We set the pollution elasticity γ to 0.011, an average estimate for the manufacturing sector reported in Shapiro and Walker (2018). The returns to scale parameter κ is set to 0.85, which is a standard value used in firm dynamics literature.

The persistence ρ_z of idiosyncratic productivity process is taken from Foster, Haltiwanger and Syverson (2008). The persistence of shocks is directly related to the spike rate: the higher the persistence is, the larger the spike rate becomes. Specifically, we find that reducing ρ_z from the baseline value of 0.8 to 0.2 reduces the spike rate from 0.4 to virtually zero. Intuitively, low persistence makes productivity shocks more transient, disincentivizing firms from making costly adjustments even in the case of large productivity shocks, since they expect productivity to revert back in the next period. Consequently, they choose not to respond, resulting in a low spike rate.

Parameters of adjustment costs (b and $\bar{\eta}$) as well as the volatility of shocks to idiosyncratic productivity σ_z are informed by the cross-sectional distribution of pollution growth rates (see Figure 3). Provided that there is no guidance on the value of unconstrained pollution adjustment parameter b in the literature, we follow research on investment dynamics (Cooper and Haltiwanger, 2006, Khan and Thomas, 2008) and set $b = 0.01$. We then pick the the upper bound for non-convex costs $\bar{\eta}$ and the volatility of shocks σ_z such that the model fits both the size of the spike at 0, as well as the fraction of observations larger than 20 percent in absolute value. Table 5 summarizes parameter values.

Regulations, Concerns, and Pollution Taxes In our quantitative implementation, we assume that the pollution tax τ_t is a function of direct and indirect pollution control instruments, and has the following functional form:

$$\tau_t = \zeta_0 e^{\zeta_1 Env_t}, \tag{13}$$

where ζ_0 and ζ_1 are parameters, and Env_t is an index of either environmental regulations or concerns at time t.

We assign value to ζ_1—the semi-elasticity of the pollution tax with respect to regulations and concerns—by indirect inference. Specifically, we select the parameter ζ_1 so that the slope coefficient in the regression of pollution intensity on indices, estimated on the model-generated data, matches the one from the actual data (see Section 3.3). Table 6 reports the corresponding estimates from the data (columns 1 and 3) and from the model-generated data (columns 2 and 4). The data estimates are borrowed from Table C6 in the Appendix.

The level coefficient ζ_0 is made consistent with the initial size of the wedge τ_0, i.e. $\zeta_0 = \tau_0 e^{-\zeta_1}$. The size of the wedge at time 0, τ_0, can be normalized since our focus is on the change in aggregate pollution relative to the start of the period.

5 Quantitative Analysis

In Section 4, we developed a quantitative general equilibrium model in which forward-looking firms choose the level of pollution in the presence of adjustment costs, stochastic productivity shocks, and time-varying distortions. In this section, our objective is to quantitatively examine the role of environmental regulations and concerns in explaining the time-series evolution of toxic releases across U.S. manufacturing industries and for the manufacturing

Table 6: Parameterization of ζ_1

	Regulations		*Env. concerns*	
	Data	Model	Data	Model
$\widehat{\beta}$	0.41	0.36	0.04	0.05
	(0.10)		(0.08)	
FE	Y	Y	Y	Y
R^2	0.01		0.01	

Notes: Table 6 reports OLS estimates of Equation $\Delta_{t-1}^{t} \log\left(\frac{Sale}{TRI}\right) = \beta \Delta Env_{j(i),t} + \lambda \mathbf{X}_{i,t} + \epsilon_{i,t}$. The vector of controls includes a constant, as well as year and industry fixed effects. Numbers in parentheses are standard errors double clustered at the industry and year level. *, **, *** denotes significance at 10%, 5%, and 1% level, respectively. Data estimates are from Table C6 in Appendix. Underlying data: Compustat and TRI.

sector overall.

We start in Section 5.1 with aggregate results by tracing the evolution of manufacturing-level pollution induced by changes in environmental regulations and concerns, as measured by our indices constructed in Section 2. In Section 5.2, we conduct analysis at the NAICS 3-digit industry level. We discuss the role of adjustment costs, idiosyncratic productivity shocks, and general equilibrium considerations in Section 5.3.

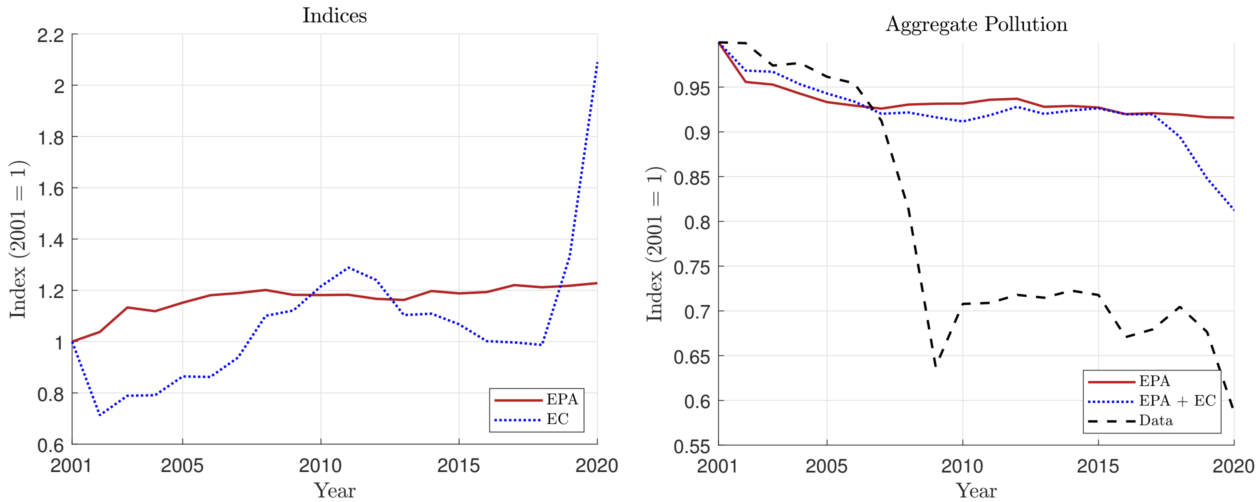
5.1 Results for Manufacturing Sector

We consider a transition dynamics exercise, whereby we trace the evolution of manufacturing pollution in the model $\int d \mathrm{d}\mu$ induced by the time-varying pollution taxes $\{\tau_t\}$. In doing so, we search for the sequences of wages $\{W_t\}$ and marginal utilities $\{MU_t\}$ such that labor market clears in each time period, and the stochastic discount factor is consistent with the household consumption. Further technical details are relegated to Appendix B.3.

The results for the manufacturing sector are shown in Figure 4. Panel (A) reports the indices constructed in Section 2, which are used to discipline the evolution of wedges in the model. Panel (B) provides the transition dynamics results. The solid red line represents the model-implied dynamics of manufacturing pollution, assuming the pollution tax τ_t is driven solely by regulations. We observe that regulations explain approximately a 9 percent decline in aggregate pollution from 2001 to 2020, which is about a quarter of the overall decline in pollution observed in the data (dashed black line).

Subsequently, we repeat the analysis, assuming that the dynamics of the pollution tax

Figure 4: Transition Dynamics: Manufacturing Sector



(A) Indices (B) Transition dynamics

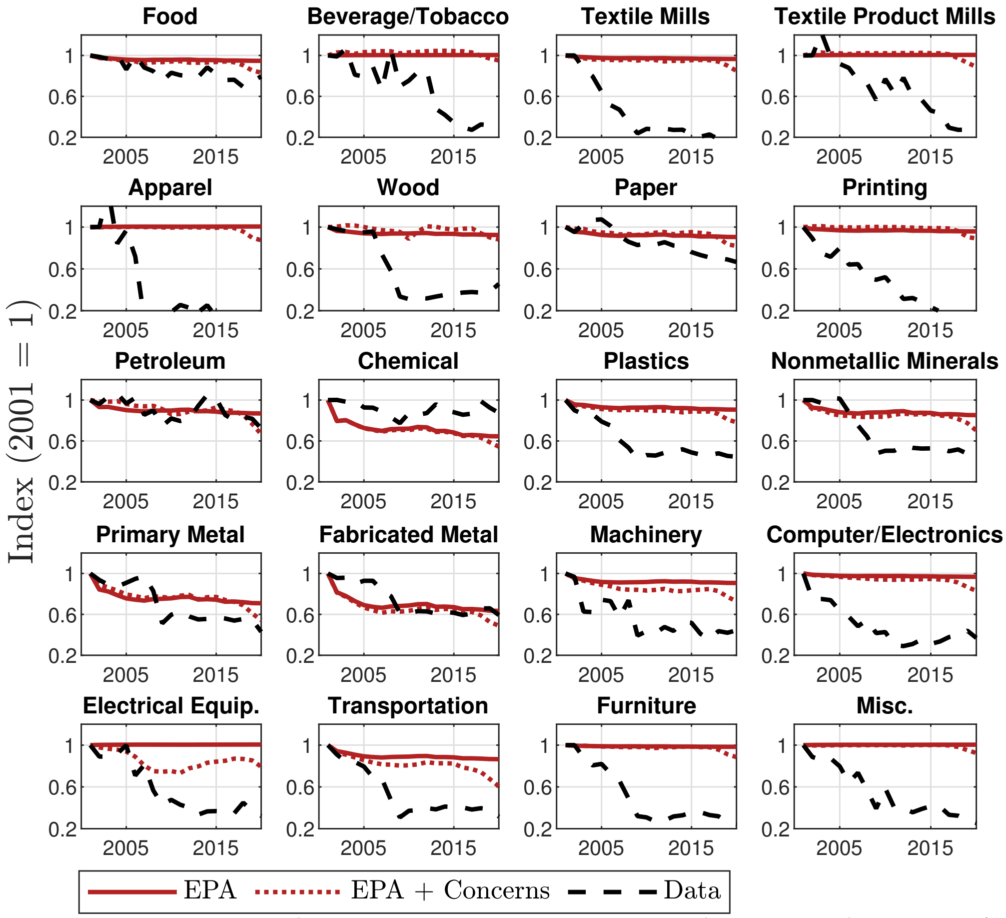
Notes: Figure 4 plots the results of the transition dynamics exercise for the U.S. manufacturing sector (see Appendix B.3 for technical details).

