Macroeconomic Effects of the Universe of EPA Regulations*

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Abstract

In this study, we examine the impact of federal environmental regulations on firm-level decisions and aggregate pollution. Utilizing a novel index to measure industry-specific regulatory intensity, we analyze the interactions between regulations and pollution levels. Our empirical analysis employs administrative data to assess the effects on firm performance. Theoretically, we develop a general equilibrium model that incorporates cross-sectoral input-output linkages and optimizing forward-looking firms. The transition dynamics exercise reveals that environmental regulations account for a 15% decline in toxic releases over the period 1999-2021.

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1 Introduction

The growing concerns about environmental-related issues have led to stricter environmental regulations. In the U.S., the environmental protection agency (EPA) is the main regulatory body of creating and enacting environmental rules. It has been shown that these regulations are successful in curbing firm pollution (e.g., Shapiro and Walker, 2018; Greenstone et al., 2012). However, firms' compliance with the rules is often accomplished through real activities, which may distort their investment and production decisions. The cost of such distortions may go above and beyond the typical estimates based on expenditures on control and monitoring equipment. In particular, environmental regulations imposed on one set of firms may affect other firms through the general equilibrium feedback effect; as a result, this can have important welfare implications. The analysis of these considerations is impossible without a fully-fledged micro-founded structural model.

In this paper, we assess the costs and consequences of environmental regulations by combining three key elements. First, we use an environmental regulation index that captures time-varying industry-level total effective environmental regulations. Second, we characterize the relationship between environmental regulation and pollution using detailed administrative data. Third, we build a state-of-the-art heterogeneous firm general equilibrium model that captures the relationship between environmental regulations and pollution observed in the data. This approach allows us not only to study the distortions created by existing environmental regulations, but also to assess various counterfactual scenarios. This way we shed light on the effectiveness of various types of environmental regulations.

The project consists of two major parts: empirical analysis and the quantitative model.

We next describe the objectives for both parts.

Empirics The existing literature on the impact of environmental regulations primarily focuses on individual rules, such as the the Clean Air Act (e.g., Greenstone et al., 2012; Ryan, 2012). These studies typically isolate the effect of individual regulations one at a time. However, over the past decades, and in light of increasing concerns over environmental issues, the EPA has implemented and modified hundreds of overlapping regulations. Many of these regulations have not been analyzed through policy evaluation tools. It is also difficult to apply the standard quasi-experimental research designs to study many of these regulations due to the lack of natural control groups.

To study the effect of all EPA regulations, we use the time-varying measure of the total new EPA restrictions at a disaggregated industry. This measure is based on the texts of all effective EPA rules contained in the Code of Federal Regulations (CFR) since 1973 and the machine-learned relevance of the regulations to each industry. We show that this measure meaningfully captures the total restrictions of EPA regulations and can identify industry specific variations.

Subsequently, we combine the constructed index with the administrative records from the Annual Survey of Manufacturers (ASM) and the Census of Manufacturers (CM) to study the impact of industry-level EPA regulations on firm-level performance, including their impact on capital investment, labor and output decisions. We use these moments to put discipline on our quantitative framework. Since our quantitative model features multiple sectors, we additionally use Census data to estimate production functions at a fine NAICS 3-digit level (following, for example, Gao and Kehrig, 2021; Smirnyagin, 2023).

Theory We develop a multi-sector firm with heterogeneous firms; the model is set in general equilibrium which is critical for the meaningful policy analysis. The model represents a natural multi-sector extension of state-of-the-art models of firm dynamics with a rich set of adjustment costs (e.g., Khan and Thomas, 2008; Winberry, 2021; Smirnyagin, 2023; Smirnyagin and Tsyvinski, 2022). The presence of various capital adjustment frictions is necessary for the success of the model at the micro-level.

Our analysis of EPA regulations in the model represents a combination of approaches developed in classical papers, i.e. Restuccia and Rogerson (2008) and Shapiro and Walker (2018). Specifically, following Shapiro and Walker (2018), we assume that firms require an input of a dirty good to produce their final output. In turn, we model the price of the dirty good as a time-varying wedge in the spirit of Restuccia and Rogerson (2008); we use the EPA index to put discipline on the time-series properties of industry-specific wedges in our model.

2 Model

We build a model of firm dynamics with multiple sectors in the spirit of Long and Plosser (1983) and Bigio and La'O (2020). Time in the model is discrete and the horizon is infinite. Each sector of the economy is populated by a representative firm; all firms are owned by a representative household. Physical capital is produced by the capital good producer. Households own shares in firms, supply labor, and consume goods.

2.1 Environment

Technology The economy is comprised of N competitive sectors; a firm in each sector j has access to a Cobb-Douglas production technology:

$$y_j = A_j k^{\alpha_j} n^{\nu_j} \left(\prod_{s=1}^{N} m_s^{\omega_j^s} \right)^{\kappa_j} d^{\gamma_j}, \tag{1}$$

where $\alpha_j, \nu_j, \kappa_j, \gamma_j > 0$ and $\alpha_j + \nu_j + \kappa_j + \gamma_j < 1$ for each j. Every firm produces output y by combining capital k, labor n, intermediate goods $\{m_s\}_{i=1}^N$ and a dirty input d with corresponding shares $\alpha_j, \nu_j, \kappa_j$ and γ_j.[1] Parameters $\{A_j\}$ capture industry-level productivity levels.

The N-by-N input-output matrix $\Omega = \{\omega_j^s\}$ contains information on how output of other industries is used in the production process of a given industry; each row of this matrix adds up to 1: $\sum_{s=1}^N \omega_j^s = 1 \quad \forall j$.

Labor Labor market is frictionless with the wage rate W_t.

Investment Firms enter period t with some predetermined level of capital k_{jt}. The capital in period $t+1$ is determined by depreciation and investment made in period t. Capital is produced by the representative capital producer; its price is Q_t. Parameter $\delta \in (0, 1)$ denotes depreciation.

[1] Such formulation of the production function is broadly applied in environmental literature; Copeland and Taylor (2003) show that in this case pollution emissions can be treated as a joint input at the price of an emission tax rate τ_j. See also the discussion in Shapiro and Walker (2018) and in Duan et al. (2021).

Financing There is a representative household which owns all firms; the proceeds from production net of depreciation and investment are paid out to the household as dividends D_{jt}. We assume no frictions on financial markets, and, thus, place no constraints on the value of D_{jt}.

Households The economy is populated by a unit mass of identical households. Each household consumes and supplies labor.

2.2 Firm Optimization

The firm enters the period with some pre-determined level of capital k. Let $v_{jt}(k)$ denote the value of the firm in sector j at the start of period t given state k. This value can be written as:

$$v_{jt}(k) = \pi_{jt}(k) + \max_{k' \geq 0} \Bigg\{ -Q_t(k' - (1-\delta)k) - W_t \times AC(k, k') + \mathbb{E}_t \left[M(\mathbf{S}, \mathbf{S}') v_{jt+1}(k') \right] \Bigg\}, \quad (2)$$

where operating profits π_{jt} are defined as:

$$\pi_{jt}(k) = \max_{n, \{m_s\}, d \geq 0} P_{jt} A_{jt} k^{\alpha_j} n^{\nu_j} \left(\prod_{s=1}^{N} m_s^{\omega_j^s} \right)^{\kappa_j} d^{\gamma_j} - W_t n - \sum_{s=1}^{N} P_{st} m_s - \tau_{jt} d. \quad (3)$$

In Equation (3), P_{jt} denotes the price on good j at time t, and τ_{jt} is the tax firm in sector j pays per unit of a dirty input d at time t. $M(\mathbf{S}, \mathbf{S}')$ is the stochastic discount factor, and $\mathbf{S}$ denotes the aggregate state comprised of the cross-industry distribution of capital stocks and taxes on dirty factor, $\mathbf{S} = \{k_j, \tau_j\}_{j=1}^N$. We study the impact of changes in $\{\tau_j\}_j^t$ on toxic releases by conducting a transition dynamics exercise in Section 4.

Following Shapiro and Walker (2018), we assume that pollution tax revenue is lost due to rent-seeking. We assume that firms incur quadratic capital adjustment costs $AC(k, k') = \varphi \left(\frac{k' - (1-\delta)k}{k} \right)^2 k$ denominated in units of labor.

2.3 Capital Good Producer

New aggregate capital is produced by a representative capital good producer using the technology $K_K^{\alpha_K} N_K^{\beta_K}$, where N_K units of labor are used to produce capital, and $K_K = \sum_j k_j$ is the aggregate capital stock at the start of the period. Profit maximization leads to the following equilibrium relative price of capital:

$$Q_t = \frac{W_t}{\beta_K K_K^{\alpha_K} N_K^{\beta_K - 1}}. \tag{4}$$

2.4 Household Optimization

The representative household supplies labor inelastically (total labor endowment is normalized to 1) and maximizes the discounted stream of utilities:

$$\max_{\{c_{1t}, \ldots, c_{Nt}\}} \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t U(c_{1t}, \ldots, c_{Nt}) \tag{5}$$

subject to the budget constraint:

$$\sum_{j=1}^{N} P_{jt} c_{jt} \leq W_t + \sum_{j=1}^{N} D_{jt}(k), \tag{6}$$

where $D_{jt}(k)$ denotes dividends of the firm in sector j with capital k:

$$D_{jt}(k) = \pi_{jt}(k) - Q_t(k' - (1-\delta)k) - W_t \times AC(k, k'). \tag{7}$$

Utility We consider the following instantaneous utility function:

$$U(c_1, \dots, c_N) = \log\left(\prod_{j=1}^{N} c_j^{v_j}\right), \tag{8}$$

where v_j denotes expenditure share on good j. The detailed definition of equilibrium is relegated to Appendix B.1.

