Pollution Abatement Investment under Financial Frictions and Policy Uncertainty

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Abstract

This paper examines how financial frictions and policy uncertainty jointly influence firms' investments in pollution abatement. Our data analyses suggest that financially constrained firms are less likely to invest in pollution abatement and are more likely to release toxic pollutants, with this pattern intensified by policy uncertainty surrounding future environmental regulations, as measured by "close" gubernatorial elections or uncertainty revealed in firms' earnings conference calls. We then develop a general equilibrium model with heterogeneous firms, including both financially constrained and unconstrained firms, in which financially constrained firms face increased marginal costs of finance from pollution abatement. These costs are further amplified by policy uncertainty, reducing firms' incentives to prevent pollution. Therefore, the aggregate effect of environmental policies depends on the distribution of financial frictions and policy uncertainty.

JEL Codes: E1, E2, E3, E6, G1, G3, K3, Q5

Keywords: Financial frictions, firm heterogeneity, policy uncertainty, pollution abatement

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1 Introduction

Under market and regulatory failures, production activities often result in excessive corporate pollution, causing damage to human health, properties, and nature (Baumol, Baumol, Oates, Bawa, Bawa, Bradford, et al., 1988). According to the 2005 Survey of Pollution Abatement Costs and Expenditures, U.S. manufacturing sectors invested $5.9 billion in capital to reduce pollution. They spent $20.7 billion in pollution abatement operating costs.[1] This amount is much less than other investments, such as research and development (R&D) and physical capital. This suggests that corporate investment in pollution abatement is insufficient to reach the social optimum, especially given recent estimates that pollution is responsible for 16% of all global deaths in 2015, according to a recent estimate by Landrigan, Fuller, Acosta, Adeyi, Arnold, Baldé, Bertollini, Bose-O'Reilly, Boufford, Breysse, et al. (2018).

Corporate investment in pollution abatement is subject to economic, regulatory, and other conditions.[2] However, little is known about the extent to which this investment is influenced by financial frictions and policy uncertainty. Corporate investment in pollution abatement is vital for manufacturing firms' long-term survival, as such firms must mitigate potential penalties and reputation costs due to pollution (e.g., fines, legal liability, damage to brand image.) However, firms may under-invest in pollution control because of financial constraints and cash flow volatility (Lovei, 1995; Xu and Kim, 2022).[3] Moreover, corporate decisions in pollution abatement rely on the degree to which pollution-related costs must be internalized (Hahn, 1989), which is subject to uncertainty in environmental regulation (Hsu, Li, and Tsou, 2022). In this paper, we exploit rich microdata to examine how firms' pollution abatement investment is affected by financial frictions and policy uncertainty, rationalize such an effect, and derive further implications with a quantitative model.

Our investigation is carried out in two stages. In the first stage, we construct empirical proxies for pollution abatement and policy uncertainty. We examine how the cross-sectional variations in pollution abatement, toxic emissions, and debt issuance relate to policy uncer-

[1] www.epa.gov/environmental-economics/pollution-abatement-costs-and-expenditures-2005-survey According to the survey, pollution abatement even decreased from 1994 to 2005. Pollution abatement capital expenditures totaled $5.9 billion in 2005 compared to $10.0 billion in 1994, and pollution abatement operating costs totaled $20.7 billion compared to $24.7 billion in 1994, all in 2005 dollars. "In both years, pollution abatement operating costs are less than 1% of total output while pollution abatement capital expenditures are less than 7% and 5% of total new capital expenditures in 1994 and 2005, respectively."

[2] There is extensive literature on how firms' physical and R&D investments are influenced by environmental laws and policies (e.g., Jaffe, Peterson, Portney, and Stavins (1995), Jaffe and Palmer (1997), Becker and Henderson (2000), and Greenstone (2002)).

[3] Aghion, Angeletos, Banerjee, and Manova (2010) and Aghion, Askenazy, Berman, Cette, and Eymard (2012) show that firms' long-term and R&D investments are limited by credit constraints under economic fluctuations.

tainty when firms face different financial constraints. In the second stage, we start with a simple model to illustrate the underlying mechanism and then propose a full-blown general equilibrium model that incorporates investment in pollution abatement as well as physical capital, borrowing constraints, and policy uncertainty regarding environmental regulation. This allows us to formalize our intuition and quantify the amplification effect of financial frictions and policy uncertainty on pollution abatement across firms.

For our empirical analysis, we begin by collecting data from the Environmental Protection Agency's Toxic Release Inventory (TRI) database, which provides comprehensive information on manufacturing firms' pollution prevention activities (such as new materials, equipment, or procedures) and their emissions of toxic chemicals at the facility-year level. With this data, we can measure each facility's investment in pollution abatement and its toxic emissions on an annual basis since 1991 (Akey and Appel, 2021). To capture the production scale of each facility, we also collect estimated revenue and employment data from the National Establishment Time-Series (NETS) database. Finally, we gather financial and accounting information for public manufacturing firms from the CRSP/Compustat database and use measures of financial constraints following the methodology of Whited and Wu (2006) and Hadlock and Pierce (2010). This data allows us to examine how the cross-sectional variations in pollution abatement, toxic emissions, and debt issuance relate to policy uncertainty and financial constraints across firms.

To measure policy uncertainty, we first use the occurrence of "close" state-level elections, which are defined as gubernatorial elections in which the votes received by the first and second-place candidates are within 5%. This proxy follows the design of prior studies, as close election outcomes are likely exogenous to firms' environmental decisions, and we refer to this measure as *election-based* uncertainty.[4] Additionally, we use a firm-level measure of uncertainty based on the textual content of earnings conference calls, developed by Hassan, Hollander, Van Lent, and Tahoun (2019), Hassan, Hollander, Van Lent, Schwedeler, and Tahoun (2020a), and Hassan, Hollander, Van Lent, and Tahoun (2020b), as a robustness check. We will refer to this alternative measure as *text-based* uncertainty.

Our regression analyses indicate that when firms are more financially constrained, their facilities report fewer pollution prevention activities; more importantly, such a relationship is more pronounced after a close gubernatorial election or an increase in firm-level textual-based

[4]There is extensive literature on the effect of tied elections on the real economy and financial markets, which includes Lee (2008), Julio and Yook (2012, 2016), Çolak, Durnev, and Qian (2017), Jens (2017), Girardi (2020), Akey and Appel (2021), and Bisetti, Lewellen, Sarkar, and Zhao (2021), among others. We use the 5% margin for a close electoral outcome following Akey (2015), Brogaard and Detzel (2015), and Bhattacharya, Hsu, Tian, and Xu (2017).

uncertainty. This result supports the proposition that firms' investment in pollution abatement is adversely affected by financial frictions, especially under high policy uncertainty. In addition, these facilities report a more significant number of released toxic chemicals after increased policy uncertainty. This finding confirms that reduced investment in pollution abatement due to financial frictions and policy uncertainty can lead to an increase in released toxic chemicals, emphasizing the potential negative consequences of unstable environmental policies on society.

We further examined a crucial implication of our model that financial frictions are exacerbated under policy uncertainty. Our results show that firms' debt growth decreases with their financial constraints after taking into account both policy uncertainty measures. This finding supports the financing mechanism proposed in our earlier results, which suggests that increased borrowing constraints resulting from policy uncertainty cause firms to reduce their investment in pollution abatement.

To jointly rationalize our empirical findings concerning pollution abatement, toxic emissions, and debt issuance, we use a simple example to demonstrate how financial constraints and policy uncertainty result in an equilibrium under-investment in pollution abatement. The key mechanism is that financially constrained firms face additional shadow marginal finance costs when investing in abatement, which are further amplified by policy uncertainty.[5] This results in a hindrance to pollution abatement caused by financial frictions, and this relation is exacerbated by heightened policy uncertainty.

To provide a more detailed analysis of our mechanism and its policy implications, we extend our simple model by building a quantitative heterogeneous firm macro-finance model of corporate pollution abatement investment under financial frictions and policy uncertainty. This model is based on Khan and Thomas (2013) and incorporates the investment decisions of firms in physical capital and pollution abatement technology, taking into account borrowing constraints and pollution penalty risks, as in Shapiro and Walker (2018). This modeling approach allows us to investigate the effects of financial constraints and policy uncertainty on pollution abatement investment, and to assess the potential impact of policy interventions aimed at mitigating these effects.

We calibrated our model to capture important aspects of firms' pollution emissions, borrowing, entry-exit dynamics, and pollution penalty in the microdata. The model's output is consistent with empirical observations and reveals a range of heterogeneity in firm behavior along productivity, net worth, and abatement technology dimensions. Unlike a representative firm model, this heterogeneity leads to significant effects on aggregate pollution abatement.

[5] See Ottonello and Winberry (2020) for an analysis of the marginal cost of finance regarding investment.

In equilibrium, less productive, dirtier, and more financially constrained firms invest less in pollution abatement, and they are less responsive to environmental regulations.

In our final analysis, we sought to determine how changes in policy uncertainty could affect the aggregate effect of environmental regulation on abatement and pollution. Our findings indicate that a doubling of policy uncertainty regarding environmental regulation leads to a negative 6% change in aggregate abatement investment. Interestingly, our calculations show that financially constrained firms are three times more susceptible to uncertainty shocks than their less constrained counterparts. This highlights that the effectiveness of environmental regulations may be hampered by financial frictions, policy uncertainty, and their interactions.

Related Literature. This paper contributes to the literature on policy uncertainty and general economic uncertainty by examining the effects of policy uncertainty on pollution abatement investment. Previous studies have shown that policy uncertainty has adverse effects on physical investment, cash flows, and innovation activities (Julio and Yook, 2012, 2016; Gulen and Ion, 2016; Bhattacharya et al., 2017).[6] However, our study focuses on a specific investment–pollution abatement–that is novel to this literature and has important implications for the aggregate economy and society. Moreover, unlike previous studies that examine aggregate policy uncertainty, we exploit cross-state variation in gubernatorial elections in our empirical investigation. Our study also contributes to the literature on general economic uncertainty by highlighting the effect of environmental regulation uncertainty, which is a meaningful addition to this literature that has mainly focused on the effects of uncertainty on aggregate productivity or idiosyncratic productivity shocks.[7]

Our study is also closely related to the recent literature on credit market frictions' role

[6]Several previous papers study changes in firm behavior associated with general economic policy uncertainty in the U.S. See Stein and Stone (2013) and Baker, Bloom, and Davis (2016), among others.

[7]Classic papers on general economic uncertainty include Romer (1990), Romer and Romer (2017), Leahy and Whited (1996), Guiso and Parigi (1999), Bloom (2009), Bachmann, Moscarini, et al. (2011), Fernández-Villaverde, Guerrón-Quintana, Rubio-Ramirez, and Uribe (2011), Fernández-Villaverde, Guerrón-Quintana, Kuester, and Rubio-Ramírez (2015), and Alfaro, Bloom, and Lin (2022). One more closely related paper that studies the causal impact of uncertainty shocks using a similar approach as in Alfaro et al. (2022) is Stein and Stone (2013). Several other papers also investigate the consumption of financial implications of uncertainty shocks (Bansal and Yaron, 2004; Segal, Shaliastovich, and Yaron, 2015). Ilut and Schneider (2014) introduce ambiguity aversion as an alternative to stochastic volatility. Basu and Bundick (2017) and Fang (2020) introduce uncertainty shocks in the New Keynesian model and study the aggregate implications. Gourio (2012) shows that disaster can be regarded as a combination of uncertainty and financial shocks through the learning channel by updating beliefs. In addition, Berger, Dew-Becker, and Giglio (2016) differentiates uncertainty from the news. Moreover, He and Krishnamurthy (2013), Brunnermeier and Sannikov (2014), and Di Tella (2017) examine the impact of uncertainty shocks on aggregate outcomes through the financial intermediary channel.

in generating fluctuations in business cycles.[8] In contrast to prior studies, we build upon the idea that financial frictions amplify the effect of uncertainty shocks, and we present the amplification effect as the combination of policy uncertainty and financial frictions, highlighting why uncertainty shocks and financial frictions must be considered jointly (rather than separately).[9] Our study differs from prior research in two important ways. First, we exploit microdata for facility pollution abatement activities and close elections to identify causal inferences. Second, our model features a novel trade-off between marginal financial costs and benefits of pollution abatement investment under policy uncertainty shocks.

Our paper also adds new evidence highlighting the conditional effectiveness of environmental policies and regulations concerning pollution control. It is well documented that governments' environmental initiatives do not always deliver satisfactory outcomes (e.g., Cohen (1987), Baumol et al. (1988), Magat and Viscusi (1990), and Eskeland and Jimenez (1992)).[10] Our empirical evidence suggests that such ineffectiveness may be attributed to financial frictions and policy uncertainty. This research is also related to prior studies examining how government policies influence firms' investment in green technologies.[11] More

[8] Quadrini (2011) and Brunnermeier, Eisenbach, and Sannikov (2012) provide for extensive reviews. The papers that are most related to ours are those emphasizing the importance of borrowing constraints and contract enforcement, such as Kiyotaki and Moore (1997, 2012), Gertler and Kiyotaki (2010), He and Krishnamurthy (2013), Brunnermeier and Sannikov (2014), and Elenev, Landvoigt, and Van Nieuwerburgh (2021). Gomes, Yamarthy, and Yaron (2015) studies the asset pricing implications of credit market frictions in a production economy. Dou, Ji, Tian, and Wang (2021) study asset pricing and welfare implications of misallocation driven by distorted investment decisions, in which leased capital is explicitly incorporated into their general equilibrium model and empirical analysis. Alessandri and Mumtaz (2019) and Lhuissier, Tripier, et al. (2016) use VAR approaches to estimate the strong interaction effect of financial constraints on uncertainty. More generally, Gilchrist and Zakrajšek (2012) and Jermann and Quadrini (2012) show that financial frictions are essential in explaining aggregate fluctuations during the most recent financial crisis. Caggiano, Castelnuovo, and Figueres (2017) find that uncertainty shocks trigger a sizable impact during economic downturns. Giroud and Mueller (2017) show that establishments with higher financial leverage tend to cut employment in response to adverse local consumer shocks.

[9] Recent works that link uncertainty and financial frictions include the following: Gilchrist and Zakrajšek (2012) study the reciprocal link between uncertainty, investment, and credit spreads to show that financial frictions amplify the effects of uncertainty through changes in credit spreads. Christiano, Motto, and Rostagno (2014) document that volatility shocks drive business cycles. Arellano, Bai, and Kehoe (2019) show that uncertainty shocks lead to higher default risk and credit spreads, further driving firms to cut employees. Alfaro et al. (2022) show how real and financial frictions amplify the impact of uncertainty shocks.

[10] On the other hand, pollution control is costly. For example, Jorgenson and Wilcoxen (1990) show that the related cost amounts to more than 10% of government purchases of goods and services and is responsible for a drop in annual GNP growth of 0.19 percentage points. In addition, Palmer, Oates, and Portney (1995) show that annual U.S. expenditures for environmental protection, net of any offsets, are at least 100 billion dollars.

[11] Brunnermeier and Cohen (2003) explore the determinants of manufacturing firms' environmental innovation. Acemoglu, Aghion, Bursztyn, and Hemous (2012) and Acemoglu, Akcigit, Hanley, and Kerr (2016) discuss how policy interventions, including taxes and subsidies, promote the adoption of clean technology. Aghion, Dechezleprêtre, Hemous, Martin, and Van Reenen (2016) find that cost-saving motivations encourage firms to develop clean technologies in the automobile industry. In addition, Jaffe and Palmer (1997)

importantly, we illustrate the advantages of the comprehensive and publicly available TRI database in researching corporate pollution control and outcome.

Finally, our work contributes to the broad literature on the determinants of corporate social responsibility (CSR) and environmental, social, and governance (ESG) practices. Prior studies have mainly focused on investors' preferences and their attention to environmental issues.[12] In contrast, our analysis examines the firms' optimization behavior under financial constraints in a general equilibrium setting. Our model highlights that due to the amplification effects of policy uncertainty on the shadow costs of finance, firms may rationally choose to reduce their pollution abatement investment, leading to higher pollution emissions.

The remainder of this paper is structured as follows. Section 2 presents our empirical findings, which demonstrate that financially constrained firms are less likely to invest in pollution abatement and that policy uncertainty exacerbates this pattern. In Section 3, we provide a theoretical explanation for our empirical results and illustrate the mechanism using a simple example of firms with financial frictions and policy uncertainty. We then develop a quantitative heterogeneous firm equilibrium model in Section 4 to further interpret our findings. In Section 5, we are currently working on calibrating the full model, validating the mechanism, and analyzing firm behavior and aggregate implications. Finally, we conclude our paper in Section 6. Additional information regarding data construction and additional empirical evidence can be found in Sections A and B of the Internet Appendix, while details about our computational methods are provided in Section C of the Internet Appendix. Our analysis is centered on firms' optimization under financial constraints in a general equilibrium framework. Our model demonstrates that policy uncertainty can amplify the shadow costs of finance, prompting firms to rationally reduce their investments in pollution abatement and increase their pollutant emissions.

and Brown, Martinsson, and Thomann (2021) show that environmental regulations substantially increase polluting firms' R&D spending.

[12]Such preferences may be due to social norms, reputation concerns, or liquidity issues. Hong and Kacperczyk (2009) argue that firms in "sin" industries are subject to funding constraints due to social norms. Krüger (2015) show that investors react negatively to negative CSR news. Hong, Li, and Xu (2019) meanwhile show that food firms of drought-stricken countries under-perform those of countries that do not experience droughts in stock returns, which can be attributed to investors' inattention. Chen, Kumar, and Zhang (2019) find that investors' social sentiment and attention to CSR explain stock returns. Bansal, Wu, and Yaron (2019) propose that households and institutional investors have stronger preferences for socially responsible investment. A growing body of literature documents that both retail and institutional investors are more willing to hold socially responsible firms and funds (Renneboog, Ter Horst, and Zhang (2008), Starks, Venkat, and Zhu (2017), Riedl and Smeets (2017), Dyck, Lins, Roth, and Wagner (2019), Hartzmark and Sussman (2019), Cao, Titman, Zhan, and Zhang (2019), and Gibson, Krueger, and Mitali (2020)). Hsu, Liang, and Matos (2021) show that state ownership enhances firms' environmental engagement.

2 Empirical Analysis

In this section, we begin by outlining our data sources and identification strategy for measuring policy uncertainty. We then describe our measures of facility-level investment in pollution prevention and toxic emissions. Using these measures, we empirically investigate whether shocks to policy uncertainty affect pollution abatement investment and toxic emissions at the facility level, as well as firm-level debt issuance. Our data analyses not only shed light on the drivers of corporate investment in pollution prevention in the face of policy uncertainty but also serve as a motivation for our subsequent model development and derived policy implications.

2.1 Data

2.1.1 Facility-Level Emissions and Pollution Prevention Activities

In this section, we describe our main data source, the Toxic Release Inventory (TRI) database, which is maintained by the United States Environmental Protection Agency (EPA). The TRI database was established in response to the Community Right to Know Act (EPCRA) of 1986, which requires certain facilities to report their emissions of toxic chemicals that pose a threat to human health and the environment.[13] Specifically, facilities in the mining, utility, manufacturing, publishing, hazardous waste, or federal industry that use or produce a TRI-listed chemical in quantities above certain thresholds and have ten or more full-time equivalent employees are required to report their emissions to the TRI database.

The TRI database contains detailed information on all chemical emissions at the facility level, including the amount of chemical pollutants, the name of chemical categories, the location FIPS/ZIP code, facility name, and parent company name. Although the TRI database has been publicly available since 1986, its coverage is incomplete and contains observable data errors up to 1990. Therefore, we start our sample from 1991 to construct our emission-related variables. Our analysis focuses on the relationship between policy uncertainty and facility-level pollution abatement and toxic emissions, using the TRI data as a primary source.

To capture corporate investment in pollution abatement, we also collect information

[13]The U.S. Congress enacted the Emergency Planning and Community Right-to-Know Act (EPCRA) in 1986, in response to public apprehension over the release of toxic chemicals from various environmental mishaps, both within the country and abroad. The EPCRA mandates that each firm make a mandatory disclosure of its chemical emissions to the environment, including the release of listed toxic substances.

from the EPA on facilities' new source reduction activities.[14] By implementing more source reduction activities, a facility can reduce the pollutants it generates during the production process. The EPA requires each facility covered in the TRI database to report details of new source reduction activities for each chemical. This information is included in the Pollution Prevention (P2) database. The new source reduction activities are classified by W-codes, which fall into eight categories: raw material modifications, product modifications, cleaning and degreasing, surface preparation and finishing, process modifications, spill and leak prevention, inventory control, and good operating practices.

To calculate a facility's total emissions, we add up the amounts of all chemicals that were released by the facility in pounds for a given year. In contrast, to measure a facility's investment in pollution abatement, we sum up the number of new source reduction activities across all chemicals implemented by the facility in that year. For instance, Alcoa Corporation reported implementing 71 abatement activities across 28 states in the United States in 1993. As an example, one of its facilities located in Iowa State (TRI Facility ID: 52808LMNMCHIGHW) implemented two activities with code W58 to reduce other process modifications and one with code W81 to change product specifications. Based on this information, we assigned an abatement investment value of 3 for this facility in 1993. To view a comprehensive list of abatement activities, please refer to Table IA.1 in the Internet Appendix.

It is important to note that while the TRI and P2 databases provide valuable information, they are not without limitations. One major limitation is that the data is self-reported by facilities, which may result in some reporting errors or failures to report. However, the EPA does conduct quality checks and analyses to ensure report accuracy and correct any mistakes. In fact, according to a quality check report by the EPA in 1998 (i.e., EPA (1998)), most industries had reporting errors within a 3% range. Furthermore, researchers such as Akey and Appel (2019, 2021) and Kim and Kim (2020) suggest that the potential criminal or civil penalties, as well as reputation costs associated with misreporting to the EPA, incentivize facilities to provide accurate data and maintain strong data quality in the TRI database.