τ_t are entirely driven by environmental concerns. Next, we combine the individual effects of regulations and concerns; the dotted blue line visualizes their cumulative impact. Environmental concerns contribute to an additional 10 percent decline in pollution over the past two decades, and both direct and indirect taxes explain approximately a half of the observed pollution reduction in the data.

Sensitivity We investigate the sensitivity of our results to the estimates presented in Table C6. Specifically, we focus on environmental regulations and repeat the transition dynamics exercise using values of ζ_1 that correspond to the 95 percent confidence interval bounds for β: $0.41 \pm 1.96 \times 0.10 = \{0.21, 0.61\}$.

The results are reported in Figure C4 in the Appendix. The value of $\widehat{\beta}$ at the upper bound of the confidence interval helps the model explain an additional 5 percentage points of the pollution decline. The value of $\widehat{\beta}$ at the lower bound of the confidence interval helps the model account for about 3 percentage points less. Overall, we conclude that assuming significantly larger or smaller pollution elasticities to measured regulations and concerns does not have a large impact on our central results.

Figure 5: Transition Dynamics: Manufacturing NAICS 3-digit Industries



Notes: Figure 5 plots the results of the transition dynamics exercise for 20 manufacturing NAICS 3-digit industries (see Appendix B.3 for technical details).

5.2 Results by Industry

We now repeat the analysis from Section 5.1 for twenty manufacturing NAICS 3-digit industries. We use estimates of industry-specific production technologies from Shapiro and Walker (2018), which are also provided in Appendix Table C2. Furthermore, we assume that no individual industry is large enough to significantly impact prices, allowing us to use the equilibrium paths of wages and marginal utilities from the analysis for the manufacturing sector.

The results of our analysis are presented in Figure 5. We find that our direct measure of regulations and concerns can explain most of the pollution dynamics in certain industries (such as food, paper, petroleum, primary metals, and fabricated metals); in other

Table 7: Pollution Elasticities

	$\overline{\eta}$	ρ_z	σ_z	GE (Y/N)
High	-8.2	-8.8	-8.4	-8.3
Low	-8.6	-7.6	-7.5	-8.6

Notes: Table 7 reports the percentage change in aggregate pollution in response to a 10 percent increase in the pollution tax τ_t. Comparison is steady-state to steady-state. *"Baseline"* corresponds to the baseline parameterization (see Section 4); *"High"* and *"Low"* refer to cases when the corresponding parameter in higher or lower relative to the baseline, respectively. For $\overline{\eta}$: 0.005 (High), 0 (Low); for ρ_z: 0.9 (High), 0.7 (Low); for σ_z: 0.09 (High), 0.05 (Low).

industries—such as electrical equipment, furniture and electronics— the decline in pollution is more pronounced than what the model predicts.

5.3 Role of Adjustment Costs, Productivity Shocks, and General Equilibrium Feedback

We now examine the quantitative impact of adjustment costs, stochastic productivity process, and general equilibrium effects on our results.

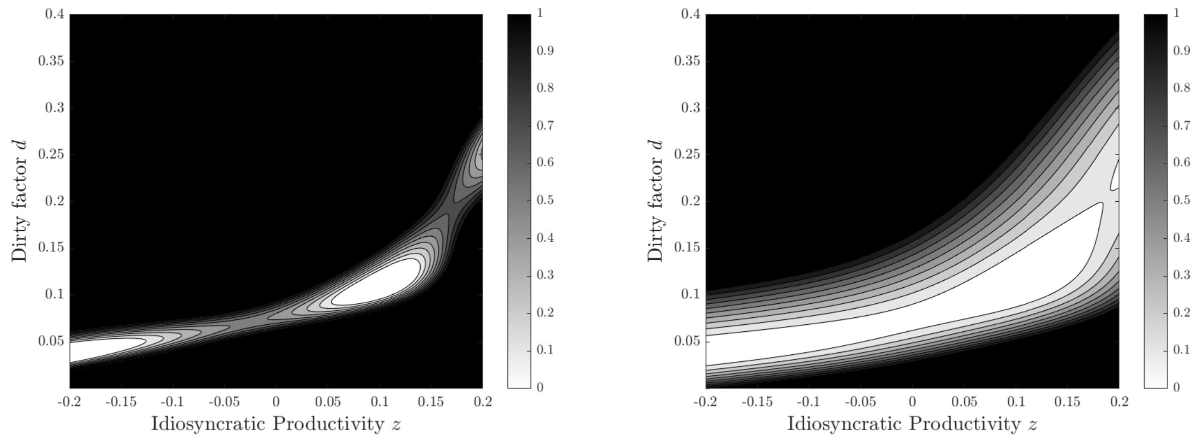
Role of Non-Convex Costs In Section 3.4, we documented significant heterogeneity in patterns of pollution changes among NAICS 2-digit sectors and manufacturing industries. In particular, we showed that the size of the inaction region is small for some groups of firms and much larger for others.

In order to explore the impact of lumpiness on the effectiveness of pollution control instruments, we repeat the transition dynamics analysis by assuming either counterfactually low or counterfactually high non-convex adjustment costs.

First, we demonstrate how the parameter governing adjustment costs in the model, $\bar{\eta}$, affects the inaction region in the model's steady state.[12] Panel (A) of Figure 6 corresponds to the baseline value of $\bar{\eta}$, showing that unproductive firms with high pollution levels and productive firms with low emissions are most likely to make an unconstrained adjustment to align their pollution levels with their productivity. Specifically, unproductive firms with high pollution levels are likely to adjust downward, while productive firms with low pollution

[12] Figure C3 in Appendix shows how the inaction region depends on the persistence and volatility of productivity shocks.

Figure 6: Non-convex Adjustment Costs and Inaction Region



(A) Low $\overline{\eta}$ (B) High $\overline{\eta}$

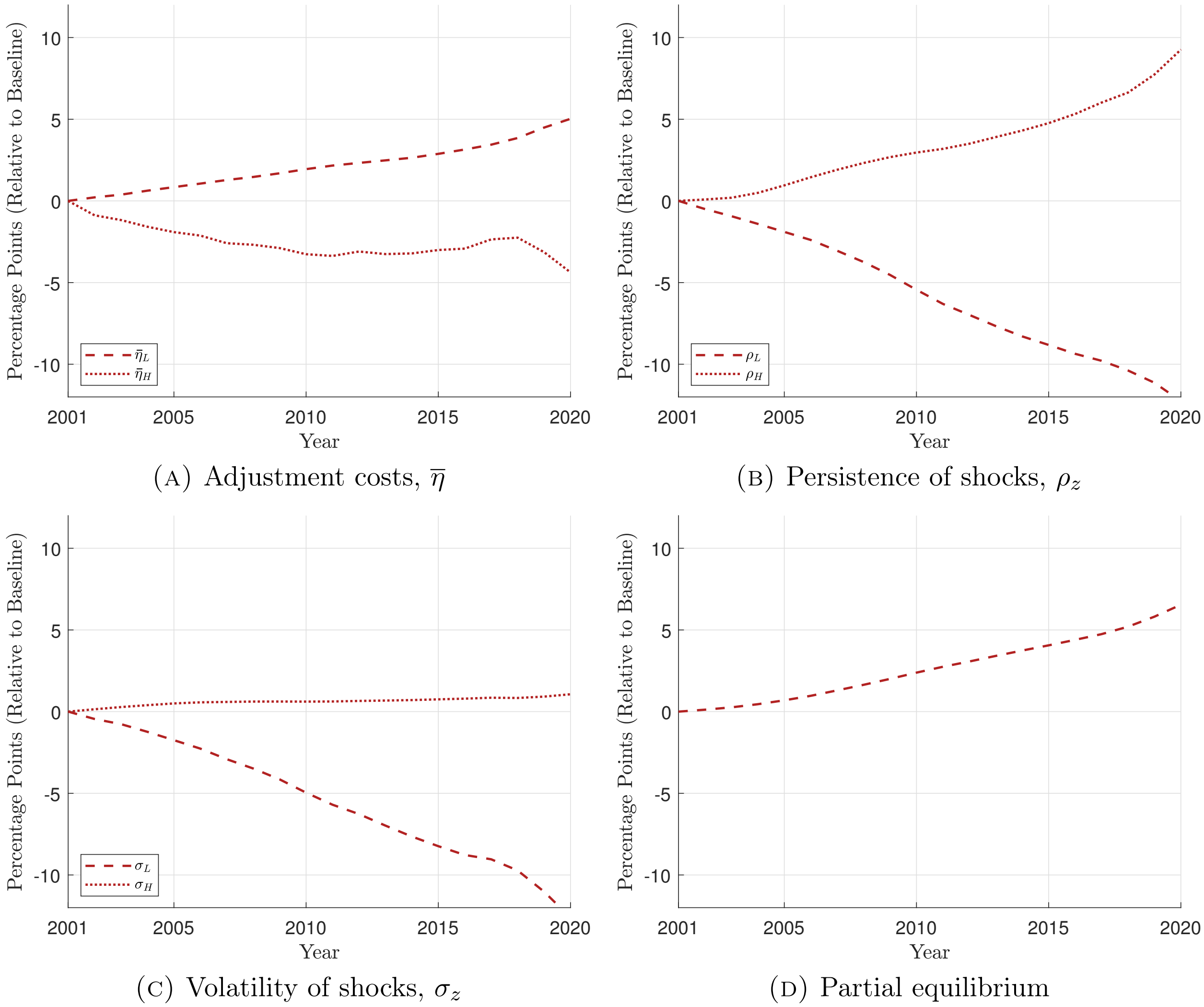
Notes: Figure 6 plots inaction regions at the steady-state of the model in the space of idiosyncratic states (d, z). Darker colors mean higher probability of adjustment. Corresponding parameters are: $\overline{\eta} \in \{0.0005, 0.005\}$.

levels are likely to adjust upward. As the upper bound of support $\bar{\eta}$ increases (Panel (B)), the inaction region expands significantly, causing more firms to become unresponsive to economic stimuli. In the aggregate, it leads to a smaller (in absolute value) elasticity of pollution to direct and indirect instruments (Table 7).