3 Parameterization and Model Fit

The model parameters can be generally categorized into three groups: preferences, technology, and pollution taxes. In the subsequent sections, we outline our approach to parameterization.

3.1 Preferences

We set the model period to be one year; this aligns with the frequency of our data. We therefore set the discount factor $\beta = 0.96$. In our quantitative implementation, model industries correspond to fifteen NAICS 3-digit manufacturing industries.[2]

Given the form of the utility function (8), parameters $\{v_s\}$ capture expenditure shares on

[2]Specifically, we consider the following industries: Food, Textile, Pulp/Lumber, Paper, Printing, Petroleum, Chemical, Plastic, Minerals, Metal, Fabricated Metal, Machinery, Electronics, Transportation Equipment, and Furniture.

Table 1: Parameter Values

Parameter	Description	Value	Target/Source	Data	Model
β	Discount factor	0.96			
$\{\upsilon_j\}$	Expenditure share	See text	BEA cons. exp.		
$\{\alpha_j\}$	Capital elasticity	See text	ASM/CM/TRI		
$\{\nu_j\}$	Labor elasticity	See text	ASM/CM/TRI		
$\{\Omega\}$	Input-output matrix	See text	BEA		
$\{\kappa_j\}$	Intermed. good elasticity	See text	ASM/CM/TRI		
$\{\gamma_j\}$	Pollution elasticity	See text	ASM/CM/TRI		
$\{A_j\}$	Industry productivity	See text	BDS		
δ	Depreciation rate	0.10	$\mathbb{E}\left[\frac{i}{k}\right]$	0.10	0.10
φ	Quadratic adj. cost	2	Benchmark value		
α_K	Cap. good producer, capital	0.33			
β_K	Cap. good producer, labor	0.67			

output of various industries. We use data on personal consumption expenditures from the BEA Input-Output table (see Figure C1 in Appendix) to assign values to these parameters.[3]

3.2 Technology

The depreciation rate, denoted as δ, is set to 0.10, which results in an average investment rate of 10%. The quadratic adjustment cost parameter φ is set at 2. This value falls within the range commonly used in the literature (Winberry, 2021; Smirnyagin, 2023).

Sectoral Production Functions We parameterize sector-specific production functions (1) in two steps. First, we combine TRI data with the Annual Survey of Manufacturers and the Census of Manufacturers to estimate production factor elasticities $\{\alpha_j, \nu_j, \gamma_j, \kappa_j\}$; we discuss the details below in Section 3.3. Furthermore, we pick sectoral productivities $\{A_j\}$ to hit the size distribution of NAICS 3-digit manufacturing industries. Specifically, we target employment shares sourced from the Business Dynamics Statistics (see Figure C2).[4]

[3] We use 2012 Use Table downloaded from https://www.bea.gov/industry/input-output-accounts-data.
[4] Data are available at https://www.census.gov/programs-surveys/bds.html.

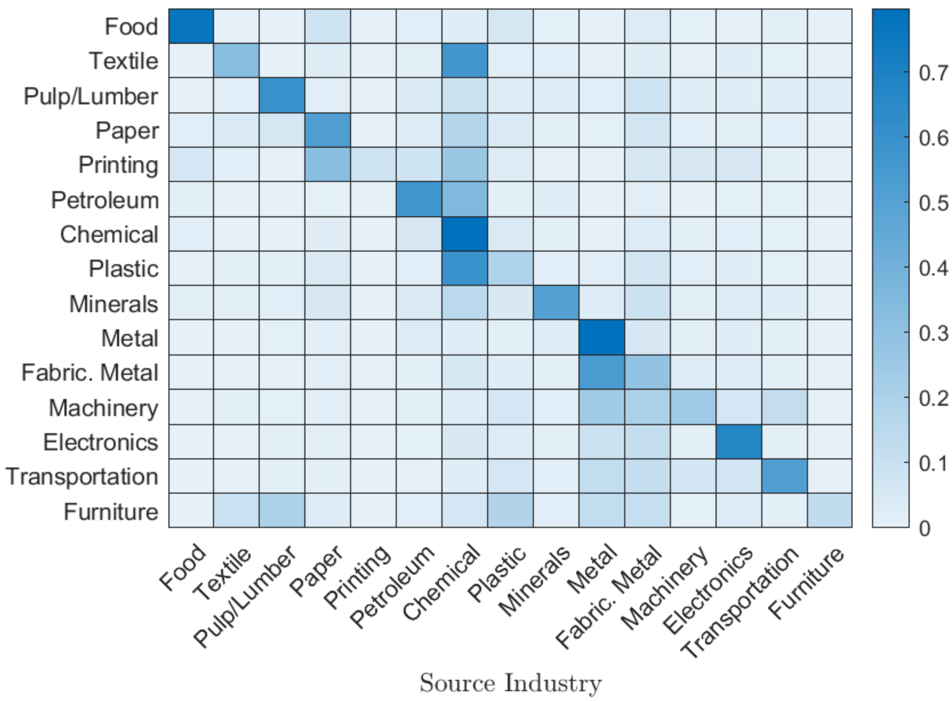
Input-Output Network We construct the Input-Output table Ω from the data; our source is the 2012 Use Table from the BEA. Each row in this table represents a sectoral commodity, while each column represents either an industry or a component of aggregate demand. Each entry in this table indicates the spending by the column's industry on the commodity produced by its respective row, measured in U.S. dollars. For alignment with our model, we consolidate this table to the NAICS 3-digit level, creating the Input-Output production matrix for the U.S. manufacturing sector (Figure 1). The figure displays a prominent diagonal, indicating the significance of an industry's output for its own production. Notably, there are some pronounced off-diagonal elements; for example, chemicals play a crucial role in the manufacturing of plastics and textiles, while the metal industry's output is extensively utilized in the production of machinery and fabricated metal.

Capital Good Producer We assume that the capital good producer's technology exhibits constant returns to scale $\alpha_K + \beta_K = 1$, and we set $\alpha_K = 0.33$. We explored how this choice affects our key quantitative results and found that its role is not significant.

3.3 Estimating Production Function with a Dirty Factor

To estimate the industry-level production function with a dirty factor, we need to combine plant-level information on output, capital, materials, and labor from ASM/CM with information on total releases of toxic chemicals from the TRI data. We first outline the process of merging the TRI data with the Census data and then delve into the details of the production function estimation. Additional details about the datasets are in Appendix A.

Figure 1: Input-Output Matrix for the Manufacturing Sector



Notes: Figure 1 visualizes the Input-Output matrix Ω used in the model. The underlying data are from the BEA 2012 Use Table.

Manufacturing Census Data Both the ASM and CM are mail-back surveys of U.S. manufacturing plants (NAICS 31-33). The CM is conducted at quinquennial frequency (years ending in 2 and 7), and covers the universe of manufacturing establishments. The ASM is conducted in non-Census years for about 50-60k establishments taken from the "mail stratum" of the manufacturing sector. The main advantage of the ASM/CM is that they provide rich plant-level information on capital expenditures, value of shipments, labor input and materials which is essential for the production function estimation.

Toxics Release Inventory The TRI Program at the EPA tracks the industrial management of toxic chemicals that may cause harm to human health and the environment.[5] The

[5] https://www.epa.gov/toxics-release-inventory-tri-program/tri-data-and-tools.

program commenced in 1987 as part of the Emergency Planning and Community Right-to-Know Act (EPCRA) in order to support and promote emergency planning as well as to provide the public with information about releases of toxic chemicals in their community. Not all plants are required to file with the TRI; the coverage of plants by the TRI depends on several factors. First, the facility needs to be operating in certain industries (manufacturing sector is included), the plant has to be sufficiently large with at least 10 employees, and, finally, the release of at least one toxic chemical is 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 been changing over time reflecting varying TRI requirements. In our analysis, we include all chemicals listed in the TRI. Additionally, we present findings for a subset of chemicals consistently reported from 1987 to 2019; in most cases, we find that the results are broadly similar.

For the purposes of the production function estimation, we need to aggregate chemicals at the plant-year level. To the best of our knowledge, there is no consensus in the literature on the best way of bringing various chemicals on equal footing. 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. We chose to weigh chemical releases by thier 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".[6]

Merging TRI Data with ASM/CM The challenge of merging the ASM/CM dataset with TRI arises from two main factors: firstly, the manufacturing sample in ASM/CM is structured at the establishment level, in contrast to the more granular facility level of the TRI; and secondly, the absence of a shared identifier across both datasets.

To circumvent these challenges, we utilized a combination of exact and fuzzy matching techniques to link TRI facilities with manufacturing plants from the ASM/CM dataset. We aggregated TRI data based on physical addresses, operating under the assumption that facilities sharing a physical address are likely part of the same plant. The ASM/CM dataset, however, does not readily provide specific addresses for establishments. To fill this gap, we sourced establishment-level addresses and names from the Business Registrar housed by the Census Bureau.