As a robustness check, we consider an alternative measure of pollution abatement activities that is adjusted for emission reductions. We aim to differentiate these activities based

[14] The EPA has established a waste management hierarchy that prioritizes different methods of managing and reducing waste. At the top of the hierarchy is source reduction, which involves eliminating or minimizing waste at the point of generation. This is considered the most effective way to reduce waste and is preferred by the EPA. Next in the hierarchy is recycling, followed by energy recovery, treatment, and finally disposal/release. The EPA views disposal as the least preferred method of waste management, as it is seen as the least effective way to reduce the environmental impact of waste. See: https://www.epa.gov/trinationalanalysis/pollution-prevention-and-waste-management

on their effectiveness in reducing emissions. Specifically, we track the lump sum of reductions in chemical emissions from 1992 to 2017 for each pollution abatement activity category (i.e., W Code in the P2 database). A larger reduction in emissions indicates that a given pollution abatement investment is more effective in reducing chemical emissions. However, we cannot directly use the corresponding reduction of emissions to construct our adjusted abatement investment due to concerns about outliers in reductions or counter-intuitive non-negative reductions.[15] To address this issue, we sort all abatement activities into five groups based on their non-negative reductions of emissions, and assign an adjusted score ranging from 6 for the highest quintile to 2 for the lowest quintile, with a score of 1 indicating all remaining categories with missing or negative reductions. This adjusted scoring ensures that our weighting is less affected by outliers. Finally, we calculate a facility's adjusted pollution abatement activities by multiplying the number of each pollution abatement activity by the corresponding adjusted score in a given year and summing across all categories.

2.1.2 Facility-Level Production Activities

We collect production activities at the facility level from the National Establishment Time-Series (NETS) database (2017 version) of Walls & Associates. This database covers a comprehensive record of establishments in the U.S. since 1990, which includes facility identifier (dunsnumber), facility name, facility location, parent company name, parent company identifier (hqduns), location, employee number, and estimated revenue at the annual frequency. In addition, the NETS database is free from survivorship bias. For example, we can trace a facility's historical path, such as its birth year and last year of active business (i.e., year of relocation), even if an establishment changes location or is shut down. Moreover, the literature has provided several justifications for the quality of the NETS database.[16] To measure a facility's production scale, we use its number of employees or estimated annual revenue.

[15] All pollution abatement activities are designed to reduce the amount of released chemical pollutants. However, in some cases, we may find that the reduction amounts and percentages of a W-code activity are negative, indicating that the activity did not effectively prevent pollution. Alternatively, negative reductions may be due to measurement errors or data limitations.

[16] As documented in Faccio and Hsu (2017), facilities tend to reveal accurate information to obtain lines of credit from suppliers or financial intermediaries. Moreover, Barrot and Nanda (2020) show that business entities report their information precisely to enhance their odds of bidding for government contracts. Finally, NETS gathers information from independent sources, including phone calls to suppliers and customers, legal and bankruptcy filings, press reports, and government records (e.g., Heider and Ljungqvist (2015)).

2.1.3 Gubernatorial Elections

The gubernatorial election results and party affiliations of governors are sourced from the Stateline database and the CQ election Electronic Library. These databases provide comprehensive details on each gubernatorial election, including the victorious candidate, election date and party, incumbent governor participation, term limit status, and election vote margin. Typically, gubernatorial elections are held on the first Tuesday of November, but the specific election year may vary between states. By leveraging these gubernatorial election data, we can create our key measures for assessing the impact of state-level policy uncertainty shocks.

The study assumes that election outcomes at the time of firms' environmental decisions, such as pollution abatement investment and toxic emissions, are exogenous, and uses the occurrence of "close" gubernatorial elections as an increase in policy uncertainty for facilities and firms. This assumption is reasonable for several reasons. First, firms cannot predict close-election winners when making environmental-related decisions. Second, corporate decisions are unlikely to materially affect a candidate's chances of winning an election.[17] Finally, the occurrence of a close election is only known on the election day or can be more accurately predicted as the election day approaches, making it easier to identify the effect of policy uncertainty on firms' responses. Therefore, tied election outcomes generate diverse impacts on endogenous corporate policies, facilitating the identification of the impact of policy uncertainty.

In our empirical analysis, we measure environmental policy uncertainty by creating a binary variable that takes the value of one if the most recent state gubernatorial election had a vote differential of within 5%, and zero otherwise. This approach is consistent with previous studies by Akey (2015), Brogaard and Detzel (2015), and Bhattacharya et al. (2017).[18] For the sake of clarity and convenience, we refer to this type of uncertainty measure as *election-based* uncertainty.

[17] As a robustness check, we also include firms' donations as a control variable to account for the possibility that firms may be politically connected or attempting to promote a specific candidate. This allows us to examine whether the effects of close gubernatorial elections on policy uncertainty and environmental decisions are robust to controlling for firms' political activities.

[18] For instance, if a state experienced a close election in 2000, the uncertainty of all facilities in this state is set to one from 2001 until the next election year, which is 2004.

2.1.4 Firm-Level Uncertainty

To obtain firm-level uncertainty, we utilize a textual analysis method developed by Hassan et al. (2019), Hassan et al. (2020a), and Hassan et al. (2020b). This approach involves analyzing quarterly earnings conference calls held by over 11,000 listed firms in 81 countries to construct a local index that separates firm-level uncertainty from aggregate uncertainty. Computational linguistics tools are used to extract information on risks in general, risks associated with politics, and risks associated with specific political topics, such as healthcare and economic policy. The textual analysis calculates the percentage of the conference call conversation that pertains to uncertainty.[19] This firm-level index is then assigned to all facilities of a firm each year and serves as an additional proxy for policy uncertainty in our empirical analysis. For convenience, we refer to this alternative uncertainty measure as *text-based* uncertainty.

2.1.5 Financial Constraints and Other Data

We collect publicly listed firms' financial information from the Compustat database. These data allow us to construct firm-level proxies for financial constraints, such as the WW and SA indexes of Whited and Wu (2006) and Hadlock and Pierce (2010), respectively. Other firm-level variables we construct include market capitalization (ME), book-to-market ratio (B/M), investment rate (I/K), return on assets (ROA), a WW index (WW), and an SA index (SA), book leverage (Leverage), leased capital ratio (Lease), and Tobin's q in our sample of firm-year observations.[20]

[19]For more information on the firm-level uncertainty measure, please visit the website "FIRM-LEVEL RISK." The data source we used to construct the firm-level measure of uncertainty can be found at the following link: https://www.firmlevelrisk.com/home

[20]The ME variable represents market capitalization deflated by CPI and measured in 2009 million USD at the end of the fiscal year. B/M is the ratio of book equity to market capitalization. I/K represents the investment rate and is calculated as capital expenditure (item CAPX) divided by property, plant, and equipment (item PPENT). ROA stands for return on assets and is calculated as operating income after depreciation (item OIADP) scaled by total assets. Debt growth is the annual log growth rate of total liability, which is the sum of current and long-term liabilities (item DLC and DLTT). WW index (WW) is the index developed by Whited and Wu (2006) and used to measure financial constraints. SA index (SA) is the size-age index used to measure financial constraints, following Hadlock and Pierce (2010). Detailed information regarding the construction of the SA and WW indexes can be found in the Internet Appendix of Farre-Mensa and Ljungqvist (2016). Book leverage is the ratio of total liability to total assets. Following Eisfeldt and Rampini (2009), the lease capital ratio is calculated as the ratio of leased capital over the sum of the leased capital and owned capital (item PPENT), in which the leased capital is ten times rental expense (item XRENT). Finally, Tobin's q is calculated as the sum of market capitalization at the end of the fiscal year and the book value of preferred shares, deducting inventories over total assets (item AT), following Eisfeldt and Rampini (2006).

Our sample includes firms that are present in the TRI(P2), NETS, and Compustat databases. Specifically, we consider firms with non-missing TRI data. To link facility-level data in the TRI/P2/NETS databases to public firms' financial data, we adopt a two-step procedure. First, we use the facility identifiers (dunsnumber) to link the TRI and P2 databases to the NETS database. Second, we use the approach of Chen, Hsieh, Hsu, and Levine (2022) to connect the facility identifier and the Compustat firm identifier (gvkey). This link is established by manually verifying the facility names and parent company names in the TRI database with firms' names in the Compustat database and the Center for Research in Security Prices (CRSP) database.

We also collect state-level economic data, such as income per capita and population, from the Bureau of Economic Agency (BEA) and the Bureau of Labor Statistics (BLS), respectively. Aggregate-level macroeconomic data are collected from the Federal Reserve Economic Data (FRED) maintained by the Federal Reserve in St. Louis.

2.1.6 Summary Statistics

In our analysis of the financing frictions-induced amplification effect of uncertainty on corporate environmental-related policies, we use panel regressions and report summary statistics of our sample. The primary variable of interest is Abatement Investment, which captures the total abatement activities undertaken by a firm's plant in a given year. We also consider Abatement-adj. Investment, which adjusts Abatement Investment for emission reductions. Emission reflects the total amount of emissions (in pounds) produced by a firm's plant in a given year. Other firm-level variables include ME (market capitalization deflated by CPI), B/M (book-to-market ratio), I/K (investment rate), ROA (return on assets), WW and SA indexes (to proxy for financial constraints), book leverage, leased capital ratio, Tobin's q, and debt growth.

[Place Table 1 about here]

Panel A of Table 1 presents the pooled summary statistics of all variables in our sample for the facility-year panel, which includes 152,621 facility-year observations with non-missing TRI information in the U.S. from 1991 through 2017. The mean of pollution abatement activities is 0.85, and the mean of emissions is 268,332 pounds. The average facility in our sample employs 575 workers and generates revenue of $144 million. In Panel B, we report the pooled summary statistics of all variables in our sample for the firm-year panel, which includes approximately 23,000 firm-year observations with facilities covered in the TRI database.

2.2 Empirical Analyses

2.2.1 Pollution Abatement Activities

We employ a differences-in-differences framework to analyze the impact of policy uncertainty and financial frictions on firms' environment-related decisions:

$$\begin{aligned} x_{p,i,s,t} \;\; &= \;\; \beta_1\, \sigma_{\tau|s,t} + \beta_2\, \sigma_{\tau|s,t} \times\; \eta_{i,t} + \beta_3\, \eta_{i,t} \\ &\quad +\beta_4\, \Gamma_{i,t} + \beta_5\, X_{s,t} + \beta_6 RepRatio_{s,t} + \psi_p + \pi_t + \varepsilon_{p,i,s,t}, \end{aligned} \tag{1}$$

for which equation (1) estimates the effect of policy uncertainty and financial frictions on (adjusted) pollution abatement activities for a facility (denoted by p) in a particular state (denoted by s), belonging to a parent firm (denoted by i) at time t. The variable of interest is the number of pollution abatement activities, and we estimate this equation using both Poisson and OLS regressions. In our Poisson regression, the dependent variable is the number of pollution abatement activities, while in our OLS regression, we use the logarithmic number of one plus the number of pollution abatement activities as the dependent variable.

In our regression analysis, $\sigma_{\tau|s,t}$ is a measure of *election-based* policy uncertainty. $\eta_{i,s,t}$ represents the financial constraint of facility p's parent firm i in year t, measured by the WW index (Whited and Wu (2006)) and SA index (Hadlock and Pierce (2010)). We also include an interaction term between $\eta_{i,s,t}$ and $\sigma_{\tau|s,t}$ to investigate whether financially constrained firms are more affected by increases in policy uncertainty. In addition to these variables, our model includes a set of firm-level controls denoted by $\Gamma_{i,t}$, such as size, book-to-market ratio, investment rate, and profitability. We also include state-level controls, denoted by $X_{s,t}$, such as income per capita and population. Finally, we include $RepRatio_{s,t}$, which is the number of Republican party wins in the past four gubernatorial elections, as an additional control variable.

Our main objective is to examine how environmental policy uncertainty, generated by tied elections, affects pollution abatement activities. In addition, we consider the role of political party affiliation on our outcomes by adding $RepRatio_{s,t}$, which measures the frequency of winning gubernatorial elections by a particular party in the past four cycles. We also control for facility-level heterogeneity that does not vary over time using facility fixed effects ψ_p and time-varying factors by adding year fixed effects π_t. To address estimation errors associated with facility-level correlation and potential autocorrelation, we cluster standard errors at the facility level.[21]

Panel A1 (Panel A2) of Table 2 presents the estimation results of equation (1) for (adjusted) pollution abatement activities. Specifications 1 to 4 (5 to 8) correspond to Poisson (OLS) regressions. Specifications 1, 2, 5, and 6 are estimated using the WW index, while Specifications 3, 4, 7, and 8 are based on the SA index. Additionally, we report results with and without firm- and state-level control variables in Specifications 1, 3, 5, and 7 (2, 4, 6, and 8).

[Place Table 2 about here]

Based on the results presented in Panel A1 of Table 1, the coefficient estimate ($\hat{\beta}_1$) for the uncertainty shock is negative in general but insignificant. However, the estimated coefficient ($\hat{\beta}_2$) for the interaction term between the uncertainty shock and financial constraints is significantly negative across all specifications, indicating that financially constrained firms experience a larger decline in abatement investment upon the realization of uncertainty. The economic significance of the findings is also discussed. The Poisson regression estimates suggest that a one-unit increase in the interaction term leads to a decline in abatement investments by a factor of $e^{\hat{\beta}_2}$, ranging from 1.06 to 1.23 across different specifications. The OLS regression estimates suggest an additional 1% drop in abatement investments on top of the 5 to 6% decrease induced by financial frictions. These declines in abatement investments are economically significant because the mean and standard deviation of abatement investments are relatively high, as reported in Panel A of Table 1. Finally, the results in Panel A2 indicate that the findings are consistent with those in Panel A1 when adjusted abatement activities are used to account for heterogeneity in pollution abatement.

To cross-validate the findings regarding the effect of financial frictions on pollution abatement activities, we implement an alternative specification that replaces the *election-based* uncertainty measure $\sigma_{\tau|s,t}$ with a firm-level *text-based* uncertainty measure $\sigma_{\tau|i,t}$. Specifically, we estimate the following regression:

$$x_{p,i,s,t} = \beta_1\ \sigma_{\tau|i,t} + \beta_2\ \sigma_{\tau|i,t} \times\ \eta_{i,t} + \beta_3\ \eta_{i,t} + \beta_4\ \Gamma_{i,t} + \beta_5\ X_{s,t} + \psi_p + \pi_t + \varepsilon_{p,i,s,t}. \qquad (2)$$

We present the estimation results of equation (2) in Panel B1 (B2) of Table 2 for (adjusted) pollution abatement activities. All model and regression designs are similar to Panels

[21] We also conducted additional estimations to ensure the robustness of our findings. Specifically, we estimated our models with standard errors clustered at the state level and used a different measure of pollution abatement activities based on the number of unique W codes. Our results, which are presented in Section B of the Internet Appendix, confirm the robustness of our primary findings.

A1 and A2. The negative and significant coefficient on the interaction of financial constraint and policy uncertainty confirms the findings documented in Panels A1 and A2 of Table 2, namely that financially constrained firms experience a more substantial decline in abatement investment when they face greater policy uncertainty.

Our results are consistent with prior studies. According to Alfaro, Bloom, and Lin (2022), firms subject to higher financial frictions are more sensitive to uncertainty shocks. The differential exposures to uncertainty shocks across firms reflect different effects of firms' financial constraints. In addition, external financing frictions depress firms' investment through the amplified real options effects inducing greater inaction regions with respect to corporate investment.[22] Overall, the effect of policy uncertainty on financially constrained firms' pollution abatement investment is thus a robust pattern in our sample.

2.2.2 Emissions

The results from Table 2 support the idea that policy uncertainty and financial constraints lead to a reduction in firms' pollution abatement investments, which in turn may contribute to an increase in toxic emissions. In order to provide additional support for this causal chain, we estimate the following ordinary least squares regression:

$$\begin{aligned} \log(1 + E_{p,i,s,t}) &= \beta_1\ \sigma_{\tau|s,t} + \beta_2\ \sigma_{\tau|s,t} \times\ \eta_{i,t} + \beta_3\ \eta_{i,t} + \beta_4\ \Gamma_{i,t} + \beta_5 X_{s,t} \\ &\quad + \beta_6 RepRatio_{s,t} + \psi_p + \pi_t + \varepsilon_{p,i,s,t},\ \text{or} \\ &= \beta_1\ \sigma_{\tau|i,t} + \beta_2\ \sigma_{\tau|i,t} \times\ \eta_{i,t} + \beta_3\ \eta_{i,t} + \beta_4\ \Gamma_{i,t} + \beta_5 X_{s,t} \\ &\quad + \psi_p + \pi_t + \varepsilon_{p,i,s,t}, \end{aligned} \tag{3}$$

for which the dependent variable in our analysis is denoted by $E_{p,i,s,t}$ and represents the total Toxic Release Inventory (TRI) emissions released by facility p in state s, belonging to parental firm i, at time t. The independent variables used in this analysis are the same as those in the empirical analysis presented in Section 2.2.1, including the key variables of interest.

[Place Table 3 about here]

Table 3 displays the estimation results. Specifications 1 to 4 use election-based uncertainty, and Specifications 5 to 8 use text-based uncertainty. Specifications 1, 2, 5, and 6 use

[22] See Bloom, Bond, and Van Reenen (2007), and Alfaro, Bloom, and Lin (2022), among others.

the WW index, while Specifications 3, 4, 7, and 8 use the SA index. Firm- and state-level control variables are excluded (included) in Specifications 1, 3, 5, and 7 (2, 4, 6, and 8).

Table 3 shows that increased policy uncertainty leads to a significant rise in emissions from facilities belonging to financially constrained firms. Across all specifications, we consistently observe positive and statistically significant coefficients on the interaction term $\hat{\beta}_2$, indicating that such facilities experience an increase in emissions under conditions of high election-based uncertainty. Notably, the significance level is higher when compared to the use of text-based uncertainty. This finding supports and reinforces our earlier results that financially constrained firms experience a further decrease in pollution abatement investment in the face of heightened policy uncertainty, which in turn is expected to result in an increase in toxic emissions.

2.2.3 Debt Financing

In this subsection, we aim to investigate the impact of policy uncertainty and financial constraints on firms' financing by examining whether firms with higher financial constraints face greater difficulty issuing debt under heightened policy uncertainty. To this end, we estimate the following regression to analyze the sensitivity of firms' debt financing to these factors:

$$\Delta \log B_{i,t+1} = \beta_1 \, \sigma_{i,t} + \beta_2 \, \sigma_{i,t} \times \; \eta_{i,t} + \beta_3 \, \eta_{i,t} + \beta_4 \, \Gamma_{i,t} + \psi_i + \pi_t + \varepsilon_{i,s,t}, \tag{4}$$

for which the dependent variable $\Delta \log B_{i,t+1}$ represents the growth rate of total debt for firm i from year t to year $t+1$, calculated as the difference in the logarithm of the sum of current and long-term liabilities (DLC+$DLTT$) deflated by the CPI index. The independent variables, including the variable of interest, are similar to those in the earlier analyses but at the firm level, without state-level controls. The variable sigma represents environmental policy uncertainty and is a binary variable that reflects the outcome of a close election in the state where the firm's headquarters are located in state s of year t or the text-based measure of firm-level uncertainty.[23] To ensure the robustness of our results, we include a broad set of control variables at the firm level, including Size (the logarithm of market capitalization), B/M (book-to-market ratio), I/K (investment rate), ROA (profitability), financial leverage,

[23] We adopt the approach of Bai, Fairhurst, and Serfling (2020) to identify the firm headquarters state by utilizing the historical headquarters data available on John Bai's personal website: https://sites.google.com/site/johnbaijianqiu.

leased capital ratio, Tobin's q, and firm and year fixed effects.[24]

[Place Table 4 about here]

Table 4 presents the results of estimating equation (4) for various specifications. In Specifications 1 and 2, the policy uncertainty measure is based on a binary variable that captures a close election in the firm's headquarters state, while in Specifications 3 and 4, the text-based uncertainty measure is used instead. Firm-level control variables are included in all specifications. The estimated coefficients on the interaction term are consistently negative and significant at the 5% level, indicating that financially constrained firms have a harder time raising debt financing under conditions of policy uncertainty. This decline in debt financing supports the financing mechanism underlying our main findings, which suggest that firms facing tightened borrowing constraints due to policy uncertainty are likely to reduce their investment in pollution abatement.

Section 2 presents empirical evidence that demonstrates the substantial impact of policy uncertainty and financial frictions on industrial pollution. The evidence suggests that environmental policy uncertainty intensifies the relationship between emissions and abatement efforts. These empirical findings highlight the need for further theoretical work. In Section 3, we present a simple model to illustrate the economic mechanism underlying these results. In Section 4, we develop a general equilibrium model to formalize our intuition and provide a quantitative explanation for these empirical observations.

3 Our Mechanism in a Simple Example

Before introducing the full-blown general equilibrium model, we will provide a simple example to clearly demonstrate the underlying mechanism without considering capital investment. In this example, we will illustrate how financial frictions and policy uncertainty regarding environmental regulations can lead to distortions that discourage firms from investing in pollution abatement.