We now show how these differences in the inaction rate translate into differences in transition dynamics. Specifically, we consider two counterfactual scenarios: first, where we eliminate non-convex costs by setting $\bar{\eta} \to 0$, and second, where we set $\bar{\eta}$ such that the probability of inaction doubles relative to the baseline. Figure 7 presents the results. We find that higher adjustment costs make the economy less responsive to rising pollution taxes (Panel (A)). In the scenario with counterfactually high costs, the decline in pollution is weaker, accumulating to nearly five percentage points over 20 years. Conversely, lower adjustment costs make the economy more responsive, resulting in about five percentage points stronger cumulative decline in pollution over time.

The intuition behind this result is as follows. In our model, the adjustment decision is characterized by an endogenous cutoff value, whereby firms undertake an adjustment if the shock value η is below the threshold. In the case of low adjustment costs, the cutoff value triggering adjustment is higher relative to the baseline parameterization. An increase in

Figure 7: Parameter Values and Cumulative Decline in Pollution



(A) Adjustment costs, $\overline{\eta}$

(B) Persistence of shocks, ρ_z

(C) Volatility of shocks, σ_z

(D) Partial equilibrium

Notes: Figure 7 contains four panels. All panels plot the cumulative difference in pollution decline relative to the baseline by varying structural parameters. The parameters are: $\overline{\eta} \in \{0, 0.005\}$; $\rho_z \in \{0.7, 0.9\}$; $\sigma_z \in \{0.05, 0.09\}$. Panel (D) reports the cumulative difference for the economy with fixed sequences of prices relative to the baseline model set in general equilibrium.

direct or indirect taxes lowers the adjustment cutoff. The effect of rising pollution taxes is stronger in the model with low adjustment costs since more firms are triggered to adjust as the cutoff is reduced from an initially high level. In the model with high adjustment costs, the original cutoff is already low; thus, rising result in fewer firms making adjustments and, consequently, a weaker overall decline in pollution.

We conclude that it is essential to use micro data to accurately determine the extent of adjustment costs in the model. The discrepancies across sectors in the overall economy are considerable and should be taken into account when studying the effects of direct and indirect pollution taxes. Firms in sectors with high adjustment costs will find it more challenging to adjust their pollution levels in response to rising pollution taxes as compared to firms in sectors where these costs are lower.

Role of Idiosyncratic Productivity Process The idiosyncratic productivity process plays a key role as it not only helps our model fit the cross-sectional evidence, but also shapes the transition dynamics in response to changing pollution taxes. We find that higher persistence and volatility of shocks significantly increase the pollution elasticity, as shown in Table 7.

Panel (B) of Figure 7 demonstrates that the persistence of shocks is central to understanding the impact of direct and indirect taxes on pollution dynamics. Specifically, higher persistence makes the policy more effective, leading to a 10 percentage point larger cumulative reduction in toxic releases. Conversely, lower persistence results in a more than 12 percentage point smaller reduction in pollution. Lower persistence makes the firm's current idiosyncratic state less informative of its future profits. As a consequence, firms become less responsive to the paths of both direct and indirect taxes, resulting in a smaller cumulative pollution decline.

Lower volatility of productivity shocks brings the model closer to a representative firm framework. That framework not only fails to account for the cross-sectional evidence as it cannot generate dispersion in pollution growth rates, but also generates quantitatively different pollution dynamics along the transition path. Panel (C) shows that the model with lower volatility of shocks leads to a more than 10 percentage point weaker cumulative decline in toxic releases. Lower volatility results in a larger fraction of firms being within the inaction region, thereby limiting the model's response to rising direct and indirect pollution taxes.

Role of General Equilibrium We next examine the role of general equilibrium in the transition dynamics. The results reported thus far were obtained by determining sequences of wages that clear the labor market along the transition path, and marginal utilities that are consistent with the household consumption.

In order to explore the role of general equilibrium effects, we conduct a transition dynamics analysis where firms operate under constant wages and a constant stochastic discount factor. Panel (D) shows that the decline in aggregate toxic releases is stronger in partial equilibrium, with a cumulative decline of 7 percentage points more relative to the general equilibrium benchmark. An increase in pollution taxes reduces the demand for labor; this puts downward pressure on wages, stimulating production and resulting in a weaker pollution decline. This is also evidenced by a larger pollution elasticity in partial equilibrium (Table 7).

We conclude that the impact of general equilibrium feedback is directly related to the share of the dirty factor in the production process. In the baseline scenario, $\widehat{\gamma}$ is only 1 percent, and yet price adjustment accounts for a 7 percent cumulative difference. The effect of general equilibrium is commensurate with the share of the dirty factor and, for instance, will be much more pronounced in the context of carbon emissions, where the typical exponent of the (dirty) energy input is in the range of 0.04-0.05 (e.g., Golosov, Hassler, Krusell and Tsyvinski, 2014, Hassler, Krusell and Olovsson, 2018).

6 Conclusion

We analyze the universe of active federal environmental regulations in the U.S. over the past two decades and construct a measure of direct pollution control instruments. We analyze two major voluntary communication channels public firms use—conference call transcripts and 8-K filings—and construct an index of material environmental concerns, which serves as our measure of indirect pollution control instruments. These indices are new empirical measures of direct and indirect pollution taxes.

We also document an important fact that the cross-sectional distribution of pollution changes is lumpy, meaning that while many firms maintain consistent levels of pollution from one period to the next, those that do change their pollution levels tend to do so in substantial amounts. In order to explain this, we develop a dynamic heterogeneous firm model with non-convex adjustment costs and stochastic productivity shocks, which aligns with the cross-sectional evidence and explains half of the pollution decline in U.S. manufacturing over the last two decades. Our findings show that the dynamics of both direct taxes (environmental regulations) and indirect taxes (environmental concerns), stochastic productivity shocks, and non-convex adjustment costs are the three important factors that shape the pollution dynamics in the U.S. manufacturing sector.

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Online Appendix

"Direct and Indirect Taxes in Pollution Dynamics"

by Vladimir Smirnyagin, Aleh Tsyvinski, and Xi Wu

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Appendix A: Empirical Appendix

A.1 Discussion of Direct and Indirect Measures of Relevance

In order to construct our index of regulations, we directly compile information from the EPA to infer the relevance between EPA rules and industries, supplementing this information with relevance scores from the Mercatus Center. The Mercatus Center relevance scores are obtained via supervised machine learning algorithms trained on the entire CFR, most of which are not environment-related. In this section, we *(1)* show the importance of directly using information from the EPA, and *(2)* demonstrate that relying solely on relevance scores from the Mercatus Center leads to significant biases.

First, we show the distribution of relevance scores from the Mercatus Center for the full sample of regulation-industry pairs and the EPA-mentioned pairs. The results are reported in Figure C6. Red bars represent the distribution of full sample pairs, while green bars correspond to the EPA-mentioned pairs. We make two observations. First, the Mercatus Center relevance scores tend to be much larger for the EPA-mentioned pairs, as highlighted by the green bars around the relevance score of one. This suggests that the Mercatus Center, on average, measures relevance scores correctly. However, there is a large fraction of regulation-industry pairs that are incorrectly assigned a relevance score of about 0, even when the EPA explicitly mentions that the corresponding parts are relevant for those individual industries; this is evidenced by the green bar around the relevance score of zero.

We provide a few examples. The EPA mentions that the chemical industry needs to comply with 40 CFR, Part 268 (Land Disposal Restrictions) and 40 CFR, Part 792 (Good Laboratory Practice Standards). However, the Mercatus Center assigns relevance scores that are close to zero in both cases. Additionally, the EPA mentions that the fabricated metal product industry needs to comply with 40 CFR, Part 420 (Iron and Steel Manufacturing Point Source Category) and 40 CFR, Part 438 (Metal Product and Machinery Point Source Category), while the Mercatus Center assigns relevance scores that are close to zero for these two cases.

Furthermore, we compare the index of regulations used in this paper with the regulatory index that only uses relevance scores provided by the Mercatus Center. Results are provided in Figure C7. Correlations between the two indices across NAICS 3-digit industries are positive on average; however, there is a significant number of industries where the correlation between the two indices is less than 0.5, and sometimes even negative.

A.2 Additional Details on Institutional Background

It was discussed in Section 2 that the mission of the EPA is to protect human health and the environment. When Congress passes an environmental law, the new law, called an act or statute, often does not include all the details on how businesses and others might follow the law. To put the law into practice, Congress authorizes the EPA to create regulations that set specific requirements about what is legal and what is not.

For example, Congress passed the Toxic Substances Control Act (TSCA) in 1976 and authorized the EPA to address the manufacturing, processing, distribution, use, and disposal of commercial and industrial chemicals. A regulation issued by the EPA to implement the TSCA would explain the levels of a toxic substance, such as lead, that affect human health and the environment. It would specify requirements for lead-safe renovations and abatements, pre-renovation education, and disclosure of information about lead paint and lead paint hazards. It would also specify the penalties when firms or other regulated entities fail to comply. Once a regulation becomes effective, the EPA inspects worksites and records of renovation firms, property managers, landlords, and real estate agents to ensure compliance. When a violation is identified, the EPA will take civil or criminal enforcement action against violators of environmental laws.

In order to issue a final rule, the EPA needs to go through several steps. First, the regulator conducts studies on the issue and, when necessary, would propose a regulation (Notice of Proposed Rulemaking). Next, the regulator collects and considers comments from the public regarding the proposed regulation and revises the regulation accordingly to issue a final rule document. The final rule is first published in the Federal Register (FR), which is the official journal of the federal government of the United States. The FR publication contains a rich set of background information about the final rule, including a summary of the environmental issues or goals to be addressed, policy statements explaining why the rule is necessary, a discussion of businesses or activities to be regulated, the agency's interpretations of comments received from the public, and the final regulatory text. Lastly, once a regulation is published in the FR as a final rule, the regulation text is codified in the CFR. The CFR is the official legal record of all regulations created by the federal government. It is divided into 50 volumes, called titles, each of which focuses on a particular area. EPA regulations are codified under Title 40 and are revised every July 1st.