Following that, we merged the TRI data with ASM and CM requiring an exact match on NAICS 4-digit codes and state identifiers. Subsequently, we fuzzy matched observations based on plant's name, street address, city, and ZIP code. This way we were able to successfully match over 70% of the unique TRI facilities with entities in the ASM/CM dataset. To bolster the accuracy of the fuzzy matching, we standardized terms within both datasets. As an example, we abbreviated terms such as "corporation" to "corp" and "street" to "str". The resulting dataset is used for the production function estimation.

Estimation of Production Function Our objective is to obtain estimates of production elasticities $\{\widehat{\alpha}_j, \widehat{\nu}_j, \widehat{\kappa}_j, \widehat{\gamma}_j\}_{j=1}^N$. We estimate (1) individually at the level of NAICS 3-digit

[6]Data are available at https://www.epa.gov/rsei/rsei-data-dictionary-chemical-data.

industries; we found that this choice strikes a balance between the granularity of an industry and the sample size within each industry cell.[7] In our empirical implementation, we combine materials with an energy input.

We experimented with three different methods of estimation: a "naive" approach, where we regressed the logarithm of output on the logarithms of inputs thereby disregarding the endogeneity bias originating from unobserved productivity, and the methods proposed by Olley and Pakes (1996) [OP] and Levinsohn and Petrin (2003) [LP]. In summary, we observed that the OP and LP methods yielded highly comparable estimates $\{\widehat{\gamma}_j\}$. Furthermore, the "naive" approach identified the same qualitative patterns (i.e., industries with high dirty factor elasticity using the "naive" approach also exhibit it high in OP and LP cases); however, the quantitative difference between the methods is significant. To render the volume of output amenable to disclosure from the Census, we opted to employ the LP method. In our perspective, this method not only accounts for unobserved productivity but also is less dependent on the longitudinal features of the data (i.e., in the OP method, one must incorporate exit dummies; although feasible, exit is not perfectly quantified due to the rotating nature of the ASM panel).

Accounting for Time-Varying Technology In order to investigate the evolution of technology over time, we divided the sample into two segments (before and after 2002) and re-estimated production functions for each subset. We treat the estimates derived from the earlier subset as indicative of the initial technology. We then assume that the elasticities

[7] We discovered that even when analyzing at the NAICS 3-digit level, certain industry categories are notably small and fail to meet the U.S. Census Bureau's disclosure concentration statistics thresholds. One example is the Apparel Manufacturing (NAICS 315), which is not included in our analysis.

Table 2: Production Function Estimates

Industry	NAICS	Capital ($\widehat{\alpha}$)	Labor ($\widehat{\nu}$)	Materials ($\widehat{\kappa}$)	Pollution ($\widehat{\gamma}$)
Food	311	0.193	0.145	0.416	0.001
		(0.0243)	(0.0080)	(0.0186)	(0.0008)
Textile	313	0.390	0.298	0.464	0.004
		(0.1616)	(0.0263)	(0.0488)	(0.0023)
Pulp/Lumber	321	0.224	0.161	0.552	0.003
		(0.0418)	(0.0097)	(0.0238)	(0.0011)
Paper	322	0.337	0.229	0.507	0.006
		(0.0547)	(0.0180)	(0.0352)	(0.0017)
Printing	323	0.052	0.364	0.437	0.003
		(0.0534)	(0.0216)	(0.0489)	(0.0052)
Petroleum	324	0.143	0.217	0.569	0.005
		(0.0740)	(0.0152)	(0.0386)	(0.0022)
Chemical	325	0.367	0.199	0.470	0.002
		(0.0314)	(0.0073)	(0.0152)	(0.0011)
Plastic	326	0.194	0.239	0.487	0.002
		(0.0194)	(0.0100)	(0.0182)	(0.0011)
Minerals	327	0.199	0.323	0.421	0.008
		(0.0354)	(0.0108)	(0.0162)	(0.0013)
Metal	331	0.295	0.266	0.482	0.004
		(0.0701)	(0.0108)	(0.0166)	(0.0013)
Fab. Metal	332	0.270	0.318	0.412	0.003
		(0.0278)	(0.0082)	(0.0137)	(0.0007)
Machinery	333	0.426	0.285	0.525	0.002
		(0.0992)	(0.0111)	(0.0266)	(0.0009)
Electronics	334	0.243	0.085	0.457	0.001
		(0.1051)	(0.0257)	(0.0237)	(0.0024)
Transportation	336	0.143	0.282	0.482	0.003
		(0.0352)	(0.0127)	(0.0189)	(0.0009)
Furniture	337	0.138	0.228	0.515	0.003
		(0.0886)	(0.0245)	(0.0391)	(0.0026)

Notes: Table 2 reports production function elasticities for NAICS 3-digit manufacturing industries estimated using Levinsohn and Petrin (2003) method. Numbers in parentheses are standard errors. Underlying data are ASM/CM and TRI.

of capital, labor, materials, and the dirty factor are linearly evolving over time ultimately aligning with the levels observed in the latter subset. Estimates for the two subsamples are reported in Appendix (see Tables D1 and D2).

3.4 Measuring Distortions

To study the aggregate effect of all EPA regulations, we use the measure of the total new EPA restrictions imposed on each industry each year. This measure is based on the texts of all effective EPA rules contained in the Code of Federal Regulations (CFR) since 1999 and the machine-learned relevance of the regulations to each industry. We show that this measure meaningfully captures the total restrictions of EPA regulations and can identify industry specific variations. The detailed explanation of how the index was constructed is TBA.

EPA Index and Aggregate Toxic Releases Figure 2 shows the time-series of the constructed EPA index and toxic releases by NAICS 3-digit industry. Chemical, metal and transportation equipment industries are the most polluting ones, while textile and printing industries are the least polluting in the aggregate. There is also a noticeable heterogeneity in the evolution of regulations across industries. For example, our index captures a significant increase in regulations on the furniture and pulp/lumber industries over the sample time period. At the same time, regulations on machinery and printing industries grew less.

3.5 Pollution Tax and EPA Regulations

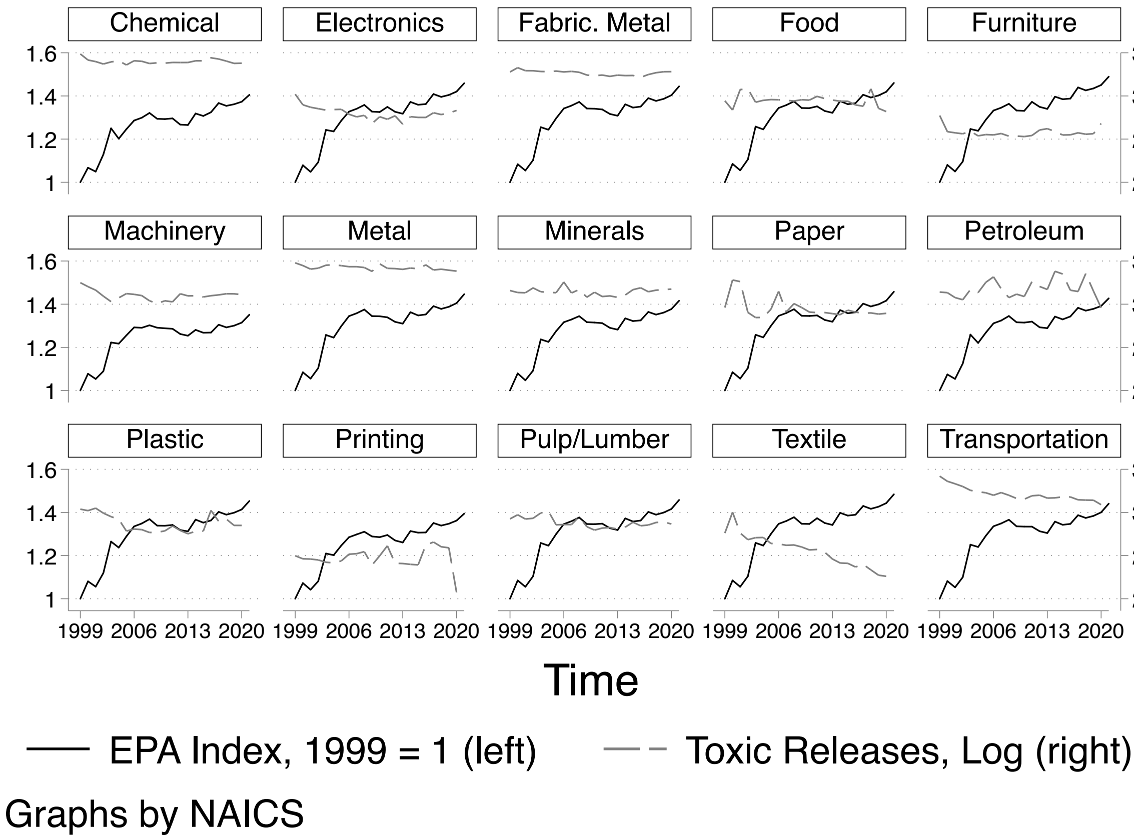
In our quantitative implementation, we assume that the cost per unit of toxic emissions in industry j is a function of EPA regulations, and has the following functional form:

$$\tau_{jt} = \kappa_0^j e^{\kappa_1 EPA_{jt}}, \tag{9}$$

where $\{\kappa_0^j\}$ and κ_1 are parameters.