We consider a hypothetical firm that faces a one-period problem with a unit discount factor, fixed output of y, and initial debt of by, where the level of indebtedness is represented

[24] The existing literature, such as Eisfeldt and Rampini (2009), Rauh and Sufi (2012), Rampini and Viswanathan (2013), Li and Xu (2020), and Li and Tsou (2022)), provides extensive evidence that leasing contracts, which are a crucial component of a firm's capital structure, can serve as a means of financing corporate investments, particularly for financially constrained firms. Hence, we consider the leased capital ratio as a control variable in our analysis.

by $b < 1$. The firm invests a portion $a \geq 0$ (abatement intensity) of its output, which is ay, in pollution abatement technology before the pollution tax is realized. The firm then produces its output, repays its external debt of by, pays a pollution emission tax of $\tau e y$, where the emission intensity e is determined by $\frac{\bar{e}}{\epsilon+a}$ and $\frac{\bar{e}}{\epsilon}$ is the default emission intensity without abatement investment, and maximizes equity payouts. After the period ends, the firm either receives a continuation value of v if it relies solely on its internal resources (where $c \geq 0$ represents a positive flow of internal funds), or receives $y(v-\phi)$ where ϕ represents the cost of being financially constrained if it relies on external financing (where $c < 0$ represents a negative flow of internal funds).[25]

The pollution tax is subject to shocks drawn from a continuous distribution $\pi_\tau(\tau)$ up to a maximum value of $\bar{\tau}$ with a volatility of σ_τ. The firm solves the following maximization problem:

$$\max_a \int_0^{\bar{\tau}} \left\{ \underbrace{[1-b-a-\tau e]}_{c} + [v - \phi \cdot \mathbf{1}(c<0)] \right\} \pi_\tau(\tau) d\tau \tag{5}$$

where the cutoff point, $\hat{\tau}$, is determined by the zero dividend condition, which is given by $1 - b - a - \hat{\tau} e = 0$. When the pollution tax rate, τ, exceeds the cutoff point $\hat{\tau}$, the firm's equity payouts become negative, and it incurs a loss of ϕ in the continuation value, reflecting the cost of being financially constrained.[26]

We begin by examining how pollution abatement investment influences the cutoff point. We introduce the term $\tilde{a} = a$ to denote the direct cost of abatement associated with the investment, and define the cutoff point as $\hat{\tau} = \frac{1-b-\tilde{a}}{e}$. The cutoff point decreases as initial indebtedness b, the debt burden from abatement cost $\tilde{a}$, and the emission intensity e increases. We assume, without loss of generality, that the maximum cutoff point $\hat{\tau}_{\max}$ exceeds the pollution tax rate $\bar{\tau}$. When abatement intensity is low ($a < \bar{a}(\bar{\tau})$), the firm has no chance of incurring negative dividends and thus avoids triggering the costly external financing constraint represented by ϕ. Consequently, any abatement level $a \in [0, \bar{a}]$ is financially unconstrained. We observe a linear marginal cost of $MC_{a \leq \bar{a}} = 1$ and a downward-sloping marginal benefit of $MB_{a \leq \bar{a}} = -E[\tau]\frac{de}{da} = \frac{\bar{e}E[\tau]}{(\epsilon+a)^2}$. Notably, neither of these factors is influenced by the initial indebtedness b.

[25] To maintain the simplicity and intuitiveness of our example, we do not introduce the costly external financing through equity or debt issuance. Instead, we assume that whenever the firm's internal funds c fall below zero, the firm must pay a cost of external financing, represented by ϕ, in the future.

[26] The non-negative dividend constraint is used in the model to capture two important observations in the corporate finance literature. Firstly, issuing new equity incurs significant costs, both direct and indirect, such as flotation costs and underwriting fees. Secondly, firms infrequently issue external equity. By imposing the non-negativity constraint, the model is able to capture the realistic costs and infrequency of external equity issuance while also simplifying the computational requirements of the model.

When the firm chooses an abatement intensity larger than $\bar{a}$, the firm will trigger a negative dividend and incur the cost of being financially constrained ϕ if the realization of τ lies between $\hat{\tau}(a)$ and $\bar{\tau}$. As a result, any abatement $a > \bar{a}$ is financially constrained and incurs both financial marginal costs and benefits. The marginal cost of abatement investment and the marginal benefit of abatement investment are as follows:

$$\begin{aligned} MC_{a>\bar{a}} &= \underbrace{1}_{\text{direct cost}} + \underbrace{(-\phi)\frac{\pi_\tau(\hat{\tau})}{1-\Pi_\tau(\hat{\tau})}\frac{d\hat{\tau}}{d\tilde{a}}\frac{d\tilde{a}}{da}}_{\text{financial cost}} = 1 + \phi\frac{\pi_\tau(\hat{\tau})}{1-\Pi_\tau(\hat{\tau})}\frac{(\epsilon+a)}{\bar{e}} \\ MB_{a>\bar{a}} &= \underbrace{-E[\tau]\frac{de}{da}}_{\text{direct benefit}} + \underbrace{(-\phi)\frac{\pi_\tau(\hat{\tau})}{1-\Pi_\tau(\hat{\tau})}\frac{d\hat{\tau}}{de}\frac{de}{da}}_{\text{financial benefit}} = \frac{\bar{e}E[\tau]}{(\epsilon+a)^2} + \phi\frac{\pi_\tau(\hat{\tau})}{1-\Pi_\tau(\hat{\tau})}\frac{(1-b-a)}{\bar{e}} \end{aligned} \tag{6}$$

in which $\frac{\pi_\tau(\hat{\tau})}{1-\Pi_\tau(\hat{\tau})}$ is the hazard rate of the firm falling into the negative dividend region $\tau \in [\hat{\tau}, \bar{\tau}]$, $\frac{d\hat{\tau}}{d\tilde{a}} = -\frac{1}{e}$ is the negative effect of the debt burden from abatement investment on the cutoff, and $\frac{d\tilde{a}}{da} = 1$ is the 100% pass through from abatement to debt burden in this simple example; similarly, $\frac{d\hat{\tau}}{de} = -\frac{1-b-\tilde{a}}{e^2}$ is the negative effect of emission intensity on the cutoff, and $\frac{de}{da} = \frac{e^2}{\bar{e}}$ is the pollution reduction effect from abatement investment.[27]

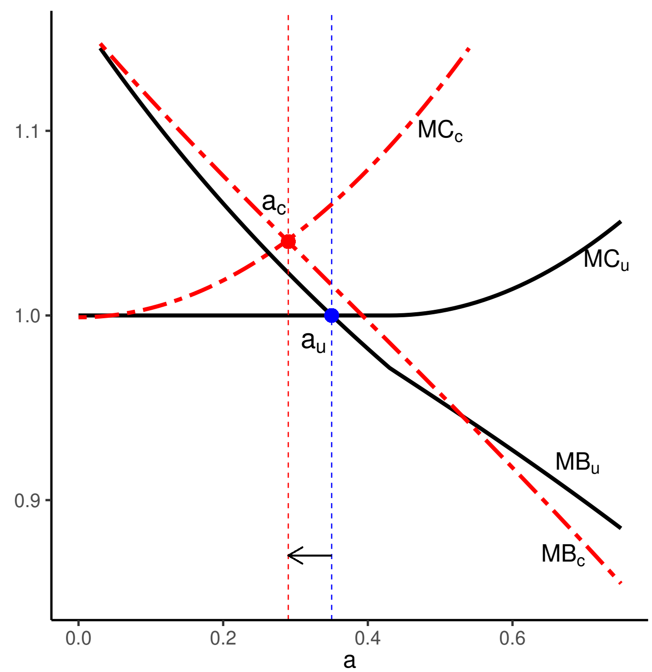
The constrained marginal costs and benefits in equation (6) are influenced by the marginal financial cost and benefit. The hazard rate of the firm falling into the negative dividend region $\frac{\pi_\tau(\hat{\tau})}{1-\Pi_\tau(\hat{\tau})}$, which is highly impacted by policy uncertainty in environmental regulation σ_τ, affects both of the marginal financial cost and benefit. Higher policy uncertainty typically results in a greater hazard rate, leading to increased marginal financial costs and benefits of constrained abatement. The marginal financial cost of constrained abatement increases with abatement investment, while the marginal financial benefit of constrained abatement decreases with both abatement investment and indebtedness. These relationships create a non-linear interacted effect of financial frictions and uncertainty on corporate abatement investment. We visualize such relationships in Figures 1 and 2.

We have two main points to highlight. First, financial frictions generally reduce pollution abatement investment among financially constrained firms due to the additional marginal costs of being constrained by the debt burden of such investment, as illustrated in Figure 1. Firms that are financially unconstrained have a low initial debt burden and, therefore, a high cutoff for being financially constrained in abatement. Consequently, their unconstrained optimal abatement investments lie at the intersection of MC_u and MB_u, without incurring additional financial costs. However, financially constrained firms typically have a high initial

[27] The total marginal effect of abatement a on $\hat{\tau}$ is $\frac{d\hat{\tau}}{da} = \frac{d\hat{\tau}}{d\tilde{a}}\frac{d\tilde{a}}{da} + \frac{d\hat{\tau}}{de}\frac{de}{da} = -\frac{(\epsilon+a)}{\bar{e}} + \frac{(1-b-a)}{\bar{e}} = \frac{(1-b-\epsilon-2a)}{\bar{e}}$.

Figure 1. Abatement Investment Subject to Financial Frictions

This figure illustrates the impact of financial frictions on corporate pollution abatement investment. The x-axis represents firms' choices of abatement investment (a), while the y-axis shows the corresponding marginal costs (MC_a) and marginal benefits (MB_a) of such investment, as defined by equation (6). Specifically, MC_u and MB_u represent the marginal cost and benefit curves when firms have low debt and are financially unconstrained, while MC_c and MB_c represent the corresponding curves when firms have high debt and are financially constrained. Constrained firms have a smaller range of unconstrained abatement choices, and their optimal investment choices lie at the intersection of MC_c and MB_c, where both the financial cost and benefit of abatement investment are present.

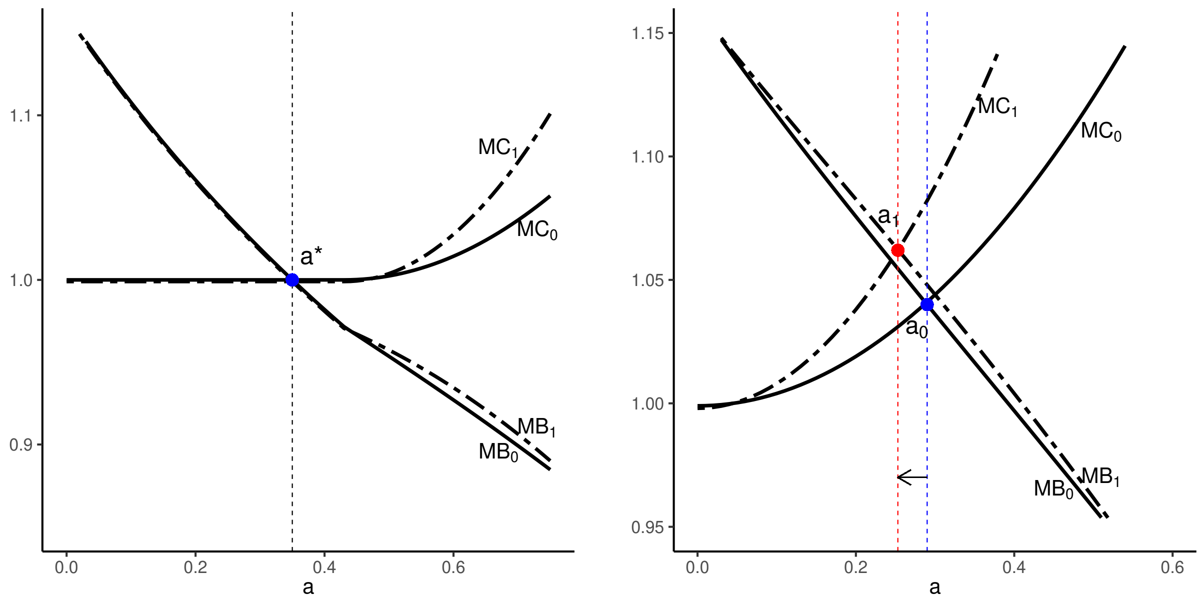


debt burden, resulting in a low cutoff for being financially constrained in abatement. This leads to their constrained optimal abatement investments being at the intersection of MC_c and MB_c, reflecting the increasing marginal cost in abatement and decreasing marginal financial benefit in both abatement and initial debt. Therefore, the constrained optimal abatement investments tend to be lower than the unconstrained optimal abatement investments. The interpretation of our model is consistent with the empirical evidence presented by Xu and Kim (2022), which suggests that financially constrained firms tend to invest less in pollution abatement. This finding underscores the importance of addressing financial frictions in promoting sustainable corporate investment.

Second, as illustrated in Figure 2, high levels of policy uncertainty in environmental regulation exacerbate the reduction in pollution abatement investment of financially constrained

Figure 2. Abatement Investment Subject to Policy Uncertainty

This figure illustrates how policy uncertainty in environmental regulation can affect corporate pollution abatement investment decisions. The x-axis represents firms' choices of abatement investment (a), while the y-axis shows the corresponding marginal costs (MC_a) and marginal benefits (MB_a) of such investment, as specified in equation (6). The figure includes two pairs of marginal cost and benefit curves. The first pair (MC_0 and MB_0) reflects the marginal cost and benefit when policy uncertainty is low, while the second pair (MC_1 and MB_1) reflects the marginal cost and benefit when policy uncertainty is elevated.



(a) Unconstrained Firm

(b) Constrained Firm

firms due to the additional marginal costs incurred from being financially constrained by debt. The increased policy uncertainty raises the hazard rate $\frac{\pi_\tau(\hat{\tau})}{1-\Pi_\tau(\hat{\tau})}$, which amplifies the existing asymmetry in the intersection of the marginal cost curve and the marginal benefit curve by increasing the marginal financial cost of abatement and decreasing the marginal financial benefit of both abatement and initial debt. In plot (a), the amplification does not affect the unconstrained optimal abatement investments since firms are not financially constrained. However, in plot (b), the asymmetric amplification resulting from the shifts of MB_0 and MC_0 to MB_1 and MC_1 leads to reduced abatement investment. In line with previous studies Alfaro, Bloom, and Lin (2022), our model emphasizes the role of policy uncertainty in reducing pollution abatement investment, particularly for financially constrained firms. Therefore, our model suggests that reducing policy uncertainty may be an effective way to alleviate the negative effects of financial frictions on pollution abatement investment by financially constrained firms.

The underlying mechanism illustrated in the simple example aligns with the findings from our empirical analysis in Section 2.2. Specifically, as shown in Figure 1, financially constrained firms tend to decrease their abatement investment, leading to higher pollution emissions, which is consistent with our findings in Tables 2 and 3. Furthermore, as demonstrated in Figure 2, elevated policy uncertainty exacerbates this effect, causing financially constrained firms to reduce their abatement investment even further and resulting in even higher pollution emissions. As emphasized in Section 2.2, we find a strongly significant interaction term between financial constraints and policy uncertainty. Finally, our findings on debt growth in Table 4 are consistent with these patterns, as we observe a reduction in debt growth for financially constrained firms when external debt is used to finance abatement investment and policy uncertainty increases.

4 The Full Model

We next build a comprehensive model of heterogeneous firms that can help explain the cross-sectional variation we have presented and explore its aggregate implications. The model consists of two blocks: a production block that captures the varying responses of firms to environmental policy uncertainty shocks, and a general equilibrium block that includes a capital producer and a representative family of households, ultimately closing the model. Our analysis takes place in a discrete and infinite time setting.

4.1 Production, Pollution, and Finance

In the production block, there is a fixed mass of heterogeneous firms that invest in physical capital and carbon-intensity technology, taking into account the presence of financial frictions. This model builds heavily on the heterogeneous firm framework developed by Khan and Thomas (2013) and Ottonello and Winberry (2020). We extend these models in three ways. First, firm production generates pollution emissions, which are proportional to the product of output and firm-specific carbon intensity. Second, firms have the option to invest in emission-reducing technology in addition to capital investment. Finally, we incorporate idiosyncratic pollution regulation penalty shocks, modeled as implicit taxes, as in Shapiro and Walker (2018).

Production In the steady state of the economy, there is no aggregate uncertainty. However, we introduce a policy uncertainty shock later in the form of an MIT shock (e.g., Boppart, Krusell, and Mitman (2018)), which is a one-time unexpected change in firms' pollution penalty. In the following subsections, we examine the transition path in response to this unexpected environmental policy uncertainty shock. In each period, a fixed unit mass of production firms exist, where each firm $j \in [0, 1]$ produces an undifferentiated good y_j using the production function:

$$y_{jt} = z_{jt} k_{jt}^{\alpha}, \tag{7}$$

where α represents the capital share and less than one, z_{jt} denotes an idiosyncratic total factor productivity shock, l_{jt} represents the firm's labor input, and k_{jt} represents the firm's capital stock. The idiosyncratic TFP shock z_{jt} follows a log-AR(1) process:

$$log z_{jt+1} = \rho log z_{jt} + \epsilon_{jt+1}, \tag{8}$$

where $\epsilon_{jt+1} \sim N(0, \sigma^2)$.

Similar to the approach in Khan and Thomas (2013), our focus is on understanding how financial constraints affect firms' decisions regarding abatement investment. To avoid having firms accumulate sufficient resources such that they never again face a binding borrowing constraint, we introduce exit and entry into the model. Specifically, each firm has a fixed probability π_d of exiting the economy after production, debt repayment, and pollution penalty in any given period. Before investment, firms learn whether they will survive to produce in the next period. If a firm exits, it is replaced by a new entrant with n_0 units of net worth from the households, the lowest abatement technology (which will be introduced later), and idiosyncratic productivity drawn from a time-invariant distribution. The new entrant then proceeds as an incumbent firm.

Pollution and Environmental Policy A firm's production results in the emission of pollutants, which are determined by the firm's emission intensity, pollution abatement efforts, and production scale. In our model, we incorporate heterogeneity in emission intensity by extending the existing pollution models for representative firms. This means that firms can accumulate pollution abatement technology through past investment and result lower emission intensity. Firm j's emissions at time t is given by:

$$e_{jt} = \frac{\bar{e}}{x_{jt}} y_{jt} \tag{9}$$

where $\bar{e}$ represents the default level of emission intensity, and x_{jt} denotes the level of accumulated abatement technology. The firm can improve its abatement technology through investment, which follows the law of motion:

$$x_{jt+1} = (1 - \delta_x) x_{jt} + a_{jt+1}, \tag{10}$$

where δ_x represents the depreciation of existing abatement technology embedded in current capital, and a_{jt+1} is the firm's current investment in abatement. As abatement technology is highly specific and investment is irreversible, we assume that all firms have a non-negative investment in abatement in each period (i.e. $a_{jt+1} \geq 0$) to reflect the capital irreversibility.

Pollution can have regulatory consequences due to environmental policies. In our model, firm j is subject to a pollution penalty, which is represented by $\tau_{jt}e_{jt}$, where τ_{jt} is an idiosyncratic pollution penalty shock and e_{jt} is the level of pollution emissions. This penalty is modeled as an implicit tax, as in Shapiro and Walker (2018), and accounts for firm-level heterogeneity, allowing the pollution penalty to differ by firms with idiosyncratic shocks. The idiosyncratic pollution penalty shock τ_{jt} follows a specific probability structure $T = \{\mu_\tau, \sigma_\tau\}$, which reflects both the severity of environmental policy μ_τ and the uncertainty of environmental policy σ_τ. This uncertainty captures firms' investigations, litigation, and penalties variability. The idiosyncratic pollution penalty shock is assumed to be i.i.d. across firms.

Without loss of generality, we assume that τ_{jt} follows a truncated log-normal process. Specifically, with probability p_τ, there is no penalty to match the fact that firms may avoid penalties at times. Otherwise, τ_{jt} follows a log-normal distribution with mean μ and standard deviation σ.[28] Here, μ_τ and σ_τ represent the mean and standard deviation of the entire distribution, respectively. At the steady state, both μ_τ and σ_τ are constant for all firms. However, during transition dynamics, shocks to the severity of environmental policy will be reflected in changes to μ_τ, while shocks to environmental policy uncertainty will be reflected in changes to σ_τ.

Financial Frictions Firms may need to seek external financing to fund their investments in physical capital and abatement technology. To model this, we assume that firm j only has access to risk-free borrowing contracts without considering for state-contingent debt, as in Rampini and Viswanathan (2010, 2013). The collateralized borrowing constraint is given by:

$$b'_j \leq \theta_k k_{jt}. \tag{11}$$

Firm j is assumed to have an opportunity to default on its contract and abscond with $1 - \theta_k$ of its capital. Because lenders can retrieve a θ_k fraction of firm j's capital upon default, borrowing is limited by $\theta_k \in [0, 1]$ as the liquidation value of a firm's capital stock. This constraint limits a firm's borrowing capacity by tying it to the value of its existing capital stock. The second constraint is that equity issuance is prohibited, so all firms must maintain

[28] Therefore, the mean and variance of the log-normal distribution are $\mu_{log} = e^{(\mu+\sigma^2/2)}$ and $\sigma_{log} = (e^{\sigma^2} - 1)e^{2\mu+\sigma^2}$, respectively. The mean and standard deviation of the distribution can be calculated from these parameters.

a non-negative dividend; that is, $d_{jt} \geq 0$ holds for all firms.

4.2 Recursive Problem for Firms

The firm's optimization problem is written recursively, where the state variables are the firm's total factor productivity z, abatement technology x, and net worth n. The net worth n is given by the expression:

$$n = zk^{\alpha} + q_t(1-\delta)k - \tau e - (1+r_t)b, \tag{12}$$

where k and b are predetermined from the last period decision, and τ represents the realized pollution penalty tax rate. The term zk^{α} represents the firm's production revenue, $q_t(1-\delta)k$ represents the depreciation-adjusted investment return, τe represents the pollution penalty, and $(1+r_t)b$ represents the cost of borrowing.

Let $v_t(z,x,n)$ denote the equity value function before forced exiting, and Λ_{t+1} denote the stochastic discount factor, then the continuing equity value function can be expressed as:

$$v_t(z,x,n) = \pi_d \cdot \theta_n n + (1-\pi_d) \cdot \left\{ \max_{a',k',b'} d + \Lambda_{t+1} \mathbf{E_t} \left[v'(z',x',n') \right] \right\} \tag{13}$$

subject to

$$0 \leq d \leq n - a' - q_{t+1}k' + b', \tag{14}$$

$$b' \leq \theta_k k', \tag{15}$$

$$0 \leq a', \tag{16}$$

$$n' \equiv z'k'^{\alpha} + q_{t+1}(1-\delta)k' - \tau' e' - (1+r_{t+1})b', \tag{17}$$

$$x' = (1-\delta_x)x + a', \tag{18}$$

where θ_n represents the proportional liquidation value of exiting firms, Λ_{t+1} is the stochastic discount factor for the firm, z' follows an AR(1) productivity process, τ' follows the log-normal i.i.d. process specified previously, and the expectation $\mathbf{E_t}$ is taken over the realization of z' and τ'.

4.3 General Equilibrium Block

In the general equilibrium model, we also include a unit mass of identical households that determines consumption and the stochastic discount factor. The households derive utility from consumption and own the economy's capital stock. We assume that households supply labor inelastically and receive a wage that is determined by the competitive labor market. The capital goods producer determines the equilibrium price of capital.