A.3 Robustness Checks

To corroborate our main empirical findings, we consider two robustness checks. First, we consider an alternative dataset (NEI). Second, we consider two ways to account for toxicity across chemicals.

Alternative Data: National Emissions Inventory We explore the link between regulations, concerns, and pollution using the comprehensive air emissions data sourced from the NEI. One important caveat of the NEI database is that it has triennial frequency, making the power of the tests lower compared to those based on TRI. Therefore, we conduct our analysis at the chemical level and focus on the level of emissions.

The results are reserved for Appendix and reported in Table C5. Given that the NEI data are only available every three years, we compute changes in regulations and concerns (ΔEPA or ΔEC) over the corresponding three-year intervals and denote them as $\Delta_{3year}EPA$ or $\Delta_{3year}EC$. We find that the coefficient estimates on $\Delta_{3year}EPA$ or $\Delta_{3year}EC$ are consistently negative and statistically significant in most specifications.

Accounting for Toxicity across Chemicals In our main empirical specification (2), we use the total toxic releases by aggregating all emissions a plant produces in a given year. To the best of our knowledge, there is no consensus in the literature on the best method to aggregate various chemicals.[13] We account for differences in toxicity across chemicals by repeating the analysis (1) at the facility-chemical level, and (2) by weighting chemicals by toxicity.

[13] Some studies (i.e., Arora and Cason, 1995, 1999) argue that weighting chemicals by their toxicity—as measured by reportable quantity (RQ) toxicological index, or the threshold planning quantity (TPQ)—leads to similar (with respect to equal weighting) results since most widely used chemicals have similar toxicity.

Studying the relationship at the chemical level allows us to alleviate concerns of composition changes and potential aggregation issues, and to control for time-by-pollutant fixed effects to ensure that pollutant toxicity does not drive the results. The results are reserved for Appendix Table C4, which shows a significant and negative relationship between toxic releases and ΔEPA or ΔEC. We interpret these results as indicating that our main findings are unlikely to be driven by composition changes or aggregation issues.

Next, we repeat the analysis by weighting toxic releases with their toxicity scores. We use toxicity weights provided by the Risk-Screening Environmental Indicators (RSEI) table housed by the Environmental Protection Agency. Specifically, the toxicity weight we use is the maximum taken over the inhalation and oral toxicity. Each of these metrics represents the inverse of the "exposure to the human population (including sensitive subgroups) that is likely to be without appreciable risk of deleterious health effects during a lifetime".[14]

We multiply the chemicals by their toxicity and then aggregate them to the facility-year level. When the toxicity of a chemical is unavailable, we assume the toxicity is one.[15] We denote the logarithm of total toxicity-weighted toxic releases as $\log(TRI_t^{tox})$. The results are reserved for Appendix Table C7; the coefficient estimates on ΔEPA or ΔEC are consistently negative, in line with the baseline results.

[14] Data are available at https://www.epa.gov/rsei.

[15] Dropping chemicals without a toxicity measure gives qualitatively similar results.

Appendix B: Model Appendix

B.1 Definition of Equilibrium

The Recursive Competitive Stationary Equilibrium for this economy (for a given $\{\tau\}$) consists of the following functions and objects:

$$\left\{v, v^{\text{adj}}, v^{\text{no adj}}, n, d', W, \hat{\eta}, H, C, \Xi, \mu\right\},$$

such that:

1. H solves the household's problem (10)-(11) and $\{C, \Xi\}$ are the corresponding policy functions,

2. $\{v, v^{\text{adj}}, v^{\text{no adj}}\}$ solve the firm's problem (4)-(9), and $\{\hat{\eta}, n, d'\}$ are the corresponding policy functions,

3. labor market clears
$$\int \left(n(d,z) + \frac{\hat{\eta}(d,z)^2}{2\bar{\eta}}\right) \mathrm{d}\mu = 1,$$
where μ is the stationary distribution of firms across idiosyncratic productivity z and pollution levels d;

4. goods market clears:
$$\int y(d,z,n)\mathrm{d}\mu = C,$$

5. the distribution of firms μ is induced by decision rule $d'(d,z)$ and the exogenous evolution of idiosyncratic productivity z (Equation 3);

6. household's decision Ξ is consistent with the stationary distribution of firms μ.

B.2 Computation Algorithm: Steady-State

We use collocation methods to solve the firm's functional equations. In practice, we use Chebyshev polynomials to approximate value functions.

We set up a grid of collocation nodes $\mathcal{D}\times\mathcal{Z}$, with N_i nodes in each dimension, $i \in \{\mathcal{D}, \mathcal{Z}\}$. The computation of the stationary state of the model proceeds in the following 4 steps:

1. guess the equilibrium wage rate, W;
2. solve for individual decision rules d';
3. given the decision rules, compute stationary histogram (distribution of firms over the state space);
4. compute the excess demand on the labor market. If it exceeds some prespecified tolerance, adjust the wage guess correspondingly and go back to Step 2. Otherwise, terminate.

B.2.1 Approximation of Value Functions

We approximate three (normalized by the household's marginal utility) value functions: $V(\cdot)$, $V^{\text{adj}}(\cdot)$ and $V^{\text{no adj}}(\cdot)$. We represent these value functions as weighted sums of orthogonal polynomials:

$$\begin{cases} V(d,z) & = \sum_{a,b=1,1}^{N_{\mathcal{D}},N_{\mathcal{Z}}} \theta_1^{ab} T^a(d) T^b(z) \\ V^{\text{adj}}(d,z) & = \sum_{a,b=1,1}^{N_{\mathcal{D}},N_{\mathcal{Z}}} \theta_2^{ab} T^a(d) T^b(z) \\ V^{\text{no adj}}(d,z) & = \sum_{a,b=1,1}^{N_{\mathcal{D}},N_{\mathcal{Z}}} \theta_3^{ab} T^a(d) T^b(z) \end{cases}$$

where $\mathbf{\Theta} = \{\theta_1^{a,b}, \theta_2^{a,b}, \theta_3^{a,b}\}$ are approximation coefficients, and $T^i(\cdot)$ is the Chebyshev polynomial of order i.

We use a collocation method to simultaneously solve for $\mathbf{\Theta}$. Collocation method requires setting the residual equation to hold exactly at $N = N_{\mathcal{D}} \times N_{\mathcal{Z}}$ points ; therefore, we essentially solve for $3 \times N$ unknown coefficients. We compute the basis matrices for Chebyshev polynomials using Miranda and Fackler (2002) Compecon toolbox. Subsequently, we solve for a vector of unknown coefficients using Newton's method. A much slower alternative is to iterate on the value function. Given the current guess of coefficients, we solve for the optimal policy $d'(d,z)$ using vectorized golden search. After we solve for the policy function, we recompute decision rules on a finer grid, and, subsequently, compute the stationary distribution.

B.2.2 Stationary Distribution

When we solve for a stationary distribution, we iterate on a mapping using firms' decisions rules:

$$L' = \mathbf{Q}'L,$$

where L is a current distribution of firms across the state space. Matrix $\mathbf{Q}$ is a transition matrix, which determines how mass of firms shifts in the (d, z)-space. It is a direct product of three transition matrices $\mathbf{Q}_d$ and $\mathbf{Q}_z$:

$$\mathbf{Q} = \mathbf{Q}_d \odot \mathbf{Q}_z,$$

which govern the shift of mass along d- and z-dimensions, respectively. While $\mathbf{Q}_z$ is completely determined by the exogenous stochastic process, matrix $\mathbf{Q}_d$ is constructed so that the model generates an unbiased distribution in terms of aggregates.[16] More precisely, element (i, j) of the transition matrix $\mathbf{Q}_d$ informs which fraction of firms with the current idiosyncratic state d_i will end up having d_j tomorrow. Therefore, this entry of the matrix is computed as:

$$\mathbf{Q}_d(i, j) = \left[\mathbf{1}_{d' \in [d_{j-1}, d_j]} \frac{d' - d_j}{d_j - d_{j-1}} + \mathbf{1}_{d' \in [d_j, d_{j+1}]} \frac{d_{j+1} - d'}{d_{j+1} - d_j}\right].$$

Tensor product of matrices $\mathbf{Q}_d$ and $\mathbf{Q}_z$ is computed using the `dprod` function from the Miranda and Fackler (2002) toolkit.

B.3 Computation Algorithm: Transition Dynamics

In this section, we outline an algorithm for computing transition dynamics. While the paper assumes perfect foresight for firms, we provide here, for completeness, an algorithm designed to compute transition dynamics for the case where firms do not know the sequence of $\{\tau_t\}$. In this context, firms receive shocks in each period along the transition path.

1. Compute the steady-state for the initial period (T_{start}); that is, EPA regulations are

[16] See Young (2010) for more details.

normalized to 1, and firms solve their problems believing that regulations will stay at that level indefinitely;

2. Move to the next year, $T_{start}+1$. Solve for the transition dynamics from the level of regulations prevalent in T_{start} to the new level of $T_{start}+1$. From the entire transition path, keep only the first period (i.e., when the shock occurred);

   Intermediate step: computation of the transition dynamics of the once-and-for-all change in regulations:

   (a) Consider a transition horizon T;

   (b) Compute two steady-states, one for $t=0$ (initial level of regulations) and $t=T$ (new level of regulations);

   (c) Guess a sequence of wages $\{\widehat{W}_t\}_{t=1}^{T-1}$ and marginal utilities $\{\widehat{MU}_t\}_{t=1}^{T-1}$;

   (d) Given that we know the value function in the terminal period T, $\tilde{v}_T$, we can solve for the optimal (unconstrained) decision in $t=T-1$:

$$\widehat{d'}_{T-1}(d,z) = \arg\max_{d'\geq 0}\left(\widehat{MU}_{T-1}\times\pi_{T-1}(d,z)+\beta\mathbb{E}_{T-1}\tilde{v}_T(d',z')\right).$$

   Note that we are using value functions scaled by the marginal utility: $\tilde{v}_t = \widehat{MU}_t \times v_t$.