In order to estimate κ_1, consider the first-order condition of the firm's profit (3) with

Figure 2: Evolution of the EPA Index and Toxic Releases by Industry



Notes: Figure 2 plots the evolution of the EPA index and aggregate toxic releases by NAICS 3-digit manufacturing industry. EPA index is normalized to 1 in 1999. See details on index construction in Section ??.

respect to the toxic releases d:

$$P_j A_j \gamma_j k^{\alpha_j} n^{\nu_j} m^{\kappa_j} d^{\gamma_j - 1} = \kappa_0^j \kappa_1 e^{\kappa_1 EPA_{jt}},$$

where m is the component combining all intermediate inputs. Dividing both sides by the revenue yields:

$$\frac{\gamma_j}{d} = \frac{\kappa_0^j \kappa_1 e^{\kappa_1 EPA_{jt}}}{P_j y_j}.$$

After taking logarithms, first-differencing the equation, as well as adding idiosyncratic inno-

TABLE 3: ESTIMATION OF κ_1

	(1)	(2)
$\widehat{\zeta}_1$	0.165**	0.278***
	(0.070)	(0.054)
Sample	All	Mnf
Industry & Year FE	✓	✓
R^2	0.090	0.086

Notes: Table 3 reports OLS estimates of Equation (10). Column (1) is based on Compustat data, while columns (2)-(3) are based on ASM/CM sample. In case of Census data, observations are weighted by the population weights reported in ASM/CM. Numbers in parentheses are standard errors clustered at the industry level. *, **, *** denotes significance at 10%, 5%, and 1% level, respectively.

vations η_{it}, we obtain:

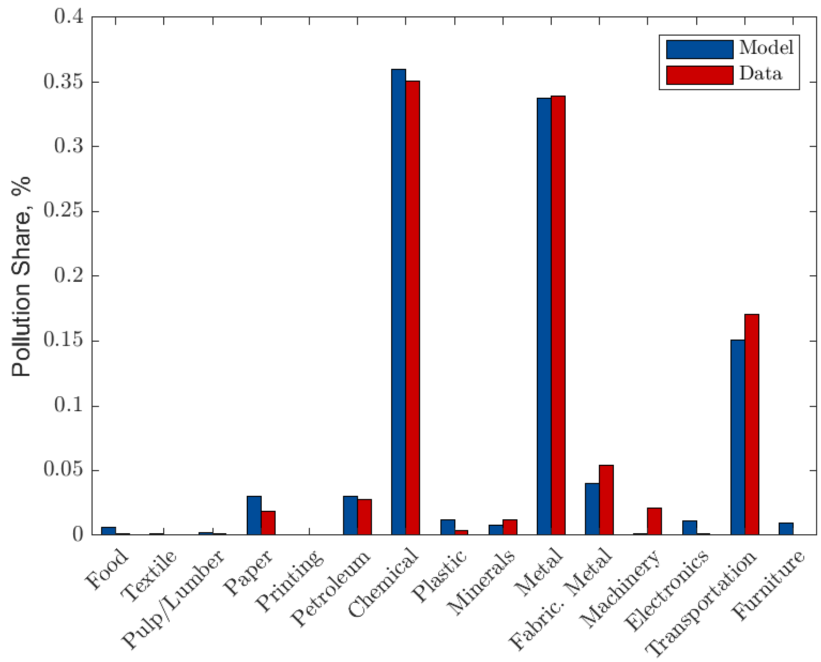
$$\Delta \log \left(\frac{\tilde{y}_{it}}{d_{it}} \right) = \kappa_1 \Delta EPA_{j(i)t} + \eta_{it}, \tag{10}$$

where $\tilde{y}$ denotes revenue.

We estimate Equation (10) on a pooled across industries sample, saturating the model with year and establishment fixed effects and normalizing the EPA index to 1 in 1999. Table 3 reports the estimation results; we find that the estimated coefficient is statistically significant; moreover, its magnitude is stable across the reported specifications.

Given the value of $\widehat{\kappa}_1$, we obtain industry-specific coefficients $\{\widehat{\kappa}_0^j\}$ by requiring the model to hit the distribution of toxic releases across industries in 1999, $\left\{ \frac{\sum_{i \in j} d_{i,1999}}{\sum_i d_{i,1999}} \right\}_{j=1}^N$, where $d_{i,1999}$ denotes toxic releases of plant i in 1999. Figure 3 demonstrates that emissions of chemicals are highly concentrated; Chemical industry (NAICS 325) accounts for more than one third of overall emissions, while Petroleum (NAICS 324), Primary Metal (NAICS 331) and Transportation Equipment (NAICS 336) industries collectively account for more than 50% of toxic releases.

Figure 3: Pollution Shares



Notes: Figure 3 visualizes pollution shares for 15 manufacturing NAICS 3-digit industries in 1999. The underlying data are from the TRI.

4 Quantitative Exploration

In Section 2, we developed a quantitative model whereby forward-looking firms are interconnected through a general equilibrium adjustment of prices and input-output linkages. In this section, our primary objective is to quantitatively examine the role of EPA regulations, along with other model components, in shaping the evolution of toxic releases in the U.S. manufacturing sector.

We start off by computing the cross-elasticities of toxic releases across manufacturing industries in response to a 10% increase in the EPA index of a specific industry. This procedure echoes the approach in Caliendo et al. (2022). When we repeat this exercise using a version of the model without input-output linkages, it becomes evident that the input-output network plays a pronounced role in propagating environmental regulations across industries. In particular, we find that input-output linkages increase many cross-elasticities thereby leading to unintended increases in toxic releases within indirectly affected industries.

We then conduct a transition dynamics exercise by feeding in the industry-specific EPA index into our model. We find that tightening of environmental regulations during 1999-2021 time period led to a 17% decline in aggregate toxic releases. Besides, we observe a substantial heterogeneity in the evolution of toxic releases across manufacturing industries over time. For example, while Chemical industry saw a 15% decline in pollution, some other industries saw a decline of over 60% (e.g., Printing and Plastics industries).

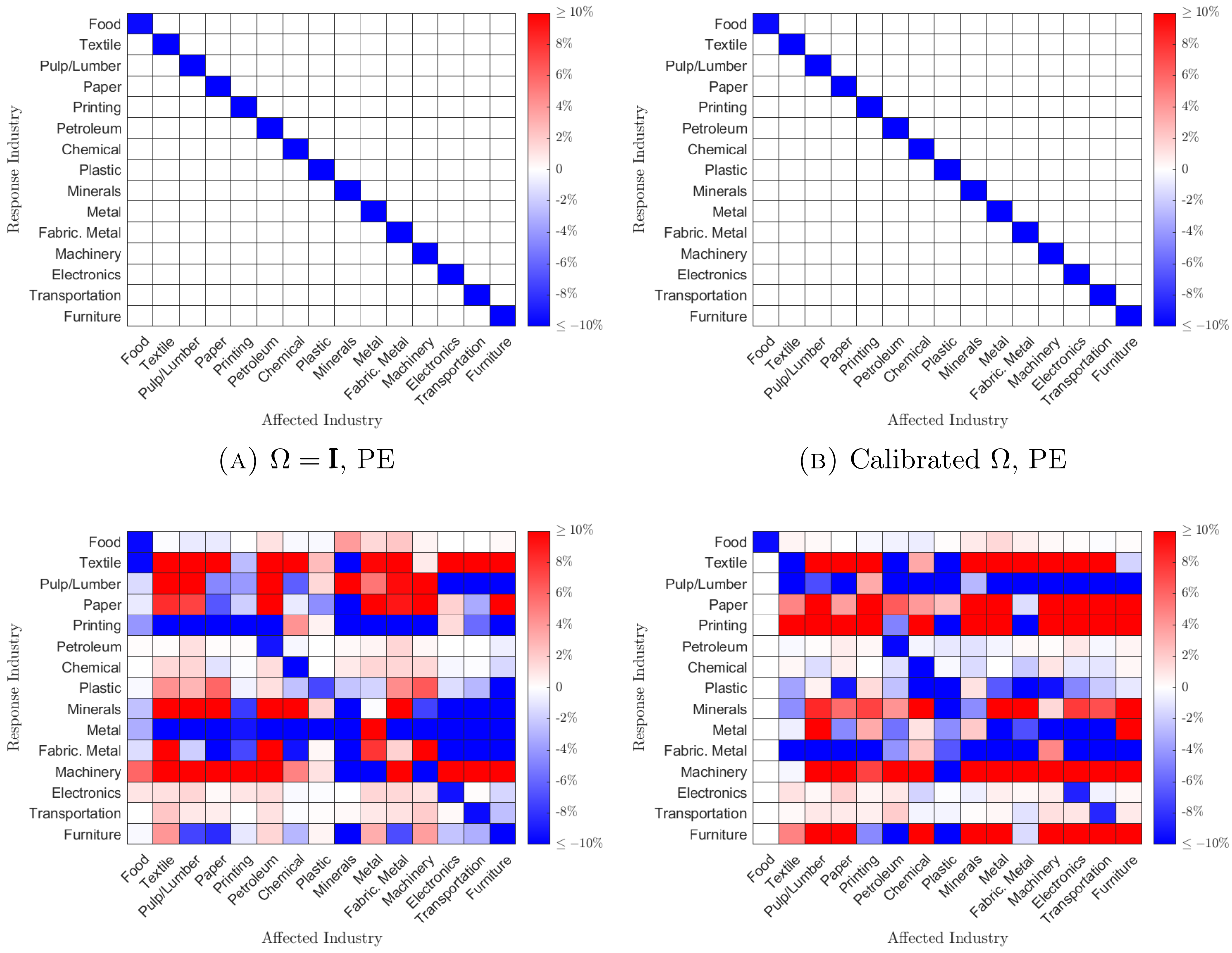
In sharp contrast with the baseline model, the version of the model without input-output linkages results in the overall similar dynamics of toxic releases across industries. This is consistent with our cross-elasticities results, whereby we argued that input-output linkages may lead to unintended increases in toxic releases.