Capital Good Producer The model assumes a representative capital good producer who uses a technology $\Phi(I_t/K_t)K_t$, which follows a constant-return-to-scale and convex function, to produce new aggregate capital, where I_t denotes units of the final good used to produce capital, K_t is the aggregate capital stock at the beginning of the period, and δ is the steady-state investment rate. Namely, one unit of the capital good costs $\Phi(I_t/K_t)K_t$ units of consumption goods. The function $\Phi(I_t/K_t)$ is given by:

$$\Phi(I_t/K_t) = \frac{\delta/\phi}{1-1/\phi}\left(\frac{I_t}{K_t}\right)^{1-1/\phi} - \frac{\delta}{\phi-1}, \tag{19}$$

where ϕ is the elasticity of substitution between capital goods. The relative price of capital, q_t, is determined by profit maximization and is given by

$$q_t = \frac{1}{\Phi'(I_t/K_t)} = \frac{I_t/K_t{}^{1/\phi}}{\delta}. \tag{20}$$

Representative Households The model assumes a unit measure continuum of identical households who own all the firms and have preferences over consumption C_t. The households' expected utility is given by

$$\mathbf{E_0}\sum_{t=0}^{\infty}\beta^t\left(\frac{C_t^{1-\gamma}}{1-\gamma} - \zeta E_t\right)$$

where β is the time discount rate, γ is the coefficient of relative risk aversion, and ζ is a constant that captures the disutility of pollution emission (Such a setting could be rationalized in the literature, i.e., Hsu et al. (2022)). The households face a budget constraint given:

$$C_t + \frac{1}{R_{f,t}}B_t \le B_{t-1} + \Pi_t,$$

where $R_{f,t}$ represents the risk-free interest rate during the period from t to $t+1$. B_t denotes the quantity of one-period risk-free bonds that households hold. Additionally, households receive capital income Π_t from firms. Households bear the disutility of environmental pollution by internalizing the negative externalities of it from the total pollution emission $E_t = \sum(e)$. The optimality of intertemporal saving decisions implies the Euler equation, which determines the stochastic discount factor (SDF) implied by households consumption:

$$\Lambda_{t+1} = \frac{\beta U_c(C_{t+1}, L_{t+1})}{U_c(C_t, L_t)} = \beta \left(\frac{C_{t+1}}{C_t} \right)^{-\gamma}, \tag{21}$$

and the risk-free interest rate must satisfy:

$$\mathbf{E_t}[\Lambda_{t+1}] R_{f,t} = 1. \tag{22}$$

Equilibrium Definition The equilibrium is a set of value functions $v_t(z, x, n)$; decision rules $k't(z, x, n)$, $b'_t(z, x, n)$, $a'_t(z, x, n)$; a pollution penalty structure μ_τ, σ_τ; the measure of firms $\mu_t(z, x, n, \tau, k, b)$; and prices q_t, Λ_{t+1} such that (i) all firms optimize, (ii) households optimize, (iii) the capital producer optimizes, (iv) the distribution of firms is consistent with decision rules, and (v) the final good market clears, i.e., $Y = C + I + A$, where $A = \sum(a')$.

4.4 The Roles of Financial Frictions and Policy Uncertainty

Before the quantitative analysis, we theoretically characterize the channels through which corporate pollution abatement investment in our model is affected by financial frictions and policy uncertainty as the mechanism illustrated in Section 3. According to Proposition 1, financially constrained firms with lower net worth are more likely to hit the borrowing limits when they pursue pollution abatement. This relationship between financial constraints, net worth, and abatement is further intensified by policy uncertainty, as in Proposition 2. Consequently, firms are more likely to hit the borrowing limits for pollution abatement when policy uncertainty is high.

Proposition 1. *Consider a firm at time t that is eligible to continue into the next period and has idiosyncratic productivity z, abatement technology x, and net worth n. For any given values of $\{z, x\}$, the firm's optimal decision can be characterized by one of the following cases.*

(i) ***Unconstrained:*** *there exists a threshold $\bar{n}(z, x)$ such that a firm is financially unconstrained if its net worth n exceeds $\bar{n}(z, x)$ (i.e., $n > \bar{n}(z, x)$). For such unconstrained firms, the optimal policies for capital accumulation, abatement investment, and borrowing follow the frictionless case, denoted by $k'^*(z, x, n)$, $a'^*(z, x, n)$, and $b'^*(z, x, n)$,*

respectively. The borrowing limit is not binding, and for any combination of realized shocks $\{z', \tau'\}$, the optimal borrowing for the next period is not constrained (i.e., $b''^{*}(z', x', n') < \theta_k k''^{*}(z', x', n')$.)

(ii) ***Constrained and Binding:*** *there exists a threshold $\underline{n}(z, x)$ such that the firm is financially constrained and binding if $n < \underline{n}(z, x)$. Constrained and binding firms follow the "binding" capital accumulation policy $k'(z, x, n) = k'^{B}(z, x, n)$, the "binding" abatement investment policy $a'(z, x, n) = a'^{B}(z, x, n)$, and the "binding" borrowing constraint $b'^{B}(z, x, n) = \theta_k k'^{B}(z, x, n)$.*

(iii) ***Constrained and Non-binding:*** *firms with $n \in [\underline{n}(z, x), \bar{n}(z, x)]$ are financially constrained but non-binding. Constrained and non-binding firms follow the "constrained" capital accumulation policy $k'(z, x, n) = k'^{C}(z, x, n)$, the "constrained" abatement investment policy $a'(z, x, n) = a'^{C}(z, x, n)$, and the "constrained" borrowing policy $b'^{C}(z, x, n) < \theta_k k'^{C}(z, x, n)$. A constrained and non-binding firm does not borrow up to its collateral constraints to avoid binding situations in the future. That is, for the optimal choices of k'^{C}, a'^{C}, b'^{C}, there exist some combinations of realized shocks z', τ' such that the next period optimal borrowing is binding (i.e., $b''^{C}(z', x', n') = \theta_k k''^{C}(z', x', n')$.)*

Proposition 2. *Consider a firm with the optimal decision in Proposition 1. When policy uncertainty in environmental regulation increases to σ_τ unexpectedly, the firm's optimal decision changes as follows.*

(i) ***Unconstrained:*** *the threshold $\bar{n}(z, x; \sigma_\tau)$, which indicates the point at which the firm becomes financially unconstrained if $n > \bar{n}(z, x; \sigma_\tau)$, increases with σ_τ. Even when the firm is unconstrained, it still follows the "frictionless" capital accumulation policy $k'(z, x, n) = k'^{*}(z, x, n)$, the "frictionless" abatement investment policy $a'(z, x, n) = a'^{*}(z, x, n)$, and the "frictionless" borrowing policy $b'^{*}(z, x, n) < \theta_k k'^{*}(z, x, n)$. Regardless of the optimal choices of $\{k'^{*}, a'^{*}, b'^{*}\}$ and the combination of realized shocks z', τ', the next period's optimal borrowing will not be binding $b''^{*}(z', x', n') < \theta_k k''^{*}(z', x', n')$.*

(ii) ***Constrained and Binding:*** *the threshold $\underline{n}(z, x; \sigma_\tau)$ such that the firm is financially constrained and binding if $n < \underline{n}(z, x; \sigma_\tau)$ decreases with σ_τ. Constrained and binding firms follow the "binding" capital accumulation policy $k'(z, x, n; \sigma_\tau) = k'^{B}(z, x, n; \sigma_\tau)$, the "binding" abatement investment policy $a'(z, x, n; \sigma_\tau) = a'^{B}(z, x, n; \sigma_\tau)$, and the "binding" borrowing policy $b'^{B}(z, x, n; \sigma_\tau) = \theta_k k'^{B}(z, x, n; \sigma_\tau)$.*

(iii) ***Constrained and Non-binding:*** *If $n \in [\underline{n}(z, x; \sigma_\tau), \bar{n}(z, x; \sigma_\tau)]$, the firm is financially constrained and non-binding. Constrained and non-binding firms follow the "con-*

strained" capital accumulation policies as in Proposition 1.

5 Quantitative Analysis

As the primary mechanism of this paper having been highlighted, we now proceed to apply the full model to the data and quantify the mechanism. To do so, we first parameterize the model to match both the dynamic and cross-sectional moments of US firms. We then present the quantitative results of increased policy volatility on pollution abatement investment, examining both cross-sectional and aggregate dynamics.

5.1 The Solution Methods

The critical challenge in solving the model is that the aggregate state includes an infinite-dimensional object μ_t, which represents the cross-sectional distribution of firms. To address this challenge, we adopt a methodology similar to that used in the MIT shock literature (e.g., Boppart et al. (2018)). Specifically, we use a one-time unexpected shock around the model's steady state, which is known as a MIT shock. This shock provides a reasonably accurate approximation and preserves the non-linearity of the transition path quite well.

The solution method for the model involves two parts. First, the *Stationary Equilibrium* at the steady state is solved, which delivers the value functions, policy functions, and steady-state aggregate variables. The *Stationary Equilibrium* also provides the cross-section moments for calibration. Second, the *Transitional Equilibrium* is solved, starting at the *Stationary Equilibrium*, given a path of MIT shocks of policy uncertainty and a long enough period for the model to transition back to the same *Stationary Equilibrium*. The *Transitional Equilibrium* then provides the dynamic moments for calibration and impulse response functions. This approach fully captures the non-linearity from the interaction between financial frictions and policy uncertainty shocks, which is critical for the quantitative results. Section C of the Internet Appendix provides further details on the solution methods.

5.2 Parameterization

Our parameterization proceeds in two steps. In the first step, we select a set of parameters to match standard cross-sectional and macroeconomic targets in the steady state. In the second step, we choose the remaining parameters such that the model can replicate additional cross-sectional moments observed in the data.

[Place Tables 5 and 6 about here]

Fixed Parameters The first part of Table 5 presents the parameters that are directly taken from the literature. The model operates at an annual frequency, and the time discount rate β is set to 0.96 to match the average real risk-free rate of 4% per year. The elasticity of intertemporal substitution is set to unity ($\gamma = 1$) for log utility. The capital share α is set to 0.65 to match a decreasing-return-to-scale of two-thirds. The annual depreciation rate of capital is set to $\delta_k = 0.10$ to match the average nonresidential fixed investment rate in Bachmann, Caballero, and Engel (2013), consistent with the standard RBC literature (e.g., Kydland and Prescott (1982)).

Fitted Parameters The second part of Table 5 presents the parameters that we calibrated to match the firm-level moments reported in Table 6. While all parameters are jointly determined, we outline the rough relationships between the parameters and moments. The first set of parameters pertains to output and finance. We set the productivity persistence parameter, ρ_z, to 0.90 and the productivity volatility parameter, σ_z, to 0.03 to match the auto-correlations of output across different horizons. To match the annual exit risk of 8.7% and the size of entrants relative to average firms at about 30%, we choose the exogenous exit risk parameter, π_d, to be 0.087 and the net worth of the entry parameter, n_0, to be 1.2. Finally, we set the collateral constraint parameter, θ_k, to 0.40, which leads to an equilibrium average firm-level leverage of 34%.

The second set of fitted parameters is related to pollution and abatement. The default pollution emission intensity $\bar{e} = 10$ and the abatement technology depreciation rate $\delta_x = 0.02$ are chosen to match the emission intensity distribution, which is measured as the emission-to-sales ratio in the model. The emission-to-sales ratio is defined as pounds of toxic emissions over millions of dollars of sales. Then, the probability of no pollution penalty $p_\tau = 0.40$, the mean of pollution penalty $\mu_\tau = 0.02$, the volatility of pollution penalty during normal periods $\sigma_\tau^l = 0.02$, and the volatility of pollution penalty during elevated policy uncertainty periods $\sigma_\tau^h = 0.04$ are chosen to match the distribution of pollution penalty, which is measured as the litigation-to-sales ratio. Currently, the monetary value of the direct costs of litigation cases over the total sales of firms is used to measure the pollution penalty.[29]

Free Parameter There is currently one free parameter in our model, which is the disutility

[29]The data source regarding the pollution penalty is available on the website of the EPA at `https://cfpub.epa.gov/enforcement/cases/`. We also collected data on the number of settlements for each case and found that the mean and median settlements for all cases are 8.27 and 0.8 million dollars, respectively.

parameter of pollution, denoted as ζ. While this parameter does not affect our current quantitative analysis of the firm side, it does have negative welfare effects on households, so we must have $\zeta > 0$. Our current data do not determine the exact value of ζ. The value of ζ will impact the optimal degree of pollution penalty (regulation) and the optimal level of abatement. In future versions of this paper, we will discuss the optimal regulation policy and the optimal level of abatement based on the value of ζ.

5.3 The Effects of Financial Frictions and Policy Uncertainty

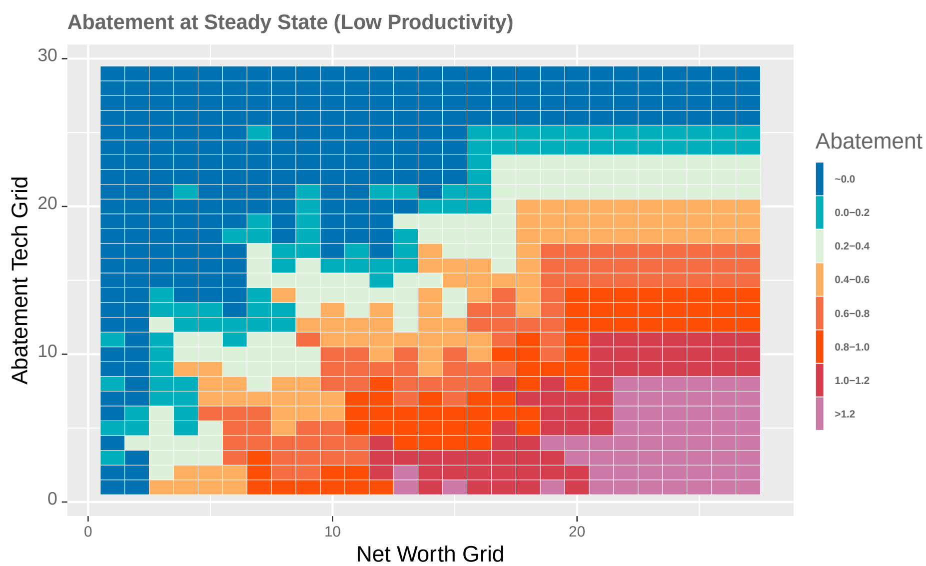
With the calibrated model, we demonstrate how financial frictions and policy uncertainty influence firms' investment in abatement. Our findings show that the quantitative model effectively explains the empirical results and mechanisms observed in the illustration example in Section 3.

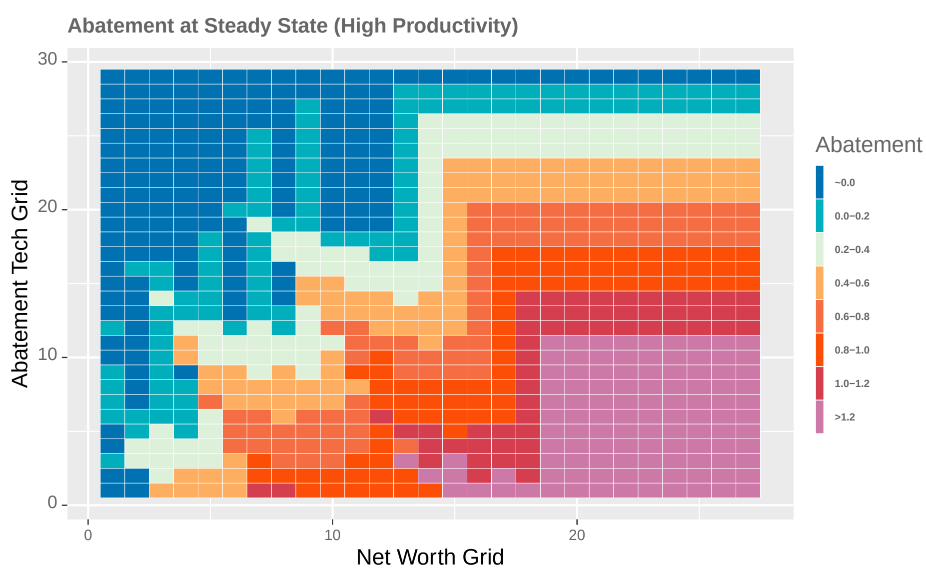
The Effects of Financial Frictions Figure 3 illustrates how firms' abatement investment policies vary with net worth, emission abatement technology, and productivity. Although the policy is a three-dimensional object, the figure shows only low versus high productivity to simplify the presentation in a heatmap. The results indicate that abatement investment is affected by productivity, abatement technology, and financial frictions. Holding net worth and abatement technology constant, more productive firms tend to invest more in abatement; holding productivity and net worth constant, firms with lower abatement technology tend to invest more in abatement; and holding abatement technology and productivity constant, less constrained firms (i.e., those with higher net worth) tend to invest more in abatement. In equilibrium, the firms' statuses in the three dimensions are positively correlated, with more productive and less constrained firms being cleaner, while less productive and more constrained firms are dirtier. Financial frictions have a particularly strong effect because more constrained firms cannot move away from being dirty due to their lower productivity and lack of external funding.

The Effects of Policy Uncertainty Figure 4 shows how the abatement investment policies in Figure 3 change when policy uncertainty in environmental regulation is elevated. In Figure 4, we can see that the effects of elevated policy uncertainty on less constrained firms are heterogeneous. Depending on their abatement technology and productivity, they may choose to increase or decrease abatement investment. However, with elevated policy uncertainty, more constrained firms with lower net worth tend to reduce their abatement investment, even with the same abatement technology. These firms trade off their investment opportunities and choose to lower their abatement investment, particularly for the highly

Figure 3. Abatement Policy at the Steady State

This figure depicts the differences in firms' abatement investment policies based on their net worth, emission abatement technology, and productivity. Due to the three-dimensional nature of the policy, the entire heatmap cannot be displayed, and only the low vs. high productivity dimension is shown. The results demonstrate that abatement investment is affected by financial frictions. Specifically, when firms have equal abatement technology and productivity levels, those with higher net worth and are less financially constrained tend to invest more in abatement.

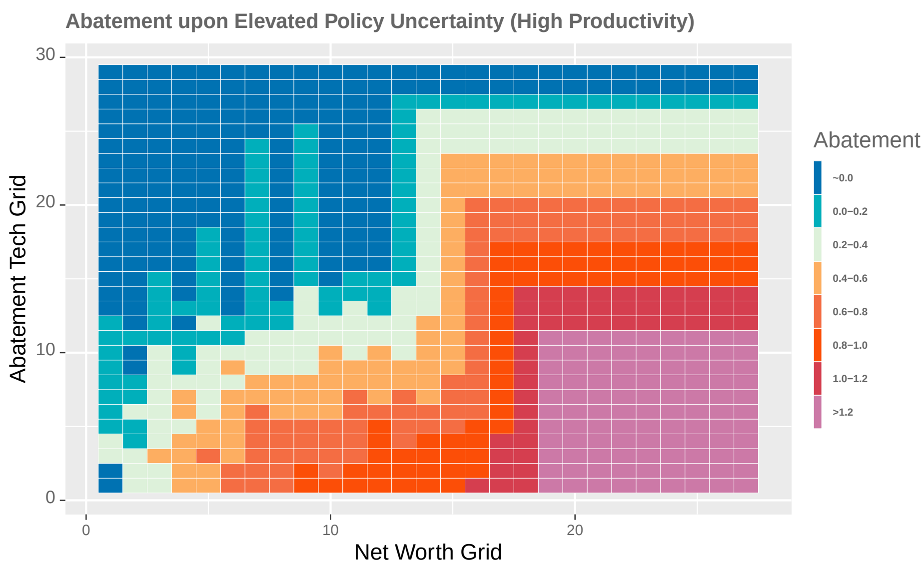




productive, constrained firms with limited internal net worth.

Figure 4. Abatement Policy upon Elevated Policy Uncertainty

This figure shows the heatmap of firms' abatement investment policies across the dimensions of net worth, emission abatement technology, and productivity upon elevated policy uncertainty, compared to Figure 3. The color scale represents the abatement investment policy, with darker shades indicating higher abatement investment. The x-axis represents the net worth dimension, the y-axis represents the abatement technology dimension, and the z-axis represents the productivity dimension. Due to the three-dimensional nature of the policy, we show only the low vs. high values for the productivity dimension in the upper and lower plots. The figure reveals that policy uncertainty certainly matters for abatement investment, as firms' investment levels are lower when they face elevated policy uncertainty, regardless of their net worth, abatement technology, or productivity. Additionally, the effect of policy uncertainty is stronger on more constrained firms with lower net worth.



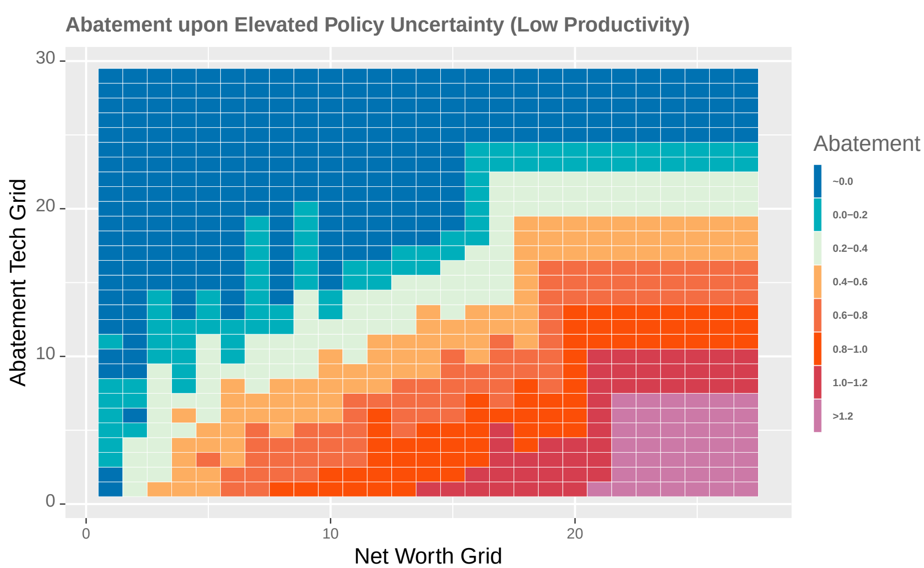
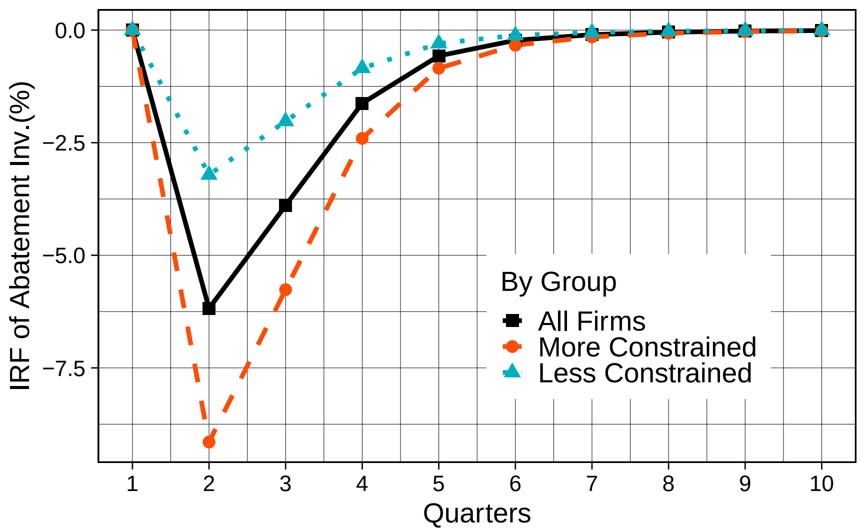


Figure 5. Impulse Responses of Abatement Investment

This figure displays the impulse response functions of abatement investment in percentage points (*IRF of Abatement Inv.(%)* on the y-axis) for different groups of firms over a ten-year horizon, following an elevated policy uncertainty shock. The economy begins in its steady state at time 1, with normal policy uncertainty. At time 2, an unexpected shock to policy uncertainty in environmental regulation occurs, doubling its volatility. Firms are categorized as either more constrained or less constrained based on their net worth, with each group accounting for approximately half of the total net worth of the economy.