   We also recover value functions $\tilde{v}^{\text{adj}}_{T-1}$ and $\tilde{v}^{\text{no adj}}_{T-1}$ that correspond to the obtained decision rule. Value function $\tilde{v}_{T-1}$ is then:

$$\begin{aligned}\tilde{v}_{T-1}(d,z) = \left(\frac{\widehat{\eta}_{T-1}(d,z)}{\bar{\eta}}\right)\left[\tilde{v}^{\text{adj}}_{T-1}(d,z) - \widehat{W}_{T-1}\frac{\widehat{\eta}_{T-1}(d,z)}{2}\right] + \\ + \left(1-\frac{\widehat{\eta}_{T-1}(d,z)}{\bar{\eta}}\right)\tilde{v}^{\text{no adj}}_{T-1}(d,z),\end{aligned}$$

   where

$$\eta^*_{T-1}(d,z) = \frac{\tilde{v}^{\text{adj}}_{T-1}(d,z) - \tilde{v}^{\text{no adj}}_{T-1}(d,z)}{\widehat{MU}_{T-1}\widehat{W}_{T-1}}$$

   and

$$\widehat{\eta}_{T-1}(d,z) = \min\{\bar{\eta}, \max\{0, \eta^*_{T-1}(d,z)\}\}.$$

Flow profits $\pi_{T-1}(d, z)$ are calculated assuming that the wage rate is $\widehat{W}_{T-1}$;

(e) Solving backwards (i.e., by repeatedly executing the previous step), we can recover the entire path of decision rules for $t = 1, \ldots, T-1$;

(f) Take the steady-state distribution for period $t = 0$. Apply the recovered sequence of decision rules, $\{\widehat{d}'_t(d, z)\}_{t=0}^{T-1}$, to compute the evolution of pollution stocks over the entire transition horizon;

(g) Compute excess demand functions on the labor market, and the deviation of the implied sequence of marginal utilities from the guessed one;

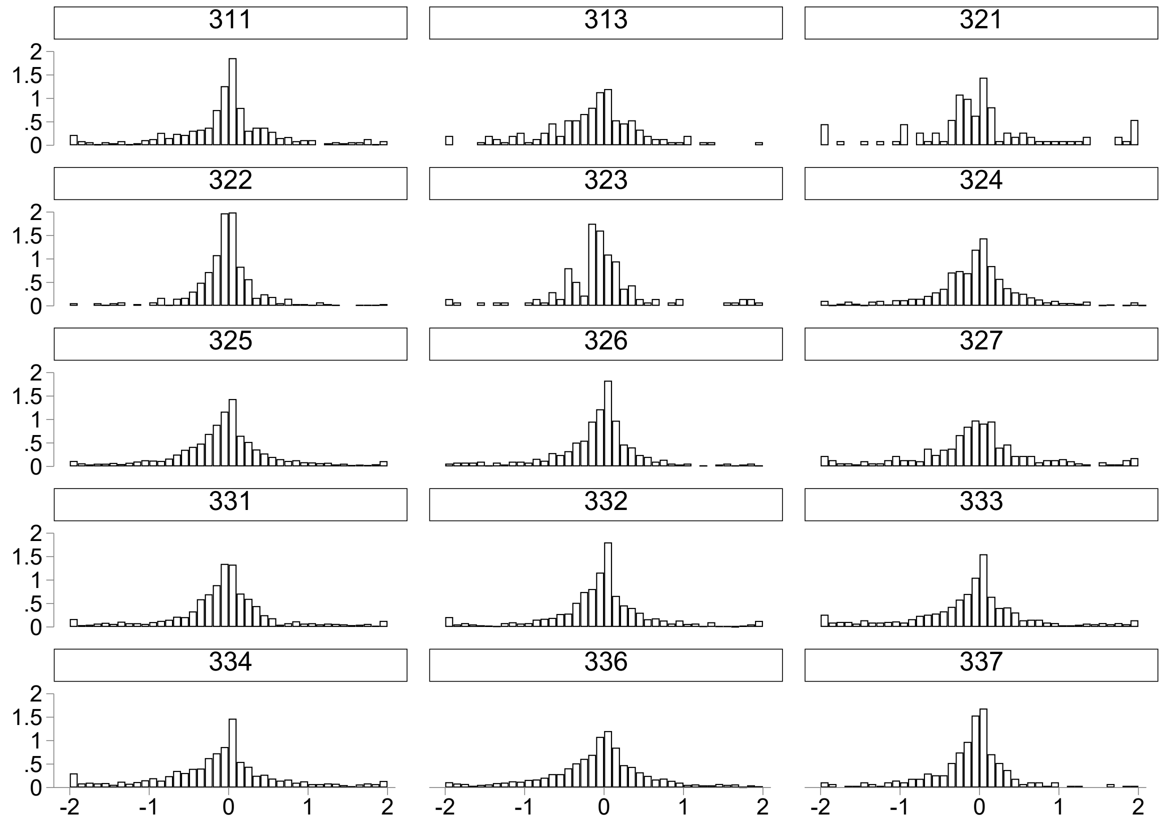
(h) If the norm of deviations taken across time is sufficiently small, terminate. Otherwise, update the guess of wages and marginal utilities and go back to step (c).

3. Repeat Step 2 for other years $T_{start} + 2 : T_{end}$, using the cross-sectional distribution saved in the previous step as a starting point for the transition;

4. The recovered sequences of pollution stocks, decision rules and prices represents the transition of the economy over the time period $T_{start} : T_{end}$, whereby firms interpret EPA regulations as unexpected each period.

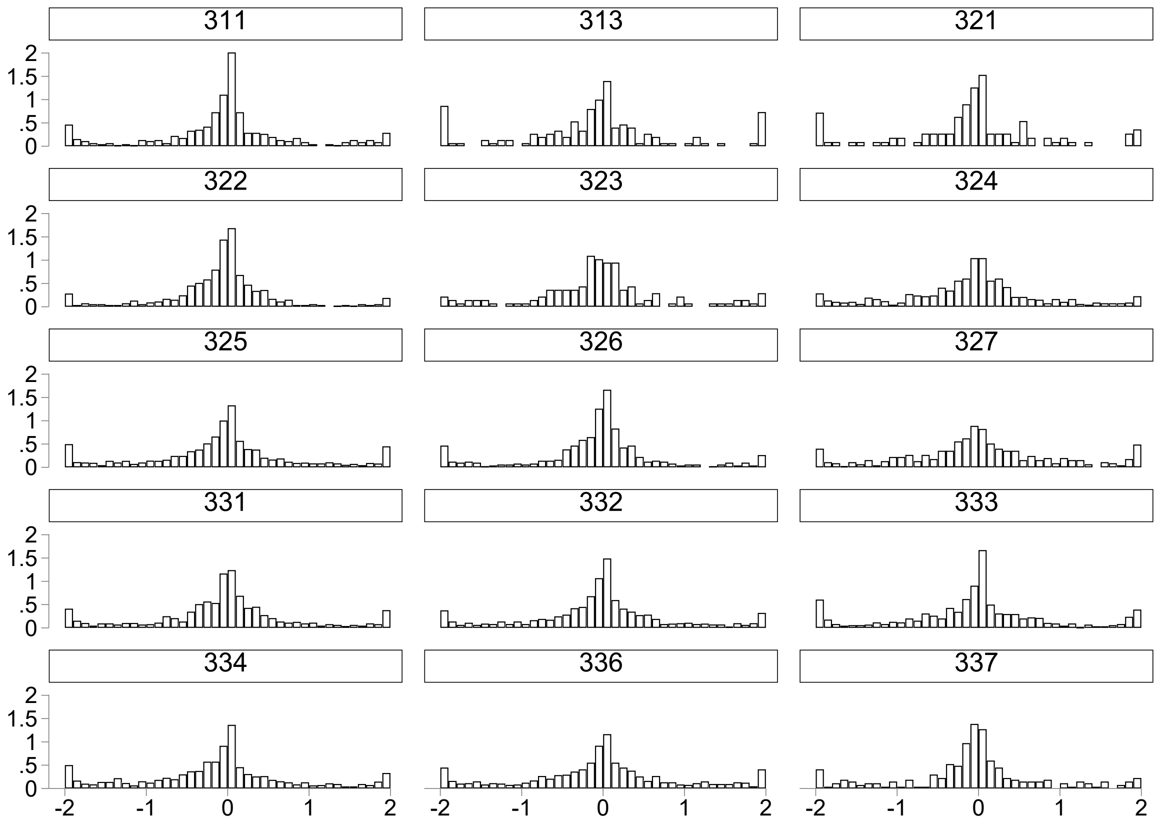
Appendix C: Figures and Tables

Figure C1: Distribution of Pollution Changes By NAICS 3-digit Industry



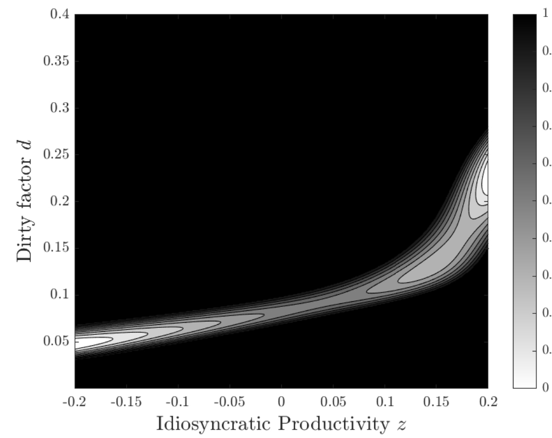
Notes: Figure C1 plots distributions of annual growth rates in toxic releases by NAICS 3-digit manufacturing industry. The growth rates are arc-growth rates (Davis, Haltiwanger and Schuh, 1996). Figure C2 in Appendix reports histograms for toxic releases weighted by toxicity. Underlying data: TRI.