4.1 Pollution Cross-Elasticities

We compute the pollution cross-elasticity of industry-level toxic releases between the initial steady-state and the steady-state corresponding to the environment where EPA index for a given industry increased by 10%. This exercise is reminiscent of the analysis of distortions in Caliendo et al. (2022).

Figure 4 presents the results. Panels (A) and (C) correspond to the version of the model without cross-industry linkages ($\Omega = \mathbf{I}$), while Panels (B) and (D) are for the version with the calibrated input-output matrix. Specifically, Panels (A) and (B) indicate that all off-

Figure 4: Cross-Elasticities of Pollution



(A) $\Omega = \mathbf{I}$, PE

(B) Calibrated Ω, PE

(C) $\Omega = \mathbf{I}$, GE

(D) Calibrated Ω, GE

Notes: Figure 4 consists of four panels. Each panel depicts the percentage change in pollution across manufacturing NAICS 3-digit industries (rows) to a 10% increase in τ_j in a given (column) industry. The top row corresponds to a partial equilibrium exercise, whereby prices are held fixed. The bottom row shows cross-elasticities in case prices are allowed to adjust. Panels (A) and (C) use the identity input-output matrix, while panels (B) and (D) use the calibrated input-output matrix Ω (as in Figure 1).

diagonal cross-elasticities are zero in the partial equilibrium analysis. It is the adjustment of prices that enables the model to generate spillovers across industries.

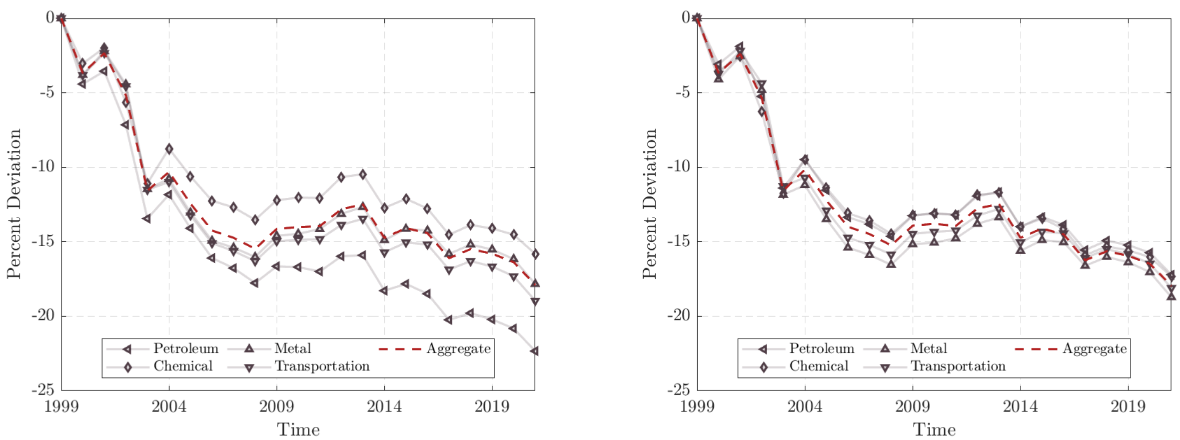
Panel (C) demonstrates that even without industry linkages, the model can generate considerable variation in cross-elasticities, with both positive and negative off-diagonal elements present. Notably, cross-elasticities are in most cases negative, a trend resulting from two combined effects. Firstly, increased regulations on an industry primarily have a negative impact on it, all other things being equal. Secondly, reduced profits from a specific sector lead to a lower household consumption, subsequently diminishing the production incentives for firms in other industries. More often than not, this combined effect outweighs the benefits of declining wages and lower price for the capital good.

Panel (D) revisits the general equilibrium analysis, this time including input-output linkages. Contrasting with Panel (C), more off-diagonal elements in this model are positive. With cross-sectoral linkages, regulations on one industry decrease the demand for intermediate goods from affected firms. As a result, the prices for those intermediates drop (all else being equal), potentially benefiting other industries that use these inputs in their production. In essence, our findings underscore the critical influence of the input-output model structure on the propagation of environmental regulation effects across industries. This often leads to unintended increases in pollution across firms that are not directly affected.

4.2 EPA Regulations and Toxic Releases

To study the effects of EPA regulations on overall toxic emissions, we conduct a transition dynamics exercise with perfect foresight. Conceptually, we feed our constructed index into the model and observe the subsequent behavior of firms. This exercise technically entails an iterative process. We first guess sequences of prices and then determine the optimal decisions of firms by working backward in time. Equipped with the optimal investment decisions of firms, we then iterate capital holdings forward to calculate the sequences of excess demands across markets for every time period along the transition path. We update our initial price

Figure 5: Environmental Regulations and Toxic Releases



(A) Calibrated Ω (B) $\Omega = \mathbf{I}$

Notes: Figure 5 consists of two panels. Panel (A) corresponds to the version of the model with input-output linkages. Panel (B) corresponds to the model where $\Omega = \mathbf{I}$. The figure demonstrates the results of the transition dynamics exercise, whereby the EPA index was fed into the model developed in Section 2. Each line shows percentage deviation of toxic releases from the 1999 level. Red dashed line is the aggregate toxic release; the other four lines (with markers) correspond to industries with the highest levels of toxic releases: Petroleum, Metal, Chemical, and Transportation Equipment. Production technologies are time-invariant, corresponding production elasticities are reported in Table 2.

guess and continue this iterative procedure until the excess demands are sufficiently small. Further computational details are relegated to Appendix B.3.

Panel (A) of Figure 5 showcases the findings. Federal environmental regulations led to approximately a 17% reduction in total toxic emissions from 1999 to 2021. A rapid increase in regulations between 1999 and 2004 (see Figure 2) is reflected in the swift decline of toxic releases during that time period.

Decomposition of Toxic Releases by Industry We also break down aggregate toxic releases by industry and plot the percent deviation from 1999 level for the 4 most contributing industries: Petroleum, Chemical, Metal and Transportation. As is evident from Figure 5, there is a sizable heterogeneity in the trajectory of emissions among sectors. For example, the chemical industry, which accounts for one-third of all toxic releases, saw a decline of about 15% during this time frame, primarily influencing the overall trend. At the same time, emissions made by the petroleum industry declined by over 23%.

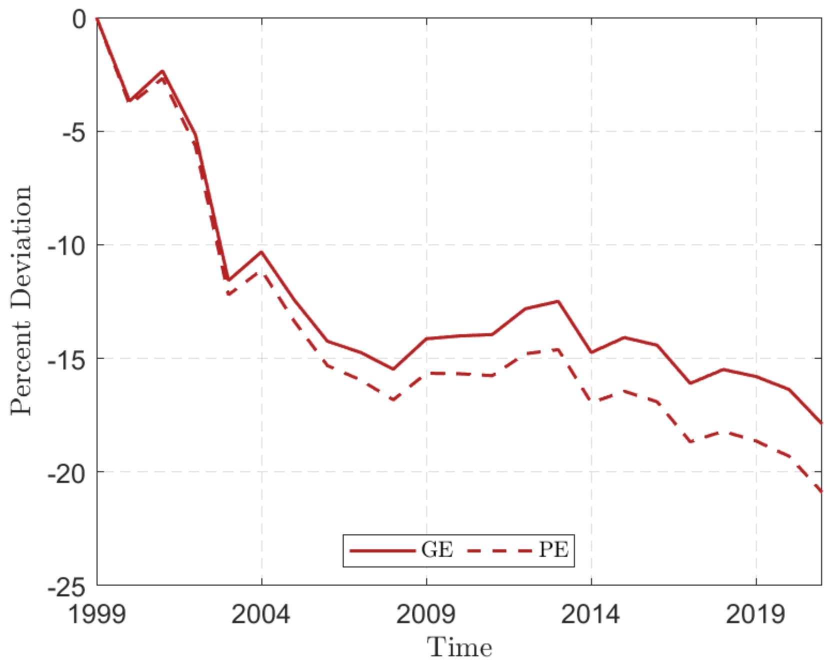
It is worth noting that while the most polluting industries experienced a decline in toxic releases in the range of 15-25%, some industries achieved even more dramatic reductions in pollution. For instance, emissions from Printing (NAICS 323) and Plastics (NAICS 326) industries dropped by over 60% over the two decades. This, however, had a minor effect in the aggregate due to the relatively small share of total releases these industries account for.

Role of Input-Output Linkages Feeding the same sequence of environmental regulations into the version of the model without input-output linkages results in the overall similar dynamics of aggregate releases (panel (B) in Figure 5). This is anticipated since input-output linkages have a relatively small impact on the magnitude of the direct effect (diagonal elements in Figure 4); therefore, the aggregate dynamics in both models are comparable. We note that, remarkably, the four most contributing industries demonstrate very similar transition paths; besides, the lines are nearly indistinguishable during 1999-2004.