5.4 Impulse Responses to Policy Uncertainty Shocks

Figure 5 displays the impulse responses of aggregate abatement investment to a calibrated policy uncertainty shock to environmental regulations. Additionally, the figure provides a breakdown of abatement investment from two groups of firms - more and less constrained - which each account for roughly half of the economy's net worth. The aggregate impulse response demonstrates that abatement investment would decrease by roughly 6% immediately following the policy uncertainty shock. Moreover, the decomposition shows that more constrained firms are approximately three times more responsive than their less constrained counterparts. These impulse responses demonstrate that both financial frictions and policy uncertainty have significant impacts on aggregate abatement investment and pollution prevention.

6 Conclusion

This paper explores the relationship between financial frictions and environmental policy uncertainty on firms' abatement investment. We address endogeneity concerns by utilizing election- or text-based measures of uncertainty and leverage both time-series and cross-sectional variations in these measures. Our analysis examines the impact of environmental policy uncertainty on firms' abatement investment, toxic emissions, and debt issuance. Empirical findings indicate that environmental policy uncertainty decreases abatement investment, increases toxic emissions, and reduces debt financing activities, particularly for financially constrained firms.

To formalize our intuitions, we develop a simple model with two essential components: financial friction and environmental policy uncertainty. This model provides predictions that the combination of financial frictions and uncertainty will negatively impact firms' abatement investment. Additionally, financially constrained firms will incur higher marginal costs of pollution abatement, leading to reduced abatement investment and higher emissions. These predictions align with our empirical findings.

To further quantify the dynamics among financial constraints, uncertainty, and abatement investments, we develop a general equilibrium model with heterogeneous firms. This model features the dynamics of financial constraints and abatement investments, allowing us to match the evidence from U.S. firms in recent decades. Overall, our model and quantitative analysis formalize our intuition and provide further support for the role of financial frictions and policy uncertainty in firms' abatement investment decisions.

With the empirical analyses and model development presented in this paper, we have identified an interactive amplification effect between financial constraints and environmental policy uncertainty. This finding has important policy implications for the effectiveness of environmental regulations and the role of external financing in mitigating environmental externalities. Specifically, our results suggest that reducing policy uncertainty and improving access to external financing for financially constrained firms can lead to more effective pollution abatement and mitigation. This highlights the need for policymakers to consider the interaction between financial constraints and environmental policy uncertainty when designing environmental regulations and financing programs.

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Table 1: Summary Statistics

This table provides facility-level summary statistics in Panel A and firm-level summary statistics in Panel B. The binary variable for election-based uncertainty equals one if the most recent state governor vote differential is within 5%, as defined by Akey (2015), Brogaard and Detzel (2015), and Bhattacharya et al. (2017). The text-based uncertainty is measured using computational linguistics to calculate the share of the conversation regarding uncertainty during conference calls, following Hassan et al. (2019), Hassan et al. (2020a), and Hassan et al. (2020b). Abatement Investment represents the number of pollution prevention activities undertaken by a facility. Abatement-adj. Investment is the number of pollution prevention activities adjusted for emission reductions. Emissions represent the total emissions produced in pounds by a facility. Employment denotes the number of employees in a facility, while Sales refer to the facility-level sales revenue. ME is the market capitalization deflated by CPI and measured in 2009 million USD at the end of the fiscal year. B/M is the ratio of book equity to market capitalization. I/K represents capital expenditure divided by property, plant, and equipment. Return on assets (ROA) is operating income after depreciation scaled by total assets. Debt growth is the annual log growth rate of the summation of current and long-term liabilities. The WW index measures financial constraints, following Whited and Wu (2006), while the SA index measures financial constraints using the size-age index, following Hadlock and Pierce (2010). Book leverage (Leverage) is the ratio of the summation of current liabilities and long-term debt to total assets. The lease capital ratio is the ratio of leased capital over the sum of leased capital and owned capital, where the leased capital is ten times rental expense. Tobin's q is the ratio of the summation of market capitalization and the book value of preferred shares to total assets, after deducting inventories. The table reports the mean, median, standard deviation (Std), 5^{th} percentile (P5), 25^{th} percentile (P25), 75^{th} percentile (P75), and 95^{th} percentile (P95) of the pooled data. Observations denote the valid number of observations for each variable. The sample period is from 1991 to 2017 at an annual frequency, except for the text-based uncertainty, which covers the period from 2004 to 2017.

	Observations	**Mean**	**Std**	**P5**	**P25**	**P50**	**P75**	**P95**
Panel A: Facility-Level Summary Statistics								
Abatement Investment	152,621	0.85	3.38	0.00	0.00	0.00	0.00	4.00
Abatement-adj. Investment	152,621	6.37	12.75	1.00	1.00	3.00	6.00	22.00
Election-based Uncertainty	152,275	0.24	0.43	0	0	0	0	1
Text-based Uncertainty	64,681	3404.26	5963.95	0.00	619.97	1632.65	3667.26	12834.26
Emissions	114,953	268,332.32	2,170,260	0.00	15.00	3,000.00	39,205.40	945,144.1
Sale	152,610	144.03	467	2.2	13.73	38.19	105.76	562.43
Employment	70,260	575.51	1,417.28	12	75	200	505	2,100
ME	152,576	25719.88	64498.5	132.88	1120.2	4486.32	17505.55	141199.3
B/M	152,314	0.61	0.84	0.16	0.32	0.49	0.74	1.30
I/K	150,892	0.17	0.09	0.06	0.11	0.15	0.20	0.32
ROA	152,416	0.13	0.07	0.04	0.09	0.13	0.17	0.24
WW	150,219	-0.42	0.10	-0.58	-0.49	-0.43	-0.36	-0.25
SA	152,618	-4.19	0.56	-4.64	-4.64	-4.47	-3.83	-3.12
Leverage	152,514	0.27	0.15	0.04	0.17	0.26	0.36	0.54
Lease	152,366	0.26	0.18	0.00	0.13	0.25	0.38	0.56
Tobin's q	141,047	1.58	0.77	0.91	1.12	1.38	1.80	2.84
Debt Growth (%)	146,797	5.20	55.37	-43.83	-12.29	-1.16	15.62	75.56
Income per Capita	152,621	32,591.72	9,802.37	18,989	24,503	31,474	39,454	49,738
Popolation	152,621	10,329,257	8,625,179	1,846,341	4,528,996	7,042,818	12,298,970	31,696,582
Rep Ratios	152,275	0.53	0.28	0.00	0.25	0.50	0.75	1.00
Panel B: Firm-Level Summary Statistics								
ME	23,645	10757.37	32718.55	41.18	325.51	1423.31	6166.25	49444.42
B/M	23,555	0.68	0.91	0.15	0.34	0.53	0.82	1.59
I/K	23,353	0.18	0.12	0.05	0.11	0.16	0.23	0.39
ROA	23,585	0.13	0.09	0.02	0.09	0.13	0.17	0.26
WW	22,970	-0.36	0.11	-0.53	-0.44	-0.36	-0.29	-0.19
SA	23,662	-3.89	0.67	-4.64	-4.57	-3.97	-3.37	-2.76
Leverage	23,615	0.26	0.16	0.00	0.14	0.25	0.36	0.55
Lease	23,570	0.29	0.21	0.00	0.13	0.26	0.42	0.68
Tobin's q	22,010	1.62	1.05	0.84	1.07	1.35	1.82	3.23
Debt Growth	21,613	4.39	71.39	-63.81	-15.26	-1.97	16.24	95.44

Table 2: Abatement Investment and Environmental Policy Uncertainty

This table presents the findings of a Poisson regression (an OLS regression) that examines the relationship between abatement investment and environmental policy uncertainty, as well as the joint link between abatement investment, environmental policy uncertainty, and financial constraint. We estimate a Poisson regression (an OLS regression) by regressing abatement investment (the logarithm of abatement investment), abatement investment is defined as a count variable reflecting the simple or the emission-reduction-adjusted total number of abatement activities for firm i's facility p located in state s, on the measure of environmental policy uncertainty, which denotes the election-based uncertainty in Panel A1 and A2 and the text-based uncertainty in Panel B1 and B2, together with other firm characteristics, including the logarithm of market capitalization (Size), book-to-market ratio (B/M), investment rate (I/K), and profitability (ROA) in year t, and local economic fundamentals in year t, including the state-level income per capita and the logarithm of population, as well as facility and year fixed effects. All independent variables are normalized to a zero mean and unit standard deviation after winsorization at the 1st and 99th percentiles to reduce the impact of outliers. t-statistics based on standard errors that are clustered at the facility level are reported in parentheses. The sample period is from 1991 to 2017 in Panel A1 and A2 and 2004 to 2017 in Panel B1 and B2, respectively.

	Panel A1: Election-Based Uncertainty							
	Poisson				**OLS**			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
σ_τ	0.00	0.01	-0.00	0.01	-0.00	-0.00	-0.00	-0.00
	(0.21)	(0.61)	(-0.05)	(0.38)	(-0.17)	(-0.12)	(-0.27)	(-0.25)
WW	-0.01	-0.03			-0.01	-0.01		
	(-0.21)	(-0.66)			(-0.74)	(-1.46)		
WW $\times$ σ_τ	-0.06	-0.06			-0.01	-0.01		
	(-3.70)	(-3.73)			(-2.86)	(-2.63)		
SA			-0.19	-0.21			-0.05	-0.06
			(-4.41)	(-4.57)			(-4.46)	(-4.51)
SA $\times$ σ_τ			-0.04	-0.04			-0.01	-0.01
			(-2.52)	(-2.61)			(-1.72)	(-1.69)
Log ME		-0.04		-0.08		-0.01		-0.02
		(-0.80)		(-1.95)		(-1.11)		(-1.80)
B/M		0.02		0.00		0.00		0.00
		(1.25)		(0.16)		(1.26)		(0.94)
I/K		-0.00		-0.00		0.00		0.00
		(-0.47)		(-0.07)		(0.35)		(0.59)
ROA		0.02		0.02		0.00		0.00
		(1.38)		(1.34)		(1.22)		(1.09)
Income per Capita		0.07		0.08		-0.05		-0.05
		(0.82)		(0.93)		(-2.42)		(-2.36)
Log Population		0.16		0.21		0.05		0.05
		(0.71)		(0.96)		(0.76)		(0.84)
Rep Ratios	-0.01	-0.00	-0.01	-0.00	0.00	0.00	-0.00	-0.00
	(-0.39)	(-0.25)	(-0.32)	(-0.21)	(0.06)	(0.02)	(-0.04)	(-0.06)
Observations	91,433	89,990	93,096	91,351	149,882	148,130	152,272	150,150
Facility FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

	Panel A2: Election-Based Uncertainty							
Adjusted Abatement	**Poisson**				**OLS**			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
σ_τ	-0.02	-0.02	-0.02	-0.02	-0.07	-0.07	-0.08	-0.08
	(-2.43)	(-2.40)	(-2.67)	(-2.60)	(-1.69)	(-1.63)	(-2.01)	(-2.00)
WW	-0.01	-0.01			-0.16	-0.09		
	(-0.45)	(-0.81)			(-1.78)	(-0.94)		
WW $\times$ σ_τ	-0.02	-0.01			-0.11	-0.11		
	(-2.44)	(-2.20)			(-2.96)	(-2.72)		
SA			-0.03	-0.04			-0.52	-0.55
			(-1.55)	(-2.00)			(-4.25)	(-4.25)
SA $\times$ σ_τ			-0.02	-0.02			-0.12	-0.11
			(-2.63)	(-2.27)			(-3.02)	(-2.68)
Log ME		-0.01		-0.02		0.07		-0.04
		(-0.70)		(-0.94)		(0.60)		(-0.32)
B/M		0.01		0.01		0.09		0.07
		(1.83)		(1.70)		(2.59)		(2.15)
I/K		0.00		0.00		0.04		0.04
		(0.85)		(0.60)		(1.86)		(1.63)
ROA		0.01		0.01		0.01		0.01
		(1.65)		(1.65)		(0.26)		(0.41)
Income per Capita		-0.05		-0.05		-0.25		-0.25
		(-1.60)		(-1.61)		(-1.25)		(-1.22)
Log Population		0.13		0.12		1.03		0.97
		(1.44)		(1.35)		(1.54)		(1.47)
Rep Ratio	0.01	0.01	0.01	0.01	0.04	0.04	0.04	0.04
	(1.23)	(1.24)	(1.20)	(1.23)	(0.96)	(0.90)	(0.88)	(0.86)
Observations								
Facility FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

	Panel B1: Text-Based Uncertainty							
	Poisson				OLS			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
σ_τ	-0.02	-0.02	-0.02	-0.02	-0.00	-0.00	-0.00	-0.00
	(-1.71)	(-1.73)	(-1.71)	(-1.78)	(-1.13)	(-1.05)	(-0.91)	(-0.83)
WW	-0.10	-0.20			-0.01	-0.01		
	(-1.50)	(-2.52)			(-0.98)	(-1.35)		
WW $\times$ σ_τ	-0.03	-0.02			-0.00	-0.00		
	(-2.55)	(-2.43)			(-2.39)	(-2.39)		
SA			-0.44	-0.47			-0.06	-0.06
			(-4.21)	(-4.43)			(-3.85)	(-3.83)
SA $\times$ σ_τ			-0.03	-0.03			-0.00	-0.00
			(-2.91)	(-2.89)			(-2.25)	(-2.22)
Log ME		-0.19		-0.15		-0.01		-0.01
		(-2.07)		(-1.88)		(-0.62)		(-0.87)
B/M		-0.02		0.00		0.00		0.00
		(-0.61)		(0.18)		(0.04)		(0.29)
I/K		-0.01		-0.01		-0.00		-0.00
		(-0.36)		(-0.27)		(-1.13)		(-0.95)
ROA		0.08		0.08		0.01		0.01
		(3.78)		(3.77)		(2.81)		(2.67)
Income per Capita		0.27		0.26		0.01		0.01
		(2.23)		(2.18)		(0.56)		(0.59)
Log Population		0.50		0.60		0.01		0.00
		(0.89)		(1.07)		(0.07)		(0.03)
Observations	25,575	25,487	25,793	25,689	64,142	63,968	64,679	64,464
Facility FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B2: Text-Based Uncertainty								
Adjusted Abatement	**Poisson**				**OLS**			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
σ_τ	-0.00	-0.00	-0.00	-0.00	-0.01	-0.01	-0.01	-0.01
	(-0.81)	(-0.77)	(-0.78)	(-0.72)	(-0.54)	(-0.45)	(-0.62)	(-0.55)
WW	-0.01	-0.02			-0.09	-0.14		
	(-1.07)	(-1.37)			(-1.22)	(-1.63)		
WW $\times$ σ_τ	-0.00	-0.00			-0.02	-0.02		
	(-1.92)	(-1.96)			(-1.73)	(-1.70)		
SA			-0.08	-0.08			-0.51	-0.52
			(-3.40)	(-3.37)			(-3.76)	(-3.82)
SA $\times$ σ_τ			-0.01	-0.01			-0.03	-0.03
			(-2.67)	(-2.65)			(-2.56)	(-2.54)
Log ME		-0.02		-0.02		-0.11		-0.13
		(-0.89)		(-1.12)		(-1.01)		(-1.31)
B/M		-0.00		-0.00		-0.01		-0.01
		(-0.19)		(-0.09)		(-0.44)		(-0.25)
I/K		0.00		0.00		0.00		0.00
		(0.09)		(0.17)		(0.03)		(0.14)
ROA		0.00		0.00		0.04		0.03
		(1.26)		(1.15)		(1.63)		(1.54)
Income per Capita		0.03		0.03		0.18		0.19
		(1.18)		(1.25)		(1.18)		(1.26)
Log Population		0.08		0.08		0.45		0.44
		(0.72)		(0.65)		(0.63)		(0.61)
Observations	63,144	62,956	63,725	63,494	64,142	63,968	64,679	64,464
Facility FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 3: Toxic Emissions and Environmental Policy Uncertainty

This table examines the relationship between toxic emissions and environmental policy uncertainty, as well as the joint link between toxic emissions, environmental policy uncertainty, and financial constraint. We regress the logarithm of the facility-level emissions on the measure of environmental policy uncertainty, which denotes the election-based uncertainty in Specifications (1) to (4) or as the text-based uncertainty in Specifications (5) to (8), together with other firm characteristics, including the logarithm of market capitalization (Size), book-to-market ratio (B/M), investment rate (I/K), and profitability (ROA) in year t, and local economic fundamentals in year t, including the state-level income per capita and the logarithm of population, as well as facility and year fixed effects. All independent variables are normalized to a zero mean and unit standard deviation after winsorization at the 1st and 99th percentiles to reduce the impact of outliers. t-statistics based on standard errors that are clustered at the facility level are reported in parentheses. The sample period is from 1991 to 2017 when we use election-based uncertainty, and from 2004 to 2017, when we use text-based uncertainty, respectively.

	Election-Based				**Text-Based**			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
σ_τ	-0.03	-0.03	0.39	0.37	-0.01	-0.01	-0.01	-0.01
	(-0.95)	(-0.82)	(1.65)	(1.56)	(-1.06)	(-1.03)	(-1.39)	(-1.33)
WW	-0.06	-0.07			-0.01	-0.01		
	(-0.83)	(-0.73)			(-1.41)	(-1.04)		
WW $\times$ σ_τ	0.08	0.08			0.02	0.02		
	(2.46)	(2.46)			(2.56)	(2.62)		
SA			-0.13	-0.16			0.02	0.02
			(-1.57)	(-1.81)			(4.06)	(4.07)
SA $\times$ σ_τ			0.18	0.17			0.01	0.01
			(1.81)	(1.71)			(2.02)	(2.09)
Log ME		0.03		-0.03		0.03		-0.02
		(0.23)		(-0.36)		(0.64)		(-0.61)
B/M		0.01		-0.00		0.00		-0.01
		(0.60)		(-0.01)		(0.12)		(-0.45)
I/K		0.01		0.02		0.01		0.01
		(0.57)		(0.85)		(1.10)		(1.16)
ROA		0.05		0.05		0.00		0.01
		(2.19)		(2.44)		(0.36)		(0.64)
Income per Capita		-0.28		-0.27		0.05		0.04
		(-1.64)		(-1.64)		(0.92)		(0.90)
Log Population		-0.06		-0.06		-0.02		0.02
		(-0.69)		(-0.71)		(-0.04)		(0.05)
Rep Ratios	-0.01	0.00	-0.01	0.00				
	(-0.23)	(0.04)	(-0.21)	(0.06)				
Observations	112,894	111,893	114,746	113,649	64,280	64,142	65,028	64,853
R-squared	0.72	0.72	0.72	0.72	0.92	0.92	0.92	0.92
Facility FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 4: Debt Issuance and Environmental Policy Uncertainty

This table examines the relationship between debt issuance and environmental policy uncertainty, as well as the joint link between debt issuance, environmental policy uncertainty, and financial constraint. We regress the debt growth on the measure of environmental policy uncertainty, which denotes the election-based uncertainty in Specifications (1) and (2) or as the text-based uncertainty in Specifications (3) and (4), together with other firm characteristics, including the logarithm of market capitalization (Size), book-to-market ratio (B/M), investment rate (I/K), and profitability (ROA), financial leverage, leased capital ratio, and Tobin's q in year t, as well as facility and year fixed effects. All independent variables are normalized to a zero mean and unit standard deviation after winsorization at the 1st and 99th percentiles to reduce the impact of outliers. t-statistics based on standard errors that are clustered at the firm level are reported. The sample period is from 1991 to 2017, when we use election-based uncertainty, and from 2004 to 2017, when we use text-based uncertainty, respectively.