FIGURE C2: DISTRIBUTION OF POLLUTION GROWTH RATES (WEIGHTED BY TOXICITY)

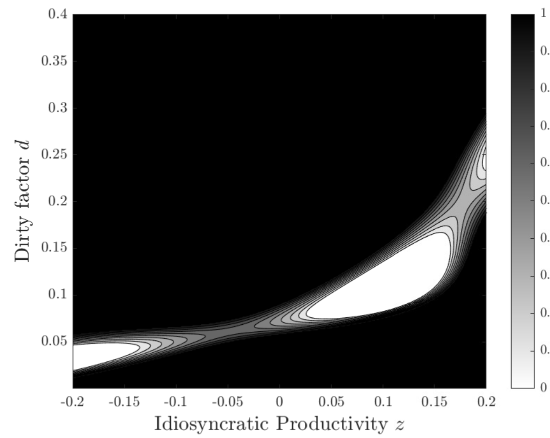


Notes: Figure C2 plots distributions of annual growth rates in toxic releases (weighted by toxicity) by NAICS 3-digit manufacturing industry. The growth rates are arc-growth rates (Davis, Haltiwanger and Schuh, 1996). Underlying data: TRI.

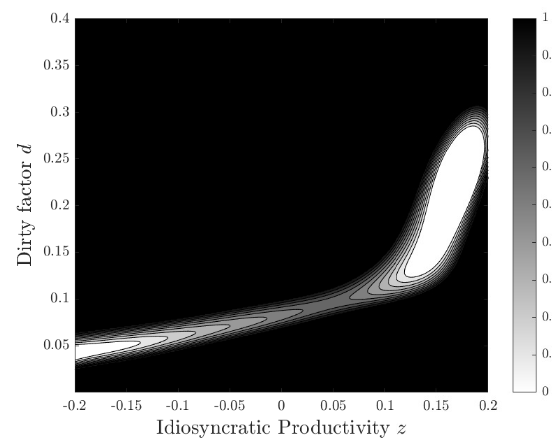
Figure C3: Idiosyncratic Productivity Process and Inaction Region



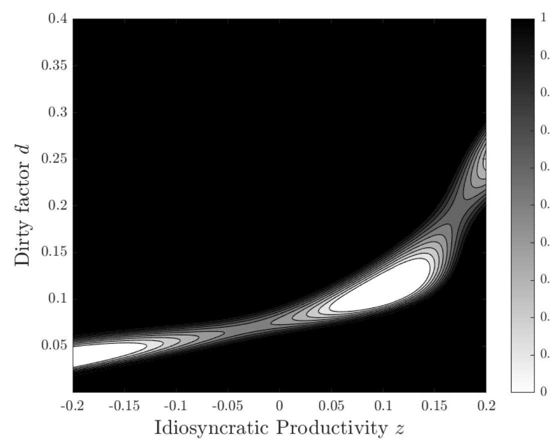
(A) Low ρ_z



(B) High ρ_z



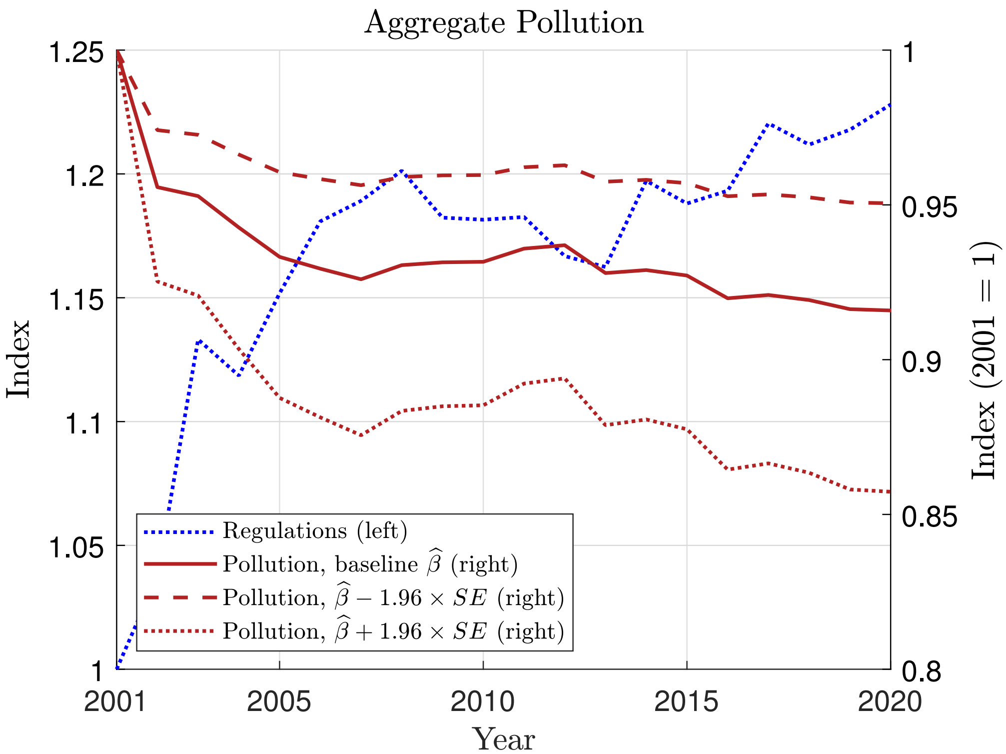
(C) Low σ_z



(D) High σ_z

Notes: Figure C3 plots inaction regions at the steady-state of the model in the space of idiosyncratic states (d, z). Darker colors mean higher probability of adjustment. Corresponding parameters are: $\rho_z \in \{0.70, 0.86\}$; $\sigma_z \in \{0.05, 0.09\}$.

Figure C4: Transition Dynamics: Sensitivity



Notes: Figure C4 plots the results of the transition dynamics exercise for the environmental regulations index (dotted blue line). Each of the red lines corresponds to a different $\widehat{\beta}$ targeted to infer ζ_1 in Equation (13). The solid red line corresponds to the baseline value of $\widehat{\beta}$, while the dashed and dotted red lines correspond to ζ_1 values consistent with the 95 percent confidence bounds for β.

Table C1: Summary Statistics: Distribution of Pollution Changes by NAICS 3-digit Industry

Industry	Obs.	$\lvert\tilde{\Delta}\rvert < 0.01$	$\lvert\tilde{\Delta}\rvert < 0.1$	$\lvert\tilde{\Delta}\rvert > 0.2$	Mean ($\tilde{\Delta}$)	Std. ($\tilde{\Delta}$)	P10 ($\tilde{\Delta}$)	P50 ($\tilde{\Delta}$)	P90 ($\tilde{\Delta}$)
311	452	0.122	0.310	0.533	-0.041	0.702	-0.840	0.000	0.704
313	150	0.067	0.233	0.633	-0.166	0.631	-1.036	-0.091	0.496
321	111	0.081	0.207	0.613	0.008	0.861	-0.937	-0.036	1.224
322	527	0.063	0.395	0.412	-0.043	0.462	-0.462	-0.021	0.381
323	137	0.036	0.270	0.460	-0.043	0.627	-0.609	-0.044	0.442
324	660	0.065	0.264	0.582	-0.066	0.600	-0.745	-0.022	0.558
325	2567	0.067	0.261	0.585	-0.065	0.658	-0.814	-0.035	0.645
326	492	0.083	0.305	0.502	-0.092	0.592	-0.784	-0.011	0.461
327	449	0.022	0.189	0.630	-0.059	0.776	-1.062	-0.031	0.911
331	1233	0.044	0.268	0.572	-0.066	0.675	-0.843	-0.038	0.579
332	1086	0.088	0.297	0.556	-0.063	0.659	-0.796	-0.009	0.642
333	838	0.080	0.260	0.606	-0.114	0.770	-1.171	-0.022	0.711
334	1354	0.083	0.233	0.640	-0.126	0.787	-1.160	-0.054	0.804
336	1046	0.050	0.228	0.617	-0.087	0.669	-0.936	-0.027	0.658
337	267	0.034	0.322	0.509	-0.129	0.567	-0.852	-0.050	0.353
Total	11369	0.068	0.267	0.577	-0.079	0.679	-0.891	-0.028	0.642

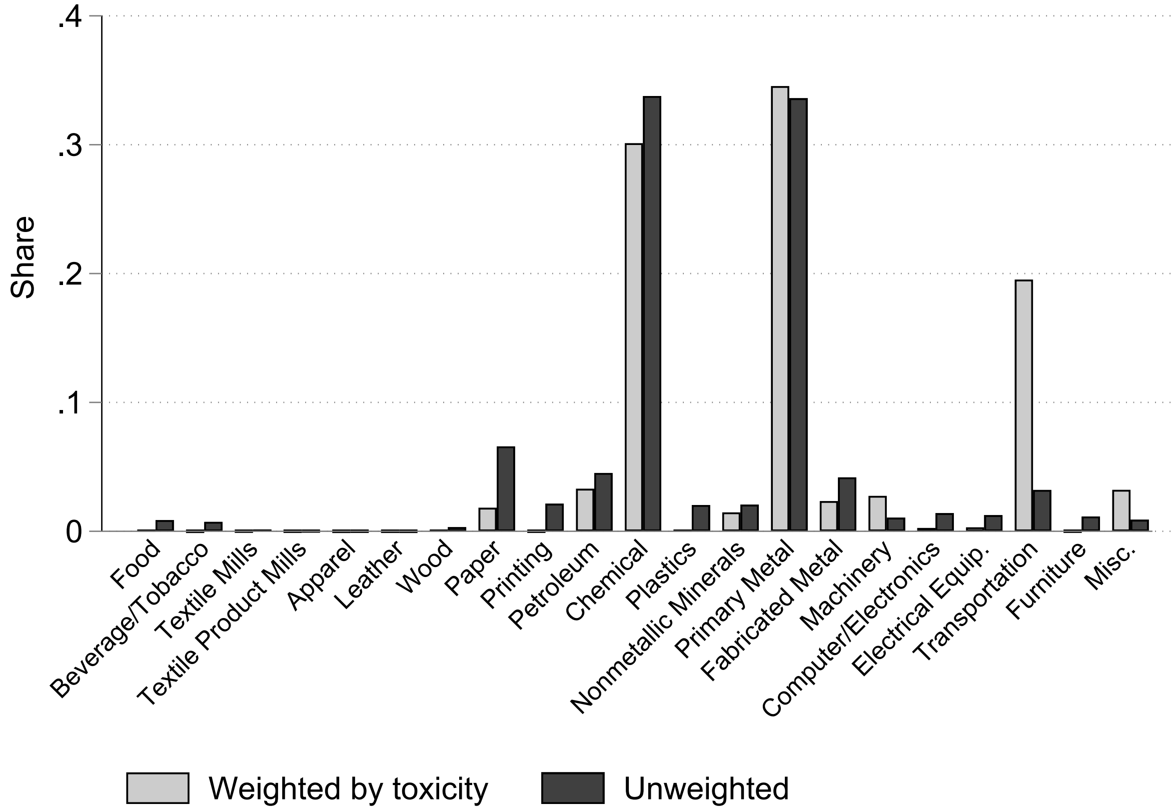
Notes: Table C1 reports summary statistics for distributions of (annual) growth rates in toxic releases by NAICS 3-digit manufacturing industry. The growth rates are arc-growth rates (Davis, Haltiwanger and Schuh, 1996). Underlying data: TRI.