In Section 4.1, we argued that input-output linkages increase many cross-elasticities, leading to some unintended increases in toxic releases within indirectly affected industries. This section demonstrates that this mechanism is quantitatively pronounced and manifests itself during the transition to the new steady state.

Role of General Equilibrium Last but not least, we examine the role of general equilibrium in the transition to a new steady state. The results reported thus far were obtained by searching for sequences of prices that clear the markets along the transition path (see

Figure 6: Environmental Regulations and Toxic Releases: General vs. Partial Equilibrium



Notes: Figure 6 demonstrates the results of the transition dynamics exercise, whereby the EPA index was fed into the model developed in Section 2. Each line shows percentage deviation of toxic releases from the 1999 level. The solid line corresponds to the model in general equilibrium, the dashed line refers to the model in partial equilibrium. Production technologies are time-invariant, corresponding production elasticities are reported in Table 2.

Appendix B.3 for computational details). To elucidate the role of general equilibrium, we conduct a transition dynamics exercise in which firms anticipate the sequence of environmental regulations, yet they operate under constant prices. Figure 6 showcases the results: we find that in a partial equilibrium scenario, the decline in aggregate toxic releases is more pronounced, decreasing by over 21% from 1999 to 2021. This is consistent with the cross-elasticity results reported earlier, where we demonstrated that in a partial equilibrium, all indirect effects are eliminated, and thus there are no spillover effects that can offset—partially or fully—the significant negative direct effects.

5 Conclusion

In this study, we examine the impact of federal environmental regulations on firm-level decisions and aggregate pollution. Utilizing a novel index to measure industry-specific regulatory intensity, we analyze the interactions between regulations and pollution levels. Our empirical analysis employs administrative data to assess the effects on firm performance. Theoretically, we develop a general equilibrium model that incorporates cross-sectoral input-output linkages and optimizing forward-looking firms. The transition dynamics exercise reveals that environmental regulations account for a 15% decline in toxic releases over the period 1999-2021.

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Internet Appendix

"Macroeconomic Effects of the Universe of EPA Regulations"

by Vladimir Smirnyagin, Aleh Tsyvinski, and Xi Wu

Table of Contents for Online Appendix

Appendix A: Empirical Appendix

This appendix provides further details for the empirical part of the paper, including data background, sample selection and additional empirical results referenced throughout the main text.

A.1 ASM and CM

The Annual Survey of Manufacturers (ASM) and the Census of Manufacturers (CM) are establishment-level datasets which cover the U.S. manufacturing sector (NAICS 31-33). As in the case of the LBD, the unit of observation is an establishment, which is defined as a single location where business is conducted. Currently, the ASM/CM are available for years 1976-2019.

A.1.1 General Information

Both the ASM and the CM are mail-back surveys; the CM covers the Census years (ending in 2 and 7), and the ASM covers the years in between them. The ASM/CM contain the information about plants in which the predominant activity is production; thus, purely administrative establishments are not included. The CM covers all the manufacturing establishments in the U.S., which amounts to 300-350 thousand observations per year. In turn, the ASM covers plants from the "mail stratum" of the manufacturing sector, which results in 50-60 thousand observations per year. The "non-mail stratum" generally consists of small establishments that collectively account for a very small fraction of aggregate activity; their chance to be selected in the ASM panel is zero. Following Kehrig (2015), in order to construct a consistent panel where the number of (weighted) observations is not driven by the sampling practices of the Census, I drop all observations from the non-mail stratum (denoted by $\texttt{ET} = 0$). The ASM covers all "large" establishments with certainty along with a selection of "small" establishments. The ASM is essentially a rotating panel, since every five years (years ending in 4 and 9) Census updates its small establishment sample. The Census provides frequency weights (the inverse of the sampling probability) which I use to infer the underlying population of manufacturing plants not surveyed by the Census.

A.1.2 Construction of Plant-level Variables

The ASM/CM contain a wealth of information on plants' sizes, productivities, inputs, sales, etc. For the purposes of this project, I only need a subset of this information. In what follows, I describe how I construct different variables using the raw data from the ASM/CM data.

Measure of Real Output Ideally, I need to obtain a measure of real production. Unfortunately, neither plant-level real output, nor prices are available. As a result, I construct a proxy for the real output following the methodology of Kehrig (2015) and Yeh (2017). In particular, I combine information on:

– total value of shipments (`tvs`),

– beginning- and end-of-year works-in-progress (`wib` and `wie`),

– beginning- and end-of-year inventories (`fib` and `fie`).

Provided that deflators for inventories are not publicly available (Kehrig, 2015), I use the 6-digit NAICS industry-level shipment price deflator `piship` from the NBER-CES Manufacturing database.[8] As a result, I construct a measure of real output of plant p in year t as follows:

$$\mathtt{Q}_{p,t} = \frac{\mathtt{tvs}_{p,t}}{\mathtt{piship}_{i(p),t}} + \frac{\mathtt{fie}_{p,t} - \mathtt{fib}_{p,t}}{\mathtt{piship}_{i(p),t}} + \frac{\mathtt{wie}_{p,t} - \mathtt{wib}_{p,t}}{\mathtt{piship}_{i(p),t}}, \tag{A.1}$$

where $i(p)$ denotes a 6-digit NAICS industry plant p operates in.

Labor Input I measure labor input as a total number of hours worked. However, the ASM/CM provide the total number of hours worked for *production* workers only (`ph`). I follow Lee and Mukoyama (2015) and Yeh (2017), and combine two additional pieces of information to infer the total hours worked. In particular, the ASM/CM provide information on the total payroll (`sw`) and the wage bill for production workers (`ww`). I then construct the labor input as follows:

$$\mathtt{L}_{p,t} = \mathtt{ph}_{p,t} \times \frac{\mathtt{sw}_{p,t}}{\mathtt{ww}_{p,t}}. \tag{A.2}$$

In rare cases when either the total payroll or production workers' wage bill is zero or negative, I use the production hours $\mathtt{ph}_{p,t}$ as a measure of the labor input.

Materials Input I measure materials as the sum of expenditures on materials and parts, resales and contract work. I deflate nominal values with a 6-digit materials deflator `pimat` from the NBER-CES data. Specifically, the value of materials is then:

$$\mathtt{M}_{p,t} = \frac{\mathtt{cp}_{p,t} + \mathtt{cr}_{p,t} + \mathtt{cw}_{p,t}}{\mathtt{pimat}_{i(p),t}}. \tag{A.3}$$

On a side note, some papers (Kehrig, 2015) treated the value of resales `cr` as finished goods rather than materials, since resales are not used in the production process. I experimented with this alternative classification of resales and found my results to be robust:

Energy Input The plant-level expenditures on energy is the sum of expenditures on fuels (`cf`) and electricity (`ee`). I deflate nominal values by the 6-digit NAICS deflator `pien` from the NBER-CES Manufacturing database. As a result, the real value of the energy input is:

$$\mathtt{E}_{p,t} = \frac{\mathtt{cf}_{p,t} + \mathtt{ee}_{p,t}}{\mathtt{pien}_{i(p),t}}. \tag{A.4}$$

Capital The construction of capital is complicated by several factors. First, the values of capital stock are reported only for years 1976-1987 (with an exception of 1986) and 1992. Second, in those years when capital stocks are reported, only the book values are available.

[8] NBER-CES Manufacturing Database is available at http://data.nber.org/nberces/.

Moreover, the imputation of capital stocks for the remaining years is complicated by the absence of information on the plant-level depreciation.

Fortunately, the ASM/CM report capital expenditures for all years, which makes it possible to construct a measure of capital using forward and backward inventory methods. I consider two types of capital: structures and equipment. In what follows, I describe a sequence of steps I undertake to construct a consistent over years measure of the capital input.

For plants which entered in or before 1985, I convert the reported end-of-year stocks of structures (`bae`) and equipment (`mae`) into market values using the current and historical industry-level cost of capital stocks from the BEA Fixed Asset Tables.[9] The ASM/CM do not provide the breakdown of the end-of-year total assets (`tae`) into structures and equipment starting from 1988 (Census year 1992 is an exception). I, nevertheless, can recover the capital stock for the remaining years for establishments which entered in or before 1985 using the forward perpetual inventory method, since the data report capital expenditures on structures (`cbe`) and machinery(`cme`) for all years.[10] In particular, the stock of structures and machinery for plant p in year t is constructed according to the following equations:

$$
\begin{aligned}
\mathrm{K}^{st}_{p,t} &= (1-\delta^{st}_{i(p),t})\mathrm{K}^{st}_{p,t-1} + \frac{\texttt{cbe}_{p,t}}{\texttt{piinv}_{i(p),t}}, \\
\mathrm{K}^{eq}_{p,t} &= (1-\delta^{eq}_{i(p),t})\mathrm{K}^{eq}_{p,t-1} + \frac{\texttt{cme}_{p,t}}{\texttt{piinv}_{i(p),t}},
\end{aligned}
$$

where $\delta^{st}_{i(p),t}$ and $\delta^{eq}_{i(p),t}$ are the 3-digit depreciation rates from the BLS Capital Tables.[11] Deflator `piinv` is available at 6-digit NAICS level from the NBER-CES Manufacturing database.

For plants which first show up in the ASM/CM sample after 1987, I initialize the capital stock using the nearest Census year when the plant is still active (the total value of assets is only reported in the CM). For that purpose, I leverage information from the NBER-CES on the amounts of industry-level capital stocks of equipment and structures. In particular, I split the plant-level amount of total assets across equipment and structures according to the 6-digit industry-level distribution of capital across equipment and structures. Once the capital stock is initialized, I use the forward and backward perpetual inventory methods to impute capital in non-Census years.