	Election-Based		**Text-Based**	
	(1)	**(2)**	**(3)**	**(4)**
σ_τ	-0.59	0.07	-0.87	-1.13
	(-0.19)	(0.02)	(-1.13)	(-1.40)
WW	-6.52		-15.87	
	(-1.92)		(-0.55)	
WW $\times$ σ_τ	-3.59		-1.71	
	(-1.23)		(-2.11)	
SA		1.41		-7.38
		(0.45)		(-1.11)
SA $\times$ σ_τ		-6.42		-1.57
		(-2.11)		(-2.00)
Log ME	-14.9	-9.29	-11.44	-11.99
	(-4.01)	(-3.00)	(-2.80)	(-3.62)
B/M	-2.84	-2.45	-9.43	-9.77
	(-2.92)	(-2.67)	(-7.21)	(-8.23)
I/K	5.54	5.27	3.40	3.85
	(5.90)	(5.71)	(2.27)	(2.68)
ROA	2.59	2.37	1.23	0.28
	(2.26)	(2.10)	(0.42)	(0.10)
Leverage	-32.34	-32.82	-42.32	-43.43
	(-28.00)	(-28.66)	(-28.87)	(-29.83)
Lease	-4.48	-4.69	-1.31	-1.98
	(-2.99)	(-3.17)	(-0.52)	(-0.80)
q	10.33	9.39	10.06	10.40
	(4.04)	(4.80)	(4.26)	(4.91)
Observations	14,299	14,313	15,562	16,196
R-squared	0.15	0.15	0.26	0.27
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Cluster SE	Yes	Yes	Yes	Yes

Table 5: Calibrated Parameter Values and Sources

This table presents the parameters used in the model, including both fixed and fitted parameters. The model operates at an annual frequency. The fixed parameters are based on existing literature and include the time discount rate ($\beta = 0.96$), chosen to match the average risk-free rate of 4% per year, and the unit elasticity of intertemporal substitution for log utility ($\gamma = 1$). On the firm side, the capital coefficient ($\alpha = 0.65$) is set to match an implied decreasing-return-to-scale of two-thirds, and capital is assumed to depreciate annually at a rate of 10% ($\delta_k = 0.10$), consistent with the average aggregate nonresidential fixed investment rate reported in Bachmann et al. (2013). The fitted parameters are chosen to match targeted moments from the firm-level data sample, which will be further discussed in Table 6.

Symbols	Descriptions	Values	Sources
Fixed Parameters			
β	Discount factor	0.96	Annual Frequency
γ	Elasticity of intertemporal substitution	1.00	Logarithmic Utility
α	Capital share	0.65	DRS of Two-thirds
δ_k	Capital depreciation rate	0.10	Bachmann et al. (2013)
ϕ	Aggregate capital adjustment cost	4.00	Bachmann et al. (2013)
θ_d	Exit liquidation value	0.40	Kermani and Ma (2023)
Fitted Parameters			
ρ_z	Productivity persistence (fixed)	0.90	Targeted Moments
σ_z	Productivity volatility	0.03	Targeted Moments
π_d	Exogenous exit risk	0.087	Targeted Moments
n_0	Net worth of entry	1.20	Targeted Moments
θ_k	Collateral constraint	0.40	Targeted Moments
δ_x	Abatement technology depreciation rate	0.02	Targeted Moments
$\bar{e}$	Default pollution emission intensity	10.0	Targeted Moments
μ	Mean of pollution penalty	0.005	Targeted Moments
p_τ	Probability of no pollution penalty (normal)	0.40	Targeted Moments
σ	Volatility of pollution penalty (normal)	0.03	Targeted Moments
p_τ^h	Probability of no pollution penalty (elevated)	0.70	Targeted Moments
σ^h	Volatility of pollution penalty (elevated)	0.075	Targeted Moments

Table 6: Targeted Moments: Model and Data

This table presents the firm-level moments that are utilized to calibrate the fitted parameters of the model. The emission intensity is measured in pounds/millions and is normalized. We start by selecting a default pollution emission intensity of $\bar{e} = 10$ and an abatement technology depreciation rate of $\delta_x = 0.02$ to simultaneously fit the distribution of emission intensity, which is measured as the emission-to-sales ratio in the model. Next, we select the probability of no pollution penalty as $p_\tau = 0.40$, the mean of pollution penalty as $\mu_\tau = 0.02$, the volatility of pollution penalty during normal period as $\sigma_\tau^l = 0.02$, and the volatility of pollution penalty during elevated policy uncertainty period as $\sigma_\tau^l = 0.04$, to simultaneously fit the distribution of pollution penalty, which is measured as the litigation-to-sales ratio.

Moments	**Data**	**Model**
Output and Finance		
1-year autocorrelation of output	0.89	0.90
3-year autocorrelation of output	0.69	0.71
5-year autocorrelation of output	0.53	0.56
Size ratio of entrant relative to average	0.28	0.28
Annual exit rate of firms	0.09	0.09
Mean of debt/asset ratio	0.34	0.34
Pollution and Abatement		
Mean of emission intensity	5.38	4.16
Median of emission intensity	5.66	4.45
Standard deviation of emission intensity	3.05	1.82
P75/P25 of emission intensity	1.98	1.56
Ratio of zero pollution penalty	0.40	0.40
Mean of pollution penalty	0.02	0.02
Standard deviation of pollution penalty (normal)	0.02	0.02
Standard deviation of pollution penalty (elevated)	0.04	0.04

Internet Appendix for "Pollution Abatement Investment under Financial Frictions and Policy Uncertainty"*

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Contents

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A The Database and Supplementary Analyses

A.1 The TRI Database

The Toxic Release Inventory (TRI) program and the resultant database are maintained by the United States Environmental Protection Agency (EPA). In 1986, the U.S. Congress passed the Community Right to Know Act (EPCRA) in response to public concerns over releasing toxic chemicals from several environmental accidents in the U.S. and overseas. The EPCRA entitles residents in their respective neighborhoods to know the source of detrimental substances, especially for their potential impacts on human health from routes of exposure.

In response to the EPCRA, the EPA established the TRI program to track and supervise certain classifications of toxic substances and chemical pollutants that endanger human health and the environment.[1] In particular, the EPA mandates a record of the amount of each TRI-listed toxic chemical being released to the environment through the air, water, or soil each year for every facility that meets the following criteria:

1. It manufactures, processes, or otherwise uses a TRI-listed chemical in quantities above threshold levels in a given year.
2. It has ten or more full-time equivalent employees.
3. It is in the mining, utility, manufacturing, publishing, hazardous waste, or federal industry.

When a facility meets all three criteria in a year, it must report to the EPA and thus enters into the TRI program. The EPA then publicizes the TRI database, which contains detailed information about the TRI program and is available for any interested third party to access.[2]

To maintain the data quality of the information in the TRI program, the EPA first identifies if a TRI form submitted by a facility contains potential errors; if so, the EPA contacts the facility. Once the EPA confirms errors, the facility is requested to resubmit a corrected TRI report. In addition, the Office of Inspector General is an independent office within the EPA that performs audits, evaluations, and investigations of the agency and its contractors to prevent and detect fraud, waste, and abuse. The EPA then conducts an extensive quality analysis of the TRI reporting data and provides analytical support for enforcement efforts led by its Office of Enforcement and Compliance Assurance (OECA).

The annual emission data of all facilities reported to the EPA are updated on the webpage of the TRI program between July and September of the following year, as shown in Figure

[1] The changes and updates of the list of these pollutants are provided in /www.epa.gov/sites/production/files/2020-01/documents/tri_chemical_list_changes_01_21_2020.pdf

[2] The EPA also provides annual data on pollutant density recorded by air monitors. A single air monitor records the density of multiple pollutants at a fixed location every hour.

IA.1. It is worth noting that the TRI program has included approximately 98% of facility-level emission data in 2020 on July 20, 2022. Thus, in our empirical tests, such as our portfolio analysis, we construct portfolios at the end of September of year t to ensure that the information with respect to facility emissions in year $t-1$ is publicly available when we sort portfolios.

[Place Figure IA.1 about here]

We also notice that the TRI database may not be comprehensive before 1991, as we observe an abnormally high ratio of reported zeros in facilities' TRI-listed chemicals in pre-1991 years. We thus download and organize the facility-level TRI data from 1991 to 2017 as follows:

Step 1: We access the TRI program via the EPA website:
https://www.epa.gov/toxics-release-inventory-tri-program

[Place Figure IA.2 about here]

Step 2: We download the annual TRI data from 1991 to 2017.

[Place Figure IA.5 about here]

Step 3: For each facility in a year, we use the value "PROD._WASTE_(8.1_THRU_8.7)," which is the sum of the total released toxic pollutants (in pounds) across all chemical categories for each plant. Despite this, there are seven items reported in Section 8 of the TRI database, including item 8.1 (amount of total releases),[3] 8.2 (energy recovery on-site), 8.3 (energy recovery off-site), 8.4 (recycling on-site), 8.5 (recycling off-site), 8.6 (treatment on-site), 8.7 (treatment off-site), and PROD._WASTE_(8.1_THRU_8.7) (the sum of the quantities in items 8.1 through 8.7).[4]

Three issues are worth discussing before we proceed. First, the TRI database provides a link table with the facility-level Dun & Bradstreet number. As a result, we exploit the identifier to bridge the TRI database to the NETS database and obtain additional facility-level information, including sales and employment. Second, the TRI database also includes a "parent name" that indicates the name of a company that owns the facility. Thus, we can further use the "parent name" to bridge the TRI database to the CRSP/Compustat

[3]Since 2003, item 8.1 (amount of total releases) has been separated into four subitems and documented as item 8.1a (on-site contained releases), 8.1b (on-site other releases), 8.1c (off-site contained releases), and 8.1d (off-site other releases).

[4]Details obtained from https://www.epa.gov/sites/production/files/2019-08/documents/basic_data_files_documentation_aug_2019_v2.pdf.

database (e.g., Xiong and Png (2019)). Third, the TRI database has not changed the coverage of chemicals and pollutants to be disclosed.

A.2 The Pollution Prevention (P2) Database

We obtain the facility-level abatement activities from the Pollution Prevention (P2) database as follows:

Step 1: We access the P2 program via the EPA website: https://www.epa.gov/p2

[**Place Figure IA.4 about here**]

Step 2: We download the annual P2 data from 1991 to 2017.

[**Place Figure IA.5 about here**]

Step 3: For each facility in a year, we count the total number of abatement activities for each plant.

[**Place Figure IA.6 about here**]

We exploit the Pollution Prevention P2 database from the EPA to analyze abatement activities. As presented in Figure IA.6, EPA provides the waste management hierarchy starting from 1991. In addition, to release quantities for a released pollutant, plants reporting in the TRI database must document specific source reduction activities that mitigate the number of hazardous substances entering the waste stream: the quantities of the chemical recycled, used for energy recovery, or treated at the facility or elsewhere in addition to the original reporting requirements on releases emitted directly into the environment or transferred off-site to disposal, treatment, or storage facilities. Moreover, plants report optional waste minimization information on source reduction activities, such as process modifications and the substitution of raw materials, newly implemented during the reporting year. The rest but the most common type of abatement activity comprises several actions: modifications to equipment, layout, or piping.

[**Place Table IA.1 about here**]

The list of various abatement activities are available in Table IA.1. In our empirical analysis, we count the frequency of these process-related abatement and operating-related activities as plants' abatement intensity.

A.3 Matching TRI (NETS) with CRSP/Compustat

We extract facilities' parental names in the TRI (NETS) database and then match these names in the TRI database to the names of U.S. public companies in the CRSP/Compustat database. We first clean parent firm names in the TRI (NETS) database and firm names in the CRSP/Compustat database following the approach of Chen, Hsieh, Hsu, and Ross (2022). Specifically, we remove punctuation and clean special characters. We then convert firm names into upper case and standardize them. For example, we standardize "INDUSTRY" to "IND," "INCORPORATION" to "INC," and "COMPANY" to "COM."

To match facilities' parental firm names with firms in CRSP/Compustat based on standardized names, we use the fuzzy name-matching algorithm via SAS, which generates matching scores for all name pairs of parent names in TRI (NETS) and firms in CRSP/Compustat.[5] We obtain a pool of potential matches based on two criteria: (1) the matching score must be precisely 0 and thus the same as those of firms in the CRSP/Compustat database, and (2) the matching score must be below 500. We then hire research assistants to identify exact matches from all potential matches manually.

B Additional Empirical Results

In this section, we present additional empirical results and robustness tests.

B.1 Possible Explanation: Political Connections

Another possible explanation for the abatement-financial-constraint relation is that firms may adopt political investment strategies rather than pollution abatement activities to mitigate the risks associated with these negative environmental incidents (e.g., Cooper, Gulen, and Ovtchinnikov (2010), Smith (2016), Gloßner (2018), and among others), and therefore, the negative link between abatement investment and financial constraint may reflect the implications of political connections. If such channels are responsible as the first-order driving force, we would expect the limited effect of environmental policy uncertainty on pollution abatement investment among these political-connected firms. Therefore, there is no amplified abatement-financial-constraint relation upon the realization of uncertainty.

To validate this explanation, we handily collect annual firm-level political donation data from OpenSecrets.org, maintained by the Center for Responsive Politics.[6] We define a firm's

[5]The matching score measures the distance between two firms' names. The index score ranges from 0 to infinity, with a score of zero being a perfect match.

[6]This database is used by Bertrand, Bombardini, and Trebbi (2014) to measure firms' lobbying activities.

political connections as the total amount of political donation (regardless of party) in a year scaled by total assets. We include political donations as controls in the same specification of equation (1) in our primary paper and report results in Table IA.2.

[Place Table IA.2 about here]

To verify the relative importance of this channel with our main story, we implement horse racing tests to rule out the alternative explanation of political connections by regressing pollution abatement investment to control for a bundle of firm characteristics, including the measure of political connections (Donations and Donations/AT). As presented in Table IA.2, the coefficients on the measure of political connects are negative and statistically significant in some specifications. Consistent with the existing literature, high-politically connected firms contribute to congresses or presidential donations as a strategic resource to neutralize or manage environmental risk and thus substitute for their pollution abatement activities. However, from each column of Table IA.2, we find no evidence to suggest that the channel of political connections dampens the amplification channel on the interaction of financial constraint and environmental policy uncertainty proxied by the tie elections in Panel A or the textual analysis in Panel B. Hence, the political connection explanation is not likely to explain the amplification effect of environmental policy uncertainty on abatement investment when firms are subject to financial friction.

B.2 Emission Reduction and Pollution Abatement Investment

According to Xu and Kim (2022), the higher release of toxic emissions is driven by insufficient investment in pollution abatement among firms subject to financial frictions. We provide direct evidence by incorporating the joint link between facility-level abatement activity and emission reduction. The Pollution Prevention database includes information on how much facilities have reduced releases of each toxic chemical to the environment by which pollution prevention each year and compare how different facilities have managed their toxic releases. We sum up these reductions at the facility level each year. In Panel A of Table IA.3, we present a negative correlation coefficient between the reduction in toxic emissions (Reduction) and the abatement investment (x), which is significant at the 1% level.

[Place Table IA.3 about here]

We then examine the relation between facility-level emission reduction and abatement activity in a more formal way by estimating OLS regressions, for which we control a list of firm-level control variables, including size, book-to-market ratio, investment rate, and profitability, and state-level control variables for local fundamentals, including income per capita and population, as well as facility and year fixed effects. Standard errors are clustered at the facility level in Specifications 1 and 2 and the state level in Specifications 3 and 4. As presented in Panel B of Table IA.3, all specifications indicate that estimated coefficients on pollution abatement investment are statistically significantly negative at the 1% level, suggesting that pollution abatement investment effectively reduces toxic emissions. More importantly, evidence in this subsection provides us with a micro-foundation of a negative relation between emission and pollution abatement investment and calls for more theoretical work.

B.3 Robustness Tests

In Table IA.4, t-statistics based on standard errors that are clustered at the state level are reported.

[Place Table IA.4 about here]

In Table IA.5, we use the firm-level measure of uncertainty constructed using textual analysis ((Hassan, Hollander, Van Lent, and Tahoun (2019), Hassan, Hollander, Van Lent, Schwedeler, and Tahoun (2020a), and Hassan, Hollander, Van Lent, and Tahoun (2020b))). t-statistics based on standard errors that are clustered at the facility and state level are reported in Tables IA.5 and IA.6, respectively.

[Place Tables IA.5 and IA.6 about here]

For the robustness, we consider an alternative measure of abatement investment, which is the number of unique pollution abatement activities (unique W codes), and implement the analyses using standard errors clustered at the facility or state levels and using close elections or firm-level uncertainty (Hassan et al. (2019), Hassan et al. (2020a), and Hassan et al. (2020b)). Our results are reported in Tables IA.7, IA.8, IA.9, and IA.10.

[Place Tables IA.7, IA.8, IA.9, and IA.10 about here]

C The Computation Methods

Part I: Solving the Stationary Equilibrium - Outer Loop

We first assume the economy is at the steady state with a specific environmental policy uncertainty structure $T^* = \{\mu_\tau^*, \sigma_\tau^*\}$ and the steady-state distribution of the firms $\mu^*(z, x, n)$.

There are no aggregate shocks to the environmental policy uncertainty and no other aggreagte shocks, so we solve the steady state as follows:

Step.1. Fix the equilibrium aggregate prices $P^* = \{\Lambda^* = \beta, q^* = 1\}$;

Step.2. Solve the firm's problem using Value Function Iteration;

Step.3. Calculate aggregate variables from the firm distribution using Young (2010);

Define $\Omega^* = \{P^*, T^*, \mu^*\}$ as the aggregate state, after solving the steady state, we have the stationary equilibrium aggregate prices $P^* = \{\Lambda^* = \beta, q^* = 1\}$, environmental policy uncertainty structure $T^* = \{\mu_\tau^*, \sigma_\tau^*\}$, aggregate quantities $\{Y^*(\Omega^*)$, $C^*(\Omega^*)$, $K^*(\Omega^*)$, $A^*(\Omega^*)\}$, firm value function $\{V^*(z, x, n; \Omega^*)$, policy functions $k'^*(z, x, n; \Omega^*)$, $a'^*(z, x, n; \Omega^*)$, $b'^*(z, x, n; \Omega^*)\}$, and distribution $\mu^*(z, x, n; \Omega^*)$ at the solved stationary steady state.

Part II: Solving the Stationary Equilibrium - Inner Loop

Now we describe more details on the inner loop, which is the Step.2 above. We choose a grid-based value function iteration method. Below we show the initiating of VFI:

Step.1. Discretize the states/choices $\{z, n, \tau, b\}$. For z, we use the Tauchen method to discretize z into N_z states, with underlying grid values $\{z_1, z_2, ..., z_{N_z}\}$ and an $N_z \times N_z$ transition matrix Π_z. For τ, we discretize it into N_τ states, with underlying grid values $\{\tau_1, \tau_2, ..., \tau_{N_\tau}\}$, and the i.i.d probability $N_\tau \times 1$ vectors P_τ. For $\{n\}$, we use the log grids to discretize into N_n states. For $\{b\}$, we discretize b (debt as a ratio of capital) into N_b choices, with underlying grid values $\{b_1, b_2, ..., b_{N_b}\}$ where $b_1 = 0$ and $b_{N_b} = \theta_k$.

Step.2. Discretize the state $\{x\}$ and the calculation of the corresponding control policy $\{a\}$. To reduce the computational burden, we choose discrete grids of the abatement technology x. We use log grid values $\{x_1, x_2, ..., x_{N_x}\}$. Corresponding, the abatement investment a depends on the firm's choice for the next period state of abatement technology. The abatement investment required to jump from x_t to x_{t+1} equals $\left(\frac{x_{t+1}}{x_t} - (1-\delta_x)\right)^{1/\eta}$. Therefore, we would have an $N_x \times N_x$ Abatement matrix A_x which the element of changing state from x_n to x_m is $A_x(x_n, x_m) = \max\left\{0, \left(\frac{x_m}{x_n} - (1-\delta_x)\right)^{1/\eta}\right\}$.

Step.3. Given the iteration t value function $v^t(z, x, n)$, we first solve the decision rules $a'(z, x, n)$, $k'(z, x, n)$, $b'(z, x, n)$, then update the value function, until convergence.

Part III: Solving the Transitional Equilibrium

With the stationary equilibrium solutions in hand, we now move to the solution of the transitional equilibrium using a shooting algorithm. The key assumption here is that after a sufficiently long time, the economy will always converge back to its initial or the new stationary equilibrium (depends on the property of the shocks) after any unexpected shocks. The following steps outline the shooting algorithm:

Step 1. Fix a sufficiently long transition period t = 1 to t = T (say 200);

Step 2. Guess a sequence of aggregate prices $\{w_t, \Lambda_t, q_t\}$ of length T such that the initial prices $\{w_1 = w^*, \Lambda_1 = \Lambda^*, q_1 = 1\}$ (simply assuming all the prices stay at steady state works well) and terminal prices $\{w_T = w^*, \Lambda_T = \Lambda^*, q_T = 1\}$. Provide a predetermined shock process of interest, i.e., the mean and uncertainty of environmental regulation $\{T_t\}_{t=1}^{T}$. This implies a time series for the aggregate state $\{\Omega_t\}_{t=1}^{T}$. The aggregate state is just time t.

Step 3. We know that at time T, the economy is back to its steady state. I have the steady state value function $V(z, x, n; \Omega_T) = V^*(z, x, n; \Omega^*)$ in hand for time T. We solve for the firms' problem by ***backward induction*** given $V(z, x, n; \Omega_T)$ and $\{w_{T-1}, \Lambda_{T-1}, q_{T-1}\}$. This yields the firm value function $V(z, x, n; \Omega_{T-1})$ and associated policy functions for capital $k'(z, x, n; \Omega_{T-1})$, abatement $a'(z, x, n; \Omega_{T-1})$, debt $b'(z, x, n; \Omega_{T-1})$, and labor $l(k, z; \Omega_{T-1})$. By iterating backward, We solve the whole series of both policy functions $\{k'(z, x, n; \Omega_{T-1})\}_{t=1}^{T}$, $\{a'(z, x, n; \Omega_{T-1})\}_{t=1}^{T}$, $\{b'(z, x, n; \Omega_{T-1})\}_{t=1}^{T}$, $\{l'(z, x, n; \Omega_{T-1})\}_{t=1}^{T}$.

Step 4. Given the policy functions and the steady state distribution as the initial distribution $\mu(z, x, n; \Omega_1) = \mu(z, x, n; \Omega^*)$, We use ***forward simulation*** with the non-stochastic simulation in Young (2010) to recover the whole path $\{\mu(z, x, n; \Omega_t)\}_{t=1}^{T}$.

Step 5. Using the distribution $\{\mu(z, x, n; \Omega_t)\}_{t=1}^{T}$, We obtain all the ***aggregate quantities***: aggregate output $\{Y\}_{t=1}^{T}$, aggregate investment $\{I\}_{t=1}^{T}$, aggregate abatement $\{A\}_{t=1}^{T}$, aggregate debt $\{B\}_{t=1}^{T}$, and aggregate labor demand $\{L\}_{t=1}^{T}$. We then use the goods market clearing condition to calculate aggregate consumption $\{C\}_{t=1}^{T}$. We then calculate the *Excessive Demand* $\{\Delta C\}_{t=1}^{T}$ by taking the differences between currently iterated $\{C\}_{t=1}^{T}$ and the previous iteration $\{C_{old}\}_{t=1}^{T}$.