Table C2: Parameter $\widehat{\gamma}$ for NAICS 3-digit Manufacturing Industries

NAICS Code	Industry	Parameter $\widehat{\gamma}$
311	Food	0.0040
312	Beverage/Tobacco	0.0040
313	Textile Mills	0.0022
314	Textile Product Mills	0.0022
315	Apparel	0.0022
321	Wood	0.0103
322	Paper	0.0223
323	Printing	0.0223
324	Petroleum	0.0212
325	Chemical	0.0205
326	Plastics	0.0048
327	Nonmetallic	0.0303
331	Primary Metal	0.0557
332	Fabricated Metal	0.0019
333	Machinery	0.0015
334	Computer/Electronics	0.0023
335	Electrical Equip.	0.0023
336	Transportation	0.0016
337	Furniture	0.0047
339	Misc.	0.0047

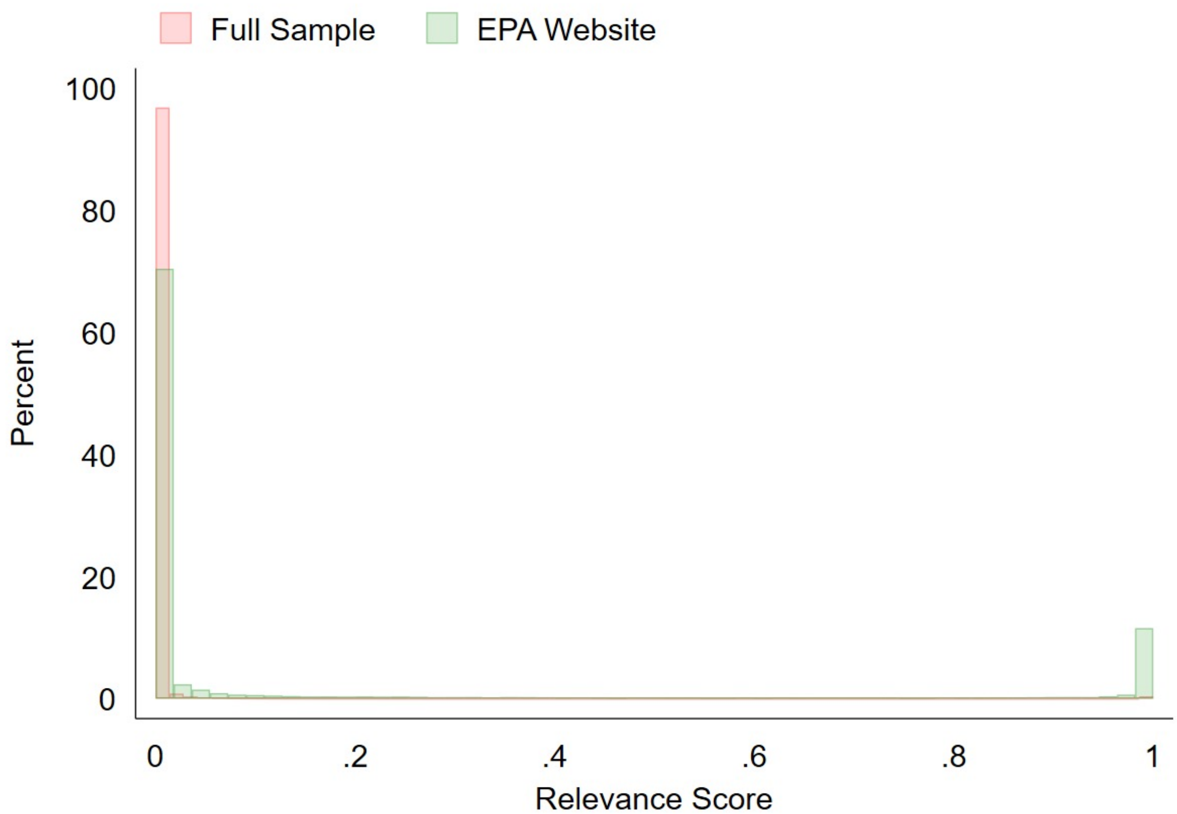
Notes: Table C2 reports exponents for the dirty factor $\{\widehat{\gamma}\}$ by NAICS 3-digit manufacturing industry used in the model. These estimates are borrowed from Shapiro and Walker (2018).

Figure C5: Distribution of Pollution by Manufacturing NAICS 3-digit Industry



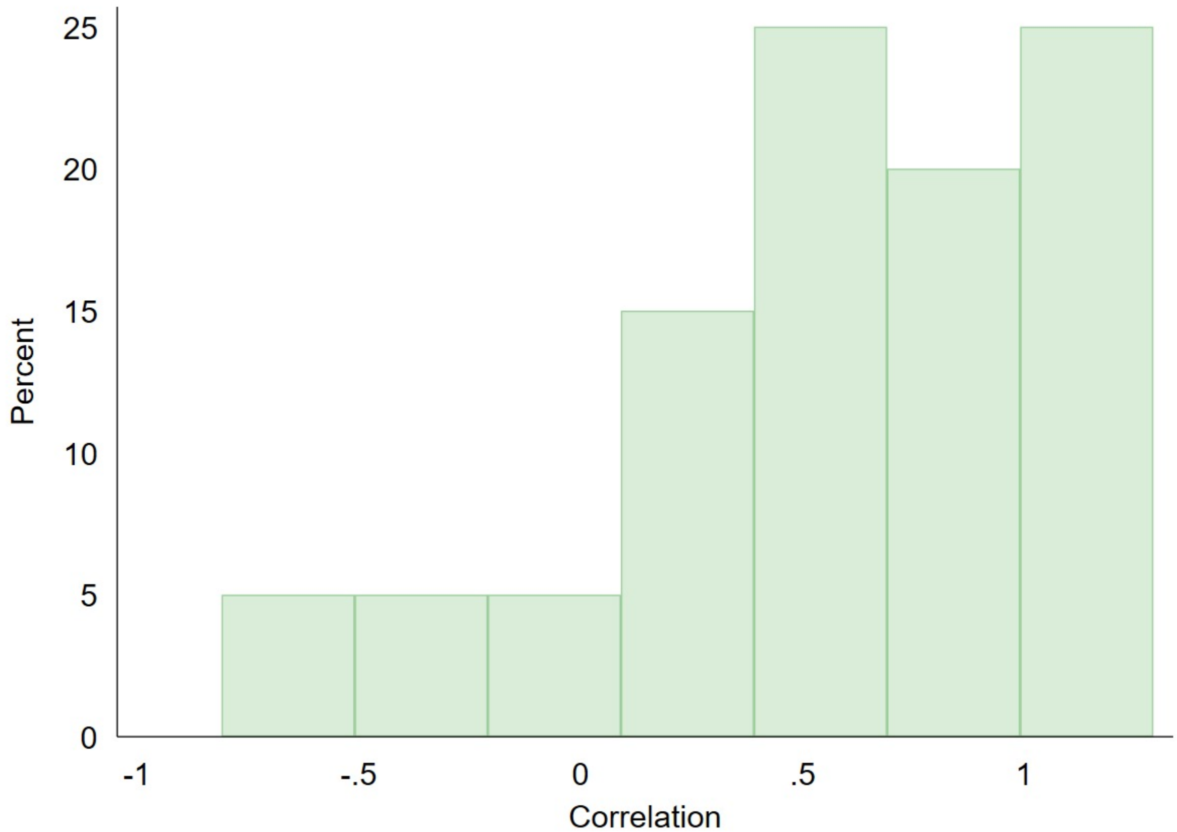
Notes: Figure C5 plots pollution shares by NAICS 3-digit manufacturing industry. Toxic releases are either weighted by toxicity level (gray bars) or unweighted (black bars). Underlying data: TRI.

Figure C6: Direct and Indirect Measures of Relevance: Comparison



Notes: Figure C6 plots the distribution of relevance scores from the Mercatus Center for the full sample of regulation-industry pairs and the EPA-mentioned pairs. Red bars represent the distribution of the full sample pairs, while green bars represent the distribution of the EPA-mentioned pairs.

Figure C7: Comparison of Regulatory Indices



Notes: Figure C7 plots the distribution of correlations across NAICS 3-digit industries between the baseline regulatory index and a regulation index constructed using relevance scores only from the Mercatus Center.

Table C3: Orthogonalized Environmental Concerns and Pollution

	$\log(TRI_t)$	$\log(TRI_{t+1})$	$\Delta_{t-1}^{t}\log(TRI)$	$\Delta_{t-1}^{t+1}\log(TRI)$
ΔEC	-0.0269**	-0.0209	-0.0256***	-0.0203
	(0.0097)	(0.0229)	(0.0088)	(0.0225)
$\log(TRI_{t-1})$	0.9245***	0.8899***	-0.0714***	-0.1069***
	(0.0059)	(0.0081)	(0.0054)	(0.0078)
Cons	0.3816***	0.5639***	0.3568***	0.5433***
	(0.0331)	(0.0464)	(0.0305)	(0.0447)
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Obs	344,681	312,463	344,681	312,463
Adj. R^2	0.8781	0.8258	0.0409	0.0602

Notes: Table C3 reports the results of regressing logarithms of current and future plant-level toxic releases $\log(TRI)$ on changes in environmental concerns ΔEC^{Orth} over the period 2001 to 2021. Only chemicals that are present throughout the sample period are included. ΔEC^{Orth} is the residual from regressing ΔEC on ΔEPA. Toxic releases are measured as the logarithm of total toxic releases plus one. Industry and time fixed effects are included, and standard errors are double-clustered at the industry and time level. The sample is restricted to the manufacturing sector (NAICS 31-33). *, **, *** denote significance at the 10%, 5%, and 1% level, respectively.

Table C4: Analysis at Toxic Chemical-Plant Level

	$\log(TRI_t^c)$	$\log(TRI_{t+1}^c)$	$\Delta_{t-1}^{t}\log(TRI^c)$	$\Delta_{t-1}^{t+1}\log(TRI^c)$	$\log(TRI_t^c)$	$\log(TRI_{t+1}^c)$	$\Delta_{t-1}^{t}\log(TRI^c)$	$\Delta_{t-1}^{t+1}\log(TRI^c)$
ΔEPA	-0.0799**	-0.0886*	-0.0709**	-0.0834*				
	(0.0359)	(0.0512)	(0.0350)	(0.0496)				
ΔEC					-0.0123*	-0.0184	-0.0119*	-0.0178
					(0.0073)	(0.0114)	(0.0071)	(0.0110)
$\log(TRI_{t-1})$	0.8823***	0.8585***	-0.1133***	-0.1365***	0.8822***	0.8584***	-0.1134***	-0.1366***
	(0.0029)	(0.0037)	(0.0027)	(0.0036)	(0.0029)	(0.0038)	(0.0028)	(0.0036)
Cons	0.7425***	0.7982***	0.7137***	0.7696***	0.7414***	0.7970***	0.7128***	0.7684***
	(0.0189)	(0.0250)	(0.0181)	(0.0241)	(0.0189)	(0.0247)	(0.0180)	(0.0238)
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Year*Pollutant FE	Y	Y	Y	Y	Y	Y	Y	Y
Obs	720,884	647,985	720,884	647,985	718,828	646,102	718,828	646,102
Adj. R^2	0.8652	0.7977	0.0657	0.0650	0.8652	0.7976	0.0658	0.0651

Notes: Table C4 reports the results of regressing logarithms of current and future chemical-level toxic releases $\log(TRI^c)$ on changes in EPA regulations (ΔEPA) or changes in environmental concerns (ΔEC) over the period 2001 to 2021. Only chemicals that are present throughout the sample period are included. The EPA regulations index (EPA) and the environmental concerns index (EC) are normalized to have a mean of zero and a standard deviation of one. Toxic releases for each chemical are measured as the logarithm of toxic releases plus one. The release of the pollutant and changes in the pollutant release are required to be non-zero. Industry and year-by-pollutant fixed effects are included, and standard errors are clustered at the industry-time level. The sample is restricted to the manufacturing sector (NAICS 31-33). *, **, *** denote significance at the 10%, 5%, and 1% level, respectively.

TABLE C5: ALTERNATIVE DATA: NATIONAL EMISSIONS INVENTORY

	$\log(NEI_t^c)$	$\log(NEI_{t+1}^c)$	$\log(NEI_t^c)$	$\log(NEI_{t+1}^c)$	$\log(NEI_t^c)$	$\log(NEI_{t+1}^c)$	$\log(NEI_t^c)$	$\log(NEI_{t+1}^c)$
$\Delta_{3year}EPA$	-0.782***	-0.390***	-0.337*	-0.168				
	(0.164)	(0.143)	(0.187)	(0.157)				
$\Delta_{3year}EC$					-0.016	-0.013	-0.026***	-0.021**
					(0.013)	(0.009)	(0.008)	(0.008)
$\log(NEI_{t-1})$			0.895***	0.721***			0.895***	0.721***
			(0.004)	(0.015)			(0.004)	(0.015)
Cons	-0.404***	-0.415***	-0.065***	-0.097***	-0.419***	-0.421***	-0.062***	-0.093***
	(0.071)	(0.073)	(0.007)	(0.019)	(0.071)	(0.073)	(0.006)	(0.018)
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Year*Pollutant FE	Y	Y	Y	Y	Y	Y	Y	Y
Obs	407,826	406,422	284,192	283,043	407,826	406,422	284,192	283,043
Adj. R^2	0.237	0.749	0.852	0.889	0.237	0.749	0.852	0.889

Notes: Table C5 reports the results of regressing logarithms of pollutant-level air pollution from NEI on changes in EPA environmental agency regulations over the previous three years ($\Delta_{3year}EPA$) or changes in environmental concerns over the previous three years ($\Delta_{3year}EC$). NEI data are available every three years. The amount of pollutant is measured as the logarithm of total air pollution plus one. The EPA regulations index (EPA) and environmental concerns index (EC) are normalized to have a mean of zero and a standard deviation of one. The release of the pollutant and changes in the pollutant release are required to be non-zero. Industry and year-by-pollutant fixed effects are included, and standard errors are clustered at the industry-time level. The sample is restricted to the manufacturing sector (NAICS 31-33) and six major air pollutants: CO, NOX, VOC, SO2, PM10, and PM2.5. *, **, *** denote significance at the 10%, 5%, and 1% level, respectively.

Table C6: Environmental Regulations, Concerns, and the Sales-to-Pollution Ratio

	$\Delta_{t-1}^{t}\log\left(\frac{Sale}{TRI}\right)$	$\Delta_{t-1}^{t+1}\log\left(\frac{Sale}{TRI}\right)$	$\Delta_{t-1}^{t}\log\left(\frac{Sale}{TRI}\right)$	$\Delta_{t-1}^{t+1}\log\left(\frac{Sale}{TRI}\right)$	$\Delta_{t-1}^{t}\log\left(\frac{Sale}{TRI}\right)$	$\Delta_{t-1}^{t+1}\log\left(\frac{Sale}{TRI}\right)$	$\Delta_{t-1}^{t}\log\left(\frac{Sale}{TRI}\right)$	$\Delta_{t-1}^{t+1}\log\left(\frac{Sale}{TRI}\right)$
ΔEPA	0.408***	0.639**	0.449***	0.689**				
	(0.101)	(0.287)	(0.087)	(0.256)				
ΔEC					0.036	0.048	0.025	0.028
					(0.080)	(0.039)	(0.077)	(0.043)
$\log\left(\frac{Sale}{TRI}{t-1}\right)$			-0.048***	-0.090***			-0.048***	-0.088***
			(0.009)	(0.018)			(0.009)	(0.019)
Cons	0.064***	0.108***	0.104***	0.178***	0.072***	0.122***	0.113***	0.193***
	(0.001)	(0.007)	(0.007)	(0.017)	(0.004)	(0.001)	(0.010)	(0.015)
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Obs	4,433	4,013	4,433	4,013	4,410	3,990	4,410	3,990
Adj. R^2	0.011	0.019	0.023	0.042	0.011	0.019	0.022	0.040

Notes: Table C6 reports the results of regressing current and future $\Delta\log(Sale/TRI)$ on changes in EPA regulations (ΔEPA) over the period 2001 to 2020. Only chemicals that are present throughout the sample period are included. The industry-level EPA regulations index is normalized to have a mean of zero and a standard deviation of one. The sample includes firms with available sales measures from Compustat. The sample is restricted to the manufacturing sector (NAICS 31-33). Industry and time fixed effects are included, and standard errors are double-clustered at the industry and time level. *, **, *** denote significance at the 10%, 5%, and 1% level, respectively.

Table C7: Environmental Regulations and Concerns: Toxicity-Weighted Results

	$\log(TRI_t^{tox})$	$\log(TRI_{t+1}^{tox})$	$\Delta_{t-1}^{t}\log(TRI^{tox})$	$\Delta_{t-1}^{t+1}\log(TRI^{tox})$	$\log(TRI_t^{tox})$	$\log(TRI_{t+1}^{tox})$	$\Delta_{t-1}^{t}\log(TRI^{tox})$	$\Delta_{t-1}^{t+1}\log(TRI^{tox})$
ΔEPA	-0.3205***	-0.5518***	-0.2956***	-0.5045***				
	(0.0255)	(0.1505)	(0.0351)	(0.1334)				
ΔEC					-0.0617***	-0.0002	-0.0628***	-0.0057
					(0.0175)	(0.0348)	(0.0180)	(0.0348)
$\log(TRI_{t-1})$	0.9123***	0.8671***	-0.0805***	-0.1259***	0.9123***	0.8672***	-0.0804***	-0.1257***
	(0.0071)	(0.0111)	(0.0059)	(0.0096)	(0.0071)	(0.0110)	(0.0059)	(0.0096)
Cons	0.8767***	1.3490***	0.7997***	1.2742***	0.8726***	1.3342***	0.7957***	1.2602***
	(0.0725)	(0.1188)	(0.0600)	(0.1029)	(0.0729)	(0.1154)	(0.0604)	(0.0998)
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Obs	346,331	314,012	346,331	314,012	345,191	312,918	345,191	312,918
Adj. R^2	0.8531	0.7839	0.0448	0.0687	0.8533	0.7843	0.0449	0.0687

Notes: Table C7 reports the results of regressing current and future logged toxicity-weighted toxic releases, $\log(TRI^{tox})$, on changes in EPA regulations (ΔEPA) or changes in environmental concern (ΔEC) over the period of 2001 to 2020. Only chemicals that are present throughout the sample period are included. The industry EPA regulation index (EPA) and industry environmental concern (EC) are normalized to have a mean of zero and a standard deviation of one. Toxic releases are measured as the logarithm of total toxicity-weighted toxic releases plus one. The release of the pollutant and changes in the pollutant release are required to be non-zero. Industry and year-by-pollutant fixed effects are included, and standard errors are clustered at the industry-time level. The sample is restricted to the manufacturing industry (NAICS 31-33). *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.