[9] The BEA contains information at the 3-digit NAICS level with some exceptions. In particular, BEA groups industries with NAICS codes 311 and 312 into "Food and beverage and tobacco products", 313 and 314 into "Textile mills and textile product mills" and 315 and 316 into "Apparel and leather and allied products". I perform necessary adjustments to make these groupings consistent with the NAICS classification. The data are available at https://www.bea.gov/national/FA2004/SelectTable.asp.

[10] For some years, the data only report total capital expenditures (`tce`) along with capital expenditures on new and used machinery (`cme`). I calculate capital expenditures on structures as the difference between `tce` and `cme`.

[11] Data is available at https://www.bls.gov/mfp/mprdload.htm.

Appendix B: Model Appendix

B.1 Definition of Equilibrium

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

$$\left\{\{v_j\}, \{n_j\}, \{k_j\}, \{k'_j\}, \{d_j\}, \{m^s_j\}, W, \{P_j\}, Q, \{c_j\}\right\},$$

such that:

1. $\{c_j\}$ solve the household's problem (5)-(6),
2. $\{v_j\}$ solves the firm's problem (2)-(3), and $\big(\{n_j\}, \{k'_j\}, \{d_j\}, \{m^s_j\}\big)$ are the corresponding policy functions,
3. Q is the market clearing price for capital,
4. labor market clears

$$1 = \sum_{j=1}^{N} [n_j + AC_j] + N_K,$$

   where $\{n_j\}$ is labor demand of industry j, $AC_j = \varphi \left(\frac{k'(k_j)-(1-\delta)k_j}{k_j}\right)^2 k_j$ denotes adjustment costs of industry j, and N_K is labor demand of the capital good producer;

5. goods market clears for each product $j \in \{1, \ldots, N\}$:

$$y_j(k) = c_j + \sum_{s=1}^{N} m^s_j(k),$$

   where m^s_j denotes the demand on good j from producers in sector s,

6. the cross-industry distribution of capital stocks $\{k_j\}$ are induced by decision rules $\{k'_j\}$.

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 $\mathcal{K}$, with $N_{\mathcal{K}}$ nodes. The computation of the stationary state of the model proceeds in the following 4 steps:

1. guess the equilibrium wage rate W, price of capital Q and goods $\{P_j\}$;
2. solve for individual decision rules $\big(\{n_j\}, \{k'_j\}, \{d_j\}, \{m^s_j\}\big)$;
3. given the decision rules, compute stationary equilibrium;
4. compute the excess demand on the labor market, as well as on N product markets. Besides, compute the implied price of capital $Q^{\text{implied}} = \frac{W}{\beta_K N_K^{\beta_K - 1} K^{\alpha_K}}$. Stack all $N+1$ excess demands as well as the difference between the guessed and implied price of capital good into one vector, and search for the price vector which returns zero excess demands. We found that a combination of the bisection method with normalizing prices to be 1 on average in cross-section works well.

B.2.1 Approximation of Value Functions

We approximate N value functions (one for each sector j): $\{v_j(\cdot)\}$. We represent these value functions as weighted sums of orthogonal polynomials:

$$\begin{cases} v_1(k) & = \sum_{a=1}^{N_{\mathcal{K}}} \theta_1^a T^a(k), \\ v_2(k) & = \sum_{a=1}^{N_{\mathcal{K}}} \theta_2^a T^a(k), \\ \dots & \\ v_N(k) & = \sum_{a=1}^{N_{\mathcal{K}}} \theta_J^a T^a(k), \end{cases}$$

where $\mathbf{\Theta} = \{\theta_j^a\}_{j=1}^N$ 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 $N_{\mathcal{K}}$ points ; therefore, we essentially solve for $N \times N_{\mathcal{K}}$ 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 $k'(k)$ 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 L_j ($j \in \{1, \dots, N\}$), we iterate on a mapping using firms' decisions rules:

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

where L_j is a current distribution of firms across the state space in sector j. Matrix $\mathbf{Q}_j$ is a transition matrix, which determines how mass of firms shifts in the k-space. It is constructed so that the model generates an unbiased distribution in terms of aggregates.[12] More precisely, element (i, j) of the transition matrix $\mathbf{Q}_{\tilde{j}}$ informs which fraction of firms with the current idiosyncratic state k_i will end up having k_j tomorrow. Therefore, this entry of the matrix is computed as:

$$\mathbf{Q}_{\tilde{j}}(i,j) = \left[\mathbf{1}_{k' \in [k_{j-1}, k_j]} \frac{k' - k_j}{k_j - k_{j-1}} + \mathbf{1}_{k' \in [k_j, k_{j+1}]} \frac{k_{j+1} - k'}{k_{j+1} - k_j}\right].$$

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

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 $\{\tau_{jt}\}$. 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 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. In practice, we set $T = 100$;

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

   (c) We approximate the paths of prices in our model using cubic polynomials. That is, we assume that each price P_{jt} in the model evolves as:

   $$P_{jt} = \alpha_0^j + \alpha_1^j t + \alpha_2^j t^2 + \alpha_3^j t^3,$$

   where t denotes time that runs from 1 to T. The algorithm outlined below searches for coefficients $\{\alpha_1^j, \alpha_2^j, \alpha_3^j\}$ for each price (and marginal utility). Note that parameters $\{\alpha_0^j\}$ are pinned down by the price level at the eventual steady-state.

   Given the guess $\{\alpha_1^j, \alpha_2^j, \alpha_3^j\}$, we recover sequences of prices $\{\widehat{P}_{jt}\}_{t=1}^{T-1}$, a sequence of wages $\{\widehat{W}_t\}_{t=1}^{T-1}$, a sequence of capital prices $\{\widehat{Q}_t\}_{t=1}^{T-1}$ and marginal utilities $\{\widehat{U}'_t\}_{t=0}^{T-1}$;

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

   $$\widehat{k'}_{j,T-1} = \arg\max_{k' \geq 0} \Big(\widehat{U}'_{T-1} \times \Big\{ \pi_j(k,z) - \widehat{Q}_t(k' - (1-\delta)k) - \\ - \widehat{W}_t \times AC(k,k') \Big\} + \beta \tilde{v}_{j,T}(k') \Big).$$

   Note that we are using value functions scaled by the marginal utility: $\tilde{v}_{j,t} = \widehat{U}'_t \times v_{j,t}$. Flow profits $\pi_j(k,z)$ are calculated assuming that the wage rate is $\widehat{W}_{T-1}$ and prices are $\{\widehat{P}_{jT-1}\}_{j=1}^{N}$. Clearly, we can also recover value functions in period $T-1$, $\tilde{v}_{j,T-1}$;

   (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, $\{\widehat{k}_{j,t}\}_{t=0}^{T-1}$, to compute the evolution of capital stocks over the entire transition horizon;

(g) Compute excess demand functions on product markets, labor market, as well as the deviation of the guessed sequence of capital good prices from the implied sequence (as per Equation 4), and the deviation of the implied sequence of marginal utilities from the guessed one;

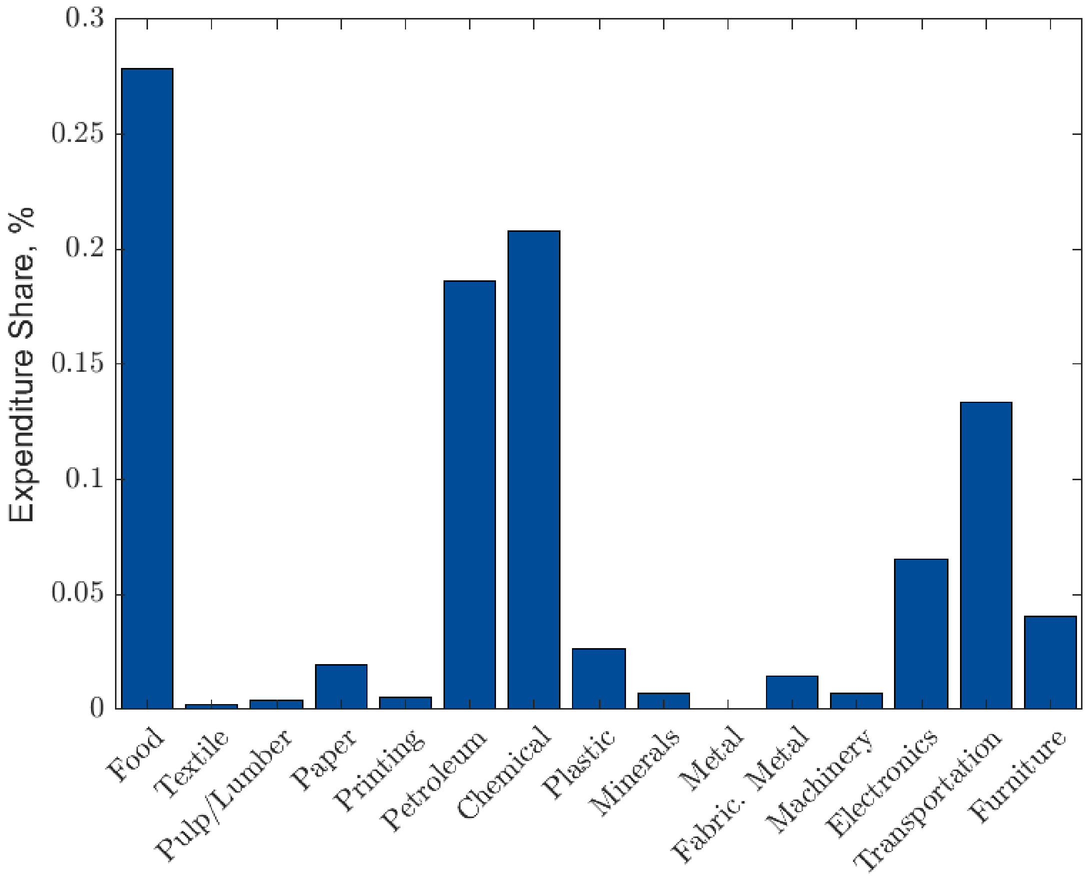
(h) If the norm of deviations taken across markets and time is sufficiently small, terminate. Otherwise, guess new polynomial coefficients and go back to step (c).

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 capital 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.

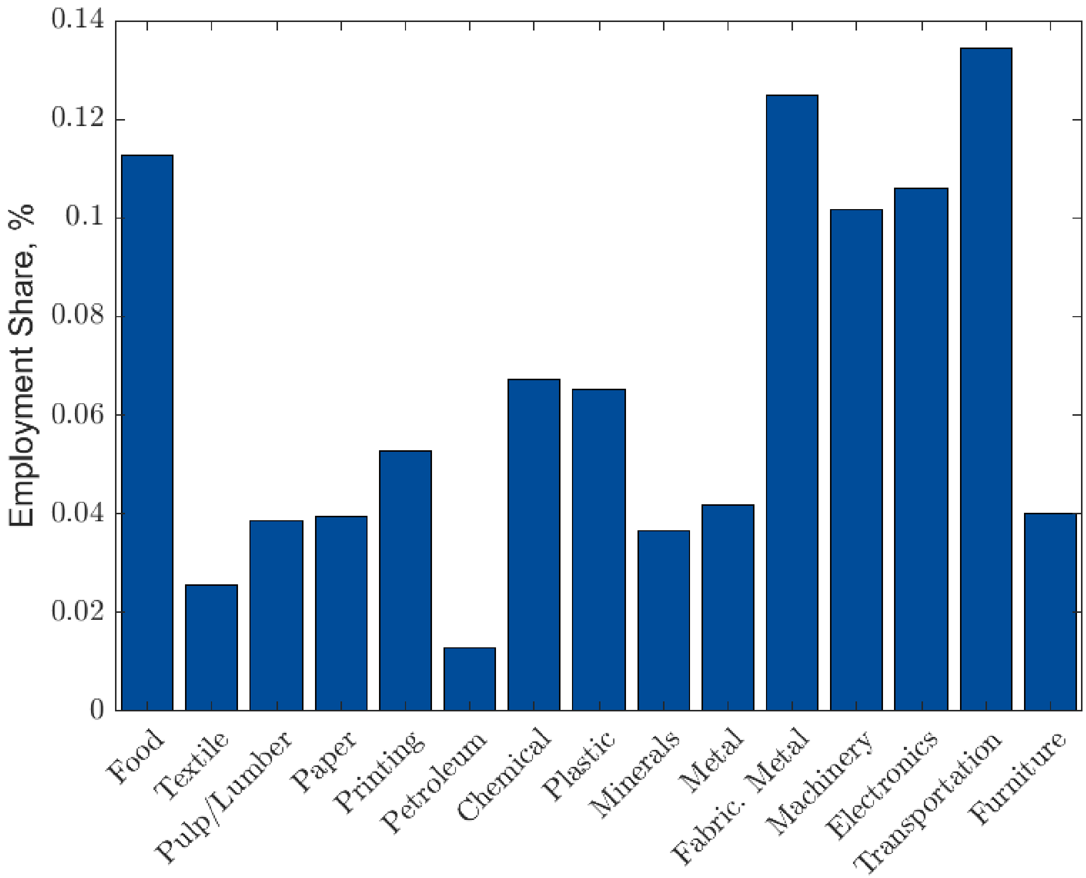
Appendix C: Figures

Figure C1: Expenditure Shares



Notes: Figure C1 visualizes personal consumption expenditures at NAICS 3-digit level for the manufacturing sector. The underlying data are from the BEA 2012 Use Table.

Figure C2: Employment Shares



Notes: Figure C2 visualizes employment shares for 20 manufacturing NAICS 3-digit industries. The underlying data are from the Business Dynamics Statistics for year 1987.

Appendix D: Tables

Table D1: Production Function Estimates: 1987-2002

Industry	NAICS	Capital ($\widehat{\alpha}$)	Labor ($\widehat{\nu}$)	Materials ($\widehat{\kappa}$)	Pollution ($\widehat{\gamma}$)
Food	311	0.158	0.150	0.514	-0.001
		(0.1203)	(0.0104)	(0.0465)	(0.0011)
Textile	313	0.369	0.279	0.540	0.000
		(0.1527)	(0.0281)	(0.0569)	(0.0026)
Pulp/Lumber	321	0.162	0.208	0.635	-0.001
		(0.0649)	(0.0126)	(0.0506)	(0.0012)
Paper	322	0.255	0.253	0.666	0.001
		(0.0945)	(0.0323)	(0.0794)	(0.0025)
Printing	323	0.034	0.319	0.423	-0.002
		(0.0740)	(0.0263)	(0.0639)	(0.0074)
Petroleum	324	0.065	0.175	0.760	0.003
		(0.0717)	(0.0195)	(0.0396)	(0.0032)
Chemical	325	0.197	0.178	0.574	-0.001
		(0.0897)	(0.0109)	(0.0250)	(0.0018)
Plastic	326	0.187	0.226	0.550	0.003
		(0.0591)	(0.0128)	(0.0336)	(0.0015)
Minerals	327	0.382	0.277	0.355	0.003
		(0.0846)	(0.0188)	(0.0363)	(0.0018)
Metal	331	0.150	0.279	0.517	0.000
		(0.0545)	(0.0104)	(0.0369)	(0.0013)
Fab. Metal	332	0.190	0.341	0.394	0.003
		(0.0508)	(0.0094)	(0.0230)	(0.0010)
Machinery	333	0.320	0.274	0.617	0.003
		(0.1504)	(0.0191)	(0.0298)	(0.0014)
Electronics	334	0.123	0.301	0.541	0.004
		(0.1387)	(0.0295)	(0.0451)	(0.0035)
Transportation	336	0.160	0.340	0.512	0.000
		(0.0614)	(0.0175)	(0.0289)	(0.0016)
Furniture	337	0.138	0.221	0.558	0.004
		(0.1041)	(0.0349)	(0.0495)	(0.0031)

Notes: Table D1 reports production function elasticities for NAICS 3-digit manufacturing industries estimated using Levinsohn and Petrin (2003) method. Numbers in parentheses are standard errors. Underlying data are ASM/CM and TRI.

Table D2: Production Function Estimates: 2003-2019

Industry	NAICS	Capital ($\widehat{\alpha}$)	Labor ($\widehat{\nu}$)	Materials ($\widehat{\kappa}$)	Pollution ($\widehat{\gamma}$)
Food	311	0.156	0.156	0.386	0.001
		(0.0282)	(0.0102)	(0.0203)	(0.0011)
Textile	313	0.148	0.402	0.389	0.009
		(0.2753)	(0.0437)	(0.0772)	(0.0049)
Pulp/Lumber	321	0.208	0.163	0.529	0.007
		(0.0449)	(0.0148)	(0.0291)	(0.0016)
Paper	322	0.368	0.262	0.464	0.010
		(0.0433)	(0.0283)	(0.0344)	(0.0031)
Printing	323	0.068	0.402	0.518	0.007
		(0.0594)	(0.0326)	(0.0582)	(0.0081)
Petroleum	324	0.077	0.217	0.558	0.004
		(0.1541)	(0.0193)	(0.0432)	(0.0035)
Chemical	325	0.382	0.205	0.441	0.003
		(0.0340)	(0.0100)	(0.0159)	(0.0017)
Plastic	326	0.193	0.269	0.464	0.002
		(0.0272)	(0.0143)	(0.0206)	(0.0014)
Minerals	327	0.174	0.343	0.426	0.011
		(0.0174)	(0.0120)	(0.0185)	(0.0019)
Metal	331	0.307	0.282	0.476	0.007
		(0.0968)	(0.0141)	(0.0215)	(0.0018)
Fab. Metal	332	0.268	0.323	0.411	0.002
		(0.0349)	(0.0107)	(0.0140)	(0.0009)
Machinery	333	0.405	0.308	0.500	0.001
		(0.1085)	(0.0135)	(0.0254)	(0.0011)
Electronics	334	0.802	0.177	0.355	0.000
		(0.2054)	(0.0379)	(0.0345)	(0.0036)
Transportation	336	0.189	0.297	0.467	0.003
		(0.0405)	(0.0168)	(0.0212)	(0.0012)
Furniture	337	0.171	0.253	0.483	0.004
		(0.1215)	(0.0370)	(0.0592)	(0.0037)

Notes: Table D2 reports production function elasticities for NAICS 3-digit manufacturing industries estimated using Levinsohn and Petrin (2003) method. Numbers in parentheses are standard errors. Underlying data are ASM/CM and TRI.

References for Appendix

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