Step 6. Given all the aggregate quantities in the previous step and the *Excessive Demand* $\{\Delta C\}_{t=1}^{T}$, We update all the ***aggregate prices***. We update all equilibrium prices with a line search: $X_t^{new} = speed \cdot f_X(\{\Delta C\}_{t=1}^{T}) + (1 - speed) \cdot X_t^{old}$. Repeat Steps 2-7 until X_t^{new} and X_t^{old} are close enough. The $f_X(\{\Delta C\}_{t=1}^{T})$ is chosen by the connections of the prices with the *Excessive Demand* $\{\Delta C\}_{t=1}^{T}$ through the equations of the prices. Updating all prices in all periods simultaneously reduces the computational burden dramatically.[7] This updating rule allows me to solve the transitional equilibrium in seconds on a standard dual-core laptop without any parallel computation.

In all the experiments with both the Taylor rule shock and a volatility shock, We set T

[7] There is an alternative updating rule which is more stable but much more time consuming. In put it here: Step 6'. Using the household first order condition for consumption $\{C\}_{t=1}^{T}$, I obtain a new $\{\Lambda\}_{t=1}^{T}$; using the household first order condition for labor, $\{C\}_{t=1}^{T}$, and $\{N\}_{t=1}^{T}$, I obtain a new $\{w\}_{t=1}^{T}$; using the definitions of the stochastic discount factor and Taylor rule simultaneously, I update π_{t+1} with Λ_t, R_t^n, then I update R_{t+1}^n with the updated π_{t+1}, and repeat until I have a new $\{R^n\}_{t=0}^{T}$ and $\{\pi\}_{t=1}^{T}$. Finally, I obtain a new $\{p^w\}_{t=1}^{T}$ through the New Keynesian Phillips curve.

= 100, and a step size of 0.01 to ensure convergence, with the necessary distance between X_t^{new} and X_t^{old} smaller than 1e-7. We also tested with various T from 50 to 400 to ensure that the choice of T = 100 does not affect the accuracy of the solution.

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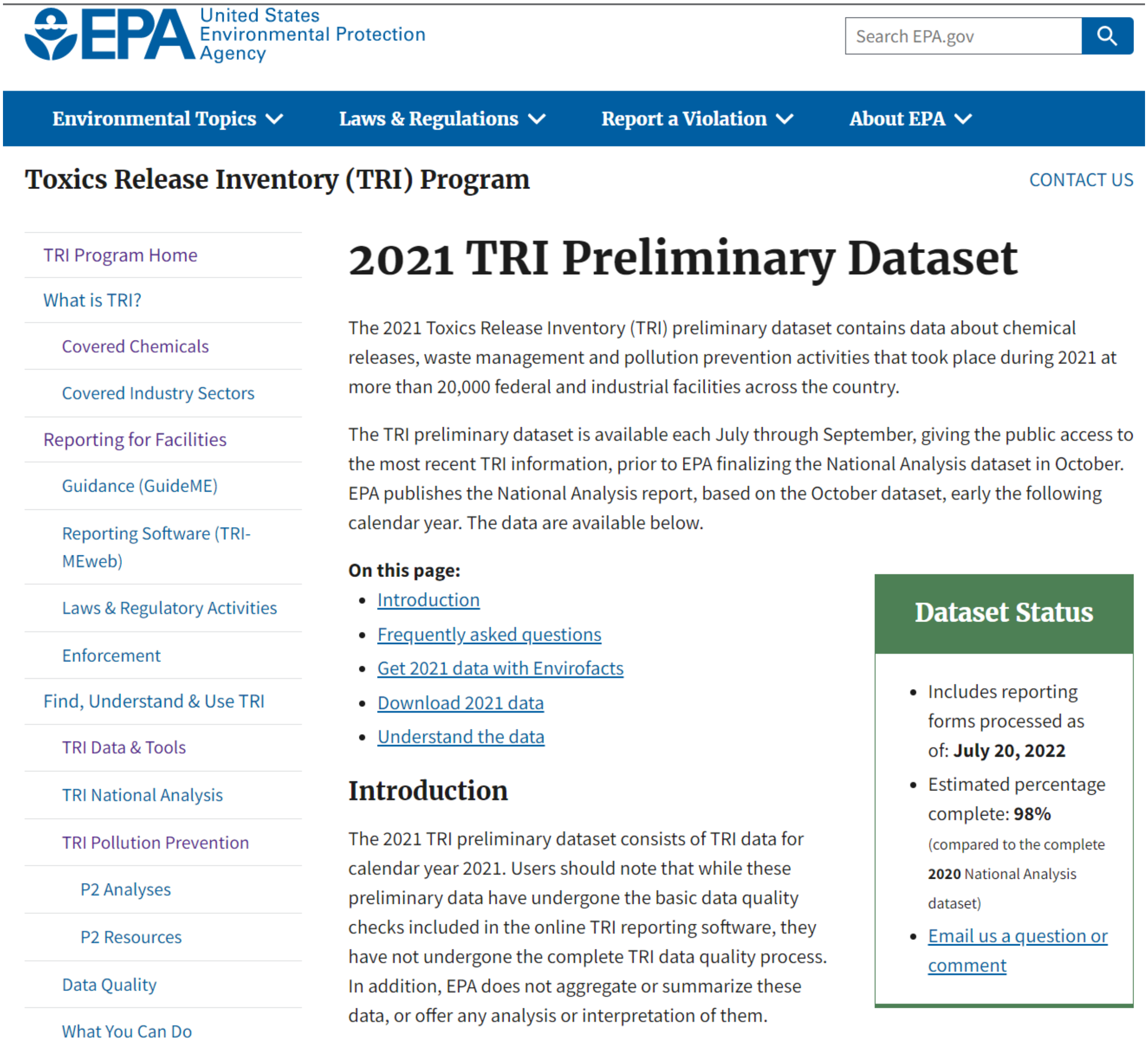
Figure IA.1. The Annual Updates of the TRI Program



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2021 TRI Preliminary Dataset

The 2021 Toxics Release Inventory (TRI) preliminary dataset contains data about chemical releases, waste management and pollution prevention activities that took place during 2021 at more than 20,000 federal and industrial facilities across the country.

The TRI preliminary dataset is available each July through September, giving the public access to the most recent TRI information, prior to EPA finalizing the National Analysis dataset in October. EPA publishes the National Analysis report, based on the October dataset, early the following calendar year. The data are available below.

On this page:

- Introduction
- Frequently asked questions
- Get 2021 data with Envirofacts
- Download 2021 data
- Understand the data

Dataset Status

- Includes reporting forms processed as of: **July 20, 2022**
- Estimated percentage complete: **98%** (compared to the complete **2020** National Analysis dataset)
- Email us a question or comment

Introduction

The 2021 TRI preliminary dataset consists of TRI data for calendar year 2021. Users should note that while these preliminary data have undergone the basic data quality checks included in the online TRI reporting software, they have not undergone the complete TRI data quality process. In addition, EPA does not aggregate or summarize these data, or offer any analysis or interpretation of them.

Source:
https://www.epa.gov/toxics-release-inventory-tri-program/2021-tri-preliminary-dataset

Figure IA.2. Access to the TRI Database

Source: https://www.epa.gov/toxics-release-inventory-tri-program

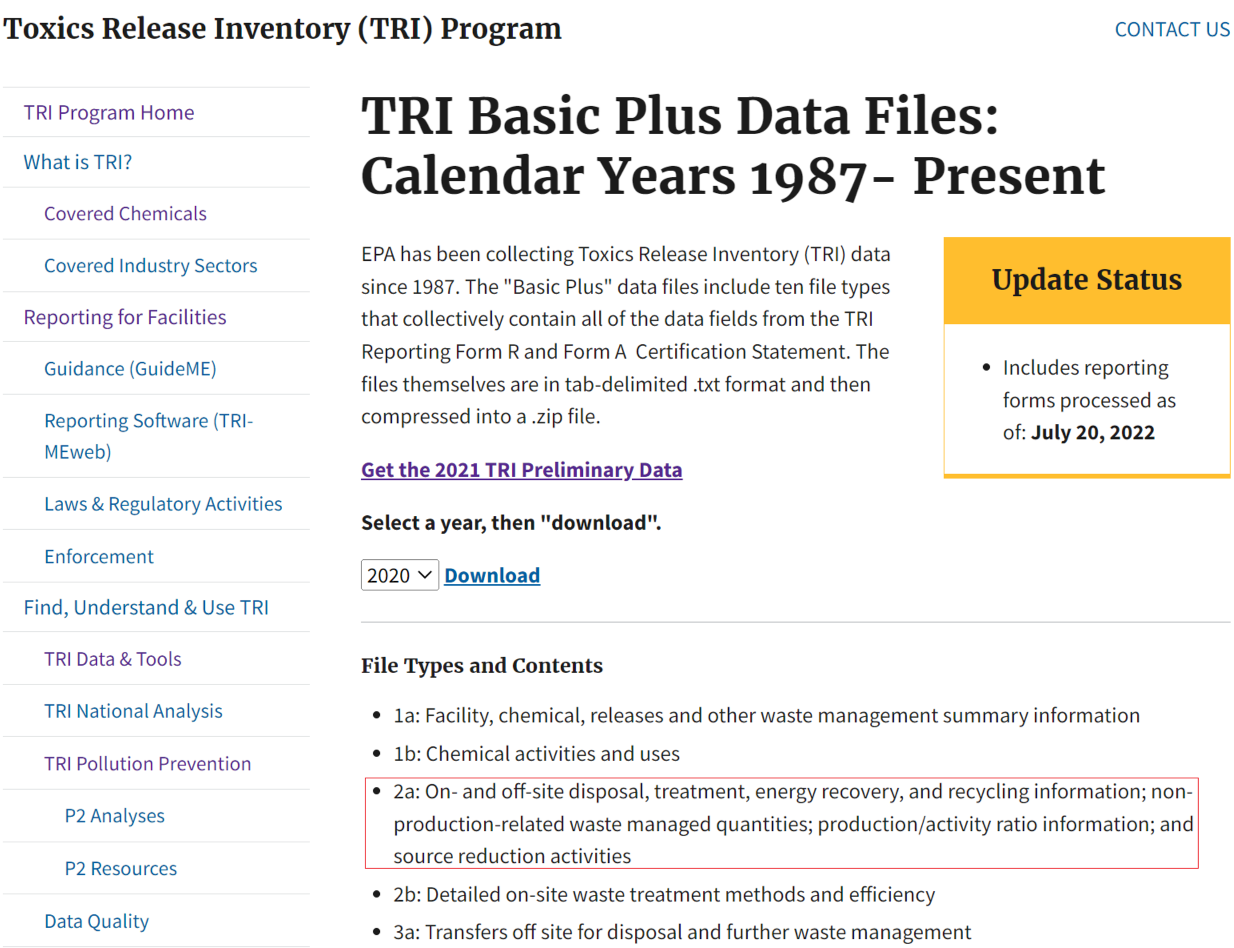
Figure IA.3. The TRI Database by Years

Source: https://www.epa.gov/toxics-release-inventory-tri-program/tri-basic-data-files-calendar-years-1987-present

Figure IA.4. Access to the P2 Database

Source: https://www.epa.gov/p2

Figure IA.5. The P2 Database by Years



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TRI Basic Plus Data Files: Calendar Years 1987- Present

EPA has been collecting Toxics Release Inventory (TRI) data since 1987. The "Basic Plus" data files include ten file types that collectively contain all of the data fields from the TRI Reporting Form R and Form A Certification Statement. The files themselves are in tab-delimited .txt format and then compressed into a .zip file.

Update Status

- Includes reporting forms processed as of: **July 20, 2022**

Get the 2021 TRI Preliminary Data

Select a year, then "download".

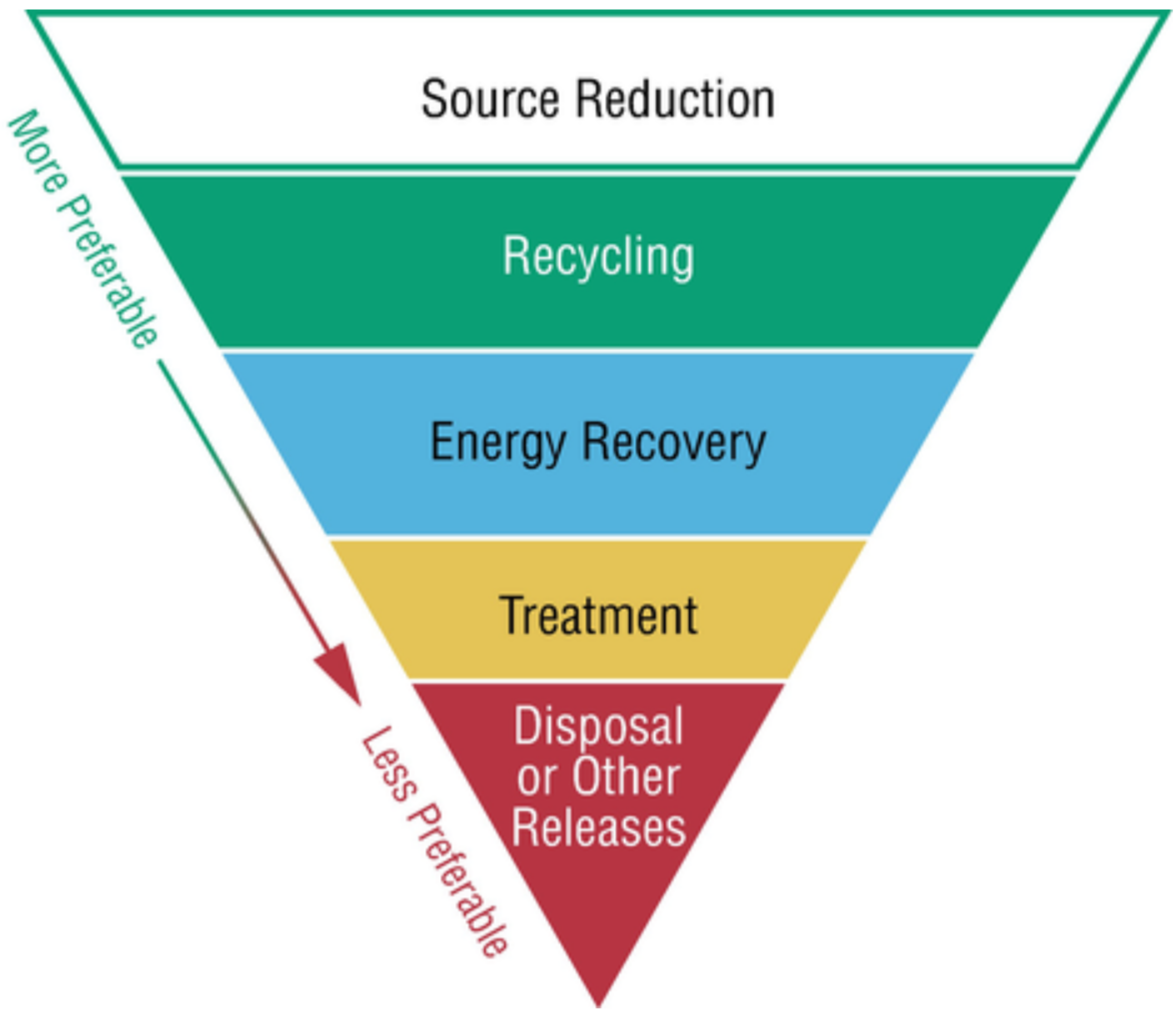
2020 **Download**

File Types and Contents

- 1a: Facility, chemical, releases and other waste management summary information
- 1b: Chemical activities and uses
- 2a: On- and off-site disposal, treatment, energy recovery, and recycling information; non-production-related waste managed quantities; production/activity ratio information; and source reduction activities
- 2b: Detailed on-site waste treatment methods and efficiency
- 3a: Transfers off site for disposal and further waste management

Source: https://www.epa.gov/toxics-release-inventory-tri-program/tri-basic-plus-data-files-calendar-years-1987-present

Figure IA.6. Waste Management Hierarchy



Source: https://www.epa.gov/smm/sustainable-materials-management-non-hazardous-materials-and-waste-management-hierarchy

Table IA.1: The List of Reported Abatement Activities

W Code	Abatement Activities
W13	Improved maintenance scheduling, record keeping, or procedures
W14	Changed production schedule to minimize equipment and feedstock changeovers
W15	Introduced an in-line product quality monitoring or other process analysis system
W19	Other changes in operating practices
W21	instituted procedures to ensure that materials do not stay in inventory beyond
W22	Began to test outdated material - continue to use if still effective
W23	Eliminated shelf-life requirements for stable materials
W24	Instituted better labeling procedures
W25	Instituted clearinghouse to exchange materials that would otherwise be discarded
W29	Other changes in inventory control
W31	Improved storage or stacking procedures
W32	Improved procedures for loading, unloading, and transfer operations
W33	Installed overflow alarms or automatic shutoff valves
W35	Installed vapor recovery systems
W36	Implemented inspection or monitoring program of potential spill or leak sources
W39	Other spill or leak prevention
W41	Increased purity or raw materials
W42	Substituted raw materials
W43	Substituted a feedstock or reagent chemical with a different chemical
W49	Other raw material modifications
W50	Optimized reaction conditions or otherwise increased efficiency of synthesis
W51	Instituted recirculation within a process
W52	Modified equipment, layout, or piping
W53	Use of a different process catalyst
W54	Instituted better controls on operating bulk containers to minimize discarding
W55	Changed from small volume containers to bulk containers to minimize discarding
W56	Reduced or eliminated use of an organic solvent
W57	Used biotechnology in manufacturing process
W58	Other process modifications
W59	Modified stripping/cleaning equipment
W60	Changed to mechanical stripping/cleaning devices (from solvents or others)
W61	Changed to aqueous cleaners (from solvents or other materials)
W63	Modified containment procedures for cleaning units
W64	Improved draining procedures
W65	Redesigned parts racks to reduce drag-out
W66	Modified or installed rinse systems
W67	Improved rinse equipment design
W68	Improved rinse equipment operation
W71	Other cleaning and degreasing modifications
W72	Modified spray systems or equipment
W73	Substituted coating materials used
W74	Improved application techniques
W75	Changed from spray to other systems
W78	Other surface preparation and finishing modifications
W81	Changed product specifications
W82	Modified design or composition of product
W83	Modified packaging
W84	Developed a new chemical product to replace the previous chemical product
W89	Other product modifications

Table IA.2: Abatement Investment, Political Connections, and Environmental Policy Uncertainty

This table reports the impact of environmental policy uncertainty on their abatement investment and the joint link of their abatement investment and toxic emissions. We estimate a Poisson regression (an OLS regression) by regressing abatement investment (the logarithm of abatement investment), abatement investment is defined as a count variable reflecting the total number of abatement activities for firm i's facility p located in state s, on the measure of environmental policy uncertainty, which denotes the election-based uncertainty in Panel A and the text-based uncertainty in Panel B, together with other firm characteristics, including the logarithm of market capitalization (Size), book-to-market ratio (B/M), investment rate (I/K), profitability (ROA), and the measure of political connections (Donations and Donations/AT) in year t, and local economic fundamentals in year t, including the state-level income per capita and the logarithm of population, as well as facility and year fixed effects. All independent variables are normalized to a zero mean and unit standard deviation after winsorization at the 1st and 99th percentiles to reduce the impact of outliers. t-statistics based on standard errors that are clustered at the facility level are reported in parentheses. The sample period is from 1991 to 2017 in Panel A and 2004 to 2017 in Panel B, respectively.

	Panel A: Election-Based Uncertainty							
	Poisson				**OLS**			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
σ_τ	0.00	0.00	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
	(0.02)	(0.03)	(-0.33)	(-0.32)	(-0.67)	(-0.69)	(-0.82)	(-0.83)
WW	0.02	0.02			-0.03	-0.03		
	(0.38)	(0.39)			(-1.06)	(-1.06)		
WW $\times$ σ_τ	-0.06	-0.06			-0.04	-0.04		
	(-3.80)	(-3.82)			(-3.07)	(-3.04)		
SA			-0.13	-0.14			-0.10	-0.11
			(-2.53)	(-2.65)			(-2.44)	(-2.51)
SA $\times$ σ_τ			-0.05	-0.05			-0.03	-0.03
			(-2.78)	(-2.78)			(-1.81)	(-1.80)
Log ME	-0.00	-0.01	-0.06	-0.06	-0.05	-0.05	-0.05	-0.06
	(-0.07)	(-0.15)	(-1.27)	(-1.37)	(-1.18)	(-1.26)	(-1.42)	(-1.51)
B/M	0.03	0.02	0.01	0.01	0.01	0.01	0.01	0.01
	(1.68)	(1.65)	(0.56)	(0.49)	(0.93)	(0.81)	(0.79)	(0.67)
I/K	-0.01	-0.01	-0.00	-0.00	0.01	0.01	0.01	0.01
	(-0.50)	(-0.50)	(-0.16)	(-0.16)	(0.98)	(0.99)	(1.08)	(1.09)
ROA	0.02	0.02	0.02	0.02	0.00	0.00	0.00	0.00
	(1.46)	(1.43)	(1.45)	(1.43)	(0.29)	(0.26)	(0.12)	(0.10)
Donnations	-0.03		-0.02		-0.01		-0.01	
	(-2.64)		(-1.98)		(-3.59)		(-3.00)	
Donnations/AT		0.00		0.00		-0.01		-0.01
		(0.17)		(0.22)		(-2.23)		(-2.23)
Income per Capita	0.14	0.13	0.15	0.15	-0.15	-0.15	-0.14	-0.14
	(1.32)	(1.29)	(1.46)	(1.44)	(-2.27)	(-2.28)	(-2.17)	(-2.18)
Log Population	0.15	0.15	0.19	0.19	-0.03	-0.03	0.00	-0.00
	(0.59)	(0.57)	(0.74)	(0.72)	(-0.12)	(-0.13)	(0.00)	(-0.01)
Rep Ratio	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.00
	(0.42)	(0.41)	(0.53)	(0.53)	(0.09)	(0.09)	(0.05)	(0.05)
Observations	68,638	68,638	69,552	69,552	115,126	115,126	116,491	116,491
Facility FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Text-Based Uncertainty								
	Poisson				OLS			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
σ_τ	-0.02	-0.02	-0.02	-0.01	-0.00	-0.00	-0.00	-0.00
	(-1.41)	(-1.36)	(-1.34)	(-1.33)	(-0.58)	(-0.54)	(-0.38)	(-0.34)
WW	-0.13	-0.14			-0.02	-0.02		
	(-1.54)	(-1.56)			(-1.03)	(-1.04)		
WW $\times$ σ_τ	-0.02	-0.02			-0.01	-0.01		
	(-2.00)	(-2.01)			(-2.19)	(-2.24)		
SA			-0.41	-0.41			-0.12	-0.12
			(-3.36)	(-3.38)			(-3.10)	(-3.12)
SA $\times$ σ_τ			-0.03	-0.03			-0.01	-0.01
			(-2.45)	(-2.45)			(-2.26)	(-2.27)
Log ME	-0.15	-0.15	-0.12	-0.12	-0.02	-0.02	-0.02	-0.02
	(-1.42)	(-1.44)	(-1.36)	(-1.38)	(-0.63)	(-0.66)	(-0.80)	(-0.82)
B/M	-0.00	-0.00	0.01	0.01	0.00	0.00	0.00	0.00
	(-0.00)	(-0.02)	(0.48)	(0.47)	(0.22)	(0.19)	(0.42)	(0.40)
I/K	-0.02	-0.02	-0.02	-0.02	-0.01	-0.01	-0.01	-0.01
	(-0.96)	(-0.97)	(-0.89)	(-0.88)	(-1.36)	(-1.36)	(-1.18)	(-1.18)
ROA	0.07	0.07	0.08	0.08	0.02	0.02	0.02	0.02
	(3.22)	(3.24)	(3.28)	(3.29)	(2.73)	(2.74)	(2.65)	(2.66)
Donnations	-0.01		-0.01		-0.00		-0.00	
	(-1.14)		(-0.54)		(-1.09)		(-0.62)	
Donnations/AT		-0.00		-0.01		-0.00		-0.00
		(-0.30)		(-0.51)		(-0.43)		(-0.35)
Income per Capita	0.39	0.39	0.38	0.38	0.06	0.06	0.06	0.06
	(2.88)	(2.86)	(2.85)	(2.84)	(1.34)	(1.33)	(1.36)	(1.36)
Log Population	0.77	0.77	0.79	0.79	0.07	0.07	0.06	0.06
	(1.24)	(1.23)	(1.26)	(1.26)	(0.34)	(0.34)	(0.29)	(0.29)
Observations	19,853	19,853	19,996	19,996	49,900	49,900	50,241	50,241
Facility FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table IA.3: Emission Reduction and Abatement Investment

This table shows the joint link between emission reduction and abatement investment. In Panel A, we present the correlation matrix to document the correlation between emission reduction and abatement investment. In Panel B, we report panel regressions of emission reduction on abatement investment, together with other firm characteristics. All variables are normalized to a zero mean and unit standard deviation after winsorization at the 1st and 99th percentiles to reduce the impact of outliers. t-statistics based on standard errors that are clustered at the facility level are reported in parentheses. ***, **, * indicate significance at the 1, 5, and 10% levels in Panel A, and all regressions in Panel B are conducted at the annual frequency. The sample period is from 1991 to 2017

Panel A: Correlation

	Reduction	x
Reduction	1	-0.11***
x		1

Panel B: Regressions

	(1)	**(2)**	**(3)**	**(4)**
x	-10.62	-10.79	-10.62	-10.79
	(-4.25)	(-4.23)	(-3.17)	(-3.21)
Log ME		-3.12		-3.12
		(-0.81)		(-0.84)
B/M		0.48		0.48
		(0.35)		(0.35)
I/K		-2.51		-2.51
		(-2.15)		(-1.69)
ROA		3.26		3.26
		(2.66)		(2.51)
Income per Capita		4.63		4.63
		(0.95)		(0.79)
Log Population		0.90		0.90
		(0.03)		(0.03)
Observations	31,165	30,536	31,165	30,536
R-squared	0.33	0.33	0.33	0.33
Facility FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Cluster SE	Yes	Yes	Yes	Yes

Table IA.4: Abatement Investment and Election-Based Uncertainty

This table reports the impact of environmental policy uncertainty on their abatement investment. We estimate a Poisson regression (an OLS regression) by regressing abatement investment (Log (1+abatement investment)), which is defined as a count variable reflecting the total number of abatement activities for firm i's plant p located in state s, on environmental policy uncertainty shock, which denotes the election-based uncertainty, together with other firm characteristics, including size, book-to-market ratio, investment rate, and profitability in year t, and local economic fundamentals in year t, including the state-level income per capital and pollution, as well as facility and year fixed effects. All independent variables are normalized to a zero mean and unit standard deviation after winsorization at the 1st and 99th percentiles to reduce the impact of outliers. t-statistics based on standard errors that are clustered at the state level are reported in parentheses. The sample period is from 1991 to 2017.

	Poisson				**OLS**			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
σ_τ	0.00	0.01	-0.00	0.01	-0.00	-0.00	-0.00	-0.00
	(0.18)	(0.56)	(-0.05)	(0.35)	(-0.16)	(-0.12)	(-0.24)	(-0.23)
WW	-0.01	-0.03			-0.01	-0.01		
	(-0.17)	(-0.58)			(-0.52)	(-1.31)		
WW $\times$ σ_τ	-0.06	-0.06			-0.01	-0.01		
	(-2.66)	(-2.73)			(-2.01)	(-1.96)		
SA			-0.19	-0.21			-0.05	-0.06
			(-4.30)	(-4.78)			(-4.10)	(-4.30)
SA $\times$ σ_τ			-0.04	-0.04			-0.01	-0.01
			(-1.96)	(-1.97)			(-1.39)	(-1.28)
Log ME		-0.04		-0.08		-0.01		-0.02
		(-0.80)		(-1.85)		(-0.89)		(-1.35)
B/M		0.02		0.00		0.00		0.00
		(1.17)		(0.16)		(1.05)		(0.79)
I/K		-0.00		-0.00		0.00		0.00
		(-0.46)		(-0.06)		(0.35)		(0.58)
ROA		0.02		0.02		0.00		0.00
		(1.37)		(1.42)		(1.19)		(1.10)
Income per Capita		0.07		0.08		-0.05		-0.05
		(0.67)		(0.75)		(-1.69)		(-1.62)
Log Population		0.16		0.21		0.05		0.05
		(0.56)		(0.75)		(0.60)		(0.66)
Rep Ratios	-0.01	-0.00	-0.01	-0.00	0.00	0.00	-0.00	-0.00
	(-0.32)	(-0.22)	(-0.26)	(-0.18)	(0.05)	(0.03)	(-0.04)	(-0.06)
Observations	91,433	89,990	93,096	91,351	149,882	148,130	152,272	150,150
Facility FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table IA.5: Abatement Investment and Text-Based Uncertainty

This table reports the impact of environmental policy uncertainty on their abatement investment. We estimate a Poisson regression (an OLS regression) by regressing abatement investment (Log (1+abatement investment)), which is defined as a count variable reflecting the total number of abatement activities for firm i's plant p located in state s, on environmental policy uncertainty shock, which is defined as a text-based measure of firm-level uncertainty, together with other firm characteristics, including size, book-to-market ratio, investment rate, and profitability in year t, and local economic fundamentals in year t, including the state-level income per capital and pollution, as well as facility and year fixed effects. All independent variables are normalized to a zero mean and unit standard deviation after winsorization at the 1st and 99th percentiles to reduce the impact of outliers. t-statistics based on standard errors that are clustered at the plant level are reported in parentheses. The sample period is from 2004 to 2017.

	Poisson				**OLS**			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
σ_τ	-0.02	-0.02	-0.02	-0.02	-0.00	-0.00	-0.00	-0.00
	(-1.71)	(-1.73)	(-1.71)	(-1.78)	(-1.13)	(-1.05)	(-0.91)	(-0.83)
WW	-0.10	-0.20			-0.01	-0.01		
	(-1.50)	(-2.52)			(-0.98)	(-1.35)		
WW $\times$ σ_τ	-0.03	-0.02			-0.01	-0.01		
	(-2.55)	(-2.43)			(-2.39)	(-2.39)		
SA			-0.44	-0.47			-0.06	-0.06
			(-4.21)	(-4.43)			(-3.85)	(-3.83)
SA $\times$ σ_τ			-0.03	-0.03			-0.00	-0.00
			(-2.91)	(-2.89)			(-2.25)	(-2.22)
Log ME		-0.19		-0.15		-0.01		-0.01
		(-2.07)		(-1.88)		(-0.62)		(-0.87)
B/M		-0.02		0.00		0.00		0.00
		(-0.61)		(0.18)		(0.04)		(0.29)
I/K		-0.01		-0.01		-0.00		-0.00
		(-0.36)		(-0.27)		(-1.13)		(-0.95)
ROA		0.08		0.08		0.01		0.01
		(3.78)		(3.77)		(2.81)		(2.67)
Income per Capita		0.27		0.26		0.01		0.01
		(2.23)		(2.18)		(0.56)		(0.59)
Log Population		0.50		0.60		0.01		0.00
		(0.89)		(1.07)		(0.07)		(0.03)
Observations	25,575	25,487	25,793	25,689	64,142	63,968	64,679	64,464
Facility FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table IA.6: Abatement Investment and Text-Based Uncertainty

This table reports the impact of environmental policy uncertainty on their abatement investment. We estimate a Poisson regression (an OLS regression) by regressing abatement investment (Log (1+abatement investment)), which is defined as a count variable reflecting the total number of abatement activities for firm i's plant p located in state s, on environmental policy uncertainty shock, which denotes the text-based uncertainty, together with other firm characteristics, including size, book-to-market ratio, investment rate, and profitability in year t, and local economic fundamentals in year t, including the state-level income per capital and pollution, as well as facility and year fixed effects. All independent variables are normalized to a zero mean and unit standard deviation after winsorization at the 1st and 99th percentiles to reduce the impact of outliers. t-statistics based on standard errors that are clustered at the state level are reported in parentheses. The sample period is from 2004 to 2017.

	Poisson				**OLS**			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
σ_τ	-0.02	-0.02	-0.02	-0.02	-0.00	-0.00	-0.00	-0.00
	(-2.24)	(-2.26)	(-2.27)	(-2.32)	(-1.37)	(-1.26)	(-1.09)	(-1.00)
WW	-0.10	-0.20			-0.01	-0.01		
	(-1.31)	(-1.85)			(-0.85)	(-1.05)		
WW $\times$ σ_τ	-0.03	-0.02			-0.01	-0.01		
	(-2.62)	(-2.50)			(-2.71)	(-2.67)		
SA			-0.44	-0.47			-0.06	-0.06
			(-3.55)	(-3.68)			(-3.23)	(-3.28)
SA $\times$ σ_τ			-0.03	-0.03			-0.01	-0.01
			(-2.88)	(-2.94)			(-2.20)	(-2.24)
Log ME		-0.19		-0.15		-0.01		-0.01
		(-1.62)		(-1.67)		(-0.51)		(-0.82)
B/M		-0.02		0.00		0.00		0.00
		(-0.53)		(0.17)		(0.04)		(0.28)
I/K		-0.01		-0.01		-0.00		-0.00
		(-0.32)		(-0.26)		(-0.99)		(-0.85)
ROA		0.08		0.08		0.01		0.01
		(3.62)		(3.52)		(2.93)		(2.69)
Income per Capita		0.27		0.26		0.01		0.01
		(1.99)		(1.91)		(0.55)		(0.58)
Log Population		0.50		0.60		0.01		0.00
		(0.94)		(1.06)		(0.09)		(0.04)
Observations	25,575	25,487	25,793	25,689	64,142	63,968	64,679	64,464
Facility FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table IA.7: Abatement Investment (Alternative) and Election-Based Uncertainty

This table reports the impact of environmental policy uncertainty on their abatement investment. We estimate a Poisson regression (an OLS regression) by regressing abatement investment (Log (1+abatement investment)), which is defined as a count variable reflecting the total number of abatement activities based on the alternative criteria for firm i's plant p located in state s, on environmental policy uncertainty shock, which denotes the election-based uncertainty, together with other firm characteristics, including size, book-to-market ratio, investment rate, and profitability in year t, and local economic fundamentals in year t, including the state-level income per capital and pollution, as well as facility and year fixed effects. All independent variables are normalized to a zero mean and unit standard deviation after winsorization at the 1st and 99th percentiles to reduce the impact of outliers. t-statistics based on standard errors that are clustered at the plant level are reported in parentheses. The sample period is from 1991 to 2017.

	Poisson				**OLS**			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
σ_τ	0.00	0.01	-0.00	0.00	-0.00	-0.00	-0.00	-0.00
	(0.13)	(0.57)	(-0.13)	(0.28)	(-0.30)	(-0.26)	(-0.37)	(-0.39)
WW	-0.03	-0.04			-0.00	-0.01		
	(-0.80)	(-1.01)			(-0.73)	(-1.48)		
WW $\times$ σ_τ	-0.04	-0.04			-0.01	-0.01		
	(-2.97)	(-3.01)			(-2.53)	(-2.29)		
SA			-0.15	-0.17			-0.04	-0.04
			(-4.17)	(-4.23)			(-4.45)	(-4.61)
SA $\times$ σ_τ			-0.03	-0.03			-0.00	-0.00
			(-2.01)	(-2.14)			(-1.48)	(-1.36)
Log ME		-0.02		-0.05		-0.01		-0.02
		(-0.53)		(-1.34)		(-1.17)		(-1.94)
B/M		0.02		0.01		0.00		0.00
		(1.56)		(0.88)		(1.72)		(1.48)
I/K		-0.00		-0.00		0.00		0.00
		(-0.57)		(-0.32)		(0.35)		(0.56)
ROA		0.02		0.02		0.00		0.00
		(1.81)		(1.74)		(1.63)		(1.59)
Income per Capita		0.05		0.06		-0.04		-0.04
		(0.65)		(0.74)		(-2.75)		(-2.71)
Log Population		0.25		0.29		0.04		0.04
		(1.27)		(1.45)		(0.74)		(0.80)
Rep Ratios	-0.00	-0.00	-0.00	-0.00	0.00	0.00	0.00	0.00
	(-0.34)	(-0.21)	(-0.24)	(-0.11)	(0.32)	(0.23)	(0.23)	(0.16)
Observations	91,433	89,990	93,096	91,351	149,882	148,130	152,272	150,150
Facility FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table IA.8: Abatement Investment (Alternative) and Election-Based Uncertainty

This table reports the impact of environmental policy uncertainty on their abatement investment. We estimate a Poisson regression (an OLS regression) by regressing abatement investment (Log (1+abatement investment)), which is defined as a count variable reflecting the total number of abatement activities based on the alternative criteria for firm i's plant p located in state s, on environmental policy uncertainty shock, which denotes the election-based uncertainty, together with other firm characteristics, including size, book-to-market ratio, investment rate, and profitability in year t, and local economic fundamentals in year t, including the state-level income per capital and pollution, as well as facility and year fixed effects. All independent variables are normalized to a zero mean and unit standard deviation after winsorization at the 1st and 99th percentiles to reduce the impact of outliers. t-statistics based on standard errors that are clustered at the state level are reported in parentheses. The sample period is from 1991 to 2017.

	Poisson				**OLS**			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
σ_τ	0.00	0.01	-0.00	0.00	-0.00	-0.00	-0.00	-0.00
	(0.11)	(0.52)	(-0.10)	(0.25)	(-0.27)	(-0.25)	(-0.33)	(-0.37)
WW	-0.03	-0.04			-0.00	-0.01		
	(-0.67)	(-0.92)			(-0.54)	(-1.34)		
WW $\times$ σ_τ	-0.04	-0.04			-0.01	-0.01		
	(-2.59)	(-2.67)			(-1.88)	(-1.72)		
SA			-0.15	-0.17			-0.04	-0.04
			(-4.06)	(-4.29)			(-4.12)	(-4.37)
SA $\times$ σ_τ			-0.03	-0.03			-0.00	-0.00
			(-1.76)	(-1.85)			(-1.19)	(-1.10)
Log ME		-0.02		-0.05		-0.01		-0.02
		(-0.62)		(-1.43)		(-1.04)		(-1.61)
B/M		0.02		0.01		0.00		0.00
		(1.64)		(0.87)		(1.61)		(1.31)
I/K		-0.00		-0.00		0.00		0.00
		(-0.57)		(-0.31)		(0.37)		(0.58)
ROA		0.02		0.02		0.00		0.00
		(1.73)		(1.72)		(1.62)		(1.60)
Income per Capita		0.05		0.06		-0.04		-0.04
		(0.50)		(0.55)		(-1.86)		(-1.80)
Log Population		0.25		0.29		0.04		0.04
		(0.86)		(0.96)		(0.49)		(0.52)
Rep Ratios	-0.00	-0.00	-0.00	-0.00	0.00	0.00	0.00	0.00
	(-0.28)	(-0.19)	(-0.19)	(-0.10)	(0.27)	(0.22)	(0.19)	(0.16)
Observations	91,433	89,990	93,096	91,351	149,882	148,130	152,272	150,150
Facility FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table IA.9: Abatement Investment (Alternative) and Text-Based Uncertainty

This table reports the impact of environmental policy uncertainty on their abatement investment. We estimate a Poisson regression (an OLS regression) by regressing abatement investment (Log (1+abatement investment)), which is defined as a count variable reflecting the total number of abatement activities based on the alternative criteria for firm i's plant p located in state s, on environmental policy uncertainty shock, which denotes the text-based uncertainty, together with other firm characteristics, including size, book-to-market ratio, investment rate, and profitability in year t, and local economic fundamentals in year t, including the state-level income per capital and pollution, as well as facility and year fixed effects. All independent variables are normalized to a zero mean and unit standard deviation after winsorization at the 1st and 99th percentiles to reduce the impact of outliers. t-statistics based on standard errors that are clustered at the plant level are reported in parentheses. The sample period is from 2004 to 2017.

	Poisson				**OLS**			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
σ_τ	-0.02	-0.02	-0.02	-0.02	-0.00	-0.00	-0.00	-0.00
	(-2.35)	(-2.35)	(-2.09)	(-2.12)	(-1.68)	(-1.64)	(-1.39)	(-1.33)
WW	-0.06	-0.11			-0.00	-0.01		
	(-1.06)	(-1.44)			(-0.64)	(-0.89)		
WW $\times$ σ_τ	-0.03	-0.02			-0.01	-0.01		
	(-2.57)	(-2.49)			(-2.23)	(-2.26)		
SA			-0.31	-0.32			-0.04	-0.04
			(-3.33)	(-3.39)			(-3.37)	(-3.34)
SA $\times$ σ_τ			-0.02	-0.02			-0.01	-0.01
			(-2.03)	(-2.01)			(-1.72)	(-1.69)
Log ME		-0.07		-0.07		-0.00		-0.01
		(-0.84)		(-0.92)		(-0.33)		(-0.70)
B/M		-0.00		0.01		0.00		0.00
		(-0.03)		(0.36)		(0.24)		(0.33)
I/K		-0.02		-0.02		-0.00		-0.00
		(-0.89)		(-0.81)		(-1.20)		(-1.03)
ROA		0.05		0.05		0.00		0.00
		(2.69)		(2.73)		(1.91)		(1.80)
Income per Capita		0.17		0.17		0.00		0.00
		(1.49)		(1.50)		(0.02)		(0.02)
Log Population		0.25		0.32		0.00		0.00
		(0.48)		(0.62)		(0.04)		(0.01)
Observations	25,575	25,487	25,793	25,689	64,142	63,968	64,679	64,464
Facility FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table IA.10: Abatement Investment (Alternative) and Text-Based Uncertainty

This table reports the impact of environmental policy uncertainty on their abatement investment. We estimate a Poisson regression (an OLS regression) by regressing abatement investment (Log (1+abatement investment)), which is defined as a count variable reflecting the total number of abatement activities based on the alternative criteria for firm i's plant p located in state s, on environmental policy uncertainty shock, which denotes the text-based uncertainty, together with other firm characteristics, including size, book-to-market ratio, investment rate, and profitability in year t, and local economic fundamentals in year t, including the state-level income per capital and pollution, as well as facility and year fixed effects. All independent variables are normalized to a zero mean and unit standard deviation after winsorization at the 1st and 99th percentiles to reduce the impact of outliers. t-statistics based on standard errors that are clustered at the state level are reported in parentheses. The sample period is from 2004 to 2017.

	Poisson				**OLS**			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
σ_τ	-0.02	-0.02	-0.02	-0.02	-0.00	-0.00	-0.00	-0.00
	(-2.98)	(-2.99)	(-2.69)	(-2.72)	(-1.95)	(-1.89)	(-1.63)	(-1.55)
WW	-0.06	-0.11			-0.00	-0.01		
	(-0.85)	(-1.15)			(-0.53)	(-0.72)		
WW $\times$ σ_τ	-0.03	-0.02			-0.01	-0.01		
	(-2.78)	(-2.64)			(-2.40)	(-2.42)		
SA			-0.31	-0.32			-0.04	-0.04
			(-2.64)	(-2.74)			(-2.81)	(-2.92)
SA $\times$ σ_τ			-0.02	-0.02			-0.01	-0.01
			(-2.06)	(-2.07)			(-1.68)	(-1.67)
Log ME		-0.07		-0.07		-0.00		-0.01
		(-0.80)		(-0.94)		(-0.29)		(-0.71)
B/M		-0.00		0.01		0.00		0.00
		(-0.02)		(0.32)		(0.20)		(0.28)
I/K		-0.02		-0.02		-0.00		-0.00
		(-0.76)		(-0.71)		(-1.03)		(-0.88)
ROA		0.05		0.05		0.00		0.00
		(2.80)		(2.75)		(2.00)		(1.80)
Income per Capita		0.17		0.17		0.00		0.00
		(1.35)		(1.31)		(0.02)		(0.02)
Log Population		0.25		0.32		0.00		0.00
		(0.54)		(0.68)		(0.05)		(0.01)
Observations	25,575	25,487	25,793	25,689	64,142	63,968	64,679	64,464
Facility FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes