The Pollution Premium

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ABSTRACT

This paper studies the asset pricing implications of industrial pollution. A long-short portfolio constructed from firms with high versus low toxic emission intensity within an industry generates an average annual return of 4.42%, which remains significant after controlling for risk factors. This pollution premium cannot be explained by existing systematic risks, investor preferences, market sentiment, political connections, or corporate governance. We propose and model a new systematic risk related to environmental policy uncertainty. We use the growth in environmental litigation penalties to measure regime change risk and find that it helps price the cross-section of emission portfolios' returns.

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Prior finance research shows that consumption and production influence expected stock returns. Little is known, however, about the role of their by-product–industrial pollution–in asset pricing. On the one hand, polluting firms may save costs by not investing in emission abatement and environmental recovery in the short run. On the other hand, the negative externalities created by such firms are monitored by the general public, media, and governments in the long run, and polluting firms could be subject to activist protests, litigation and reputational risk, and penalties imposed by regulatory authorities.[1] Motivated by this gap in the literature, in this paper we empirically examine the pricing impact of industrial pollution.

Our investigation proceeds in two stages. In the first stage, we construct empirical proxies for firm-level pollutants and examine the cross-sectional variation in the relation between stock returns and industrial pollution. In the second stage, we propose an extensive list of possible explanations for such return predictability and perform various tests to shed light on the true underlying mechanism.

To study the empirical relation between industrial pollution and expected stock returns at the firm level, we construct a measure of "emission intensity" using pollution data from the Toxic Release Inventory (TRI) database. Specifically, for each year over period 1991 to 2016, we first capture a firm's toxic emissions by summing the amount of emissions of all types of chemicals across all plants listed in the TRI database, a comprehensive database of mandatory pollution reports maintained by the United States Environmental Protection Agency (EPA). Institutional background on the TRI database is provided in Section I.A in the Internet Appendix. We then calculate a firm's emission intensity as its ratio of toxic emissions to total assets: which we obtain from Compustat. Firms with higher emission intensity are associated with a higher frequency or probability of being involved in environment-related

[1] Anecdotal evidence abounds of environmental contamination cases associated with well-known, publicly-listed firms that trigger governmental interventions. For example, in 2002 Dow Chemical agreed to settle a lawsuit in California by spending $3 million on wetlands restoration, in 2008 the federal government intervened and claimed damages for nearby residents negatively impacted by airborne contamination from Dow Chemical's nuclear weapon plant in Colorado, and in 2011 Dow Chemical negotiated with the regulators regarding violations of the Clean Air Act that caused the dioxin contamination in Michigan. See the Corporate Research Project: http://www.corp-research.org/dowchemical.

lawsuits. These firms are also associated with significantly higher contemporaneous profits.

We next assign firms to quintile portfolios based on their emission intensity relative to industry peers, given that chemical emissions tend to vary across industries. Such portfolio sorts show that firms producing more emissions are associated with higher subsequent stock returns: a high-minus-low portfolio strategy that takes a long (short) position in the quintile portfolio with the highest (lowest) emission intensity yields a statistically significant average return of 4.42% per annum. We also find that the significant alphas of the high-minus-low portfolio are unaffected by known return factors for other systematic risks. In a cross-validation test, we perform Fama and MacBeth (1973) regressions by introducing a wider set of controls and find that the emission-return relation remains economically and statistically significant irrespective of the control variables that we consider.

To further examine whether such return predictability is related to environmental policies, we calculate quintile portfolio cumulative abnormal returns (CARs) in response to Donald Trump 2016 U.S. presidential election win.[2] Following Trump's win, high-emission firms had significantly positive CARs that were higher than those of lower-emission counterparts. Specifically, we find a monotonic pattern in CARs across quintile portfolios and a prominent contrast between the top portfolio (6.31%) and the bottom portfolio (3.64%) within a 10-day window around the 2016 U.S. presidential election. This finding supports the view that the general public–and equity investors in particular–pay attention to environmental policies and firm-level emissions.

We consider several possible explanations proposed in the literature for the cross-sectional variation in emission portfolios' returns, including existing systematic risks, investors' preferences and underreaction, corporate governance, and political connections.[3] Fama and

[2]We consider this event as it is exogenous to environmental policies, as argued by Wagner, Zeckhauser, and Ziegler (2018), Ramelli et al. (2021), and Child et al. (2021). Di Giuli and Kostovetsky (2014) also show that firms with low social responsibility scores observe significantly positive three-day CARs after Republican election victories.

[3]First, existing systematic risks that may explain the documented pollution premium include capital age (Lin, Palazzo, and Yang (2020)), financial constraints (Li (2011), Lins, Servaes, and Tamayo (2017)), economic and political uncertainty (Brogaard and Detzel (2015), Bali, Brown, and Tang (2017)), and adjustment costs (Kim and Kung (2016), Gu, Hackbarth, and Johnson (2017)). Second, both retail and

MacBeth (1973) regressions and two-way-sorted portfolios suggest that the emission-return relation is not eliminated when we control for firm characteristics related to these explanations. We also consider policy uncertainty exposures as in Bali, Brown, and Tang (2017) and show that the emission-driven return spread cannot be attributed to general policy uncertainty.

Given the results above, we propose a new systematic risk based on environmental policy uncertainty following Pástor and Veronesi (2012, 2013) and develop a general equilibrium model in which firms' cash flows are subject to policy changes with respect to environmental regulation.[4] In our model, the government acts as a social planner and considers the negative externality of toxic emissions. It optimally replaces the weak-regulation regime with the strong-regulation regime if environmental costs are sufficiently high (i.e., above a

institutional investors have preferences against firms with a poor social image, such as those that perform poorly with respect to corporate social responsibility issues (Hong and Kacperczyk (2009), Fabozzi, Ma, and Oliphant (2008), Renneboog, Ter Horst, and Zhang (2008), Starks, Venkat, and Zhu (2017), Riedl and Smeets (2017), Gibson and Krueger (2018), Dyck, Lins, Roth, and Wagner (2019), Pástor, Stambaugh, and Taylor (2021), Hartzmark and Sussman (2019), and Ramelli, Wagner, Zeckhauser, and Ziegler (2021)). Third, retail investors are more subject to behavioral bias and may panic in response to some firms' emission news (Krüger (2015) and Ottaviani and Sørensen (2015)), selling all of their stocks at deep discounts. Fourth, high-emission firms could operate under weaker governance or monitoring (Masulis and Reza (2015), Cheng, Hong, and Shue (2013), Glossner (2018), Hoepner, Oikonomou, Sautner, Starks, and Zhou (2019)), and their stock prices may be discounted by investors who are concerned about governance or the associated risk and uncertainty (e.g., Gompers, Ishii, and Metrick (2003)). Fifth, since political connections are positively related to future stock returns (e.g., Liu, Shu, and Wei (2017)) or may result a risk premium (Santa-Clara and Valkanov (2003)), high-emission firms may be more politically connected, with their profits and stock prices subject to greater uncertainty with respect to governmental oversight.

[4]Our model differs from that of Pástor and Veronesi (2012, 2013) in several ways. First, we consider an endogenous decision problem whereby firms to choose emission intensity. In addition, we introduce into agents' utility with the environmental costs that trigger governmental policy shifts. However, while agents know about the policy impact and know that the price of risk is negative in our model, they must learn about the policy impact as in Pástor and Veronesi (2012, 2013). In terms of differences in empirical tests, we focus on the cross-sectional variation in expected stock returns, while Pástor and Veronesi (2012, 2013) focus on time-series fluctuations in the aggregate equity market value. In the Internet Appendix we further introduce the role of debt financing, which amplifies the emission-return relation.

given endogenous threshold). Before the government makes its decision, agents learn about the welfare costs of toxic emissions under the weak-regulation regime in a Bayesian fashion by observing signals, which determines their perceived probability that the government will adopt strong-regulation regime. Adopting a strong-regulation regime will lower emissions but reduce firms' profitability. In particular, the profitability of high-emission firms drops more than that of low-emission firms, leading to a stronger negative impact on valuations of firms with high emission intensity. On the one hand, a shift to the strong regime is assumed to negatively affect economy-wide average profitability, which leads to an upward spike in the stochastic discount factor (SDF); on the other hand, since high-emission firms' profitability is more sensitive to such the regime shift than the profitability of low-emission firms, high-emission firms observe a larger stock price decline when a regime shift occurs and are more negatively exposed to the risk of a regulation regime shift, which results in higher average excess returns ex-ante.

Our model assumptions and predictions are supported by additional empirical tests. We first measure regime shift risk (i.e., the perceived likelihood of tighter environmental regulations) using the growth rate in the aggregate amount of all civil penalties level against pollution by the EPA.[5] We find that when regime shift risk increases, firms with higher emissions experience a more pronounced decline in their long-term profits. When we use the generalized method of moments (GMM) estimation of Cochrane (2005) to test the price of regime change risk (i.e., λ_c) and the exposure to such risk of emission portfolios, we find that regime change risk is significantly negatively priced and that emission portfolios' betas on regime change risk decrease with emission intensity, both of which are consistent with the model. As a result, the high-minus-low emission portfolio delivers higher expected returns because it has negative exposure to regime change risk that is negatively priced.

In sum, our emission intensity measure captures risk characteristics that are distinct from others documented in the literature, and our model identifies a new source of systematic risk for investors: the risk of a regime shift in environmental regulation that impacts high-emission firms more than low-emission firms. While we acknowledge that environmental regulation uncertainty is only one (particular) type of policy uncertainty, such uncertainty is

[5]We thank an anonymous reviewer for suggesting this measure to us.

a substantial yet under explored part of policy uncertainty. More importantly, JT difference test results show that our measure of environmental policy change risk is distinct from *general* policy uncertainty, as adding our measure of environmental policy change risk to the stochastic discount factor (SDF) of the general economic policy uncertainty factor of Bloom (2009) significantly reduces pricing errors.

This paper builds on a growing literature that investigates the policy implications of environmental pollution. Most of the papers in this literature focus on the economic consequences of global warming and climate change.[6] Here, we focus instead on the asset pricing implications of environmental policy changes.

Our work also adds to the literature that explores investment strategies related to climate change, corporate social responsibility (CSR), and environmental, social, and governance (ESG) scores. Prior studies in this literature can be classified into several classes: long-run risk, downside risk, attention, preferences, and cost of capital. Climate change and environmental issues constitute long-run risks, and polluting firms therefore carry higher risk exposure (Bansal and Ochoa (2011), Bansal, Kiku, and Ochoa (2016), Bolton and Kacperczyk (2019, 2020)).[7] Some studies suggest that high-CSR firms are less risky because their CSR reputation helps them survive financial downturns (Lins, Servaes, and Tamayo (2017),

[6] Acemoglu (2002) shows that two major forces bias technological change: price effects and market size effects. Acemoglu, Aghion, Bursztyn, and Hemous (2012) suggest policy interventions to direct innovation from dirty technologies to clean ones, if two types of technologies are substitutable. If the dirty technology is more advanced, Acemoglu, Akcigit, Hanley, and Kerr (2016a) show that interventions, such as taxes and subsidies, can promote transitions to clean technology. In their study of the automobile industry, Aghion, Dechezleprêtre, Hemous, Martin, and van Reenen (2016) find that cost-saving motivations encourage firms to develop clean technologies, and Brown, Martinsson, and Thomann (2022) show that country-level taxes on noxious emissions lead to substantial increases in polluting firms' R&D spending. In contrast to studies that consider carbon emissions, Currie, Davis, Greenstone, and Walker (2015) investigate the impact of toxic emissions on housing value and infant health.

[7] Bansal and Ochoa (2011) and Bansal, Kiku, and Ochoa (2016) use climate change risks to proxy for long-run risks in dividends and consumption dynamics, and Andersson, Bolton, and Samama (2016) propose a hedging strategy against climate risks. Bolton and Kacperczyk (2019, 2020) find that high-CO2 emitters deliver significantly higher stock returns and suggest that these firms carry higher systematic risk, such as renewable technology risk.

Hoepner, Oikonomou, Sautner, Starks, and Zhou (2019), and Albuquerque, Koskinen, and Zhang (2019)).[8] In addition, investor under- or overreaction to news about pollution or climate change can result in return predictability (Krüger (2015), Hong, Li, and Xu (2019), Chen, Kumar, and Zhang (2019)),[9] and it is well known that investors are more willing to hold socially responsible firms and funds due to social reputation, or liquidity concerns, which also impact stock prices.[10] Such preferences may also influence systematic risk exposure (Bansal, Wu, and Yaron (2019), Pástor, Stambaugh, and Taylor (2021)).[11] Heinkel, Kraus, and Zechner (2001), Chava (2014), and Hong, Wang, and Yang (2021) further show that firms associated with environmental concerns face high equity and debt financing costs. Distinct from most prior empirical studies in this direction, we derive regulation regime

[8]Dunn, Fitzgibbons, and Pomorski (2018) provide empirical evidence showing that higher-ESG firms have lower future risk, including total risk and beta.

[9]Krüger (2015) finds that investors show strongly negative CSR responses to adverse CSR news. Hong, Li, and Xu (2019) find that food companies in drought-stricken countries underperform those in countries that do not experience droughts, and they attribute this pattern to investor inattention. Chen, Kumar, and Zhang (2019) find that stocks that are more sensitive to CSR have significantly higher returns due to investors' social sentiment.

[10]Hong and Kacperczyk (2009) and Fabozzi, Ma, and Oliphant (2008) find that firms in "sin" industries (i.e., alcohol, tobacco, and gaming) outperform those in non-sin industries in stock returns because the former group is subject to funding constraints due to social norms. Cao, Titman, Zhan, and Zhang (2019) find that institutional investors are reluctant to sell high-CSR stocks but are more willing to sell low-CSR stocks, which leads to return predictability. Renneboog, Ter Horst, and Zhang (2008), Starks, Venkat, and Zhu (2017), Riedl and Smeets (2017), Gibson and Krueger (2018), Dyck, Lins, Roth, and Wagner (2019), and Hartzmark and Sussman (2019) document that both retail and institutional investors are more willing to hold socially responsible firms and funds. One possible explanation for this preference could be liquidity and funding risk. Stocks with bad reputations may be subject to greater financing constraints due to insufficient investor demand (e.g., Hong and Stein (2007)). However, Bessembinder (2016) points out that such preferences may incur substantial costs due to liquidity. Pedersen, Fitzgibbons, and Pomorski (2021) suggest that firms' ESG activities may predict stock returns because these activities are correlated with firm fundamentals and investor preferences.

[11]Pástor, Stambaugh, and Taylor (2021) propose that investors' ESG preferences for the stocks and products of green firms give rise to ESG systematic risk in equilibrium. Bansal, Wu, and Yaron (2019) argue that socially responsible investment carries higher systematic risk exposure because households have stronger preferences for socially responsible investment during good economic times.

change risk in a general equilibrium setting, and we use *actual* toxic emissions, which are less subject to errors than estimations or surveys.

Our paper also adds a new perspective to asset pricing implications of macroeconomic uncertainty, a topic for which Pástor and Veronesi (2012, 2013) provide a comprehensive literature review. Prior empirical studies examine the role of uncertainty in economic policy, politics and elections, and tax and fiscal conditions.[12] Distinct from these papers, we explore the financial effect of uncertainty in environmental policies and regulations. Finally, our paper contributes to the literature that relates consumption or productivity risk to stocks' risk premium from the perspective of pollution, which is an unavoidable by-product of production and consumption.[13]

[12]With respect to economic uncertainty, Brogaard and Detzel (2015) examine how stock returns relate to the economic policy uncertainty index constructed by Baker, Bloom, and Davis (2016). In similar work,Bali, Brown, and Tang (2017) suggest that uncertainty is priced in the cross-section using the alternative economic uncertainty index proposed by Jurado, Ludvigson, and Ng (2015). With respect to political uncertainty, Santa-Clara and Valkanov (2003) relate the equity risk premium to political cycles, and Liu, Shu, and Wei (2017) provide direct evidence that stock prices of politically sensitive firms respond more to political uncertainty. Other studies examine tax and fiscal uncertainty (Sialm (2006, 2009), Croce, Kung, Nguyen, and Schmid (2012a), Croce, Nguyen, and Schmid (2012b), and Belo, Gala, and Li (2013)).

[13]A large number of theoretical and empirical papers relate consumption or productivity risk to the equity risk premium. Ait-Sahalia, Parker, and Yogo (2004) and Lochstoer (2009) show that luxury consumption can explain the equity premium. Yogo (2006) separates durable consumption from nondurable consumption to study time-series asset pricing implications, while Gomes, Kogan, and Yogo (2009) further show that durable good producers are riskier than nondurable good producers since the demand for durable goods is more procyclical. Savov (2011) uses garbage release data to capture volatile consumption, and Da, Yang, and Yun (2015) use electricity data to proxy for missing homemade goods. Kroencke (2017) suggests that unfiltered consumption explains why garbage data outperform NIPA consumption data in matching the equity premium. The literature also explores the asset pricing implications of production risk referred to as production-based asset pricing, which links investment to stock returns. Zhang (2005) provides an investment-based explanation for the value premium. Eisfeldt and Papanikolaou (2013) develop a model of organizational capital and expected returns. Kogan and Papanikolaou (2013, 2014) study the relation between investment-specific technology shocks and stock returns. Binsbergen (2016) documents the cross-sectional return spread by sorting on producer prices. Finally, Loualiche (2022) studies the cross-sectional difference in exposure to the globalization risk premium, and argues that such risk is an extension of the displacement risk proposed by Gârleanu, Kogan, and Panageas (2012).

The rest of the paper is organized as follows. In Section I, we discuss data construction and present summary statistics as well as our baseline results. In Section II, we discuss and empirically test several possible explanations for the positive emission-return relation that we document. In Section III, we examine how litigation risk and profits relate to emission intensity using an event study analysis. We describe an equilibrium model and analyze its quantitative asset pricing implications in Section IV. We further test our model and its testable implications in Section V. We conclude in Section VI. Details on data construction are provided in the Internet Appendix. The Internet Appendix also contains additional empirical evidence, details on our model solution, calibration and sensitivity analyses, and an extended model that introduces debt financing.

I. Firm-Level Emissions and Pollution Premium

In this section, we first discuss our measurement of firm-level toxic emissions. We then examine the relation between toxic emissions and the cross-section of stock returns. We show that emissions positively predict stock returns in one-way portfolio sorts and that such an emission-return relation is unaffected by known return factors for other systematic risks. In the third subsection, we implement Fama and MacBeth (1973) regressions to examine whether the positive relation between emissions and stock returns is mitigated by other firm characteristics, and in the forth subsection we double sort on size and emissions and confirm that the pollution premium is not driven by the size effect.

A. Data Sources

To obtain firm-level emissions of U.S. public companies, we collect plant-level chemical pollutants data from the Toxic Release Inventory (TRI) database constructed and maintained by the United States Environmental Protection Agency (EPA).[14] The TRI database contains

[14]The U.S. Congress passed the Community Right to Know Act (EPCRA) in 1986 in response to public concerns over the release of toxic chemicals from several environmental accidents, both domestic and overseas. The EPCRA entitles residents in their respective neighborhoods to know the source of detrimental chemicals, especially in terms of their potential impacts on human health from routes of exposure. The EPCRA also requires that firms disclose chemical releases to the environment that exceed allowed limits for all

detailed information on all U.S. chemical emissions at the plant level each year since 1986. Specifically, the TRI data contain report year, level of chemical pollutants in pounds, name of chemical categories, location Federal Information Processing Standards (FIPS) code, and company names.[15] While the TRI database has been a publicly available since 1986, its coverage was fairly limited and contains data errors until 1990. As a result, we use the emission data from 1991 to 2016 to construct our emission-related variables.

Our sample consists of firms that lie in the intersection of Compustat, Center for Research in Security Prices (CRSP), and the TRI database (Xiong and Png (2019)). We obtain accounting data from Compustat and stock price data from CRSP. Our sample firms include those with nonmissing TRI data and nonmissing standard industrial classification (SIC) codes, as well as those with domestic common shares (SHRCD = 10 and 11) trading on NYSE, AMEX, or NASDAQ. We identify firms in our sample that were involved in litigation from Key Developments in Capital IQ. Following the literature, we exclude financial firms that have four-digit SIC codes between 6000 and 6999 (e.g., finance, insurance, trusts, and real estate sectors). To mitigate backfilling bias, we require that firms to be listed on Compustat for two years before we include them in our sample.

We collect civil cases about firms involved in environmental litigation from the Enforcement and Compliance History Online (ECHO) system provided by the EPA. Section I.B in the Internet Appendix details our procedure for quantifying environmental litigation. ECHO contains information on federal- and state-level administrative and judicial cases and tracks all formal administrative and judicial enforcement actions taken by the U.S. EPA. This

listed toxic substances. Following the EPCRA, the EPA set up the TRI database to track and supervise certain classifications of toxic substances from chemical pollutants that can endanger human health and the environment.

[15]We acknowledge that the TRI database is subject to some data limitations, such as a failure to report and reporting errors, as Currie, Davis, Greenstone, and Walker (2015) pointed out. The EPA checks report quality to correct errors and conducts regular quality analysis that is further examined by the Office of Enforcement and Compliance Assurance (OECA). In a quality check report, EPA (1998) shows that reporting errors in the TRI are within a 3% range for most industries. Akey and Appel (2021) and Kim and Kim (2020) affirm that TRI data must be high quality and argue that misreporting in the TRI can lead to criminal or civil penalties.

database provides information on the dollar amount of penalties for pollution in each civil case in the EPA record. We search these civil cases in the database from 1990 to 2017. We then identify firms involved in litigation that is related to violations of environmental regulations and count the frequency of these cases for each firm and year.

Finally, we collect firm-level environmental scores from Thomson Reuters' ASSET4 Environmental, Social, and Corporate Governance database.[16] We use the environmental score (ENVSCORE) and its components, which are assigned to a firm annually.

B. Summary Statistics

Table I, Panel A reports pooled summary statistics. Specifically, Panel A reports the pooled mean, median, standard deviation (Std), 5^{th} percentile (P5), 25^{th} percentile (P25), 75^{th} percentile (P75), and 95^{th} percentile (P95) of the variables of interest, as well as the valid number of observations for each variable. Our main variable, *Emissions*, is the sum of all emissions (in pounds) produced in all plants owned by firm i in year $t-1$ scaled by total assets (in million dollars). Because a firm's emissions in year $t-1$ are recorded in the TRI database and become public information by the end of September of year t, we scale its emissions by its total assets disclosed by the end of March of year t. The emission data are discussed in more detail in Sections I.A and I.C of the Internet Appendix. The other variables include market capitalization (ME), book-to-market ratio (B/M), investment rate (I/K), return on assets (ROA), return on equity (ROE), tangibility (TANT), a Whited and Wu (WW) index to capture financial constraints, operating leverage (OL), and book leverage (Lev).[17]

We have a total of 9,989 firm-year observations with nonmissing emissions. The average *Emissions* is 6,568, suggesting that one million dollars in book assets is associated with 6,568

[16]The database has been used in previous studies of ESG issues (e.g., Ferrell, Liang, and Renneboog (2016), Liang and Renneboog (2017), Dyck et al. (2019), and Hsu, Liang, and Matos (2021)). The ASSET4 sample covers more than 4,500 global public firms included in major equity indices, such as the S&P 500, Russell 1000, and NASDAQ 100, among others. Data are collected from multiple sources, including company reports, company filings, company websites, nongovernmental organization (NGO) websites, CSR reports, and reputable media outlets.

[17]Detailed information on variable construction can be found in Table I.

pounds of chemical emissions. Industry-level summary statistics for *Emissions* are presented in Section I.D in the Internet Appendix.

Table I, Panel B presents a correlation matrix for all of variables considered in Panel A. We find that *Emissions* is generally not highly correlated with the other variables, with the exception of its correlation coefficients with size (ME), asset tangibility (TANT), financial constraints (WW), and operating leverage (OL), which are -0.03, 0.05, 0.07, and 0.07, respectively.

To shed light on whether some of the firm characteristics above predict firm *Emissions*, we run pooled regressions in which we regress the logarithm of firm-level emission intensity (*Emissions*) in year $t + 1$ on the logarithm of current emission intensity in year t, all firm characteristics in year t, and industry-year joint fixed effects. As shown in Table IA.1 in the Internet Appendix, we find that only firm size and asset tangibility have consistent predictive ability for future emissions.[18] Emission intensity significantly decreases with firm size and significantly increases with asset tangibility. These findings are intuitive because firms with higher market value can rely more on intangible assets and thus are less dependent on manufacturing, while firms with more tangible assets are naturally more manufacturing-oriented.[19] Below we conduct factor regressions, Fama-MacBeth regressions, and two-way portfolio sorts to separate the pollution effect from the size effect. We consistently find that

[18]Standard errors are clustered at the firm level to accommodate firm-level autocorrelation (Panel A) or at the industry-year level to accommodate variation within an industry (Panel B). The book-to-market ratio (B/M) is the only firm characteristic in the specification (column (2)); the marginal predictive power of B/M disappears when we pool the other characteristics together in column (9). In contrast, the financial constraint measure (WW index) is significant only when we include the other firm characteristics.

[19]We also examine whether some macroeconomic variables predict aggregate emission intensity in a time-series regression in which we regress the logarithm of aggregate emission intensity (across all sample firms) in year $t+1$ on lagged emission intensity as well as on a battery of macroeconomic variables in year t including unemployment rate (Unep), GDP growth (dy), economic policy uncertainty index (EPU), price-dividend ratio (P/D), cyclically adjusted price-to-earnings (CAPE), TED spread (TED), and default premium (DEF). We calculate the aggregate emission intensity as the market value-weighted average of public firms' emissions scaled by their total assets. As Table IA.2 of the Internet Appendix shows, we find that none of these variables is able to predict aggregate emissions. As a result, the industrial emissions that we focus on likely comprise a unique variable that is distinct from other macroeconomic variables and hence, merits further investigation.

other firm characteristics cannot predict emissions.

C. Univariate Portfolio Sorting: Returns, Firm Characteristics, and Factor Regressions

To investigate the link between emissions and the cross-section of stock returns, we construct quintile portfolios sorted on firms' emissions scaled by total assets (AT) in Panel A, property, plant, and equipment (PPENT) in Panel B, sales (SALE) in Panel C, and market equity (ME) in Panel D, and report each portfolio's post-formation average stock return. As mentioned above, because the EPA updates each emission data by the end of September each year, we form portfolios at the end of each September in year t (from 1992 to 2017) (see Section I.A and Figure IA.1 in the Internet Appendix). Specifically, each year we first sort all sample firms with positive scaled emissions in year $t-1$ into five groups from low to high within the 49 Fama and French (1997) industries. As a result, we have industry-specific break points for quintile portfolios for each September. We then assign all firms with positive scaled emissions in September of year t into quintile portfolios. The low (high) quintile portfolio contains firms with the lowest (highest) emissions in each industry. After forming the five portfolios sorts (from low to high), we calculate the value-weighted monthly returns on these portfolios over the next 12 months (i.e., October of year t to September of year $t+1$). To examine the emission-return relation, we also form a high-minus-low (H-L) portfolio that takes a long position in the high-emission portfolio and a short position in the low-emission portfolio and calculate the return on this portfolio.

In Panels A to D of Table II, the top row presents the *annualized* average excess stock return in percentage (E[R]-R_f, in excess of the risk-free rate), t-statistic, standard deviation, and Sharpe ratio for the six portfolios we consider. The table shows that a firm's emissions forecast stock returns. Taking Panel A, which uses emissions scaled by total assets (our primary proxy of emission intensity), as an example, the quintile portfolio sorts from low to high have annualized excess returns of 6.90%, 9.68%, 9.08%, 9.11%, and 11.32%, respectively. More importantly, the H-L portfolio has an annualized excess return of 4.42% with a t-statistic of 3.66. In addition, the Sharpe ratios of the quintile portfolios are 0.45, 0.57, 0.58, 0.55, and 0.69, respectively, and that of the high-minus-low portfolio is 0.46, which is comparable to the Sharpe ratio of the aggregate equity premium. Similar patterns obtain in other panels. The finding that the return on the H-L portfolio is economically large and statistically significant across all panels suggests significant predictive ability of firm-level emissions for stock returns.

Overall, Table II provides empirical evidence that firm-level emissions help explain subsequent stock returns. In the rest of our analyses, we focus on emission intensity defined as annual emissions scaled by total assets and the associated portfolios.

Table III reports the average firm characteristics across quintile portfolios. We find that, on average, firms in the high-emission group generate emissions of 3,106,629 pounds per year, while firms in the low-emission group generate emissions of 18,808 pounds per year. In addition, the emission intensity of the high (low) group is 8,146.43 (15.52). We further find that high-emission firms are smaller and have higher asset tangibility as well as higher operating leverage, while there is little variation in book-to-market ratio, investment rate, ROA, financial constraints, and financial leverage across emission-sorted portfolios. These results confirm our earlier regression results.

In Table IV, we follow standard procedure and investigate the extent to which the variation in the average returns of the emission-sorted portfolios can be explained by existing risk factors. The table reports the alphas from the leading risk factor models, including the capital asset pricing model (CAPM), the Fama-French five-factor model (Fama and French (2015)), and the HXZ q-factor model (Hou, Xue, and Zhang (2015)). We find that the cross-sectional return spread across portfolios sorted on emission intensity cannot be captured by these risk factors, and the alphas in the long-short portfolio remain statistically significant. Therefore, the positive emission-return relation that we document cannot be attributed to common risk exposure.

D. Fama-MacBeth Regressions and Double Sorting on Size

In Table IV, we examine the emission-return relation by running Fama-MacBeth regressions to control for a variety of firm characteristics as described in Section II.B of the Internet Appendix. The results of these regressions are consistent with the results that obtain we sort portfolios on emission intensity, which show that emission intensity significantly positively predicts future stock returns. In addition, the predictability of emission intensity is not subsumed by known predictors of stock returns in the literature, even when we include all control variables jointly to run a horse race.

We also implement independent double sorts for emission intensity and size to alleviate the concern that the return predictability we document is driven by firm size. We find that high-emission firms continue to outperform low-emission firms in stock returns for both large-firm and small-firm groups. We provide further discussion of these results in Section II.C of the Internet Appendix.

II. Possible Explanations for the Pollution Premium

In this section, we examine whether the positive emission-return relation can be attributed to any of several possible explanations, including behavioral explanations, corporate policies and governance, and relevant risks documented in the literature. Due to space limitations, all tables are provided in the Internet Appendix.

A. Behavioral Explanations

A.1. Emissions Preferences

The literature documents that both retail and institutional investors disfavor firms with a poor social image, such as those that perform poorly with respect to CSR concerns.[20] Prices of these firms therefore tend to be discounted by the market, resulting in higher dividend yields. In a context, when polluting firms reduce their emissions in response to CSR concerns, their prices will be discounted less, resulting in a positive emission-return relationship. There may also exist investors who prefer high dividend yields to a stock's reputation. When these investors earn more dividends, they may buy more high-emission stocks, pushing up the prices of these stocks. In sum, the emission-return relation could be

[20]See Hong and Kacperczyk (2009), Fabozzi, Ma, and Oliphant (2008), Renneboog, Ter Horst, and Zhang (2008), Starks, Venkat, and Zhu (2017), Riedl and Smeets (2017), Gibson and Krueger (2018), Dyck, Lins, Roth, and Wagner (2019), Pástor, Stambaugh, and Taylor (2021), Hartzmark and Sussman (2019), Ramelli, Wagner, Zeckhauser, and Ziegler (2021), and Goldstein, Kopytov, Shen, and Xiang (2022), among others.

driven by investors' preferences on emissions.

To test this explanation, we measure institutional investors' "emission preferences" and examine whether the emission-return relation varies across different types of institutional investors.[21] If the emission preference explanation holds, we expect emission-driven return predictability to be absorbed by institutional investors' emission preferences. We control for emission preferences in our Fama-MacBeth regressions in column (1) Table IA.3 in the Internet Appendix. The results show that emission intensity continues to significantly positively predict future stock returns after controlling for emission preferences.

We also form double-sorted portfolios based on firm emissions and institutional investors' emission preferences.[22] We present the average returns of our double-sorted (5 by 2) portfolios as well as t-statistics in Panel A of Table IA.5 in the Internet Appendix; we annualize portfolio returns by multiplying them by 12. In the high-emission-preference group, the H-L return spread based on emission-sorted portfolios is 4.98%, significant at the 1% level; in the low-emission-preference group, the H-L return spread based on emission-sorted portfolios is 4.72%, significant at the 5% level with a t-statistic of 2.03. These results suggest that the emission-related return predictability holds in the sample without emission preferences, consistent with the main Fama-Macbeth regression results. Therefore, the pollution premium cannot be attributed to differences in investor preferences with respect to pollution.

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[21]We capture institutional investors' emission preferences following a two-step procedure. In the first step, we collect institutional holdings data at the end of September of year t from the Thomson Reuters Institutional Holdings (13F) database and calculate an institutional investor's exposure to emissions in year t as the valued-weighted emission intensity in year $t-1$ of the firms that it holds. This method is motivated by the sustainability footprint of Gibson and Krueger (2018), and the weighting factor is based on the market values of all firms held by an institutional investor. In the second step, we calculate the pressure on a firm from institutional investors' emission preferences in year t as the value-weighted average of institutional investors' exposure to the firm's emissions. The weighing factor is based on the shares owned by all institutional investors that hold the focal firm.

[22]In particular, we independently sort firms into two portfolios based on their institutional investors' emission preferences and into five portfolios based on their emission intensity at the end of September of year t, all relative to industry peers. We then calculate the value-weighted return on each portfolio from October of year t to September of year $t+1$.

A.2. Investor Underreaction to Emission Abatement

High-emission firms may be subject to greater pressure from the community and government and may be thus more likely to cut back emissions. However, the literature documents that investors may underreact to market news due to limited attention or a lag in information diffusion.[23] If investors who prefer firms with a higher social image underreact to high-emission firms' reduction in emissions in the future, the stock prices of these firms may increase, resulting in the emission-return relation that we find. This explanation is not supported by Table IA.1 in the Internet Appendix, which shows a persistent pattern in firm-level emissions. That said, this table does not rule out the possibility that the pollution premium may be driven by a subset of high-pollution firms that significantly reduce their emissions in the future, leading subsequent stock prices to rise.

To provide further evidence on this possibility, we focus on firms in the highest emission quintile portfolios that we further sort into two portfolios based on their emission intensity in year t (i.e., future emissions). The HL portfolio includes firms with future emission intensity below the median of the high group and the HH portfolio includes firms with future emission intensity above the median of the high group.[24] If the underreaction explanation holds, the emission-return relation should be evident in the HL group but not in the HH group. Panel B of Table IA.5 in the Internet Appendix presents the average portfolio return in the lowest quintile portfolio (L) as well as the return difference between the HL and L groups and the return difference between the HH and L groups. The empirical results show that although the HL-L difference is significantly positive on average (3.96% with a t-statistic of 3.31), the HH-L difference is also significantly positive on average (5.39% with a t-statistic of 2.34). In other words, even high-pollution firms that do not reduce their emissions in the future provide

[23]Prior studies suggest that investors tend to underreact to new information (e.g., Bernard and Thomas (1990)), especially complex information (e.g., You and Zhang (2009)). For example, in the innovation literature, the evidence suggests that investors tend to overdiscount the cash flow prospects of R&D-intensive or patenting firms due to high uncertainty and complexity associated with innovations or fail to account for the benefits of innovation due to limited attention, which results in the underpricing of innovation (see, for example, Hall (1993), Lev and Sougiannis (1996), Aboody and Lev (1998, 2000), Chan, Lakonishok, and Sougiannis (2001), and Hirshleifer, Hsu, and Li (2013, 2017)).

[24]We present the transition matrix in Section I.E of the Internet Appendix.

significantly higher returns than low-pollution firms. Hence, the underreaction explanation is unlikely to explain the cross-sectional variation in stock returns due to emissions.

A.3. Retail Investors' Behavioral Bias

In contrast to institutional investors who are more rational and have more complete information, retail investors may be subject to greater behavioral bias (See Daniel, Hirshleifer, and Subrahmanyam (1998), Barberis, Shleifer, and Vishny (1998), and Hong and Stein (1999), among others). For example, retail investors may panic in response to negative emission news (Krüger (2015) and Ottaviani and Sørensen (2015)) and sell all their stock holdings at deep discounts. If such overreaction explains the pollution premium, we would expect the emission-return relation to exist only among stocks that experience a significant drop in the share of retail investors.

To test this explanation, we first conduct the percentage share of retail investors as one minus the percentage share owned by institutional investors at the end of each quarter. We control for changes in retail investors' share (*Share*) in our Fama-MacBeth regressions in column (2) of Table IA.3 in the Internet Appendix. We find that emission intensity significantly positively predicts future stock returns, while the coefficient on changes in retail investors' share is statistically insignificant. We next form double-sorted portfolios based on firm emissions and changes in retail investors' share. At the end of September of year t, we sort all stocks with emission intensity into three portfolios (30-40-30) based on the change in retail investors between June and September of year t within each industry. The high (low) group includes stocks that experience the strongest increase (decrease) in retail investors' share. Then, within each group, we further sort stocks into quintile portfolios based on firm emissions within a industry. Panel C of Table IA.5 in the Internet Appendix shows that, for the middle tercile (Group 2), the return spread (4.08% with a t-statistic of 2.96) is significant and comparable to that in the univariate portfolio sorting, and the change in retail investors' share is close to zero (the mean and median are 0.05 and 0.04, respectively). In contrast, for other groups (Group 1 or 3, respectively) the lowest and highest changes in retail investors' share, the return spread (i.e., the return on the H-L portfolio) is insignificant. These results suggest that the emission-return relation is orthogonal to the ownership of retail investors, who are more subject to overreaction bias. As a result, the positive emission-return relation does not reflect retail investors' behavioral bias.

B. Corporate Governance and Political Connections

B.1. Corporate Governance

Another possible explanation for the emission-return relation is that high-emission firms are subject to weaker governance or monitoring (Masulis and Reza (2015), Cheng, Hong, and Shue (2013), Glossner (2018), Hoepner, Oikonomou, Sautner, Starks, and Zhou (2019)) and hence their stock prices are discounted by investors concerned about weak governance and the associated risk and uncertainty (e.g., Gompers, Ishii, and Metrick (2003)). Such low prices may attract bidders or active investors that seek to these firms' governance and monitoring, in which case, stock prices show increase and lead to return predictability. If such channels are responsible for the emission effect, we would expect there to be no emission-return relation among firms with strong corporate governance. To test this explanation, we control for firms' G index and E index, respectively, in our Fama-MacBeth regressions in column (3) and (4) of Table IA.3 in the Internet Appendix. We find that emission intensity continues to significantly positively predict future stock returns, while G index or E index loads insignificantly.

We also double sort firms' G index or E index into two portfolios (low and high) and firms' emission intensity into quintile portfolios (low, 2, 3, 4, and high), all relative to their industry peers.[25] Panel A of Table IA.6 in the Internet Appendix shows that returns on the H-L portfolio sorted on emission intensity remain statistically significant among firms in the strongest governance (i.e., low G index or E index) group. In particular, within the low G index group (upper panel), the H-L portfolio return is equal to 5.52%, significantly at 1% level. Therefore, our emission-return relation cannot be attributed to differences in governance and monitoring.

[25] Detailed information on the G index and E index comes from Gompers, Ishii, and Metrick (2003) and Bebchuk, Cohen, and Ferrell (2008), respectively.

B.2. Political Connections

It is also possible that high-emission firms may be more politically connected. Since political connections are positively related to future stock returns (e.g., Liu, Shu, and Wei (2017)), and results in a risk premium (Santa-Clara and Valkanov (2003)), the emission-return relation may, therefore, reflect the asset pricing implications of political connections. Under this explanation, we would expect there to be no emission-return relation among firms with low political connections.

To test this explanation, we collect annual firm-level political donation data from OpenSecrets.org maintained by the Center for Responsive Politics.[26] We define a firm's political connections as the total amount of its political donation (regardless of party) in a year scaled by total assets.[27] We control for political donations in our Fama-MacBeth regressions in columns (5) and (6) of Table IA.3 in the Internet Appendix. We find that emission intensity significantly positively predicts future stock returns, while political donations do not. We also double sort firms by political connections into portfolios (low and high) and by emission intensity into five portfolios (low to high). Panel B of Table IA.6 in the Internet Appendix shows that returns on the H-L portfolio sorted on emission intensity are statistically significant in both political donation groups. The return spread is as high as 6.20% (with a t-statistic of 2.29) in low political donation group, which is even larger than the return spread of 4.26% (with a t-statistic of 4.85) in the high political donation group and the return spread of 4.42% in the univariate portfolio. These results indicate that political connections cannot explain the pollution premium.

C. Existing Systematic Risks

We also explore possible explanations based on systematic risks posited in prior studies. In particular, we consider four alternative channels that may drive variations in our emission-sorted portfolios: technology obsolescence (Lin, Palazzo, and Yang (2020)), financial constraints (Li (2011), Lins, Servaes, and Tamayo (2017)), economic and political uncertainty

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

[27] If a firm with positive emission intensity does not make any political contributions, we set its political connections to zero.

(Brogaard and Detzel (2015), Bali, Brown, and Tang (2017)), and adjustment costs (Kim and Kung (2016), Gu, Hackbarth, and Johnson (2017)). The rationale for these explanations in a context is as follows. High-emission firms employ more obsolete technology as they invest less in advanced production capital. The arrival of new technology forces these firms to upgrade their production capital, and hence their cash flows are likely sensitive to frontier technology shocks. In addition, high-emission firms may be subject to financial constraints due to litigation and penalties related to environmental issues. High-emission firms may also be more subject to risk associated with macroeconomic uncertainty, such as economic downturns or trade conflicts, and political uncertainty, such as changes of the ruling party. Finally, high-emission firms may deliver higher expected returns because it is costly for them to adjust their capital stock, especially during economic downturns.

C.1. Technology Obsolescence

To capture firm-level technology obsolescence, we follow Lin, Palazzo, and Yang (2020) and employ both capital age and the investment rate. A firm with older capital or a lower investment rate faces higher exposure to technology frontier shocks and hence is more exposed to risk. We control for capital age and investment rate (I/K) in our Fama-MacBeth regressions in columns (7) and (8), respectively, of Table IA.3 in the Internet Appendix. We find that emission intensity significantly positively predicts future stock returns. We also implement two-way sorting. In Panel A of Table IA.7 in the Internet Appendix, we show that the H-L emissions return spread is comparable to that in the univariate portfolio sort in both of the capital age and both of the investment rate groups. Specifically, the return spread is 4.07% (with a t-statistic of 2.44) in the young capital age group and 4.24% (with a t-statistic of 2.50) in the old capital age group, and it is 4.16% (with a t-statistic of 4.28) in the low investment rate group and 5.31% (with a t-statistic of 3.22) in the high investment rate group. If technology obsolescence is the main force driving the pollution premium, we should observe significant return spreads only in the old capital age and low investment rate groups. In contrast, the return spreads are significant in the young capital age and high investment rate groups. Therefore, the pollution premium cannot be explained by technology obsolescence.

C.2. Financial Constraints

To test the role of financial constraints, we employ the financial constraints measures of the WW index (Whited and Wu (2006)) and SA index (Hadlock and Pierce (2010).)[28] A higher value of the SA or WW index suggests that the firm is likely subject to greater financial constraints. We control for the SA index and the WW index in columns (9) and (10), respectively, in our Fama-MacBeth regressions in Table IA.3 in the Internet Appendix. We find that emission intensity continues to significantly positively predict future stock returns. In Panel B of Table IA.7 in the Internet Appendix, we further show that the return spread from emissions is significantly positive in both less and more financially constrained groups. The fact that financially unconstrained firms' emissions still predict stock returns suggests that financial constraints cannot explain the pollution premium.

C.3. Economic and Political Uncertainty

To measure the exposure to political and macroeconomic uncertainty, we estimate the firm-level exposure using rolling window regressions, following Bali, Brown, and Tang (2017) to estimate firm-level exposure to the macroeconomic uncertainty index based on Jurado, Ludvigson, and Ng (2015) and the political uncertainty index based on Bloom (2009).[29] We control for firm-level exposure to macroeconomic uncertainty (UNC Beta) and political uncertainty (EPU Beta) in Columns 11 and 12, respectively, in our Fama-Macbeth regressions of Table IA.3 in the Internet Appendix. We find that emission intensity continues to significantly positively predict future stock returns. We also implement two-way sorts. The left and right sides of Table IA.7, Panel C in the Internet Appendix present the returns of the 12 portfolios sorted on macroeconomic uncertainty and political uncertainty, respectively. Within both high and low macroeconomic or political uncertainty exposure

[28]Detailed information on the construction of the SA and WW indexes can be obtained from Farre-Mensa and Ljungqvist (2016).

[29]For each stock with positive emissions in each month in our sample, we estimate the uncertainty exposure from monthly regressions of excess returns on the macroeconomic uncertainty index over a 60-month rolling window controlling for empirical risk factors, including the market (MKT), size (SMB), value (HML), momentum (UMD), liquidity (LIQ), investment (I/A), and profitability (ROE).

groups, the return spreads sorted on emission intensity are significantly positive. These findings suggest that the emission-return relation is not driven by different levels of exposure to macroeconomic or political uncertainty.

C.4. Adjustment Costs

We follow Kim and Kung (2016) and Gu, Hackbarth, and Johnson (2017) to measure a firm's asset redeployability and inflexibility, respectively.[30] If the adjustment costs of asset redeployability (inflexibility) drive the pollution premium, we would expect such a premium not to exist in firms with the high asset redeployability (low inflexibility), which is associated with lower adjustment costs. We control for asset redeployability and inflexibility in our Fama-MacBeth regressions in columns (13) and (14), respectively, of Table IA.3 in the Internet Appendix and find that emission intensity again significantly positively predicts future stock returns. When we implement two-way sorts in Panel D of Table IA.7 in the Internet Appendix, the emission-return relation appears significantly positive in both high-asset-redeployability and low-inflexibility groups, which suggests that the return predictability we document is unrelated to systematic risk associated with adjustment costs.

Overall, we find that high-emission firms earn higher stock returns than low-emission firms in all groups with less exposure to systematic risks, as documented in the literature. These results thus point to the unique role that emissions play with respect to return predictability.

III. Additional Empirical Evidence

In this section, we examine the association between firm-level emissions and environmental litigation and profits. We also examine whether the emission-return relation is related to Trump's U.S. presidential election win on November 8, 2016, which is an exogenous event with respect to environmental policies.

[30]Detailed information on the construction of the asset redeployability index is provided in Table IA.7 of the Internet Appendix.

A. Environmental Litigation

To check that our emission intensity measure is a valid proxy for firms' pollution, we examine whether firms with higher emission intensity have a significantly higher probability of facing litigation for pollution.

To do so, We begin by collecting all federal- and state-level cases against pollution to obtain a more accurate estimate of the probability of litigation associated with environmental issues.[31] Using these data, we estimate the regression

$$N_{i,t+5} = a + b_1 \times Emissions_{i,t} + c \times Controls_{i,t} + \varepsilon_{i,t}, \tag{1}$$

where the left-hand-side variable denotes firm i's future litigation status. Specifically, $N_{i,t+5}$ is defined as a binary variable that indicates whether a firm is involved in litigation or as a count variable that reflects the total number of lawsuits from year $t+1$ to year $t+5$. When we use binary measure, we estimate equation (1) using a Probit regression; when we use count variable, we estimate equation (1) using a Poisson count and negative binomial regression, respectively. We control for a firm's fundamentals, including size, book-to-market ratio, investment rate, current profitability, tangibility, financial constraints, book leverage, and operating leverage in year t. We also include industry-year fixed effects.[32]

In Table VI, we find that emissions in all predictive regressions significantly positively predict environmental-related lawsuits in all specifications. In our sample, 26% of firms will be sued for environmental issues in the following five years, and an average firm will be involved in 1.56 lawsuits in the following five years. The coefficients suggest that a one-standard-deviation increase in emission intensity is associated with a 16.20% higher probability or 2.46 times higher frequency of litigation. Such an increase in litigation probability or frequency is value-relevant because the mean and standard deviation of penalties are as high

[31] More details about these data sources are provided in Section I.B of the Internet Appendix.

[32] Standard errors are clustered at the industry-year level to accommodate within-industry variation (Specifications 1 and 3) or at the firm level to accommodate firm-level autocorrelation (Specifications 4 to 6). We standardize all explanatory variables in equation (1) to facilitate interpretation of economic magnitudes, and report the estimated coefficients in Table VI.

as 1.57 and 8.93 million dollars (real), respectively. These results indicate that our emission intensity well captures firm-level pollution as it predicts firms' likelihood of experiencing environmental litigation.

B. *Current Cash Flows (Profitability)*

We next examine the relation between firm-level emissions and profits by estimating the OLS regression

$$ROA_{i,t} = a + b_1 \times Emissions_{i,t} + c \times Controls_{i,t} + \varepsilon_{i,t}, \tag{2}$$

where $ROA_{i,t}$ is firm i's profitability as measured by ROA, $Emissions_{i,t}$ denotes firm i's emission intensity in year t, and control variables include lagged ROA in year $t-1$, size, book-to-market ratio, investment rate, lagged profitability, tangibility, financial constraints, book leverage, and operating leverage in year t, as well as industry-year fixed effects.[33] Specifications 1 and 2 of Table VII show that the estimated coefficient on *Emissions* (b_1) is significantly positive, suggesting that high-emission firms enjoy higher current profitability by saving on pollution abatement and environmental recovery costs.

To shed light on the negative relation between pollution abatement costs and contemporaneous profitability, we provide direct evidence by including the firm-level abatement costs into control among the control variables in the regressions.[34] In Panel A of Table VIII, we

[33]All independent variables are normalized to have zero mean and unit standard deviation after winsorization at the 1st and 99th percentiles to reduce the impact of outliers. We standardize all explanatory variables to facilitate interpretation of economic magnitudes. Standard errors are clustered at the firm level to accommodate firm-level autocorrelation (Specification 1) or at the industry-year level to accommodate within-industry variation (Specification 2). We include industry-year fixed effects in Table VII for current and future profitability for the following reasons. First, it is well known that industry-specific, time-varying competition, business cycles, or technological development influence the profits of all firms in an industry (Giroud and Mueller (2010)). Second, in an unreported test, we add industry-average ROA (excluding the focal firm) as a control variable in all regressions of Table VII and find that it carries significantly positive coefficients, which supports industry-specific, time-varying trends in firm-level ROA.

[34]The abatement cost measure refers to the ENER and ENRR variables from the ASSET4 database. ENER measures a company's commitment and effectiveness in reducing air emissions, waste, water discharge,

find a significantly negative correlation between firms' emission intensity and their efforts to reduce environmental pollution (as measured by ENER and ENRR in Thomson Reuters' ASSET4 database). In Panel B of Table VIII, Specifications 1 and 2 present consistent results when we control for various proxies for firm fundamentals.

C. Event Study

To provide additional evidence on whether the emission-return relation is related to environmental policies, we analyze stock price reactions on the date of Trump's U.S. presidential election win on November 8, 2016 as a prominent environmental policy shock, following Ramelli, Wagner, Zeckhauser, and Ziegler (2021), Brown and Huang (2020), and Child, Massoud, Schabus, and Zhou (2021).[35] To isolate the impact of new information on stock prices, we consider CARs calculated with respect to the CAPM.[36] We then compute the average CAR of all stocks in each quintile portfolio (based on firms' emission intensity at the end of September 2016) in response to the presidential election and include them in Table IX.

The CARs of emission-sorted portfolios display a largely monotonic increasing pattern from the lowest to the highest portfolios in relation to the U.S. presidential election event. In addition, the difference in CARs for stocks in the lowest and highest portfolios is sizable at

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and spills or its impact on biodiversity. ENRR measures a company's ability to reduce the use of materials, energy, or water and to pursue more eco-efficient solutions by improving supply chain management.

[35]Di Giuli and Kostovetsky (2014) also show that firms with low social responsibility scores provide significantly positive three-day CARs after Republican election victories. The authors in Acemoglu et al. (2016b) document positive CARs for financial firms connected with Timothy Geithner following his nomination for U.S. Treasury Secretary in 2008. Wagner, Zeckhauser, and Ziegler (2018) present evidence of positive spikes in stock prices among firms with high tax burdens following the 2016 U.S. presidential win. Brown and Huang (2020) find that firms with connections to the Obama administration experienced lower stock returns following Trump's victory. Child et al. (2021) show that firms with presidential ties enjoyed greater CARs around the 2016 election.

[36]Following standard practice in the literature, we adopt a 250-trading day estimation window ending 25 days prior to the event day. To do so, we first calculate the market-adjusted CAR of each stock over one date after the U.S. presidential election to ten days after the event date, which we refer to as the (0,10) window.

66.97% in annualized terms, significant at the 5% level. This result suggests that the stock market perceived the 2016 U.S. presidential outcome as good news for high-emission firms, anticipating that environmental regulations were likely to be relaxed. High-emission firms therefore retain their profitability advantage when weak regulation regimes are confirmed, with their stock prices reacting positively. More importantly, this finding indicates that the documented emission-return relation is indeed related to governments' environmental regulation policies. This result calls for more theoretical work.

IV. A General Equilibrium Model

Given the pollution premium and several interesting empirical patterns that we document above, we next build a general equilibrium asset pricing model that features risk related to environmental policy regime shifts to explain the role that industrial pollution plays with respect to expected stock returns. Our specification of policy regime shifts is similar to that of Pástor and Veronesi (2012, 2013). The basic intuition is that high-emission firms are more exposed to risks of environmental policy regime change and therefore require higher expected returns as compensation.

A. The Model Economy

Production. We consider an economy with a finite horizon $[0, T]$ and a continuum of firms $i \in [0, 1]$. Let B_t^i denote firm i's capital at time t. Debt financing is not taken into account—firms in our economy rely entirely on equity financing.[37] Therefore, firm i's total capital equals B_t^i. At time 0, all firms are endowed with the same amount of capital, which we normalize to $B_0^i = 1$. Firm i invests its capital in a linear production technology with a stochastic rate of return denoted by $d\Pi_t^i$. All profits are reinvested, so that firm i's capital dynamics are given by $dB_t^i = B_t^i d\Pi_t^i$. Since $d\Pi_t^i$ equals profits over capital, we refer to it as

[37]In Section IV of the Internet Appendix, we further extend our model to explicitly allow for regime-switching debt financing. We show that this additional channel amplifies the emission-return relation.

the profitability or ROA of firm i. For all $t \in [0, T]$, profitability follows the process

$$d\Pi_t^i = (\mu + \xi^i g)dt + \sigma dZ_t + \sigma_I dZ_t^i, \tag{3}$$

where $(\mu, g, \sigma, \sigma_I)$ are observable and constant parameters, Z_t is a Brownian motion, and Z_t^i is an independent Brownian motion that is specific to firm i. The parameter g denotes the impact of different environmental policy regimes (i.e., weak- or strong-regulation regimes) on mean profitability process across firms. When $g = 0$, the environmental policy regime is "neutral" with zero impact on firm i's profitability.

The impact of an environmental policy regime shift, g, is constant when the regime is not changed. At time τ (i.e., $0 < \tau < T$), the government makes an irreversible decision as to whether to change its environmental policy from the weak regulatory regime to the strong regulatory regime. As a result, g is a simple step function over time,

$$g = \begin{cases} g^{\mathrm{W}} & \text{for } t \leqslant \tau \\ g^{\mathrm{W}} & \text{for } t > \tau \text{ if no policy regime shift occurs} \\ g^{\mathrm{S}} & \text{for } t > \tau \text{ if a policy regime shift occurs,} \end{cases} \tag{4}$$

where g^{W} denotes the impact of environmental policy under the weak-regulation regime at the onset. An environmental policy change replaces the weak regulation, denoted by W, by the strong regulation, denoted by S. Such a policy decision replaces g^{W} by g^{S}, inducing a permanent change in firms' average profitability. We further assume that firms with different levels of emission intensity have heterogeneous exposure to the environmental policy regime shift, as captured by the parameter ξ^i. We assume that ξ^i is positively proportional to firms' emission intensity and is drawn from a uniform distribution on the interval $[\xi^{min}, \xi^{max}]$ at time 0 after which it remains unchanged. For now, we take ξ^i to be exogenously given. In Section IV.E, we discuss how emission intensity is endogenously chosen ex-ante by firm i. Without loss of generality, we normalize the distribution of ξ^i, which has a mean equal to one. As we detail in Section V of the Internet Appendix, we calibrate the parameters such that $g^{\mathrm{S}} < 0 < g^{\mathrm{W}}$ and establish the interval of ξ as [0,2].[38]

This setup together with its calibrated parameters has two implications. First, as $g^{\mathrm{S}} < g^{\mathrm{W}}$ and ξ^i has unit mean, the environmental policy change from the weak- to the strong-regulation regime has an adverse effect on average profitability in the economy.

Second, the parameter ξ^i governs the heterogeneous exposure of firms' profitability with respect to regime change risks across firms with different levels of emission intensity. Suppose that there are two firms: a high-emission firm (ξ^H) and a low-emission firm (ξ^L, such that $\xi^L < \xi^H$). Owing to lower abatement costs under the weak regime, a high-emission firm's average profitability is higher than that of a low-emission firm by the magnitude $g^{\mathrm{W}}(\xi^H - \xi^L)$. This assumption is consistent with the empirical evidence in Section III.B: that high-emission firms enjoy higher current ROA than their low-emission counterparts, as take on fewer costs of pollution abatement and environmental recovery. In stark contrast, because $g^{\mathrm{S}} < 0$, high-emission firms' average profitability drops more than low-emission firms under the strong-regulation regime.[39] As another piece of suggestive evidence, in Section V.B we show that, upon the arrival of policy change shocks that increase the perceived likelihood of a regime shift, high-emission firms' future ROA drops more than that of low-emission firms. As we discuss below, the cross-sectional dispersion in firms' emission intensity, ξ^is, by the assumption above is an important factor in generating heterogeneous firms' exposure to aggregate regime changes and therefore in determining different risk premia across emission-sorted portfolios in equilibrium.

The firms are owned by a continuum of identical households that maximize expected utility derived from terminal wealth.[40] For all $j \in [0, 1]$, investor j's utility function is given

[38]In Section V of the Internet Appendix, we show that such calibration allows our model to reproduce a monotonically increasing pattern of firms' current profitability (ROA) and a flat pattern of firms' future ROA, consistent with our data.

[39]For this assumption, we present supportive evidence in Section V of the Internet Appendix for the quantitative implication. In particular, we show that although high-emission firms' current ROA is higher, their average future ROA is similar to that of their low-emission counterparts. This implies that high-emission firms' ROA tends to be more negatively affected than that of low-emission firms when strong regulation is enacted with some positive probability.

[40]This setting is consistent with our empirical design of scaling emissions by total assets.

by

$$U(W_T^j) = \frac{(W_T^j)^{1-\gamma}}{1-\gamma}, \tag{5}$$

where W_T^j is investor j's wealth at time T and $\gamma > 1$ is the coefficient of relative risk aversion. At time 0, all investors are equally endowed with the same shares of firm stocks. Stocks pay dividends at time T.[41] Households observe whether regime shifts occur at time τ.

When making its policy decision at time τ, the government maximizes the same objective function as households, except that it internalizes the negative externalities of pollution as the environmental cost $\Phi(c)$ if the economy is under the weak environmental regulation regime. The government commits to a change in environmental policy only if the government's expected utility under the strong regulation is higher than that when under the weak regulation. Specifically, the government solves the optimization problem

$$\max_{\tau>t}\left\{ \mathrm{E}_\tau\left[\frac{\Phi(c)W_T^{1-\gamma}}{1-\gamma}\middle|\mathrm{W}\right], \mathrm{E}_\tau\left[\frac{W_T^{1-\gamma}}{1-\gamma}\middle|\mathrm{S}\right]\right\}, \tag{6}$$

where $W_T = B_T = \int_0^1 B_T^i di$ is the final value of aggregate book equity and $\Phi(c) = 1 + e^c$ is the *environmental cost* if the goverment retains the weak-regulation regime. We refer to $\Phi(c) > 1$ as the cost to the society because, given $\gamma > 1$, a higher value of $\Phi(c)$ translates into lower utility since $W_T^{1-\gamma}/(1-\gamma) < 0$. The value of c is randomly drawn at time τ from a normal distribution as below, which implies that $E[e^c] = 1$, and

$$c \sim Normal\left(-\frac{1}{2}\sigma_c^2, \sigma_c^2\right), \tag{7}$$

where c is independent of the Brownian motion in equation (3). We assume that the environmental cost c is unknown to all agents until time τ and follows a prior distribution as in equation (7). We refer to σ_c as *regime shift uncertainty.* Due to the uncertainty about environmental costs before time τ, stock prices respond to environmental cost signals, as we show in Section III.C.

[41]No dividends are paid before time T because households' preferences do not involve intermediate consumption. Firms in our model reinvest all of their earnings, as mentioned above.

B. Learning about Environmental Costs

The environmental cost c is unknown to all agents until time τ. At time $t < \tau$, agents start to learn about c by observing unbiased signals. We model these signals as *the true value of signals plus noise*, which takes the following form in continuous time:

$$ds_t = cdt + dZ_t^c. \tag{8}$$

The signal ds_t is assumed to be independent of other shocks in the economy. We refer to these shocks as environmental cost signals, and note that they capture the steady flow of news related to environmental issues that are of concern to both the media and regulatory authorities. Combining the signals in equation (8) with the prior distribution in equation (7), we obtain the posterior distribution of c at any time $t < \tau$,

$$c \sim Normal(\hat{c}_t, \hat{\sigma}_{c,t}^2), \tag{9}$$

where the posterior mean and variance evolve according to

$$d\hat{c}_t = \hat{\sigma}_{c,t}^2 d\hat{Z}_t^c, \text{and} \tag{10}$$

$$\hat{\sigma}_{c,t}^2 = \frac{1}{\frac{1}{\sigma_c^2} + t}. \tag{11}$$

Equation (10) shows that agents' beliefs about c are driven by the Brownian motion shocks $d\hat{Z}_t^c$, which reflect the differences between the cost signals ds_t and their expectations ($d\hat{Z}_t^c = ds_t - \mathrm{E}_t[ds_t]$). Since the cost signals are independent of all fundamental shocks in the economy (i.e., dZ_t and dZ_t^i), the innovations $d\hat{Z}_t^c$ represent signal shocks to the true value of environmental costs. These shocks shape agents' beliefs about which environmental policy is likely to be adopted in the future, above and beyond the effect of fundamental economic shocks. Accordingly, we refer to such signal shocks as *regime change risks*. Later, we emphasize that these shocks command a risk premium in equilibrium. Moreover, since firms with different levels of emission intensity have heterogeneous exposure to regime shifts, they exhibit different levels of risk compensation with respect to regime change risks.

C. *Optimal Regulation Regime Changes*

After a period of learning about c, the government decides whether to change policy regime at time τ. If the government changes the policy regime, then the value of g changes from g^{W} to g^{S}. According to equation (6), the government changes policy regime if and only if

$$\mathrm{E}_\tau\left[\frac{W_T^{1-\gamma}}{1-\gamma}\middle|\mathrm{W}\right] > \mathrm{E}_\tau\left[\frac{\Phi(C)W_T^{1-\gamma}}{1-\gamma}\middle|\mathrm{S}\right]. \tag{12}$$

Since a regime change permanently affects future profitability, the two expectations in equation (12) are determined by different stochastic processes for aggregate capital $B_T = \int_0^1 B_T^i di$.[42]

According to Lemma A.1 in Section III.A of the Internet Appendix, the inequality can be further simplified into a rule that explains the policy regime change, as we show in the following proposition.

PROPOSITION 1: *A regulation regime change occurs at time τ if and only if*

$$\underline{c}(\tau) < c, \tag{13}$$

where

$$\underline{c}(\tau) = \log\left\{e^{(\gamma-1)(g^W-g^S)(T-\tau)} - 1\right\} > 0. \tag{14}$$

The probability of the policy regime change at $\tau-$ is denoted by $p_{\tau-}$,

$$p_{\tau-} = 1 - Normal(\underline{c}(\tau); \hat{c}_{\tau-}, \hat{\sigma}^2_{c,\tau-}), \tag{15}$$

where $Normal(x; \hat{c}_{\tau-}, \hat{\sigma}^2_{c,\tau-})$ denotes the cumulative density function (c.d.f.) of a normal distribution with mean $\hat{c}_{\tau-}$ and variance $\hat{\sigma}^2_{c,\tau-}$.

Proof: See the Proof in Section III.B of the Internet Appendix.

COROLLARY 1: *Agents' time-t perceived probability of policy regime change at time τ con-*

[42]The aggregation of capital at time T is further derived in Section III.A of the Internet Appendix.

ditional on information at time t $(t < \tau)$ *is given by* $p_{\tau|t}$,

$$p_{\tau-|t} = 1 - Normal(\underline{c}(\tau); \hat{c}_t, \hat{\sigma}^2_{c,t}), \tag{16}$$

where $Normal(x; \hat{c}_t, \hat{\sigma}^2_{c,t})$ *denotes the c.d.f. of a normal distribution with mean* $\hat{c}_t$ *and variance* $\hat{\sigma}^2_{c,t}$.

Proof: See the Proof in Section III.C of the Internet Appendix.

The intuition behind Corollary 1 provides us two testable implications for our empirical analysis in Section V. First, using the growth in civil penalties as a proxy for regime change shocks, we show that such shocks that increase the perceived probability of a regime change lead to negative changes in asset prices. Second, Corollary 1 is consistent with our finding in Section III.C: upon Trump's U.S. presidential victory as a *negative* regime change shock, the perceived probability of switching to a strong policy regime is revised downwards. Thus, high-emission firms' stock prices react more positively to these events than to those of low-emission firms.

D. Asset Pricing Implications

In this section, we derive the asset pricing implications of regime change risks as follows. First, we show the impact of regime change risks on the state price density. Second, we show how stock prices vary with fundamental shocks and regime change shocks. Finally, we decompose firms' risk premia into risk compensation to fundamental shocks and risk compensation to regime change shocks. We find that the heterogeneity in firms' emission intensity translates into cross-sectional differences in expected stock returns with respect to regime change risks.

D.1. State Price Density

Our main focus is on the response of stock prices before regime shift uncertainty is resolved at time τ. Before time τ, agents learn about the environmental cost under weak regulation. This learning generates stochastic variation in the posterior mean of c according to equation (8), which represents a stochastic state variable that affects asset prices before time τ. In contrast, the posterior variance of c varies deterministically over time as in equation (9).

The dynamics of the state price density π_t are essential for understanding the source of risks in this economy.[43] An application of Ito's Lemma to π_t determines the SDF as shown in Proposition 2.

PROPOSITION 2: *The SDF follows the process*

$$\frac{d\pi_t}{\pi_t} = E_t\left[\frac{d\pi_t}{\pi_t}\right] - \lambda dZ_t - \lambda_{c,t} d\hat{Z}_t^c, \tag{17}$$

where the price of risk for fundamental shocks is given by

$$\lambda = \gamma\sigma, \tag{18}$$

and the price of risk for uncertainty shocks is given by

$$\lambda_{c,t} = \frac{1}{\Omega_t}\frac{\partial \Omega_t}{\partial \hat{c}_t}\hat{\sigma}_{c,t}^2 \eta^{-1} < 0. \tag{19}$$

Proof: See the Proof of Proposition 2 in the Internet Appendix.

Equation (17) shows that the prices of risk λ and $\lambda_{c,t}$ measure the sensitivity of the SDF with respect to fundamental shocks and regime change shocks. Fundamental shocks are represented by the Brownian motion dZ_t, which drives the aggregate fundamentals (profitability) of the economy. The first term of the SDF shows that fundamental shocks affect the SDF in the same way when all parameters are known. The second type of shocks consists of regime change shocks. Although unrelated to fundamental shocks (i.e., $dZ_t \cdot d\hat{Z}_{c,t} = 0$), regime change shocks affect expected utility by affecting the perceived probability of a regime change and hence are priced. Equation (19) shows that regime change shocks impact the SDF more when the sensitivity of marginal utility to variation in $\hat{c}_t$ is larger (i.e., $\partial\Omega_t/\partial\hat{c}_t$ is larger) and when the posterior variance $\hat{\sigma}_{c,t}$ is larger. As we prove in the Internet Appendix, the sign of $\lambda_{c,t}$ is negative. Thus, upon a positive regime change shock, both the marginal

[43] We determine the level of the state price density in Section III.D of the Internet Appendix.

value of wealth and the state price of density increase and hence regime change shocks carry a negative price of risk.

D.2. Stock Prices and Risk Premia

In this subsection, we present analytical expressions for the dynamics of firm i's stock price, which are summarized in the following proposition.[44]

PROPOSITION 3: *Firm i's realized stock returns at $t < \tau$ follow the process*

$$\frac{dM_t^i}{M_t^i} = E_t\left[\frac{dM_t^i}{M_t^i}\right] + \sigma dZ_t + \sigma_I dZ_t^i + \beta_{M,t}^i d\hat{Z}_t^c, \tag{20}$$

where firm i's risk exposures to fundamental and firm-specific shocks are denoted by σ and σ_I, respectively, and risk exposure to policy regime change shocks is denoted by

$$\beta_{M,t}^i \equiv \frac{1}{\Theta_t^i}\frac{\partial \Theta_t^i}{\partial \hat{c}_t}\hat{\sigma}_{c,t}^2 < 0, \tag{21}$$

where the functional form of $\beta_{M,t}^i$ is given by equation (IA.60) in the Internet Appendix. Firm i's exposure to policy regime shift shocks depends on ξ^i, which is the sensitivity of profitability to policy regime changes,

$$\frac{\partial \beta_{M,t}^i}{\partial \xi^i} < 0. \tag{22}$$

Proof: See the Proof of Proposition 3 in the Internet Appendix.

Since firms' exposure to fundamental shocks is homogeneous, the emission-sorted portfolios' return spread in the cross-section is determined solely by heterogeneous levels of exposure to regime change shocks, $\beta_{M,t}^i$, the properties of which are summarized in Proposition 3. In equation (22), we show that a firm with a higher ξ^i experiences a larger collapse than does a firm with a lower ξ^i in realized stock returns.

In equilibrium, risk premia are determined by the Euler equation that characterizes the covariance of a firm's returns with the SDF. To characterize the risk compensation for

[44] Detailed derivations for the level of firm i's stock price are provided in Section III.F of the Internet Appendix.

fundamental shocks and regime change shocks, we derive the expression for the conditional risk premium. In particular, firm i's expected stock return equals its risk premia,

$$\begin{aligned} \mathrm{E}_t\left[\frac{dM_t^i}{M_t^i}\right] &= -\mathrm{Cov}_t\left(\frac{dM_t^i}{M_t^i}, \frac{d\pi_t}{\pi_t}\right) \\ &= \sigma\lambda dt + \beta_{M,t}^i \lambda_{c,t} dt. \end{aligned} \tag{23}$$

In equation (23), we show that firm i's risk premia are determined by its exposure to fundamental shocks and regime change shocks. The first term captures the risk premium of fundamental shocks and is homogeneous across firms. The risk premium of regime change shocks is given by the second term of equation (23). As we show in Propositions 2 and 3, upon a positive regime change shock, stock prices decrease precisely when the marginal utility–and thus the SDF–is high. Thus, agents demand positive compensation for their exposure to such regime change shock.

More importantly, the heterogeneous risk compensation for regime change risks is responsible for the cross-sectional difference in expected returns across firms with different levels of emission intensity. As shown in equation (22), firm i's risk exposure to a regime change shock (i.e., $\beta_{M,t}^i$) depends negatively on its emission intensity ξ_i. When the regulatory regime changes, stock values of high-emission firms with high ξ decrease more than do those of low-emission firms. Heterogeneous levels of exposure to regime change risks translate into cross-sectional differences in expected stock returns. Our model predicts that high-emission firms require a higher expected return than do low-emission firms. This prediction is strongly supported by a statistically significant H-L return spread among emission-sorted portfolios. We refer to this return spread as the pollution premium.

E. Endogenous Decision to Choose Emission Intensity

In this section, we endogenize firm i's decision to choose emission intensity ξ^i. Our key idea is to introduce a trade-off between firm value and costly emission abatement. Based on our previous benchmark model, due to a higher discount rate (i.e., the pollution premium), choosing a higher emission intensity leads to a lower valuation (i.e., market-to-book ratio). As a trade-off for a lower valuation, a higher emission intensity leads to lower abatement costs. For model tractability, we consider a static decision whereby firm i chooses ξ^i at time 0 and maintains the same emission intensity until terminal time T.

Firm value immediately after the choice of ξ^i is given by $M_0^i \equiv M_0^i/B_0^i$, where $B_0^i = 1$ for all firms at time 0. Based on the choice of parameter values given in Section V of the Internet Appendix, a firm's valuation decreases in its emission intensity at a decreasing rate. By using the log-linear approximation around the average ξ^i, denoted by ξ_0, firm i's marginal value with respect to ξ^i can be express as

$$\frac{\partial M_0^i}{\partial \xi^i} \approx -\omega_0 + \omega_1 \xi^i, \tag{24}$$

where $\omega_0 > 0$ and $\omega_1 > 0$ are the Taylor expansion parameters evaluated at ξ_0, which are provided in Section III.G of the Internet Appendix. We focus on $\xi^i < \xi^{max} \equiv \frac{\omega_0}{\omega_1}$ so that the marginal value is negative (i.e., $\frac{\partial M_0^i}{\partial \xi^i} < 0$). This implies that a higher ξ^i reduces a firm's value, mainly due to a higher discount rate to reflect the pollution premium. In addition, $\omega_1 > 0$ implies that firm i's valuation decreases at a slower rate as ξ^i increases.

We denote firm i's abatement cost by $\Psi_0^i \equiv \Psi_0(\xi^i; \eta^i)$, paid at time 0. We directly specify the marginal abatement cost with respect to emission intensity ξ^i as

$$\frac{\partial \Psi_0(\xi^i, \eta^i)}{\partial \xi^i} = \omega_1 \eta^i (\xi^i - \bar{\xi}), \tag{25}$$

where $\bar{\xi}$ is the emission intensity when it incurs zero marginal abatement cost. We assume that a firm's marginal cost depends on firm characteristic η_i. This assumption has two important implications. First, over the range $\xi^i \in [0, \bar{\xi}]$, the marginal abatement cost is negative, which implies a benefit of abatement cost savings when allowing a higher level of emissions. Second, it is increasingly costly to further reduce emissions when emission intensity is low. The marginal abatement cost increases to $\omega_1 \eta^i \bar{\xi}$ as firm i's emission intensity approaches zero.

Firm i determines its level of emission intensity by maximizing its stock price subject to abatement cost Ψ_0^i:

$$\max_{\xi^i} M_0^i - \Psi_0^i. \tag{26}$$

The optimal ξ^{i*} is defined by the first-order condition in the following proposition.

PROPOSITION 4: *In the equilibrium with $\bar{\xi} < \xi^{max}$, the optimal emission intensity ξ^{i*} satisfies*

$$\frac{\partial M_0^i}{\partial \xi^i} = \frac{\partial \Psi_0^i}{\partial \xi^i}, \tag{27}$$

and

$$\xi^{i*} = \bar{\xi} + \frac{-\omega_0 + \omega_1 \bar{\xi}}{\omega_1(\eta^i - 1)}. \tag{28}$$

We show that the optimal ξ^{i*} exhibits the following properties:

1. *When $\bar{\xi} < \xi^{max}$, ξ^{i*} must exist and is smaller than $\bar{\xi}$.*

2. *ξ^{i*} is increasing in η^i, and $\lim_{\eta^i \to \infty} \xi^{i*} = \bar{\xi}$.*

3. *$\Psi_0^H < \Psi_0^L$ for two firms with $\eta^H > \eta^L > 1$.*

Proof: See the Proof of Proposition 4 in the Internet Appendix.

At the optimal emission intensity level, the marginal value improvement of lower emission intensity is equal to the marginal abatement cost. The intuition behind the above proposition is as follows. First, when we assume $\bar{\xi} < \xi^{max}$, the optimal emission intensity ξ^{i*} in equation (28) must exist over the range $[0, \bar{\xi}]$. Second, since the marginal cost of reducing emission intensity increases in η^i, a firm with a higher η^i chooses a higher optimal emission intensity at the optimum. Second, when we assume $\bar{\xi} < \xi^{max}$, the optimal level of emission intensity ξ^{i*} in equation (28) must exist over the range $[0, \bar{\xi}]$. In the extreme case, the optimal level of emission intensity ξ^{i*} converges to the $\bar{\xi}$ with zero abatement cost as η^i goes to infinity. The intuition is that an infinitely high marginal abatement cost motivates firm i to choose the maximum emission intensity level. Finally, the marginal abatement cost is heterogeneous across firms. Because firms with higher η^i optimally choose higher levels of emission intensity, we can prove that they pay a lower overall abatement cost than firms with lower η^i. In this study, we do not intend to endogenize the cross-sectional heterogeneity in η^i. That said, we provide a plausible interpretation by relating η^i to financial constraints and leave the micro-foundation of η^i to future research. We conjecture that firms with higher η^i are more financially constrained. It is more costly for these firms to further reduce lower levels of emission intensity since they are financially constrained and since the shadow value of internal funds is high. Such an interpretation is consistent with the empirical finding documented by Xu and Kim (2022) that more financially constrained firms tend to spend less on abatement costs.

COROLLARY 2: *Suppose that η^i is drawn from an inverse uniform distribution on the interval $[\eta^{min}, \eta^{max}]$ at time 0 and then remains unchanged. The optimal emission intensity ξ^{i*} follows a uniform distribution on the interval $[\xi^{min*}, \xi^{max*}]$.*

Proof: See the Proof of Corollary 2 in the Internet Appendix.

Corollary 2 shows that the distribution ξ^i is consistent with the exogenously specified distribution of ξ^i in our model presented in Section IV.A.

In summary, in this extension we characterize the endogenous choice of emission intensity across firms and provide a micro-foundation for higher current profitability among firms with higher emission intensity since high-emission firms save costs associated with pollution abatement and environmental recovery. In particular, our model suggests a negative correlation between emission intensity and firms' abatement costs, consistent with the negative link between emission intensity and measures of abatement costs (i.e., ENER and ENRR) in Table VIII. Moreover, our model further provides a testable implication for our empirical analysis in Section III.B.

V. Empirical Tests for Regime Change Risk

In this section, we explore the predictions of our model in the data by examining several key testable implications that would support a regime change risk explanation. First, we use the growth in aggregate civil penalties initiated against polluting firms to proxy for the perceived likelihood of an environmental regulation policy change (i.e, regime change risk). Second, we find that regime change risk affects the profitability of high-emission versus low-emission firms in a manner that is consistent with our model assumption. We then implement a GMM test to show that our regime change risk proxy is negatively priced in the cross-section of test assets' returns. Together with a decreasing pattern of emission portfolios' exposure to regime change risk, we are able to clearly identify the mechanism underlying the pollution premium.

A. Our Proxy for Regime Change Risk

To empirically test the regime change risk explanation, we proxy for regime change risk using the annual log growth of aggregate civil penalties initiated against polluting firms in the EPA's statistics since 1991, Δn_t.[45] This measure is intuitive, observable, and quantifiable: a larger number of aggregate civil penalties initiated by federal and state governments against polluting firms would suggest an increase in the perceived probability of an environmental policy regime change.[46] Figure 1 plots the time series of the growth rate (orange line) and the total emissions (blue line).

B. Future Profitability and Regime Change Risk

One key premise of our model is that high-emission firms' future profitability drops following a strengthening of environmental regulations, which impose higher costs on polluting firms. We acknowledge that it is difficult to directly test this premise because our model allows for only one regime change. For feasibility's sake, we test whether high-emission firms' future profitability drops more when the growth of aggregate civil penalties against pollution increases. To validate this premise, in Table VII we estimate

$$\overline{ROA}_{i,t+1\to t+10} = a + b_1\, Emissions_{i,t} + b_2\, \Delta n_t + b_3\, Emissions_{i,t} \times \Delta n_t + c\, Controls_{i,t} + \varepsilon_{i,t}, \tag{29}$$

where $\overline{ROA}_{i,t+1\to t+10}$ is firm i's moving-average ROA from year t+1 to t+10 and $Emissions_{i,t}$ denotes firm i's emission intensity in year t. We interact $Emissions_{i,t}$ and Δn_t to examine the prediction that high-emission firms are more likely to be adversely influenced by regime

[45]These data source are available on the EPA website at: https://echo.epa.gov/facilities/enforcement-case-search. More details about these data are provided in Section I.B in the Internet Appendix. The mean and standard deviation of settlements across all cases are 1.57 and 8.93 million dollars (real), respectively.

[46]A higher level of aggregate civil penalties can be regarded as a positive signal shock $d\hat{Z}_t^c$ as in equation (10), which would lead directly to an increase in the perceived probability of a policy regime change.

changes. The vector *Controls* includes control variables ROA, change in ROA, size, book-to-market ratio, investment rate, tangibility, financial constraints, book leverage, and operating leverage in year t, as well as industry-year fixed effects.

Specifications 3 and 4 of Table VII, Panel A report the estimation results for equation (29). The estimated coefficient on the interaction term $\hat{b}_3$ is significantly negative, which suggests that firms producing more toxic emissions observe larger profitability decline in the future when regulation is more likely to be tightened. This is consistent with our model setting, and also highlights that the relation between emissions and future profitability is conditional on governments' environmental policies and regulations. In contrast, the estimated coefficient $\hat{b}_1$ on emissions remains significantly positive when we control for the interaction term; nevertheless, its economic magnitude is fairly small when compared to the interaction term, which is consistent with our model premise that high-emission firms observe lower profits under stronger regulation.

Our model also suggests that the pollution premium comes from the variation in cash flow sensitivity to changes in environmental regulations.

To test this prediction, we measure cash flows using the value-weighted future profitability (i.e., moving-average ROA from year $t+1$ to $t+10$) at the portfolio level and examine whether the cash flows of portfolios with higher emission levels exhibit more negative loadings on regime change risk. Panel B of Table VII shows that the cash flow sensitivity of emission-sorted portfolios displays a downward-sloping pattern, ranging from -0.31 to -0.54 with respect to regime change risk. Such a finding again highlights the main economic mechanism in our paper, namely, that high-emission firms carry more negative exposure to regime change risk.

C. Market Price and Regime Change Risk Exposure

In this section, we first test the price of regime change risk, which is negative as suggested in equation (20). We then examine emission-sorted portfolios' exposure to regime change risk. Our model implies a two-factor model in which the market excess return is the first factor and the regime change risk is the second factor. To test the prices of these two factors using the procedure detailed in Cochrane (2005) (revised edition, pages 236-239), we first specify the SDF as

$$\text{SDF}_t = 1 - \lambda \times \text{MKT}_t - \lambda_c \times \Delta n_t. \tag{30}$$

In equation (30), investors' marginal utility is driven by two aggregate shocks: MKT_t, the market factor in the CAPM, and Δn_t, the growth of the logarithmic amount of all civil cases' penalties as our proxy for regime change risk. We seek to estimate λ_c, which is the sensitivity to Δn_t and is proportional to the price of regime change risk $\lambda_{c,t}$ in equation (19).

To estimate λ_c, we consider the following test assets: our six emission-sorted portfolios (as presented in Table II), six size-momentum portfolios, and five industry portfolios.[47] We then conduct GMM estimation using the moment conditions

$$\text{E}[R_i^e] = -\text{Cov}(\text{SDF}, R_i^e), \tag{31}$$

which is the empirical equivalent to equation (23) in our model, but with the conditional moments replaced by their unconditional counterparts. In effect, we assess the ability of Δn_t to price test assets on the basis of residuals of the Euler equation.

In addition, we follow the literature (e.g., Papanikolaou (2011), Eisfeldt and Papanikolaou (2013), and Kogan and Papanikolaou (2014)) to estimate two statistics for the cross-sectional fit—the sum of squared errors (SSQE) and mean absolute percent errors (MAPE)—as well as the J-statistic of overidentifying model restrictions.[48] An insignificant J-statistic would suggest that the null hypothesis of an SDF model's pricing errors being equal to zero is not rejected.

In Panel A of Table X, we present the results of a CAPM and our two-factor SDF model. In Specifications 1 and 2, we separately report the price of regime change risk and market risk. We find that the price of regime change risk λ_c is significantly negative in

[47]This choice of test assets follows Lewellen, Nagel, and Shanken (2010), Belo, Li, Lin, and Zhao (2017), Lin, Palazzo, and Yang (2020), and a suggestion from an anonymous reviewer. The return data on the six size-momentum portfolios and the five industry portfolios are collected from the website of Professor Kenneth French.

[48]Given the Euler equation $\text{E}[\text{SDF} \times R_i^e] = 0$, our SSQE and MAPE are based on each test asset i's moment error u_i as follows: $u_i = \frac{1}{T}\sum_{t=1}^{T}\left[\widehat{\text{SDF}} \times R_{i,t}^e\right]$. SSQE and MAPE are defined as $\sum_{i=1}^{N} u_i \times u_i$ and $\frac{1}{N}\sum_{i=1}^{N}|u_i|$, respectively, where N denotes the number of testing assets.

Specification 1, while the price of market risk λ is significantly positive in Specification 2. When we combine the market factor with the regime change risk in Specification 3 as our benchmark, the price of regime change risk remains significantly negative (-0.99). In terms of asset pricing errors, the SSQE and MAPE of CAPM (Specification 2) are 2.16% and 8.47%, respectively. After we introduce regime change risk to our model (Specification 3), the SSQE and MAPE decrease to 1.54% and 6.63%. Although the J-test is statistically insignificant in Specifications 2 and 3, we show that regime change risk still improves the model fit by reducing pricing errors. The JT difference test between the CAPM model and our two-factor model is 2.725 with marginal significance. Overall, regime change risk improves upon the performance of the CAPM model in pricing stock returns.

To differentiate our regime change risk from general political uncertainty, we first compare an alternative two-factor model that includes the market factor and the economic policy uncertainty index of Bloom (2009), which reflects general economic policy uncertainty risk according to Bali, Brown, and Tang (2017). As shown in Specification 4, the estimated price of risk with respect to economic uncertainty is negatively significant, and the JT difference test supports a substantial improvement in pricing when we include the economic uncertainty index in the SDF. In Specification 5, when our regime change risk measure is further considered in the SDF, we find that both the economic uncertainty index and regime shift risk are negatively priced. Finally, in comparison with Specification 4, the inclusion of regime change risk rejects the JT difference test by significantly reducing pricing errors. These results thus support the view that our environmental policy risk is distinct from general policy risk.

To further differentiate our regime change risk from aggregate economic growth, we consider an alternative two-factor model that includes the market factor and GDP shocks.[49] As shown in Specification 6, the estimated price of risk with respect to GDP shocks is significantly positive, and the JT difference test supports a substantial pricing improvement when we include GDP shocks in the SDF. In Specification 7, when regime change risk is

[49]Following Covas and Den Haan (2011), our measure of GDP shocks is real GDP of the corporate sector filtered using the Hodrick-Prescott filter (Hodrick and Prescott (1997)) to extract the cyclical component of GDP.

further added to the SDF, we find that it is significantly negatively priced and reduces pricing errors according to the JT difference test. Our environmental policy risk is thus different from economic growth in asset pricing.

In Panels B to E of Table X, we present emission-sorted portfolios' risk exposure (GMM-implied betas) with respect to various factors in the SDF, together with their alphas estimated from $\mathrm{E}[R_i^e] - \beta^{\mathbf{i}}\lambda$ in Specifications 2 to 5 in Panel A, respectively.[50] We find that the betas with respect to the market factor (β^i_{MKT}) are flat across emission-sorted portfolios in all panels. More importantly, we observe a decreasing pattern in $\beta^i_{\Delta n}$ from the low-emission portfolio to the high-emission portfolio. These portfolios present a downward-sloping pattern of covariances with our proxy for regime change risk. Taken together, these results support our environmental risk argument that high-emission firms provide higher expected stock returns because they carry more negative betas on regime change risk that is negatively priced. We also find that the addition of regime change risk reduces the economic magnitude and statistical significance of emission portfolios' alphas when we compare Panel C to Panel B and when we compare Panel E to Panel D. These findings further support our environmental risk argument for the pricing errors associated with emissions.

VI. Conclusion

Environmental protection awareness has surged over the past several decades. This paper investigates the implications of industrial pollution on asset pricing. We use firm's mandatory emission reports filed with EPA to capture firms' annual toxic releases. A long-short portfolio constructed from firms with high versus low toxic emission intensity relative to their industry peers generates an average excess return of around 4.42% per year. This positive emission-return relation cannot be explained by common risk factors and holds in Fama and MacBeth (1973) regressions that control for other firm characteristics. When we empirically examine if this positive emission-return relation can be attributed to several explanations proposed in the literature, such as investors' emission preferences, underreaction to emis-

[50] In this revision, we modify the code of Kan, Robotti, and Shanken (2013) to calculate test assets' alphas and t-statistics based on Chapter 12 of Cochrane (2005).

sion abatement, retail investors' behavioral bias, corporate governance, political connections and risk, and other potentially related systematic risks (including technology obsolescence, financial constraints, economic and political uncertainty, and adjustment costs). We find that the return predictability related to toxic emissions cannot be satisfactorily explained by these aforementioned factors.

In additional tests we find some interesting patterns. First, firms with more toxic emissions are associated with higher current profitability and more environmental litigation. Second, high-emission firms' future profitability is lower after governments impose stricter environmental regulations. Third, high-emission firms observe a favorable shock as response to Donald Trump's 2016 U.S. presidential election win, which suggests a connection between emission-related return predictability and changes in environmental policies and regulations. Motivated by these findings, we develop a general equilibrium asset pricing model in which firms' cash flows face regime change uncertainty with respect to emission regulation policies. We argue that the government optimally replaces a weak regulation regime by a strong one if pollution costs are perceived to be sufficiently high. Since high-emission firms' profitability is more negatively affected than that of low-emission firms upon a shift from a weak to a strong regulation regime, high-emission firms are more exposed to regulation regime change risk and thus earn higher average excess returns as risk premia. This model is supported by our asset pricing tests: regime change risk is negatively priced, and high-emission firms carry more negative exposure to this risk, thereby earning higher risk premia.

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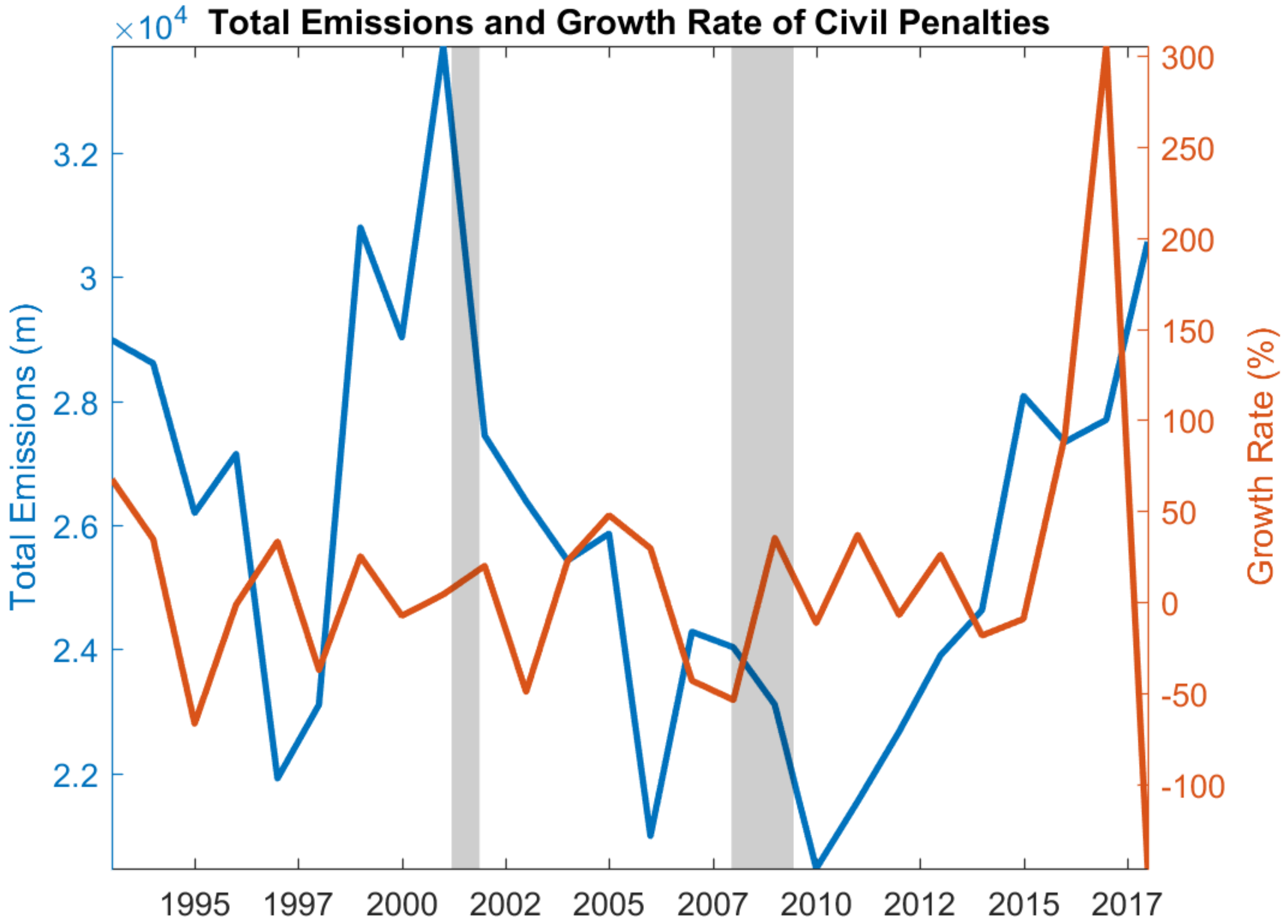


Figure 1. Time-series patterns of the number of cvil cases.
This figure plots the time series of total emissions in the EPA's TRI database (blue line on the left vertical axis) and the log growth in civil penalties (Δn_t) (orange line on the right vertical axis). The data are downloaded from the Enforcement and Compliance History Online (ECHO) system that contains information on civil penalties provided by the EPA. Shaded bands are labeled as recession periods according to NBER recession dates. The sample period is 1992 to 2017.

Table I. Statistics and Correlations

This table presents summary statistics in Panel A and a correlation matrix in Panel B for the firm-year sample. Emissions are measured as the sum of all emissions in pounds produced in all plants owned by a firm, scaled by total assets (item AT) in million dollars. ME is market capitalization deflated by CPI (measured in 2009 millions USD) at the end of September. B/M is the ratio of book equity to market capitalization. I/K is capital expenditures (item CAPX) divided by property, plant, and equipment (PPENT). Return on assets (ROA) is operating income after depreciation (item OIADP) scaled by total assets. Return on equity (ROE) is operating income after depreciation scaled by total assets. Tangibility (TANT) is property, plant, and equipment divided by total assets. WW index (WW) is the Whited and Wu index used to measure financial constraint, following Whited and Wu (2006). Operating leverage (OL) is the summation of cost of goods sold (item COGS) and selling, general, and administrative expenses (item XSGA) scaled by total assets. Book leverage (Lev) is the summation of current liabilities (item DLC) and long-term debt (item DLTT) scaled by total assets. We report the pooled mean, standard deviation (Std), 5^{th} percentile (P5), 25^{th} percentile (P25), median, 75^{th} percentile (P75), and 95^{th} percentile (P95). Observations denote the valid number of observations for each variable. The sample period is 1991 to 2016 at an annual frequency.

	Emissions	ME	B/M	I/K	ROA	ROE	TANT	WW	OL	Lev
Panel A: Summary Statistics										
Mean	6567.88	6272.44	0.67	0.18	0.09	0.19	0.33	-0.35	0.99	0.23
Std	44586.41	21765.23	0.61	0.11	0.08	2.71	0.18	0.10	0.56	0.17
P5	1.80	47.44	0.16	0.06	-0.02	-0.10	0.09	-0.51	0.24	0.00
P25	75.67	362.96	0.35	0.11	0.05	0.12	0.19	-0.42	0.62	0.15
Median	465.04	1302.75	0.55	0.16	0.09	0.20	0.30	-0.35	0.90	0.26
P75	2372.91	4448.09	0.83	0.22	0.13	0.30	0.44	-0.29	1.25	0.37
P95	23254.81	26056.43	1.50	0.37	0.22	0.58	0.71	-0.19	1.97	0.56
Observations	9,989	9,691	9,736	9,934	9,989	9,989	9,989	9,698	9,989	9,973
Panel B: Correlation										
Emissions	1	-0.03	-0.01	0.01	0.02	0.00	0.05	0.07	0.07	0.00
ME		1	-0.11	0.03	0.05	0.02	0.00	-0.41	-0.17	0.07
B/M			1	-0.19	-0.37	-0.11	0.16	0.1	-0.02	0.09
I/K				1	0.22	0.00	-0.27	0.16	0.16	-0.24
ROA					1	0.16	-0.10	-0.05	0.13	-0.20
ROE						1	-0.02	-0.02	0.04	0.12
TANT							1	-0.21	-0.23	0.21
WW								1	0.41	-0.22
OL									1	-0.18
Lev										1

Table II. Univariate Portfolio Sorting

This table shows average excess returns for five portfolios sorted on emissions scaled by total assets (AT) in Panel A, by property, plant, and equipment (PPENT) in Panel B, by sales (SALE) in Panel C, and by market equity (ME) in Panel D relative to their industry peers, for which we use the Fama and French (1997) 49 industry classifications, and rebalance portfolios at the end of each September. The sample runs from October 1992 to September 2018 and excludes financial industries. We report average excess returns over the risk-free rate (E[R]-R_f), *t*-statistics, standard deviations (Std), and Sharpe ratios (SR) across five portfolios in each panel. Portfolio returns are value-weighted by firms' market capitalization, and are multiplied by 12 to make the magnitude comparable to annualized returns. *t*-statistics are based on standard errors using the Newey-West correction for 12 lags.

	L	2	3	4	H	H-L
			Panel A: AT			
E[R]-R_f (%)	6.90	9.68	9.08	9.11	11.32	4.42
[t]	2.02	2.91	2.84	2.73	3.30	3.46
Std (%)	15.33	16.94	15.64	16.46	16.30	9.53
SR	0.45	0.57	0.58	0.55	0.69	0.46
			Panel B: PPENT			
E[R]-R_f (%)	7.87	8.60	8.66	9.37	10.64	2.78
[t]	2.71	2.24	2.74	2.67	3.14	2.00
Std (%)	14.77	17.39	15.34	16.71	16.25	9.00
SR	0.53	0.49	0.56	0.56	0.66	0.31
			Panel C: SALE			
E[R]-R_f (%)	7.45	10.43	7.51	9.49	9.62	2.17
[t]	2.41	3.33	1.90	2.83	2.85	1.73
Std (%)	14.71	16.03	17.33	17.36	15.58	8.51
SR	0.51	0.65	0.43	0.55	0.62	0.25
			Panel D: ME			
E[R]-R_f (%)	7.23	9.10	8.95	7.94	12.44	5.21
[t]	2.39	2.60	2.70	1.99	3.73	2.63
Std (%)	14.76	16.86	16.02	17.73	16.65	10.11
SR	0.49	0.54	0.56	0.45	0.75	0.52

Table III. Firm Characteristics

This table reports the time-series average of the cross-sectional medians of firm characteristics for five emission-sorted portfolios. Raw emissions are measured as the sum of all emissions in pounds produced in all plants owned by a firm. Emissions are measured as raw emissions in pounds scaled by total assets in million dollars. Portfolio characteristics are described in Table I. The sample period is 1991 to 2016.

	L	2	3	4	H
Raw Emissions	18808.25	243610.89	796053.89	1488382.07	3106629.16
Emissions	15.52	134.09	487.54	1501.08	8146.43
Log ME	7.51	7.45	7.45	7.42	7.09
B/M	0.56	0.57	0.56	0.57	0.57
I/K	0.16	0.16	0.16	0.15	0.15
ROA	0.08	0.08	0.09	0.09	0.10
TANT	0.26	0.24	0.28	0.31	0.34
WW	-0.36	-0.36	-0.36	-0.37	-0.34
OL	0.81	0.88	0.86	0.87	0.97
Lev	0.27	0.27	0.26	0.26	0.27
Num	79	76	76	76	72

Table IV. Asset Pricing Factor Tests

This table shows asset pricing factor tests for five portfolios sorted on emissions scaled by total assets relative to their industry peers, for which we use the Fama and French (1997) 49-industry classifications and rebalance portfolios at the end of each September. The results reflect monthly data. The sample runs from October 1992 to September 2018 and excludes financial industries. To adjust for risk exposure, we perform time-series regressions of emission-sorted portfolios' excess returns on the market factor (MKT) as the CAPM model in Panel A, on the Fama and French (1996) three factors (MKT, the size factor-SMB, and the value factor-HML) in Panel B, on the Fama and French (1996) three factors plus Carhart (1997) factor (MKT, SMB, HML, and the momentum factor-UMD) in Panel C, on the Fama and French (2015) five factors (MKT, SMB, HML, the profitability factor-RMW, and the investment factor-CMA) in Panel D, and on the Hou, Xue, and Zhang (2015) q-factors (MKT, SMB, the investment factor-I/A, and the profitability factor-ROE) in Panel E, respectively. Data on the Fama-French five factors and Carhart factor come from Kenneth French's website. Data on the I/A and ROE factors are provided by Kewei Hou, Chen Xue, and Lu Zhang. These betas, together with alphas, are annualized by multiplying by 12. *t*-statistics are based on standard errors estimated using the Newey-West correction for 12 lags.

	L	2	3	4	H	H-L
			Panel A: CAPM			
α_{CAPM}	-0.88	1.22	1.49	1.33	3.19	4.07
[t]	-0.61	0.61	0.94	0.66	2.13	3.41
MKT	0.93	1.01	0.91	0.93	0.97	0.04
[t]	13.94	16.11	12.02	11.19	31.07	0.86

	L	2	3	4	H	H-L		L	2	3	4	H	H-L
			Panel B: FF3								Panel C: FF4		
α_{FF3}	-1.82	0.67	1.01	0.37	2.90	4.72	α_{FF4}	-1.16	0.60	1.29	0.75	2.99	4.15
[t]	-1.54	0.42	0.72	0.24	2.17	3.73	[t]	-0.89	0.39	0.93	0.53	2.10	3.33
MKT	0.96	1.05	0.92	0.97	0.99	0.02	MKT	0.93	1.06	0.91	0.96	0.98	0.05
[t]	28.85	24.70	16.91	21.30	37.41	0.71	[t]	25.23	24.50	13.79	18.73	28.91	1.33
SMB	0.00	-0.11	0.01	-0.05	-0.02	-0.02	SMB	0.02	-0.12	0.01	-0.04	-0.02	-0.03
[t]	0.01	-2.18	0.10	-0.49	-0.31	-0.34	[t]	0.25	-2.11	0.22	-0.43	-0.26	-0.65
HML	0.30	0.28	0.15	0.35	0.11	-0.19	HML	0.27	0.29	0.14	0.33	0.10	-0.17
[t]	4.10	4.27	1.73	2.45	1.50	-2.57	[t]	4.75	4.17	1.63	2.40	1.60	-2.64
							UMD	-0.07	0.01	-0.03	-0.04	-0.01	0.06
							[t]	-1.96	0.21	-0.56	-0.76	-0.22	1.75
			Panel D: FF5								Panel E: HXZ		
α_{FF5}	-3.26	-0.89	-1.24	-3.08	0.52	3.78	α_{HXZ}	-2.54	-0.38	-0.04	-2.12	2.12	4.66
[t]	-2.49	-0.52	-0.79	-1.82	0.32	2.98	[t]	-1.90	-0.24	-0.03	-1.21	1.72	3.70
MKT	1.02	1.12	1.02	1.12	1.09	0.06	MKT	1.01	1.14	1.00	1.11	1.05	0.04
[t]	25.78	19.77	15.55	23.72	26.83	1.62	[t]	25.48	27.61	16.74	25.46	32.23	0.80
SMB	0.05	-0.09	0.05	0.06	0.05	0.00	SMB	-0.02	-0.10	0.02	-0.05	-0.02	-0.00
[t]	0.70	-1.62	0.92	1.10	0.81	0.03	[t]	-0.31	-2.65	0.35	-0.59	-0.44	-0.00
HML	0.19	0.13	-0.07	0.09	-0.09	-0.28	I/A	0.38	0.41	0.27	0.56	0.23	-0.15
[t]	2.81	1.83	-0.92	0.78	-1.11	-2.76	[t]	3.50	3.66	2.74	4.06	2.33	-1.23
RMW	0.18	0.14	0.21	0.42	0.27	0.09	ROE	0.08	0.15	0.12	0.24	0.11	0.03
[t]	3.04	2.12	2.96	6.67	4.34	1.27	[t]	1.56	2.00	1.90	2.84	1.77	0.59
CMA	0.14	0.26	0.36	0.33	0.28	0.14							
[t]	2.12	2.26	3.05	3.23	2.63	1.19							

Table V. Fama-MacBeth Regressions

This table reports Fama-MacBeth regressions of individual stock excess returns on their emission intensity in logarithm and other firm characteristics. We conduct cross-sectional regressions for each month from October of year t to September of year $t+1$. In each month, monthly returns of individual stock returns (annualized by multiplying by 12) are regressed on emission intensity in logarithm of year $t-1$ (that is reported by the end of September of year t), different sets of control variables known by the end of September of year t, and industry fixed effects. Control variables include the natural logarithm of market capitalization (Size), the natural logarithm of book-to-market ratio (B/M), investment rate (I/K), return on equity (ROE), tangibility (TANT), WW index, book leverage, and industry dummies based on Fama and French (1997) 49-industry classifications. All independent variables are normalized to 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 estimated using the Newey-West correction are reported. The sample period is October 1992 to September 2018.

	(1)	(2)
Log Emissions	1.39	0.91
[t]	2.74	2.40
Log ME	6.11	33.72
[t]	6.08	12.24
Log B/M	6.19	13.48
[t]	6.15	11.86
I/K	0.55	-1.05
[t]	0.77	-1.48
ROE	1.64	3.68
[t]	1.50	3.44
TANT		-0.63
[t]		-0.89
WW		30.70
[t]		12.96
Lev		3.23
[t]		4.75
Observations	112,848	109,679
R-squared	0.13	0.16
Industry FE	Yes	Yes

Table VI. Predictive Regressions for Litigation

This table reports the impact of firms' emission intensity on their frequencies of being litigated for pollution. We collect a firm's lawsuits relevant to environmental issues from the Integrated Compliance Information System. We estimate a Probit (negative binomial and Poisson regression) by regressing firm i's future litigation status over the next five years (i.e., $t+1$ to $t+5$), which is defined as a binary variable reflecting whether a firm is involved in litigation or as a count variable reflecting the total number of cases from year $t+1$ to year $t+5$, on firm i's emission intensity in logarithm in year t and other controls for firm i's fundamentals, including size, book-to-market ratio, investment rate, current profitability, tangibility, WW index, book leverage, and operating leverage in year t, as well as industry-year fixed effects. All independent variables are normalized to 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 or at the industry-year level are reported. The sample period is from 1991 to 2016 based on coverage of the Enforcement and Compliance History Online (ECHO) system.

	(1) Probit	(2) NB	(3) Possion	(4) Probit	(5) NB	(6) Possion
Log Emisisons	0.66	1.24	1.24	0.66	1.24	1.24
[t]	24.99	26.74	17.38	12.41	15.12	8.88
Log ME	0.50	0.70	0.34	0.50	0.70	0.34
[t]	11.04	7.83	2.45	6.29	5.96	1.63
Log B/M	0.09	0.05	-0.07	0.09	0.05	-0.07
[t]	3.71	1.10	-1.35	2.25	0.87	-0.73
I/K	-0.05	-0.03	-0.00	-0.05	-0.03	-0.00
[t]	-2.41	-0.66	-0.06	-1.41	-0.51	-0.04
ROA	0.01	-0.05	0.02	0.01	-0.05	0.02
[t]	0.46	-1.09	0.38	0.28	-0.76	0.21
TANT	0.07	0.19	0.16	0.07	0.19	0.16
[t]	2.88	4.07	4.24	1.49	2.45	1.30
WW	-0.20	-0.64	-1.03	-0.20	-0.64	-1.03
[t]	-4.85	-8.06	-6.46	-2.68	-5.41	-4.71
Lev	0.09	0.18	0.16	0.09	0.18	0.16
[t]	3.57	5.28	2.68	1.90	2.82	1.53
OL	0.13	0.24	0.19	0.13	0.24	0.19
[t]	4.64	4.90	4.82	2.82	3.34	2.04
Observations	8,707	8,707	8,707	8,707	8,707	8,707
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster SE by Firm	No	No	No	Yes	Yes	Yes
Cluster SE by Industry × Year	Yes	Yes	Yes	No	No	No

Table VII. Cash Flow Sensitivity

This table shows firms' cash flow sensitivity to litigation shocks. In Panel A, we report panel regressions of future and current profitability on their emission intensity, litigation shocks, and their interactions, together with other firm characteristics in year t, where future profitability refers to moving-average profitability from year $t+1$ to $t+10$. The sample excludes financial industries. We control for industry-year fixed effects based on Fama and French (1997) 49-industry classifications. We measure litigation shocks (Δn) using the log difference (i.e., growth rate) of civil penalties provided by the EPA. All independent variables are normalized to 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 or at the industry-year level are reported. In Panel B, we show the cash flow sensitivity of emission-sorted portfolios to the litigation shock. Portfolio-level cash flow refers to future profitability as used in Panel A. We regress portfolio-level future profitability on litigation shocks together with other firm characteristics, and then report estimated coefficients on cash flow. Coefficients on litigation shocks are multiplied by 100. Standard errors are estimated using Newey-West correction. All regressions are conducted at the annual frequency. The sample period is from 1991 to 2016.

Panel A: Profitability Regressions

	Current ROA		Future ROA	
	(1)	(2)	(3)	(4)
Log Emissions	0.017	0.017	0.005	0.005
[t]	2.154	2.433	5.991	12.525
Log Emissions × Δn			-0.128	-0.128
[t]			-2.596	-2.516
Log ME	0.146	0.146	0.023	0.023
[t]	7.110	7.257	12.357	20.154
Log B/M	-0.260	-0.260	-0.003	-0.003
[t]	-15.750	-19.710	-3.227	-5.565
I/K	0.007	0.007	-0.005	-0.005
[t]	0.680	0.738	-5.514	-8.105
ROA			0.023	0.023
[t]			18.178	32.676
ΔROA			-0.095	-0.095
[t]			-9.151	-9.181
TANT	-0.001	-0.009	-0.001	-0.001
[t]	-0.071	-0.076	-1.111	-2.236
WW	0.081	0.081	0.013	0.013
[t]	3.940	4.283	7.247	12.171
Lagged ROA	0.549	0.549		
[t]	33.023	33.007		
Lev	-0.701	-0.701	-0.010	-0.010
[t]	-10.636	-12.486	-1.861	-3.701
OL	0.070	0.0700	0.004	0.004
[t]	5.415	6.387	3.444	6.531
Observations	13,857	13,857	13,849	13,849
R-squared	0.639	0.639	0.549	0.549
Industry × Year FE	Yes	Yes	Yes	Yes
Cluster SE by Firm	Yes	No	Yes	Yes
Cluster SE by Industry × Year	No	Yes	No	Yes

Panel B: Portfolio-level Future Profitability

	L	2	3	4	5	H-L
Δn	-0.31	-0.44	-0.23	-0.44	-0.54	-0.35
[t]	-1.01	-1.26	-0.49	-2.97	-1.98	-2.18

Table VIII. Profitability, Emission, and Abatement Costs

This table shows the joint link between profitability, emissions, and abatement costs. In Panel A, we present the correlation matrix to document the correlation between emissions and measures of abatement costs (ENER and ENRR). In Panel B, we report panel regressions of current profitability on abatement costs and their interactions, together with other firm characteristics. The sample excludes financial industries. We control for industry and year fixed effects based on Fama and French (1997) 49-industry classifications. All independent variables are normalized to 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 clustered at the firm level are reported. All regressions are conducted at the annual frequency. ***, **, and * indicate significance at the 1%, 5%, and 10% level.

Panel A: Correlation

	Emission	ENER	ENRR
Emission	1	-0.09***	-0.11***
ENER		1	0.80***
ENRR			1

Panel B: Regressions

	(1)	(2)
ENER	-0.009	
[t]	-2.495	
ENRR		-0.012
[t]		-3.483
Log ME	0.010	0.012
[t]	1.317	1.542
Log B/M	-0.031	-0.031
[t]	-5.859	-6.076
I/K	0.008	0.008
[t]	1.406	1.405
TANT	-0.006	-0.006
[t]	-0.9556	-1.062
WW	-0.005	-0.005
[t]	-0.512	-0.479
Lev	-0.016	-0.016
[t]	-4.660	-4.783
Observations	1,513	1,513
R^2	0.468	0.473
Industry FE	Yes	Yes
Year FE	Yes	Yes
Cluster SE	Yes	Yes

Table IX. Event Studies

This table presents cumulative abnormal returns around the 2016 U.S. presidential election of stocks sorted into emissions-sorted portfolios. The table reports daily and annualized cumulative returns over a 10-day window from one day after the presidential election date to 10 days after the election, which we refer to as a (0,10) window. These cumulative abnormal returns are equally weighted across emissions-sorted portfolios.

	Event Studies: Presidential Election					
CAR (%)	L	2	3	4	H	H-L
Daily Ret.	3.64	5.35	5.03	3.75	6.31	2.68
Annualized Ret.	90.89	133.87	125.82	93.85	157.86	66.97
[t]	4.55	5.62	5.14	3.84	5.11	1.98

Table X. Estimating the Market Price of Risk

In Panel A, we present GMM estimates of the parameters of the stochastic discount factor, $SDF = 1 - \lambda \times \text{MKT} - \lambda_c \times \Delta n$, using the quintile portfolios sorted on emission intensity. Δn denotes the log difference (growth rate) in the number of civil cases to proxy for litigation shocks (Δn). We do the normalization such that $E[m] = 1$ (see, for example, Cochrane (2005)). We report t-statistics based on standard errors estimation using the Newey-West procedure adjusted for three lags. As a measure of fit, we report the sum of squared errors (SSQE), mean absolute pricing errors (MAPE), and the J-statistic of overidentifying model restrictions. Given the Euler equation $\text{E}[\text{SDF} \times R_i^e] = 0$, SSQE and MAPE are based on each testing asset i's moment error u_i: $u_i = \frac{1}{T}\sum_{t=1}^{T}\left[\widehat{\text{SDF}} \times R_{i,t}^e\right]$. SSQE and MAPE are defined as $\sum_{i=1}^{N} u_i \times u_i$ and $\frac{1}{N}\sum_{i=1}^{N}|u_i|$, where N denotes the number of test assets. In Panel B, we present GMM-implied test portfolios' risk exposure (β^i_{MKT} and $\beta^i_{\Delta n}$) to the market factor and litigation shocks, together with estimated pricing errors ($\alpha^i = \bar{R} - \beta^i \times \lambda$) in percentage.

Panel A: Price of Risk							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MKT		0.69	0.67	0.47	0.51	0.55	0.63 t¿t
		10.57	8.6	3.16	5.10	7.50	7.85
Δn	-1.66		-0.99		-0.81		-0.95 t¿t
	-6.23		-4.37		-5.42		-3.81
Uncertainty				-0.99	-0.64		t¿t
				-8.43	-6.42		
GDP						0.48	0.18 t¿t
						5.22	1.47
SSQE (%)	21.78	2.16	1.54	1.89	1.43	1.88	1.55
MAPE (%)	30.12	8.47	6.63	9.10	6.66	7.51	6.56
J-Test	6.600	6.776	6.667	6.405	6.260	6.489	6.379
p	0.97	0.99	0.95	0.96	0.93	0.95	0.93
JT-Diff			2.725	9.266	3.65	7.173	2.748
p			0.099	0.002	0.056	0.007	0.097

	L	2	3	4	H	H-L		L	2	3	4	H	H-L
Panel B: SDF (MKT) in Panel A (2)							Panel C: SDF (MKT + Δn) in Panel A (3)						
β^i_{MKT}	15.74	17.14	17.49	17.83	16.59	0.18	β^i_{MKT}	15.77	17.2	17.49	17.81	16.55	0.78 t¿t
	11.94	16.9	10.05	8.18	14.28	0.26	[t]	9.63	11.95	8.61	7.07	11.13	0.90
$\alpha^i = \bar{R} - \beta^i \times \lambda$	-3.89	-0.60	-1.35	-1.28	0.82	-3.53	$\beta^i_{\Delta n}$	1.45	2.69	-0.41	-0.85	-1.46	-2.91 t¿t
	-1.66	-0.26	-0.58	-0.55	0.35	-1.47	[t]	1.39	3.05	-0.33	-0.65	-1.24	-3.45
							$\alpha^i = \bar{R} - \beta^i \times \lambda$	-3.09	0.65	-1.57	-1.74	0.19	-3.48
							[t]	-1.19	0.26	-0.60	-0.67	0.07	-1.37
Panel D: SDF (MKT+EPU) in Panel A (4)							Panel E: SDF (MKT+EPU+Δn) in Panel A (5)						
β^i_{MKT}	15.39	16.94	17.74	17.86	16.09	0.69	β^i_{MKT}	15.41	16.96	17.73	17.85	16.08	0.67 t¿t
	10.12	11.42	8.56	7.18	10.58	0.71	[t]	9.76	11.01	8.43	7.12	10.8	0.81
β^i_{EPU}	-1.47	-0.81	1.01	0.14	-2.10	-0.64	$\beta^i_{\Delta n}$	1.55	2.75	-0.47	-0.86	-1.34	-2.89 t¿t
	-1.49	-0.95	1.08	0.11	-3.81	-0.53	[t]	1.55	2.99	-0.36	-0.63	-1.19	-3.32
$\alpha^i = \bar{R} - \beta^i \times \lambda$	-4.36	-0.74	-0.42	-0.88	-0.06	-3.26	β^i_{EPU}	-1.56	-0.99	1.04	0.20	-2.02	-0.46 t¿t
	-1.60	-0.27	-0.16	-0.32	-0.02	-1.16	[t]	-1.51	-1.15	1.05	0.14	-3.6	-0.35
							$\alpha^i = \bar{R} - \beta^i \times \lambda$	-3.74	0.13	-0.73	-1.26	-0.35	-3.23
							[t]	-1.41	0.05	-0.28	-0.47	-0.13	-1.21

Internet Appendix for "The Pollution Premium"*

PO-HSUAN HSU, KAI LI, and CHI-YANG TSOU

*Po-Hsuan Hsu, Kai Li, and Chi-Yang Tsou, Internet Appendix for "The Pollution Premium," *Journal of Finance*. Please note: Wiley is not responsible for the content or functionality of any supporting information supplied by the authors. Any queries (other than missing material) should be directed to the authors of the article.

I. The TRI Database and Supplementary Analyses

A. Institutional Background of the TRI Database

The Toxic Release Inventory (TRI) program and the resulting database are maintained by the U.S. Environmental Protection Agency (EPA). In 1986, the U.S. Congress passed the Community Right to Know Act (EPCRA) in response to public concerns over the release of toxic chemicals from several environmental accidents, both in the U.S. and overseas. The EPCRA entitles residents in their respective neighborhoods to know the source of detrimental chemicals, especially 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 10 or more full-time equivalent employees; and (3) it is in the mining, utility, manufacturing, publishing, hazardous waste, or federal industry. When a facility meets all three criteria in a given year, it must report to the EPA and thus enters into the TRI program. The EPA then publishes the TRI data, which contain detailed information from the TRI program and are available for any interested third party to access.[2]

To maintain the data quality of information in the TRI program, the EPA first identifies whether a TRI form submitted by a facility contains potential errors; if so, the EPA contacts the facility. If the EPA confirms errors, the facility is asked to resubmit a corrected TRI report. In addition, the Office of Inspector General, an independent office within the EPA, performs audits, evaluations, and investigations of the agency and its contractors to prevent and detect fraud, waste, and abuse. The EPA also conducts 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 next year, as shown in Figure IA.1. The figure shows that the TRI program included approximately 99% of facility-level emission data for 2015 by August 17, 2016. Thus, in our empirical tests (e.g., in 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.

We notice that the TRI database may not be comprehensive before 1991 as we observe an

[1] Changes to the list to 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 as recorded by air monitors. A single air monitor records the density of multiple pollutants at a fixed location every hour.

abnormally high ratio of reported zeros in facilities' TRI-listed chemicals in the pre-1991 period. We thus download and organize the facility-level TRI data from 1991 to 2016 using the following procedure:

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

Step 2: We download the annual TRI data from 1991 to 2016.

Step 3: For each facility in a given year, we use the value "PROD._WASTE_(8.1_THRU_8.7)," which is the sum of the amounts of all emissions (in pounds) across all chemical categories. There are seven items reported in Section 8 of the TRI database, as demonstrated in Figure IA.4 below, 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 observations are worth discussion before we proceed. First, the TRI database also includes a "parent name" that indicates the name of a company that owns the facility. We can therefore use the "parent name" to bridge the TRI database to the CRSP/Compustat database (Xiong and Png (2019)). Second, the TRI database has not changed the coverage of chemicals and pollutants to be disclosed. Third, we acknowledge that some chemicals are more toxic than others. We therefore also adjust toxic emissions according to their toxicity in Section I.G.

B. Data Collection of Civil Cases against Pollution

To collect the number and dollar amount of civil cases against pollution in the EPA record, we use the following procedures:
Step 1: We access the Enforcement and Compliance History Online (ECHO) system that contains information on civil cases provided by the EPA:
`https://echo.epa.gov/tools/data-downloads/icis-fec-download-summary`

Step 2: We next download all cases from the "PENALTIES" file on the webpage. Different types of civil penalties are reported for each case, as well as the case identifier, the total federal penalty amount, the state or local penalty amount, the total supplemental environmental project amount, the total complying action amount, and the federal cost recovery awarded amount.

Step 3: Moreover, we access facility-case-level information from the "Facilities in Case" file, including the facility identifier, the case identifier, and detailed address information about the location of a facility in each case. Finally, using this file, we trace back to the TRI database via the facility identifier and collect the number and dollar amount of litigation civil cases at the firm level for our

[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`.

empirical analysis.

C. Matching TRI with CRSP/Compustat

We construct sum of firm-level emissions (in pounds) as the facility-level emissions in each year by parent names in the TRI database. We next match parent 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 database and firm names in the CRSP/Compustat database following the approach of Hall, Jaffe, and Trajtenberg (2001). 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."

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

D. Summary Statistics across Industries

In Table IA.8, we report summary statistics for raw emissions (Panel A) and emission intensity (Panel B) of firms in each industry according to the Fama and French (1997) 49-industry classifications (FF49). Some industries have more firms reporting to the TRI database, such as the Machinery, Chips, and Chemicals industries. There is relatively large cross-industry variation in chemical emissions. Specifically, the standard deviation of emission intensity ranges from 30,400 for the Chemicals industry to 1,213 for the Medical Equipment industry. Therefore, to make sure our results are not driven by any particular industry, we control for industry effects in our further analyses.

E. Transition Matrix

Whether firms' emission intensity is persistent is important for our analysis of the emission-return relation. To examine such persistence, in Table IA.9 we present the transition across quintiles over time. The left panel of Panel IA.9 shows the transition of firms' emission intensity from year t to year t+1, while the right panel shows the transition of firms' emission intensity from year t to year t+5. For firms in the top or bottom quintile of the distribution of emission intensity, the probability of staying in the same quintile in the next year (five years later) is above 87% (71%).

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

The persistent emission intensity is intuitive because firms cannot easily adjust their production designs and processes. More importantly, such persistence has important asset pricing implications: if there is any emission-return relation, then it should be attributed to long-lasting fundamental issues rather than transitory effects such as overreaction (underreaction) or mispricing.

F. *A Case Study of a Public Firm's Environmental Impact*

Figure IA.6 illustrates a case of environmental contamination by Dow Chemical. In 2002, Dow Chemical agreed to settle a lawsuit in California by spending $3 million on wetlands restoration. In 2008 the federal government intervened and claimed damages to nearby residents' health from airborne contamination from Dow Chemical's nuclear weapon plant in Colorado. In 2011 Dow Chemical negotiated with the regulator for violations of the Clean Air Act, which caused the dioxin contamination in Michigan.[6] On November 9, 2019, Dow Inc., which merged with DuPont Co. in 2017, settled an environmental complaint at an estimated cost of $77 million in projects and funding for the restoration of injured fish, wildlife, and habitats after hazardous chemical pollutants were released over several decades from Dow's facility located in Midland, Michigan.[7]

G. *Emission Intensity Adjusted for Toxicity*

In this subsection, we consider an alternative (albeit related) measure of emission intensity to test the robustness of our measure of emissions. In the main paper, our measure of emission intensity is considered by summing the amounts of all TRI-listed chemicals, when we treat different pollutants as having identical toxicity. In this subsection we attempt to differentiate chemical categories by estimating their toxicity.

In particular, for each chemical category j, we estimate county-year panel regressions using expanding windows as follows:

$$Mortality_{i,t\to t+n} = a + b^j \times \log Chem^j_{i,t} + c \times Unep_{i,t} + d \times \log PI_{i,t} + CT_i + Year_t + \varepsilon_{it}, \quad \text{(IA.1)}$$

where $Mortality_{i,t\to t+n}$ is the moving average of the mortality rate in county i from year t to $t+n$.[8] To account for the delayed impact on mortality of chemical pollutants released in year t, we construct a moving average of county-level mortality rates at three- or five-year windows (i.e., $n = 2, 4$). The variable $Chem^j_{it}$ is the level of chemical pollutants in category j, $j = 1, ..., J$, released by all facilities reported in the TRI database in county i. We also control for local economic fundamentals, including the county-level unemployment rate, $Unep_{i,t}$, and real personal income per capita, $PI_{i,t}$, deflated by the CPI index.[9] In addition, we control for county fixed effects, CT_i, and

[6] See Corporate Research Project: `http://www.corp-research.org/dowchemical`.

[7] Dow's settlement: `https://www.michigan.gov/ag/0,4534,7-359-92297_47203-511944--,00.html`.

[8] Data source of U.S. mortality rates by county: `http://www.corp-research.org/dowchemical`.

[9] County-level unemployment rates, $Unep_{i,t}$, are downloaded from the U.S. Bureau of Labor Statistics (BLS): `https://www.bls.gov/lau/`. County-level person income per capital $\mathrm{PI}_{i,t}$ are downloaded

year, $Year_t$, fixed effects, respectively. For each chemical category, we estimate b^j at expanding windows (to be discussed later). Standard errors are clustered at the county level. We use the coefficient on b^j for the degree of toxicity of a given chemical category j in a year. A higher estimate of b^j suggests that category j is more hazardous to human beings. However, b^j cannot be directly used to construct our toxicity-weighted emissions because the estimation for b^j could result in some outlier coefficients of very negative or very positive numbers. Thus, for each year, we sort all categories with nonmissing and positive estimates into five groups based on the estimated b^j, and then assign a toxicity score ranging from 6 to the highest quintile to 2 to the lowest quintile, with a score of 1 indicating all remaining categories.[10] Such toxicity scoring ensures that our weighting is less affected by outliers.

There is a remaining issue related to this method of toxicity weighting: there is a two-year lag in the county-level mortality information being available in the Human Mortality Database (HMD). For example, the mortality rate in 1993 will not be known by the public until 1995. To control for the look-ahead bias in our calculation of emission intensity, we use the following procedure for the case of $n = 2$ (i.e., using the three-year moving average of the mortality rate): we start with county-level emissions in 1990 and 1991 and the average mortality rates in 1990 to 1992 and 1991 to 1993 (which are known in 1995) to estimate b^js and toxicity scores that are used to weigh a firm's chemical emissions in 1995. A firm's toxicity-Adjusted emission intensity in 1995 is calculated as the "Toxicity-Adjusted Emissions" in 1995 divided by total assets and is used to form portfolios at the end of September in 1996. In the next window, we use emissions in 1990, 1991, and 1992 (and the mortality rate in 1990 to 1992, 1991 to 1993, and 1992 to 1994, respectively), to estimate toxicity degrees and scores to emissions adjustment score and to calculate toxicity-adjusted emission intensity in 1996, and to form portfolios at the end of September of 1997. We follow a similar procedure until 2012 by using 23-year county-level panels. The estimated toxicity is adjusted for emissions in 2016, and we form portfolios at the end of September in 2017. We follow similar steps to estimate toxicity in the case of $n = 4$ (a five-year moving average of mortality rate).

In the following subsections, we examine the relation between toxicity-adjusted emissions and the cross-section of stock returns. We first show that toxicity-adjusted emissions positively predict stock returns in portfolio sorts. We next show that the return spread sorted on toxicity-adjusted emissions is not fully captured by existing empirical factors for systematic risks in the literature. Finally, we investigate the link between toxicity-adjusted emissions and other firm-level characteristics on the one hand and future stock returns in the cross-section on the other, using Fama and MacBeth (1973) regressions as a valid cross-check.

from the U.S. Bureau of Economic Analysis (BEA): `https://www.bea.gov/data/income-saving/personal-income-county-metro-and-other-areas`.

[10] All chemical pollutants are supposed to have negative impacts on human health. However, owing to measurement errors and data limitations, we may have negative coefficients for some b^j or too few observations to estimate b^j.

G.1. Univariate Portfolio Sort on Toxicity-Adjusted Emissions

We construct five portfolios sorted on firms' current toxicity-adjusted emission intensity (i.e., toxicity-adjusted emissions scaled by total assets) and report these portfolios' post-formation average stock returns. We focus on annual rebalancing (as opposed to monthly rebalancing) to minimize transaction costs of the investment strategy. At the end of September of year t from 1996 (1999) to 2017 in the left (right) panel for the effect of chemicals on mortality in the following three-year (five-year) window, we rank firms by their toxicity-adjusted emissions relative to their industry peers and construct portfolios as follows. We sort all firms with positive toxicity-adjusted emission intensity in year t into five groups from low to high within Fama and French (1997) 49 industries. The low (high) portfolio contains firms with the lowest (highest) toxicity-adjusted emission intensity in each industry. Finally, we construct a high-minus-low (H-L) portfolio that takes a long position in the highest portfolio and a short position in the lowest portfolio.

After forming the six portfolios (from low to high and H-L), we calculate the value-weighted monthly returns on these portfolios over the next 12 months (i.e., October in year t to September in year $t+1$). In Panel A of Table IA.10, the top row presents the *annualized* average excess stock returns ($E[R]-R_f$, in excess of the risk-free rate), t-statistics, standard deviations, and Sharpe ratios of the five portfolios sorted on emissions. The upward-sloping pattern in both the left and the right panel implies that firms with currently high toxicity-adjusted emissions earn subsequently higher returns, on average, than their counterparts. The average excess return in the H-L portfolio amounts to a significant 3.22% (3.25%) with a t-statistic of 2.30 (2.80) and a Sharpe ratio of 0.36 (0.38). Taken together, the evidence suggests that the positive emission-return relation holds when we adjust for heterogeneous toxicity across chemical pollutants.

Next, as presented in Panel B of Table IA.10, we determine whether the positive toxicity-adjusted emission-return relation is driven by the variation in the market factor in the CAPM model. The slope of the market beta is flat across portfolios sorted on toxicity-adjusted emissions in both the left and the right panel of Panel B. Moreover, differential exposures to market risk cannot explain variation in portfolio returns sorted on toxicity-adjusted emissions since the risk-adjusted returns (intercepts) of the H-L portfolio remain both statistically and economically significant. As a result, it is unlikely that the CAPM model explains the differences in toxicity-adjusted emission-sorted portfolio returns. Second, when considering the Fama and French (1996) three factors (MKT, the size factor-SMB, and the value factor-HML), we find that the risk-adjusted returns in the H-L portfolio remain statistically significant, amounting to 3.57% (2.96%) in the left (right) panel of Panel C. In Panel D, we further add the momentum factor (UMD) and obtain consistent results. Third, when introducing the Fama and French (2015) five-factor model, we find that the risk-adjusted returns in the H-L portfolio remain statistically significant, amounting to 3.04% (2.62%) in the left (right) side of Panel E, with the intercepts two standard errors above zero; in addition, t-statistics are significant at the 5% level. Turning to Panel F, the alpha of the H-L portfolio in the Hou, Xue, and Zhang (2015) q-factor model is larger in magnitude and statistically significant with a t-statistic above 2.5 (3) in the left (right) side of the panel. As a result, common risk factors cannot explain portfolios sorted on toxicity-adjusted emissions.

Overall, results in Table IA.10 confirm the positive pollution-return relation when we take heterogeneous toxicity across chemical pollutants into account.

G.2. Fama-Macbeth Regressions

We further investigate the ability of toxicity-adjusted emissions predict cross-sectional stock returns using Fama-MacBeth cross-sectional regressions (Fama and MacBeth (1973)). We also control for an extensive list of firm characteristics that predict stock returns and further examine whether the positive emission-return relation is driven by other known predictors at the firm level. We conduct cross-sectional regressions for each month from October of year t to September of year $t+1$. In each month, we regress monthly returns of individual stock returns (annualized by multiplying by 12) on toxicity-adjusted emission intensity of year $t-1$ (that is reported by the end of September of year t), control variables known by the end of September of year t, and industry fixed effects.

In Table IA.11, we report the average slopes from monthly regressions, and the corresponding t-statistics are the average slopes divided by their time-series standard errors. We annualize the slopes. The results support the return predictive ability of toxicity-adjusted emissions estimated by a three-year (five-year) moving average of mortality rates from Specification 1 to 3 (4 to 6). In Specification 1 (4), toxicity-adjusted emissions significantly positively predict future stock returns with a slope coefficient of 1.01 (1.30) and a t-statistic of 2.00 (2.33). This finding is consistent with the predictability and implies that a one-standard-deviation increase in toxicity-adjusted emissions leads to a significant increase in the annualized stock return of 1.01% (1.30%).

From Specification 2 (5), toxicity-adjusted emissions positively predict stock returns with statistically significant slope coefficients when we include control variables known to predict stock returns in the cross-section: size, book-to-market ratio, investment rate, and ROE. Finally, Specification 3 (6) confirms the predictive ability of toxicity-adjusted emissions when we further control for asset tangibility, financial constraints, and financial leverage.

H. Univariate Portfolio Sort on Environmental Scores (ASSET4)

To further corroborate the link between emissions and future stock returns in the cross-section, we construct five portfolios sorted on firms' environmental scores. We collect the ASSET4, which contain various indexes related to public firms' corporate social responsibility (CSR) performance. We focus on firms' environmental scores that summarize their environmental performance at an annual frequency (Hsu, Liang, and Matos (2021)). The environmental scores are available since 2002. Panel A of Table IA.12 presents summary statistics for the firm-level environmental scores, including the time-series average of the cross-sectional mean, median, and standard deviation of environmental scores in each portfolio sorted by environmental scores (discussed below). Moreover, in the column “All,” we report the pooled mean, median, and standard deviation of environmental scores for all sample firms.

At the end of June of year t from 2003 to 2014, we rank firms by environmental scores in year $t-1$ relative to their industry peers and construct portfolios as follows. Specifically, we sort all firms with positive environmental scores in year $t-1$ into five groups from low to high within the corresponding Fama-French 49 industries. As a result, we have industry-specific breaking points for quintile portfolios for each June. We then assign all firms with positive environmental scores in year $t-1$ into these portfolios. Thus, the low (high) portfolio contains firms with the lowest (highest) environmental scores in each industry. To examine the environmental score-return relation, we form a L-H portfolio that takes a long position in the low environmental score portfolio and a short position in the high environmental score portfolio. After forming the six portfolios (from low to high and L-H), we calculate the value-weighted monthly returns on these portfolios over the next 12 months (July in year t to June in year $t+1$). To compute the portfolio-level average excess stock return in each period, we weigh each firm in the portfolio by the size of its market capitalization at the time of portfolio formation. This weighting procedure enables us to give relatively more weight to large firms in the economy, which minimizes the effect of very small (and hence potentially difficult to trade) firms on the results.

Panel B of Table IA.12 presents the *annualized* average excess stock returns ($E[R]-R_f$, in excess of the risk-free rate), t-statistics, standard deviations, and Sharpe ratios to the five portfolios sorted on environmental scores. The table shows that, consistent with our main result from univariate portfolio sorts on emission intensity, a firm's environmental score also forecasts stock returns. Firms with currently low environmental scores earn subsequently higher returns, on average, than firms with currently high environmental scores. Moreover, the average excess return on the L-H portfolio is a significant 4.30% with a t-statistic of 3.42 and a Sharpe ratio of 0.41. Thus, this result is both economically large and statistically significant.

Panel C of Table IA.12 shows that the negative environmental score-return relation is not driven by variations in the market factor in the CAPM model. Firms in the lowest portfolio exhibit higher exposure to market risk than those in the highest portfolio. However, differential exposure to market risk cannot capture variations in portfolio returns since the risk-adjusted returns (alphas) of the L-H portfolio remain both statistically and economically significant. As a result, it is unlikely that the CAPM model explains differences in environmental score-sorted portfolio returns. Second, the risk-adjusted returns of the environmental score-sorted L-H portfolio are even larger and more significant, amounting to 4.49% for the Fama and French (2015) five-factor model in Panel D. The alpha is three standard errors above zero, with statistical significance at the 1% level. However, the alpha of the L-H portfolio in the Hou, Xue, and Zhang (2015) q-factor model is smaller in magnitude and only marginally significant, as shown in Panel E.

Taken together, the results in Table IA.12 suggest that firms with low environmental performance are associated with higher subsequent stock returns and confirm the positive emission-return relation that we report in our main paper.

II. Additional Empirical Evidence

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

A. Factor Regressions and Risk Exposure

In this subsection, we investigate the extent to which the variation in the average returns of the emission-sorted portfolios can be explained by exposure to standard risk factors, including the market factor in the CAPM model, the three factors in Fama and French (1993) (FF3), the four factors in Carhart (1997) (FF4), the five factors in Fama and French (2015) (FF5), and the four factors in Hou, Xue, and Zhang (2015) (HXZ).[11] To adjust for risk exposure, we perform time-series regressions of emission-sorted portfolios' excess returns on the market factor (MKT) in the CAPM model in Panel A, on Fama-French three factors (MKT, the size factor-SMB, and the value factor-HML) in Panel B, on Carhart four factors (MKT, SMB, HML, and the momentum factor-UMD) in Panel C, on the Fama and French (2015) five factors (MKT, SMB, HML, the profitability factor-RMW, and the investment factor-CMA) in Panel D, and on the Hou, Xue, and Zhang (2015) q-factors (MKT, SMB, the investment factor-I/A, and the profitability factor-ROE) in Panel E, respectively. Such time-series regressions enable us to estimate the betas (i.e., risk exposures) of each portfolio's excess return on various risk factors and to estimate each portfolio's risk-adjusted return (i.e., alphas). These betas and annualized alphas (in %) are reported in Table IV.

First, as we show in Table IV, the positive emission-return relation cannot be explained by the market factor in the CAPM model. The market betas are flat across quintile portfolios sorted on emission intensity, suggesting that high-emission firms do not face higher market risk exposure. In addition, the intercept (i.e., alpha or risk-adjusted return) of the H-L portfolio is 4.07% with a t-statistic of 3.78, which is both statistically and economically significant. Second, in Panels B to E, the risk-adjusted returns of the emission-sorted H-L portfolio remain large and significant, ranging from 3.78% for the FF5 model in Panel D to 4.72% for the FF3 model in Panel B, with t-statistics well above 3. Lastly, the H-L portfolio carries insignificant loadings on most risk factors except the value factor. In summary, results from factor regressions in Table IV suggest that the cross-sectional return spread across portfolios sorted on emission intensity cannot be eliminated by existing risk factors. Hence, common risk exposure cannot explain the positive emission-return relation that we document.

We then examine how the time-series pattern of the risk-adjusted returns with respect to the Fama-French five-factor model and HXZ q-factor model affects the return on the H-L portfolio,

[11] The Fama and French factors are downloaded from Kenneth French's data library (`http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`). We thank Kewei Hou, Chen Xue, and Lu Zhang for kindly sharing their factors.

which is our proxy for pollution premium. Figure IA.8 plots the cumulative, risk-adjusted returns of the H-L portfolio from October of 1992 to September of 2018.

The positive emission-return relation that we find appears to be a fairly persistent pattern across most years and appears to be unrelated to economic downturns (denoted by economic recessions in shaded areas).

B. Fama-MacBeth Regressions

We further investigate the predictive ability of emissions for stock returns using Fama-MacBeth cross-sectional regressions (Fama and MacBeth (1973)). This analysis allows us to control for an extensive list of firm characteristics that predict stock returns and to further examine whether the positive emission-return relation is driven by other known predictors at the firm level.[12] We conduct cross-sectional regressions for each month from October of year t to September of year $t+1$. In each month, monthly returns of individual stock returns (annualized by multiplying by 12) are regressed on the emission intensity of year $t-1$ (which is reported by the end of September of year t), control variables known by the end of September of year t, and industry fixed effects. Control variables include the natural logarithm of market capitalization (Size), the natural logarithm of the book-to-market ratio (B/M), investment rate (I/K), return on equity (ROE), tangibility, WW index, book leverage, and industry dummies based on Fama and French (1997) 49-industry classifications. All independent variables are normalized to zero mean and unit standard deviation after winsorization at the 1st and 99th percentiles to reduce the impact of outliers.

In Table V, we report the average slopes (i.e., coefficient estimates) from monthly regressions. The corresponding t-statistics are the average slopes divided by their time-series standard errors.[13] We annualize the slopes and standard errors. Our results support the predictive ability of emission intensity for returns.[14]

From Specification 1, emissions positively predict stock returns with a statistically significant slope when we further control for variables known to predict stock returns in the cross-section, including size, book-to-market ratio, investment rate, and ROE. Additionally, Specification 2 highlights that the predictive ability of emissions is not subsumed by the existence of asset tangibility, financial constraints, and leverage. Overall, Table V suggests that the positive emission-return relation cannot be attributed to other known predictors and confirms that emissions have unique return predictive power.

[12] Fama-MacBeth cross-sectional regressions provide a reasonable cross-check for the portfolio tests, as it is difficult to include multiple sorting variables with unique information about future stock returns by using a portfolio approach.

[13] Our standard errors are based on Newey and West (1987).

[14] The Fama-MacBeth regressions weigh each observation equally, and thus place substantial weight on small firms. However, our finding for the pollution premium from sorted portfolios is based mainly on value-weighted portfolios.

C. Double Sorting on Size

To alleviate the concern that the return predictability we document is driven by firm size, we conduct two-way sorts for emission intensity and size.

At the end of September of year t, we assign firms into big (B) and small (S) groups based on their market capitalization relative to industry peers and group firms into quintile emission portfolios (from low to high) based on their emission intensity relative to industry peers. We then track the value-weighted returns on each portfolio from October of year t to September of year $t+1$. We report the annualized portfolio returns by multiplying by 12, as well as t-statistics, in Table IA.4.

If size is responsible for the emission effect, then we would expect the return spread to concentrate on the small or big group. However, as shown in Table IA.4, high-emission firms still outperform low-emission ones in terms of stock returns for both big and small groups. Moreover, the returns on the H-L portfolios are both economically and statistically significant among both big and small firms. Consequently, the positive emission-return relation is not driven by size effects.

D. Event Studies as Extensions

To rule out cherry-picking concerns, we conduct CAR tests around three policy shocks: Pruitt's appointment as EPA head on December 7, 2016, and Bush's electoral victories on November 7, 2000 and November 2, 2004, respectively.[15] These events motivate us to assess the relation between emission intensity and an alternative policy shock. As in Section III.C, we compute the average CAR of all stocks in each emission-sorted quintile portfolio for these events and present them in Table IA.13.

The results in Table IA.13 suggest that firms' stock prices hold as the market absorbs the policy shock and reflects it in the price. Despite the fact that Scott Pruitt had been regarded as a hostile candidate for the appointment with the EPA, the market anticipated on the date of Trump's victory and therefore was less unexpected. Moreover, the nomination event itself could be an idiosyncratic rather than a systematic news event in the financial market. Hence, we find no evidence of systematically higher returns among high-emission firms on the nomination date.

We conduct portfolio sorting around the 2004 and 2000 post-election periods associated with George W. Bush, and test whether abnormal returns of high-emission firms significantly increased following Bush's election victories. Across five emission-sorted quintile portfolios in Panel A (Panel B), we find an upward-sloping pattern of CARs. In annualized terms, the return difference between two extreme portfolios amounts to 88.00% (126%) at the 1% (1%) significance level.[16]

[15]There is a large literature on the effect of tied elections on the real economy and financial markets. Inspired by Lee (2008) and Girardi (2020), the margin of an electoral victory within 5% is regarded as a close electoral outcome, and we use such an event as an alternative policy shock.

[16]The primary reason we focus on Trump's presidential election is that it is highly related to environmental policy, as Trump promised throughout his electoral campaign that he would revoke a large part of his predecessor's environmental

E. Other Explanations for the Pollution Premium

In addition to regime change risk as discussed in Section IV, the positive emission-return relation could also be attributed to other explanations, including behavioral bias, corporate policies and governance, as well as relevant risks documented in the literature. We discuss these possible explanations in this section.

E.1. Fama-MacBeth Regressions and Other Risk-Based Explanations

As a cross-validation of two-way double sorting in Table IA.3, we rule out alternative explanations by running Fama-Macbeth regressions to control for a bundle of firm characteristics as in Section II. From columns (1) to (14), we find no evidence to suggest that these variables dampen the predictability of emission intensity. In the last column, the predictability of emission intensity remains significant when we put all variables together, except for a few variables, including the G index, and E index, and political donations, due to data limitations in a horse race.

E.2. Behavioral Explanations

Preferences on emissions. The literature documents that both retail and institutional investors disfavor firms with a poor social image, such as those that perform poorly with respect to CSR issues.[17] Due to such preference, prices of these firms tend to be discounted by the market and result in good dividend yields. When these polluting firms reduce their emissions in the future, their prices will be discounted less, resulting in a positive emission-return relationship. In addition, when investors who prefer high dividend yields to a stock's reputation, earn more dividends, they may buy more high-emission stocks and thus push up the prices of these stocks. In sum, the emission-return relation could therefore be driven by investors' preferences on emissions.

To test this explanation, we measure the "emission preference" of institutional investors and examine if the emission-return relation varies across different types of institutional investors. If the emission preference explanation holds, we expect emission-driven return predictability to be absorbed by institutional investors' emission preferences. We construct a measure of institutional investors' emission preferences in two steps. In the first step, we collect institutional holdings data at the end of September in year t from the Thomson Reuters Institutional Holdings (13F) database, and we calculate an institutional investor's exposure to emissions in year t as the valued-weighted emission intensity in year $t-1$ of all firms it holds.[18] In the second step, we calculate a firm's

policies.

[17]See Hong and Kacperczyk (2009), Fabozzi, Ma, and Oliphant (2008), Renneboog, Ter Horst, and Zhang (2008), Starks, Venkat, and Zhu (2017), Riedl and Smeets (2017), Gibson and Krueger (2018), Dyck, Lins, Roth, and Wagner (2019), Pástor, Stambaugh, and Taylor (2021), Hartzmark and Sussman (2019), and Ramelli, Wagner, Zeckhauser, and Ziegler (2021), among others.

[18]This method is motivated by the sustainability footprint of Gibson and Krueger (2018). The weighing factor is based on the market values of all firms held by an institutional investor.

pressure from institutional investors' emission preferences in year t as the value-weighted average of its institutional investors' exposure to emissions.[19]

We form double-sorted portfolios based on firm emissions and institutional investors' emission preferences. In particular, we independently sort firms into two portfolios based on their institutional investors' emission preferences and into five portfolios based on their emission intensity at the end of September of year t, all relative to industry peers. We then calculate the value-weighted returns on each portfolio from October in year t to September in year $t+1$. We present the average returns of our double-sorted (2×5) portfolios in Panel A of Table IA.5. We include t-statistics and annualize the portfolio returns by multiplying by 12. In the high-emission preference group, the return spread based on emission-sorted portfolios amounts to 4.98%, significant at the 1% level. In the low-emission preference group, the return spread based on emission-sorted portfolios is 4.72%, significant at the 5% level with a t-statistic of 2.03. Given that the emission-related return predictability is not eliminated when we control for institutional investors' emission preferences, the pollution premium cannot be attributed to investors' different preferences on pollution.

Underreaction to emission abatement. The literature well documents that investors may underreact to market news due to limited attention or lags in information diffusion.[20] It is possible that high-emission firms are subject to strong pressure from the community and government and thus are more likely to cut back emissions in the next period. If investors concern about CSR issues underreact high-emission firms' improvement, the stock prices of these firms may increase in the future, resulting in the emission-return relation that we find. This explanation, however, is not supported by Tables IA.2 and IA.1, both of which present a persistent pattern of firm-level emissions. Nevertheless, these tables can not rule out the possibility that the pollution premium is driven by a subset of high-pollution firms that significantly improve their emissions later, which results in increased stock prices. To further examine this possibility, we implement the two-way portfolio sorting based on firms' current and future emission intensity. At the end of September of year t, we first sort stocks into five portfolios (from low "L" to high "H") based on firms' emission intensity in year $t-1$ (i.e., current emissions). The firms in the highest quintile portfolios are then further sorted into two portfolios based on their emission intensity in year t (i.e., future emissions).[21] The HL portfolio includes firms with future emission intensity below the median of the high group and the HH group includes those with future emission above the median of the high group. If the underreaction explanation holds, then the emission-return relation should exist only in the HL group but not in the HH group.

We calculate the value-weighted portfolio returns of these two portfolios over the following 12

[19]The weighing factor is based on the shares owned of all institutional investors that hold the focal firm.

[20]Prior studies suggest that investors tend to underreact to new information (e.g., Bernard and Thomas (1990)), especially complex information (e.g., You and Zhang (2009)). For example, in the innovation literature, the evidence suggests that investors tend to overdiscount the cash flow prospects of R&D-intensive or patenting firms due to high uncertainty and complexity associated with innovations or fail to take into account the benefits of innovation due to limited attention, which results in underpricing of innovation (see, e.g., Hall (1993), Lev and Sougiannis (1996), Aboody and Lev (1998, 2000), Chan, Lakonishok, and Sougiannis (2001), and Hirshleifer, Hsu, and Li (2013, 2017)).

[21]We present the transition matrix in Section I.E of the Internet Appendix.

months and report their time-series average returns in the second and third columns of Table IA.5, Panel B. We also report t-statistics. We additionally report the average portfolio return in the lowest quintile portfolio (L) and the return difference between the HL and L groups and the return difference between the HH and L groups. Our empirical results show that although the HL-L difference is significantly positive on average (3.96% with a t-statistic of 3.31), HH-L is also significantly positive on average (5.39% with a t-statistic of 2.34). In other words, even high-pollution firms that do not improve their emissions in the future provide significantly higher returns than low-pollution firms. Hence, the underreaction explanation is not likely to explain the cross-sectional variation in stock returns due to emissions.

Retail investors' behavioral bias. Different from institutional investors, who are more rational and have more complete information, retail investors may be more subject to behavioral bias (e.g., Daniel, Hirshleifer, and Subrahmanyam (1998), Barberis, Shleifer, and Vishny (1998), and Hong and Stein (1999), among others.). For example, retail investors may panic when they hear about some firms' emission news (Krüger (2015) and Ottaviani and Sørensen (2015)) and sell all of their stocks at deep discounts. If such overreaction explains the pollution premium, then the emission-return relation should exist only among stocks that experience a significant drop in the share of retail investors. To examine this explanation, we first define the share of retail investors in percentage as one minus the share owned by institutional investors in percentage at the end of each quarter. At the end of September of year t, we first sort all stocks with emission intensity into three portfolios by 30-40-30 based on the change in retail investors between June and September in year t within each industry. The high (low) group includes stocks that experience the strongest increase (decrease) in retail investors' share. Then, within each group, we further sort stocks into quintile portfolios based on firms' emissions within a particular industry. Moreover, within each portfolio of changes in retail investors' share, we form a H-L portfolio that takes a long position in the high-emission portfolio and a short position in the low-emission portfolio. As a result, we form total 18 portfolios.

In Panel C of Table IA.5, we report the annualized monthly averages of value-weighted returns on all portfolios, as well as t-statistics. In addition, we report the mean (value-weighted) and median of each group of changes in retail investors' share. We first find that, within the middle tercile (Group 2), the return spread (4.08% with a t-statistic of 2.96) is significant and comparable to that in the univariate portfolio sorting. In addition, the change in retailed investors' share is close to zero in the middle tercile (the mean and median are 0.05 and 0.04, respectively). In contrast, within the groups with the lowest or highest changes (Group 1 or 3) in retailed investors' share, the return spread (i.e., the return on the H-L portfolio) is *insignificant*. These results suggest that the emission-return relation is orthogonal to the ownership of retail investors who are more subject to overreaction bias.

E.3. Corporate Policies and Governance

Corporate governance and monitoring. Another possible explanation for the emission-return relation is that high-emission firms could be under weaker governance or monitoring (Masulis and Reza (2015), Cheng, Hong, and Shue (2013), Glossner (2018), Hoepner, Oikonomou, Sautner, Starks, and Zhou (2019)), and thus their stock prices are discounted by investors who are concerned about governance or associated risk and uncertainty (e.g., Gompers, Ishii, and Metrick (2003)). Such low prices may attract bidders or active investors that seek improve these firms' governance and monitoring, in which case stock prices increase and lead to return predictability. If such governance or monitoring channels are responsible for the emission effect, we would expect there to be no emission-return relation among firms with strong corporate governance. To examine this explanation, we double sort firms' G index (E index) into two portfolios (low and high) and firms' emission intensity into quintile portfolios (low, 2, 3, 4, and high), all relative to their industry peers.[22] Moreover, within each governance portfolio, we form a H-L portfolio that takes a long position in the high-emission portfolio and a short position in the low-emission portfolio. As a result, we form total 12 portfolios.

In Panel A of Table IA.6, we report the monthly averages of value-weighted returns on all 12 portfolios, as well as t-statistics. We find that the returns on the H-L portfolio sorted on emission intensity remain statistically significant among firms in the strongest governance (i.e., low G or E index) group. In particular, within the low G index group (upper panel), the H-L portfolio's return is still significant and amounts to 5.52%. Therefore, our emission-return relation cannot be attributed to differences in governance and monitoring.

Political connection. It is also possible that high-emission firms may be more politically connected, in which case their profits and stock prices may be subject to uncertainty with respect to governance. Since political connections are positively related to future stock returns (e.g., Liu, Shu, and Wei (2017)) or result in a risk premium (Santa-Clara and Valkanov (2003)), the emission-return relation may reflect the asset pricing implications of political connections. Under this explanation, we would expect there to be no emission-return relation among firms with few political connections.

To test this explanation, we collect annual firm-level political donation data from OpenSecrets.org of the Center for Responsive Politics.[23] We then implement independent double sorts by grouping all firms into two portfolios (low and high) by their political connections and into five portfolios (from low to high) by their emission intensity. We define a firm's political connections as its total political donations (regardless of which party) made in a year scaled by its total assets.[24] Moreover, within each political donation portfolio, we form a H-L portfolio that takes a long position in the high-emission portfolio and a short position in the low-emission portfolio. As a result, we form a total of 12 portfolios.

[22] Detailed information on the G and E indexes can be found in Gompers, Ishii, and Metrick (2003) and Bebchuk, Cohen, and Ferrell (2008), respectively.

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

[24] If a firm with positive emission intensity does not make any political contribution, we set its political donation to zero.

In Panel B of Table IA.6, we report the annualized monthly averages of value-weighted returns on all 12 portfolios, as well as t-statistics. We find that the returns on the H-L portfolio sorted on emission intensity are statistically significant in both political donation groups. Within the low-political donation group, the return spread is as high as 6.20% (with a t-statistic of 2.29), which is even larger than the return spread of 4.26% (with a t-statistic of 4.85) in the high-political donation group and the return spread in the univariate portfolio. As a result, political connections cannot explain the pollution premium.

E.4. Other Risk-Based Explanations

Lastly, we explore possible explanations based on systematic risks posited in prior studies. In particular, we consider four alternative channels that may drive variation in our emission-sorted portfolios, including technology obsolescence (Lin, Palazzo, and Yang (2020)), financial constraints (Li (2011), Lins, Servaes, and Tamayo (2017)), economic and political uncertainty (Brogaard and Detzel (2015), Bali, Brown, and Tang (2017)), and adjustment costs (Kim and Kung (2016) and Gu, Hackbarth, and Johnson (2017)).

We elaborate on these alternative explanations as follows. High-emission firms adopt more obsolete technology and invest in less advanced capital in production. The arrival of new technology forces these firms to upgrade their capital, and hence their cash flows are sensitive to the frontier technology shock. High-emission firms may be subject to risk associated with financial constraints due to potential litigation risk and penalties related to environmental issues. In addition, these firms may be subject to risk associated with macroeconomic uncertainty (such as economic downturn or trade conflict) and political uncertainty (such as changes in the ruling party). Finally, these firms earn higher expected returns because it is costly for them to adjust their capital stock, especially during economic downturns.

To examine if the predictive ability of emission intensity can be attributed to other explanations of risk, we implement independent two-way sorts by assigning all sample firms by their values for a proxy for one of the alternative explanations (relative to their industry peers) into two groups (low and high) and by their emission intensity into quintile portfolios (low, 2, 3, 4, and high). In addition, within each portfolio sorted by the proxy for a risk-based explanation, we form a H-L portfolio that takes a long position in the high-emission portfolio and a short position in the low-emission portfolio. As a result, we form a total of 12 portfolios for each risk-based explanation. We report the annualized monthly averages of the value-weighted returns on all 12 portfolios in Table IA.7.

Technology obsolescence. We consider the capital age and investment rate to measure firm-level technology obsolescence, following Lin, Palazzo, and Yang (2020). A firm with older capital age or a lower investment rate faces higher exposure to technology frontier shocks and hence is riskier. In Panel A of Table IA.7, we show that the return spread from emissions (i.e., return on the H-L portfolio) remains comparable to that in the univariate portfolio sort in both young and old capital age (investment rate) groups. The return spread is 4.07% (with a t-statistic of 2.44) in the young capital age group and 4.24% (with a t-statistic of 2.50) in the old capital age group. The return spread is 4.16% (with a t-statistic of 4.28) in the low investment rate group and 5.31% (with a t-statistic of 3.22) in the high investment rate group. If technology obsolescence is the main force driving the pollution premium, then we should only observe significant return spreads in the old capital age and low investment rate groups. In contrast, the return spreads are also significant in the young capital age and high investment rate groups. Therefore, the pollution premium cannot be explained by technology obsolescence.

Financial constraints. We consider the financial constraints measures of WW (Whited and Wu (2006)) and SA indexes (Hadlock and Pierce (2010)), respectively.[25] A higher value of the SA or WW index suggests that the firm is more subject to financial constraints. In Panel B of Table IA.7, we show that the return spread from emissions is significantly positive in both less and more financially constrained groups. When we use the SA index, the return spread is 4.21% (with a t-statistic of 3.47) in the low-constraint group and 8.05% (with a t-statistic of 2.19) in the high-constraint group. When we use the WW index, the return spread is 3.44% (with a t-statistic of 3.90) in the low-constraint group and 4.14% (with a t-statistic of 2.33) in the high-constraint group. The fact that financially unconstrained firms' emissions continue to predict stock returns suggests that financial constraints cannot explain the pollution premium.

Economic and political uncertainty. We follow Bali, Brown, and Tang (2017) to estimate firm-level exposure with respect to the macroeconomic uncertainty index based on Jurado, Ludvigson, and Ng (2015) and with respect to the political uncertainty index based on Bloom (2009) by using rolling window regressions.[26] The results in the left and right sides of Table IA.7, Panel C present the returns of the 12 portfolios sorted on macroeconomic uncertainty and political uncertainty, respectively. Within both high and low macroeconomic (political) uncertainty exposure groups, the return spreads sorted on emission intensity are significantly positive. These findings suggest that the emission-return relation is not driven by different levels of exposure to macroeconomic (political) uncertainty.

Adjustment costs. We follow the method of Kim and Kung (2016) and Gu, Hackbarth, and Johnson (2017) to measure a firm's asset redeployability and inflexibility, respectively.[27] If the adjustment costs in asset redeployability (inflexibility) drive the pollution premium, such premium should not exist in firms in the high-asset redeployability (low-inflexibility) group, which are associated with lower adjustment costs. However, as shown in Panel D of Table IA.7, the return spread sorted on emission intensity is 4.73% with a t-statistic of 2.37 in the low asset redeployability group and 3.98% with a t-statistic of 2.18 in the high-inflexibility group. In contrast, the return spread

[25] Detailed information regarding construction of the SA and WW indexes can be found in Farre-Mensa and Ljungqvist (2016).

[26] For each stock with positive emissions in each month in our sample, we estimate the uncertainty exposure from monthly regressions of excess returns on the macroeconomic uncertainty index over a 60-month rolling window by controlling for empirical risk factors, including the market (MKT), size (SMB), value (HML), momentum (UMD), liquidity (LIQ), investment (I/A), and profitability (ROE).

[27] Detailed information regarding construction of the asset redeployability index can be found in Table IA.7.

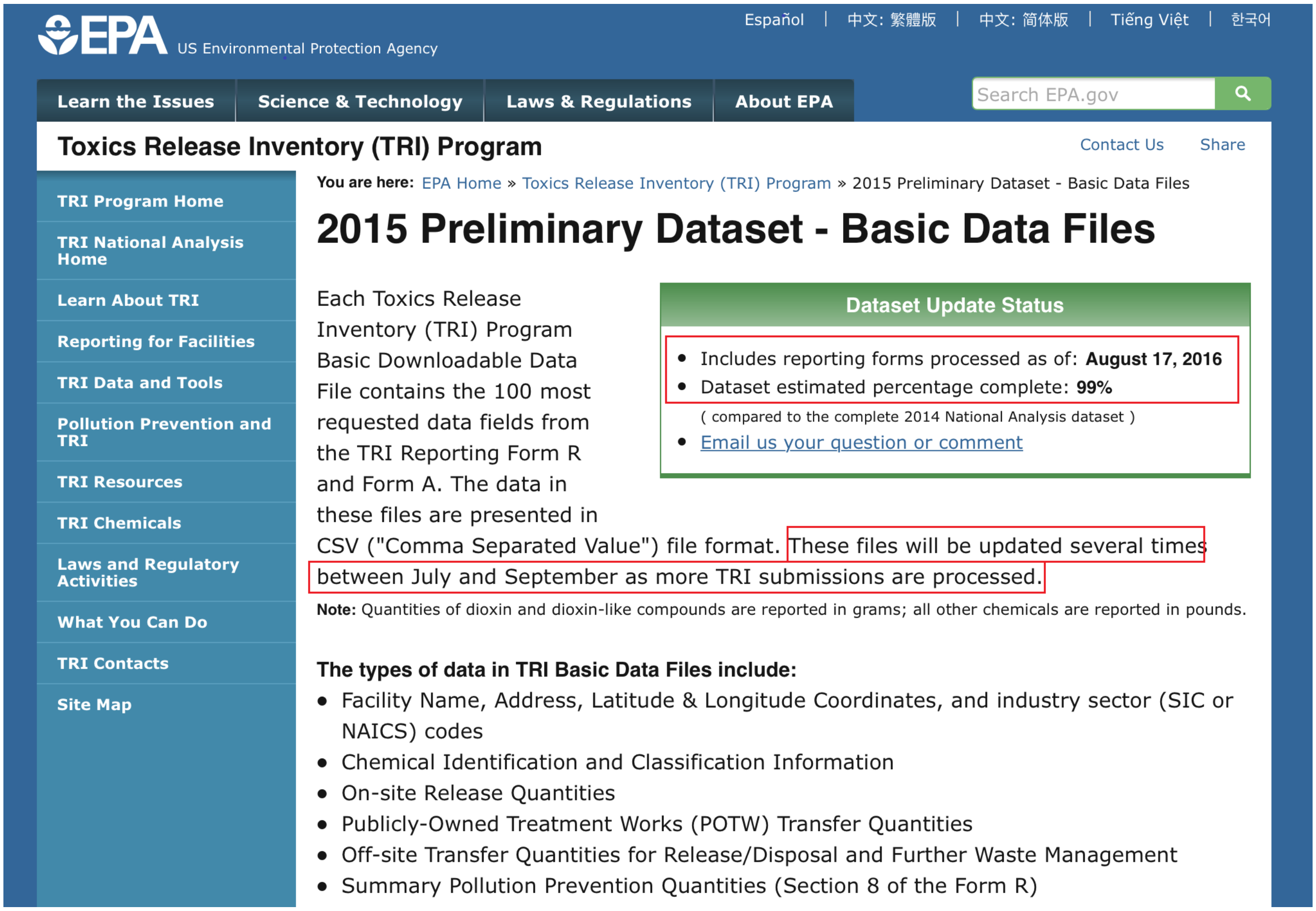
sorted on emissions is 7.84% at the 1% significance level in the high-asset redeployability group. The return spread in the low inflexibility group is also statistically significant at the 5% level and equal to 7.58%. The fact that the emission-return relation appears significantly positive in both high-asset redeployability and low-inflexibility groups suggests that the return predictability we document is unrelated to systematic risk associated with adjustment costs.

Overall, we find that high-emission firms earn higher stock returns than low-emission firms in all groups that represent low levels of exposure to systematic risks as documented in the literature. Taken together, these results point to the unique role of emissions in return predictability and support our model is new risk factor.

E.5. Other Risk-Based Explanations (Aggregate Level)

In this section, we consider alternative explanations based on aggregate proxies for macroeconomic risks that drive variation in the civil penalties of litigation cases. To do so, Table IA.14 we run contemporaneous or predictive regressions by regressing the growth of civil penalties on an extensive list of macro variables, including the current or lagged value of the unemployment rate (Unep), GDP growth (dy), economic policy uncertainty index (EPU), price-dividend ratio (P/D), cyclically adjusted price-to-earnings (CAPE), TED spread (TED), and default premium (DEF).

These results suggest that policy change risk (i.e., the growth rate of civil penalties) cannot be attributed to other macroeconomic factors (at least those that we can think of).



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Toxics Release Inventory (TRI) Program

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2015 Preliminary Dataset - Basic Data Files

Dataset Update Status

- Includes reporting forms processed as of: **August 17, 2016**
- Dataset estimated percentage complete: **99%**

(compared to the complete 2014 National Analysis dataset)

- Email us your question or comment

Each Toxics Release Inventory (TRI) Program Basic Downloadable Data File contains the 100 most requested data fields from the TRI Reporting Form R and Form A. The data in these files are presented in CSV ("Comma Separated Value") file format. These files will be updated several times between July and September as more TRI submissions are processed.

Note: Quantities of dioxin and dioxin-like compounds are reported in grams; all other chemicals are reported in pounds.

The types of data in TRI Basic Data Files include:

- Facility Name, Address, Latitude & Longitude Coordinates, and industry sector (SIC or NAICS) codes
- Chemical Identification and Classification Information
- On-site Release Quantities
- Publicly-Owned Treatment Works (POTW) Transfer Quantities
- Off-site Transfer Quantities for Release/Disposal and Further Waste Management
- Summary Pollution Prevention Quantities (Section 8 of the Form R)

Figure IA.1 Annual updates of the TRI program.

Source: https://www.epa.gov/toxics-release-inventory-tri-program/tri-basic-data-files-calendar-years-1987-2016.

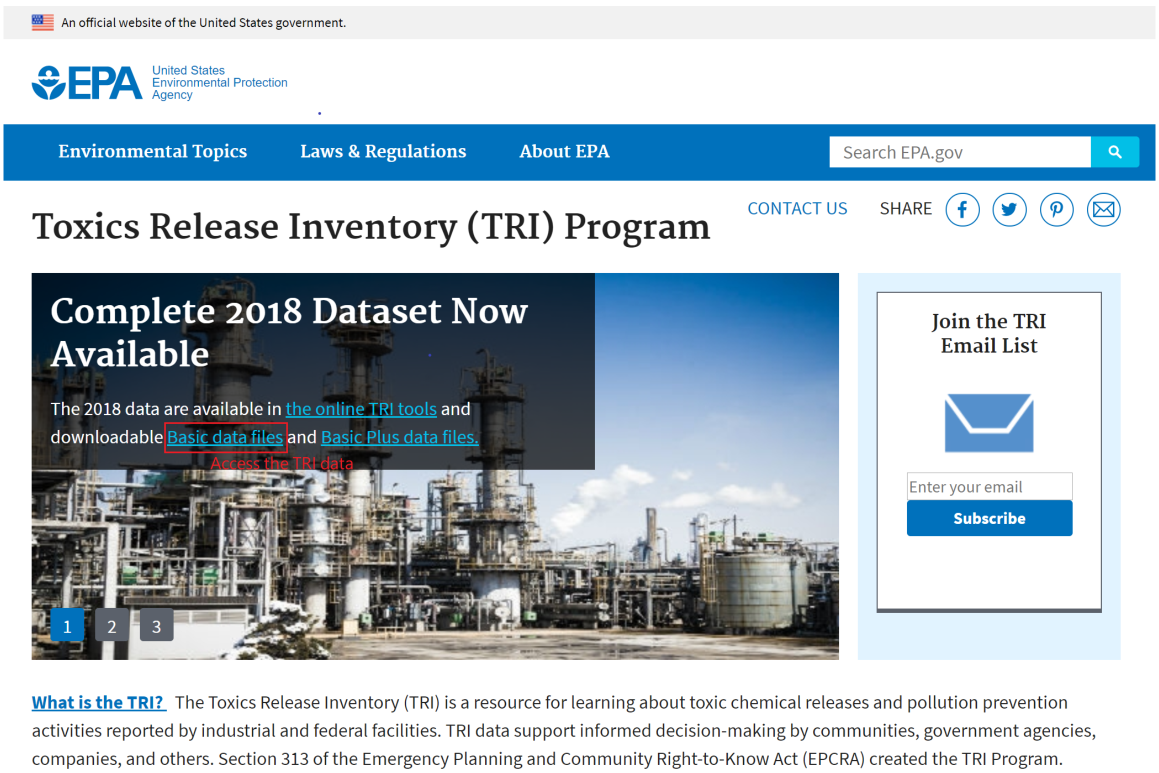


Figure IA.2 Access to the TRI database.

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

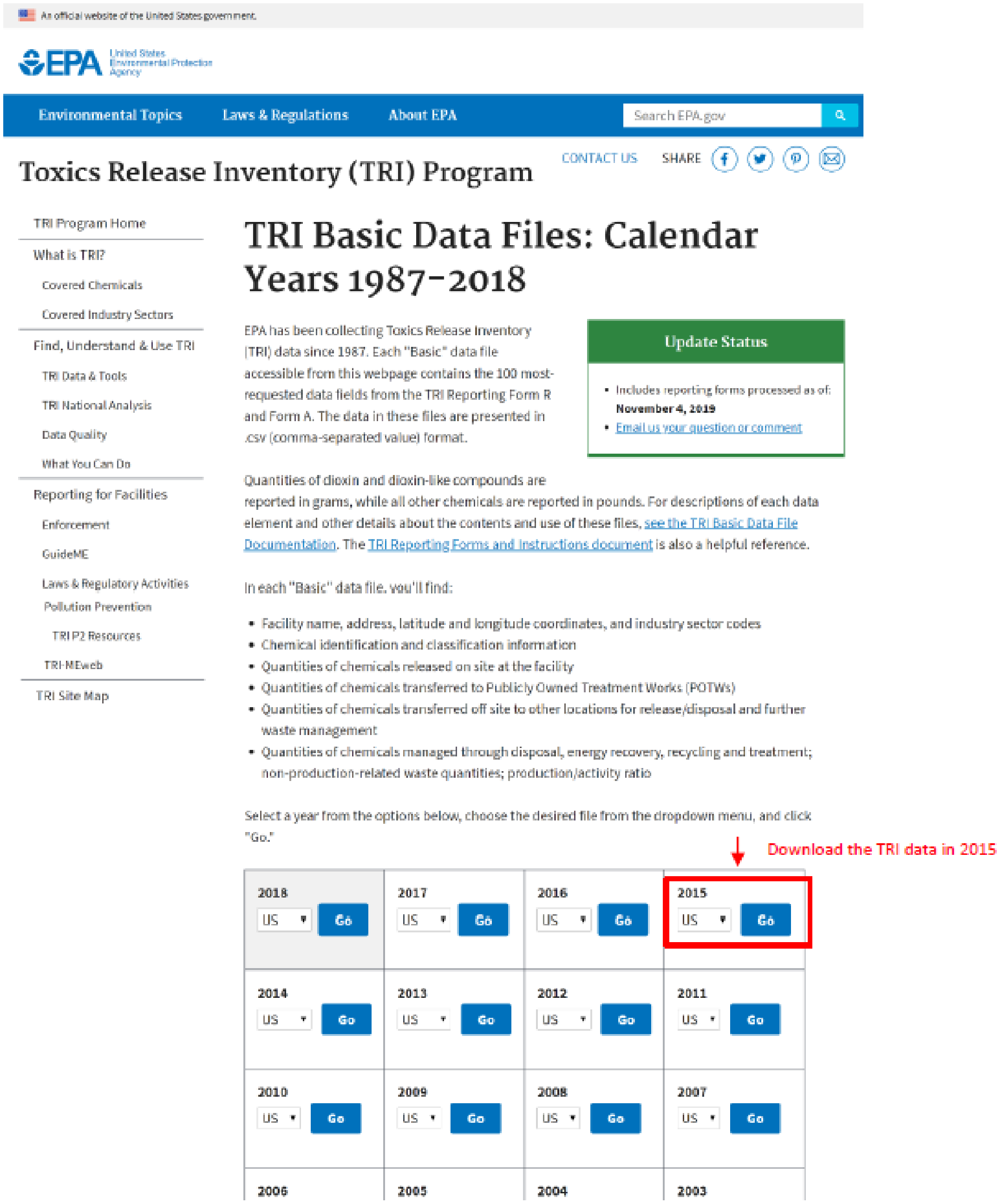
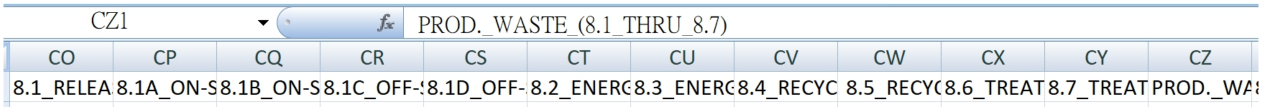


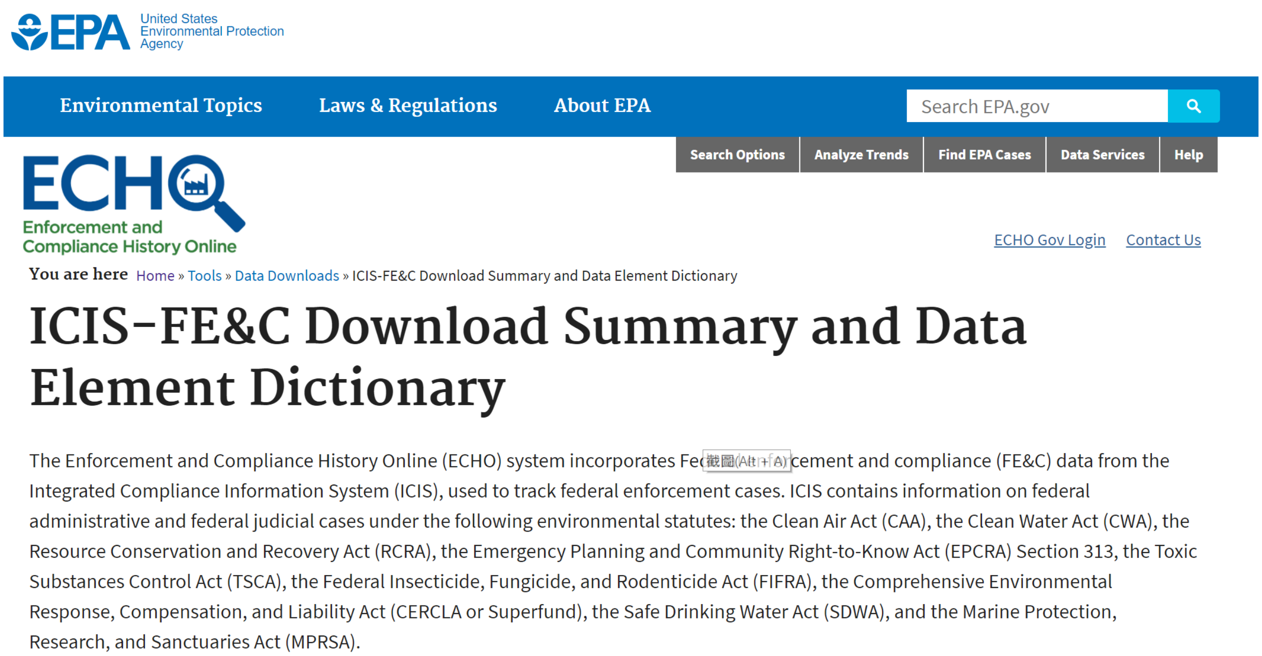
Figure IA.3 The TRI Database by years.

Source: `https://www.epa.gov/toxics-release-inventory-tri-program/tri-basic-data-files-calendar-years-1987-2018`



	CO	CP	CQ	CR	CS	CT	CU	CV	CW	CX	CY	CZ
CZ1 f_x PROD._WASTE_(8.1_THRU_8.7)	8.1_RELEA	8.1A_ON-S	8.1B_ON-S	8.1C_OFF-S	8.1D_OFF-	8.2_ENERG	8.3_ENERG	8.4_RECYC	8.5_RECYC	8.6_TREAT	8.7_TREAT	PROD._WAS

Figure IA.4 Variables in the TRI database.



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ICIS-FE&C Download Summary and Data Element Dictionary

The Enforcement and Compliance History Online (ECHO) system incorporates Fe[illegible]cement and compliance (FE&C) data from the Integrated Compliance Information System (ICIS), used to track federal enforcement cases. ICIS contains information on federal administrative and federal judicial cases under the following environmental statutes: the Clean Air Act (CAA), the Clean Water Act (CWA), the Resource Conservation and Recovery Act (RCRA), the Emergency Planning and Community Right-to-Know Act (EPCRA) Section 313, the Toxic Substances Control Act (TSCA), the Federal Insecticide, Fungicide, and Rodenticide Act (FIFRA), the Comprehensive Environmental Response, Compensation, and Liability Act (CERCLA or Superfund), the Safe Drinking Water Act (SDWA), and the Marine Protection, Research, and Sanctuaries Act (MPRSA).

Figure IA.5 Civil cases and settlements.

Source: `https://echo.epa.gov/tools/data-downloads/icis-fec-download-summary`

Figure IA.6 Dow's environmental settlement.

Source: `https://intercontinentalcry.org/dow-chemical-agrees-to-77-million-environmental-restoration-settlement/` and `https://www.michiganradio.org/post/why-does-it-take-40-years-clean-polluted-river`.

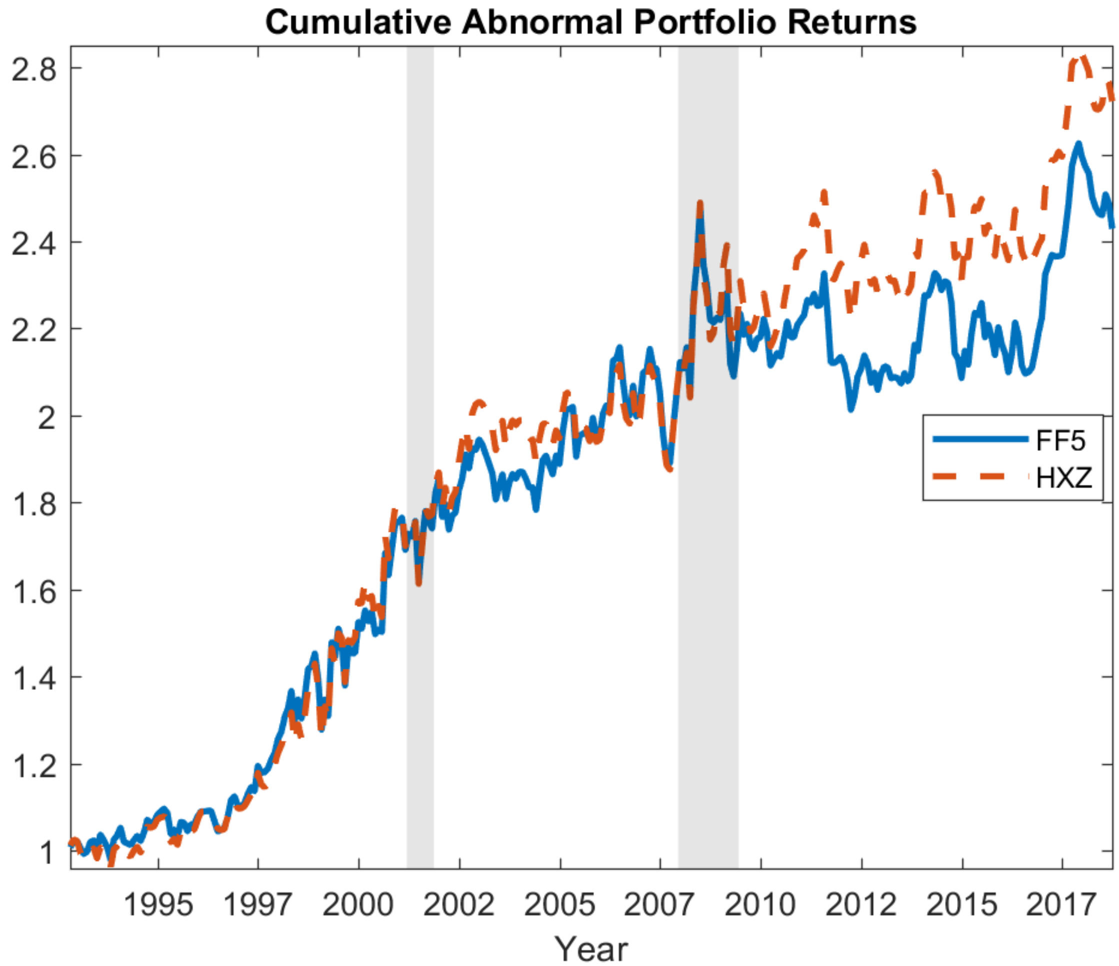

Figure IA.7 Cumulative abnormal returns of the high-minus-Low portfolio.

Cumulative abnormal returns are computed for the risk-adjusted returns (based on FF5 and HXZ models) on the high-minus-low portfolio sorted by emission intensity. FF5 and HXZ models are defined in Table IV. We plot the time-series of the cumulative abnormal returns from an initial investment of one dollar. The shaded bands are labeled as recession periods, according to NBER recession dates. The sample period is October 1992-September 2018.

Table IA.1 Firm-Level Predictive Regressions for Emissions

This table reports panel regressions of firm-level emission intensity (*Emissions*) in logarithm in year t+1 on current emission intensity in year t and all firm characteristics in year t, as well as industry-year joint fixed effects. Firm characteristics include size, book-to-market ratio (B/M), investment rate (I/K), return on equity (ROE), book leverage (Lev), tangibility (TANT), operating leverage (OL), and the WW index. The sample period is 1991 to 2016 at an annual frequency. Industry classifications are based on Fama-French 49-industry classifications. All independent variables, except the logarithm of current emission intensity in year t, are normalized to zero mean and unit standard deviation after winsorization at the 1st and 99th percentiles of their empirical distribution. t-statistics based on standard errors clustered at the firm level and industry-year level are reported in Panel A and Panel B, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Panel A: Standard Errors Clustered at the Firm Level								
Log Emissions	0.96	0.96	0.96	0.96	0.96	0.96	0.96	0.96	0.96
[t]	166.17	169.85	167.76	169.38	169.61	164.10	168.84	166.67	161.46
Log ME	-0.02								-0.07
[t]	-2.16								-2.49
Log B/M		0.02							0.00
[t]		1.99							0.26
I/K			-0.02						0.00
[t]			-1.50						0.40
ROE				-0.01					-0.01
[t]				-0.78					-0.48
Lev					0.02				0.01
[t]					1.91				0.49
TANT						0.04			0.04
[t]						2.96			2.96
OL							-0.01		-0.02
[t]							-1.06		-1.35
WW								-0.00	-0.06
[t]								-0.04	-2.26
Constant	0.06	0.04	0.05	0.04	0.04	0.05	0.04	0.04	0.06
[t]	1.52	1.10	1.23	1.16	1.15	1.37	1.11	1.05	1.45
Observations	9,377	9,313	9,493	9,546	9,530	9,546	9,546	9,267	8,849
R-squared	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Panel B: Standard Errors Clustered at the Industry-Year Level								
Log Emissions	0.96	0.96	0.96	0.96	0.96	0.96	0.96	0.96	0.96
[t]	141.67	145.21	145.24	146.59	146.92	143.26	146.22	141.52	134.78
Log ME	-0.02								-0.07
[t]	-1.78								-2.34
Log B/M		0.02							0.00
[t]		1.75							0.24
I/K			-0.02						0.00
[t]			-1.38						0.38
ROE				-0.01					-0.01
[t]				-0.92					-0.52
Lev					0.02				0.01
[t]					1.73				0.46
TANT						0.04			0.04
[t]						2.56			2.52
OL							-0.01		-0.02
[t]							-1.07		-1.34
WW								-0.00	-0.06
[t]								-0.04	-2.08
Constant	0.06	0.04	0.05	0.04	0.04	0.05	0.04	0.04	0.06
[t]	1.41	1.04	1.17	1.11	1.09	1.31	1.06	0.98	1.33
Observations	9,377	9,313	9,493	9,546	9,530	9,546	9,546	9,267	8,849
R-squared	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table IA.2 Aggregate Predictive Regressions for Emissions

This table reports time-series regressions of aggregate future emissions in logarithm on current emissions in logarithm and other macroeconomic fundamentals, including unemployment rate (Unep), GDP growth (dy), economic policy uncertainty index (EPU), price-dividend ratio (P/D), cyclically adjusted price-to-earnings (CAPE), TED spread (TED), and default premium (DEF). Unemployment rate (Unep) represents the number of unemployed as a percentage of the labor force. GDP growth (dy) is the log difference in aggregate output, which is available from the Federal Reserve Bank of San Francisco. Economic policy uncertainty index is the news-based measure of uncertainty based on media in the United States from Nicholas Bloom's website. Price-dividend ratio (P/D) is the aggregate stock price to dividend ratio, and cyclically adjusted price-to-earnings (CAPE) is the price divided by the average of 10 years of earnings (moving average), adjusted for inflation. P/D and CAPE are available from Robert Shiller's website. Default premium (DEF) is Moody's BAA corporate bond rate minus AAA corporate bond rate, both from FRED. TED spread (TED) is the LIBOR rate minus the one-month Treasury bill (T-bill) return. Unep, DEF, and TED are available from Federal Reserve Economic Data (FRED). The sample period is 1991 to 2016 at an annual frequency. Macroeconomic variables are normalized to zero mean and unit standard deviation. t-statistics based on Newey-West standard errors are reported.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log Emissions	0.85	0.82	0.88	0.87	0.86	0.86	0.85	0.84
[t]	11.08	12.28	12.69	11.85	10.84	14.00	12.71	9.46
Unep	-0.04							0.01
[t]	-1.10							0.24
dy		0.08						0.07
[t]		1.83						1.67
EPU			0.01					0.03
[t]			0.30					0.74
P/D				0.04				-0.00
[t]				0.96				-0.01
CAPE					0.05			0.03
[t]					1.70			0.38
TED						0.04		0.04
[t]						0.86		1.09
DEF							-0.03	-0.01
[t]							-1.06	-0.39
Constant	1.05	1.27	0.87	0.90	0.99	0.96	1.05	1.15
[t]	1.85	2.57	1.72	1.68	1.72	2.11	2.12	1.75

Table IA.3 Fama-Macbeth Regressions: Other Explanations

This table reports Fama-MacBeth regressions of individual stock excess returns on their emission intensity in logarithm and variables as alternative explanations in Tables IA.5, IA.6, and IA.7. We conduct cross-sectional regressions for each month from October of year t to September of year $t+1$. In each month, monthly returns of individual stock returns (annualized by multiplying by 12) are regressed on the logarithm of emission intensity in year $t-1$ (that is reported by the end of September of year t), control variables known by the end of September of year t, and industry fixed effects. Industry classifications are based on Fama and French (1997) 49-industry classifications. All independent variables are normalized to zero mean and unit standard deviation after winsorization at the 1st and 99th percentiles to reduce the impact of outliers. t-statistics based on Newey-West standard errors are reported. The sample period is October 1992 to September 2018.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Log Emissions	1.71	1.60	0.66	0.98	1.71	1.74	1.43	1.73	1.62	1.38	1.76	1.75	1.83	1.89	0.93
[t]	4.28	3.87	1.95	2.54	3.94	3.86	2.40	3.94	4.16	3.81	4.04	3.96	3.97	4.13	1.65
Preference	-0.72														0.38
[t]	-0.97														0.40
Share		0.14													0.62
[t]		0.30													1.13
G index			0.21												
[t]			0.55												
E Index				-0.45											
[t]				-1.00											
Donations					-0.72										
[t]					-1.03										
Donations/AT						0.57									
[t]						1.29									
Cap Age							0.65								0.84
[t]							0.98								1.31
I/K								-0.90							-1.81
[t]								-1.55							-2.76
SA									1.02						-0.82
[t]									1.32						-0.91
WW										2.19					2.21
[t]										2.50					2.43
UNC Beta											0.77				-1.28
[t]											0.53				-0.66
EPU Beta												0.42			0.67
[t]												0.41			0.57
Redeployability													0.11		1.05
[t]													0.16		1.38
Inflexibility														-0.71	-0.84
[t]														-1.58	-1.79
Observations	184,239	185,035	114,573	122,097	187,824	187,824	118,729	186,535	187,824	182,355	179,985	179,985	180,767	174,533	107,653
R-squared	0.14	0.14	0.20	0.19	0.14	0.14	0.16	0.14	0.14	0.15	0.14	0.14	0.14	0.14	0.21
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table IA.4 Double Sorting - Size

This table reports average excess stock returns of 10 portfolios independently double-sorted on five portfolios based on emission intensity and two portfolios based on size, all relative to their industry peers based on Fama and French (1997) 49-industry classifications. At the end of September of year t, we assign firms to big (B) and small (S) groups based on their market capitalization relative to industry peers and group firms into quintile emission portfolios (from low to high) based on their emission intensity relative to industry peers. We then track the value-weighted returns of each portfolio from October of year t to September of year $t+1$. We report the annualized portfolio returns by multiplying them by 12. t-statistics are also reported.

	L	2	3	4	H	H-L
B	6.90	7.41	8.72	8.25	10.57	3.67
[t]	2.43	2.56	3.44	2.81	3.43	3.32
S	2.72	1.85	3.98	2.10	8.64	5.92
[t]	0.65	0.46	1.16	0.53	2.33	2.13

Table IA.5 Double Sorting - Behavioral

This table reports average excess stock returns of portfolios double-sorted on emission intensity and a behavioral explanation measure relative to their industry peers based on Fama and French (1997) 49-industry classifications. In Panel A, we report average excess stock returns of two × five portfolios independently sorted on emission intensity and institutional investors' emission preferences. We construct the measure of institutional investors' emission preferences in two steps. In the first step, we collect institutional holdings data at the end of September in year t from the Thomson Reuters Institutional Holdings (13F) database, and calculate an institutional investor's exposure to emissions in year t as the valued-weighted emission intensity in year $t-1$ of all firms it holds. In the second step, we calculate a firm's pressure from institutional investors' emission preferences in year t as the value-weighted average of its institutional investors' exposure to emissions. The sorting on emissions is reported across columns L to H, and the sorting on the measure of institutional investors' emission preferences is reported across rows L and H. The column H-L stands for the high-minus-low portfolio (across columns) within portfolios sorted on institutional investors' emission preferences. In Panel B, at the end of September of year t, we first sort stocks into five portfolios based on firms' emission intensity in year $t-1$. Firms in the high-quintile portfolio are then further sorted into two portfolios based on their emission intensity in year t. We report their portfolio returns denoted by HL and HH, respectively. We also report the average portfolio return in the low-quintile portfolio sorted on emissions at the end of September of year t. Finally, we calculate the return difference between HL and L portfolios (HL-L) and the return difference between HH and L portfolios (HH-L). In Panel C, we report average excess stock returns of three × five portfolios in dependently sorted on changes in the fraction of firm shares outstanding owned by retail investors and then on emission intensity in year $t-1$. The sorting on emissions is reported across columns L to H, and the sorting on changes in the fraction of firm shares outstanding owned by retail investors is reported across rows L, 2, and H. The column H-L stands for the high-minus-low portfolio (across columns) within each portfolio sorted by the fraction of firm shares outstanding owned by retail investors. Panel C also reports the time-series average of the cross-sectional mean and median of changes in the fraction of firm shares outstanding owned by retail investors across tercile portfolios. All portfolio returns correspond to value-weighted returns by firm market capitalization. We report annualized portfolio returns by multiplying by 12. t-statistics are also reported. The sample period is October 1992 to September 2018.

Panel A: Emission Preference

	L	2	3	4	H	H-L
L	7.57	7.53	11.6	10.29	12.29	4.72
[t]	2.41	2.25	3.78	3.25	3.14	2.01
H	5.28	9.25	8.92	7.95	10.26	4.98
[t]	1.63	3.42	3.37	2.69	3.33	3.66

Panel B: Underreaction

	HL	HH	L	HL-L	HH-L
E[R]-R_f (%)	10.86	12.29	6.90	3.96	5.39
[t]	2.92	3.45	2.03	3.31	2.34

Panel C: Overreaction

	L	2	3	4	H	H-L	Mean	Median
L	8.26	8.21	10.81	9.31	10.25	1.99	-2.35	-2.31
[t]	3.04	2.69	4.12	2.70	2.39	0.77		
2	6.38	9.62	6.44	9.00	10.45	4.08	0.05	0.04
[t]	2.16	2.92	2.05	2.60	3.35	2.96		
H	5.43	10.13	10.81	8.60	9.11	3.68	2.39	2.64
[t]	1.43	2.82	3.21	2.63	2.15	1.57		

Table IA.6 Double Sorting - Real Effects

This table reports average excess stock returns of two × five portfolios independently sorted on emission intensity and the measure of corporate governance, (the G or E index) in Panel A, or the measure of political connections (Donations and Donations/AT) in Panel B, all relative to their industry peers based on Fama and French (1997) 49-industry classifications. At the end of September of year t, we assign firms into low (L) and high (H) groups based on their corporate governance (political connections). We then track the value-weighted returns on each portfolio from October of year t to September of year $t+1$. We report the annualized portfolio returns by multiplying by 12. t-statistics are also reported.

	L	2	3	4	H	H-L
Panel A: Governance						
G Index						
L	5.80	8.91	9.58	9.10	11.32	5.52
[t]	2.02	3.25	3.62	2.85	3.93	3.61
H	6.16	7.49	8.36	6.47	10.83	4.67
[t]	1.78	2.47	2.71	2.12	2.89	2.66
E Index						
L	6.45	8.78	9.94	8.48	9.64	3.19
[t]	2.34	3.08	3.68	2.83	3.28	2.31
H	6.87	6.74	7.46	7.26	13.01	6.13
[t]	2.1	2.42	2.87	2.15	3.18	2.15
Panel B: Political Connections						
Donations						
L	5.48	6.08	8.84	6.47	11.68	6.20
[t]	1.65	1.96	2.4	1.62	2.74	2.05
H	6.17	9.99	9.30	8.54	10.43	4.26
[t]	2.04	3.46	3.85	3.03	3.49	3.99
Donations/AT						
L	5.49	6.29	8.16	8.10	10.47	4.98
[t]	1.69	2.20	2.44	2.14	2.40	2.06
H	6.14	9.90	9.19	7.68	10.74	4.59
[t]	2.01	3.35	3.52	2.61	3.65	3.88

Table IA.7 Double Sorting - Other Risks

This table reports average excess stock returns of portfolio double-sorted into high and low technology obsolescence (capital age and investment intensity) in Panel A, financial constraints (SA and WW index) in Panel B, exposure to economic uncertainty (macroeconomic uncertainty and political uncertainty index) in Panel C, and adjustment costs (asset redeployability and inflexibility) in Panel D, and into emission intensity into quintile portfolios. Asset redeployability is constructed in three steps. First, we compute asset-level redeployability as the proportion of industries that use a given asset. Second, we construct an industry-level redeployability index as the value-weighted average of each asset's redeployability. Finally, we obtain the firm-level measure of asset redeployability as the value-weighted average of industry-level redeployability indices across the business segments in which the firm operates. The asset redeployability data come from Howard Kung's website. In addition, within each portfolio sorted by the risk-based explanation of interests, we form a high-minus-low portfolio (H-L) that takes a long position in the high-emission portfolio and a short position in the low-emission portfolio. As a result, we form a total of 12 portfolios for each risk-based explanation. We report the monthly averages of value-weighted returns on all 12 portfolios. We annualize portfolio returns by multiplying by 12. We also report t-statistics.

	L	2	3	4	H	H-L	L	2	3	4	H	H-L
Panel A: Technology Obsolescence												
	Capital Age						Investment Intensity					
L	5.37	9.53	7.88	7.45	9.44	4.07	6.32	7.83	8.24	8.91	10.49	4.16
[t]	1.62	3.03	2.73	2.30	2.88	2.45	2.21	2.68	3.12	2.95	3.43	3.63
H	7.57	9.16	9.67	8.39	11.81	4.24	5.96	8.60	10.02	8.00	11.27	5.31
[t]	2.45	2.99	3.62	2.65	3.81	2.01	1.85	2.86	3.25	2.65	3.24	3.07
Panel B: Financial Constraints												
	SA Index						WW Index					
L	6.04	8.66	9.50	8.44	10.24	4.21	6.29	8.16	8.64	8.63	9.74	3.44
[t]	1.92	3.18	3.81	2.89	3.45	3.77	2.11	3.03	3.21	3.06	3.01	3.21
H	4.84	8.60	7.59	8.85	12.89	8.05	9.69	10.92	10.42	6.25	13.83	4.14
[t]	1.47	2.47	1.95	2.40	2.78	2.22	2.70	3.09	3.30	1.55	3.65	2.06
Panel C: Uncertainty												
	UNC Beta						EPU Beta					
L	4.22	8.31	7.57	8.58	10.24	6.02	4.67	9.90	8.57	6.67	8.66	3.99
[t]	0.97	2.69	2.79	2.96	3.33	2.21	1.31	3.21	2.96	1.97	2.65	2.72
H	6.61	7.71	10.84	8.36	10.69	4.07	7.59	8.12	9.42	8.67	12.47	4.89
[t]	2.68	2.95	4.66	2.63	3.33	2.27	3.07	3.23	3.34	2.89	4.25	2.60
Panel D: Adjustment Cost												
	Redeployability						Inflexibility					
L	5.22	6.78	9.11	8.54	9.96	4.73	3.84	10.34	8.00	9.82	11.42	7.58
[t]	1.58	2.57	3.63	2.74	3.15	2.66	0.95	3.43	2.39	3.10	2.83	2.48
H	5.95	10.75	10.46	9.80	13.79	7.84	6.00	8.19	8.89	8.63	9.98	3.98
[t]	1.74	3.24	2.80	2.68	3.59	3.24	1.92	2.86	3.28	3.02	2.83	2.34

Table IA.8 Summary Statistics across Fama-French 49 Industries

This table reports summary statistics for firm-year observations of nonmissing emission intensity (Panel A) and raw emissions (Panel B) across industries with emission data, including the pooled mean (Mean), standard deviation (Std), 5th percentile (P5), 25th percentile (P25), median (P50), 75th percentile (P75), and 95th percentile (P95). Firm-level emission intensity is measured as the sum of all emissions in pounds produced in all plants owned by a firm, scaled by total assets in million dollars. Raw emissions is the sum of all emissions in pounds produced in all plants owned by a firm. Obs denotes the number of firm-year observations with nonmissing emissions in each industry. Industries are based on Fama-French 49 industry classifications (FF49), excluding financial industries. The sample period is 1991 to 2016.

FF49	Name	Obs	Mean	Std	P5	P25	Median	P75	P95
				Panel A: Emission Intensity					
2	Food	274	2341.20	8339.22	2.24	38.52	232.79	1745.86	10199.99
9	Consumer Goods	502	6985.30	37571.41	6.17	120.79	623.11	2669.14	15718.27
12	Medical Equipment	66	555.44	1213.80	0.17	4.22	46.55	291.99	3677.35
13	Drugs	145	6733.45	30712.81	5.38	57.72	267.42	1099.33	15320.69
14	Chemicals	1083	11010.58	30400.66	3.00	225.68	1711.43	7054.19	46266.52
15	Rubber and Plastic	21	2476.79	3325.43	5.32	54.25	575.37	4089.61	7838.92
16	Textiles	21	4361.71	10336.44	70.05	235.32	1287.58	2037.24	17791.31
17	Construction Materials	901	10851.91	70868.74	1.67	112.88	624.55	3191.70	35686.27
19	Construction	899	12456.96	24423.21	14.18	468.72	2671.39	13132.43	58987.67
21	Machinery	1498	2656.13	15160.68	4.06	56.20	248.50	899.02	8268.23
22	Electrical Equipment	357	8019.68	23308.29	4.94	80.69	542.39	3127.26	61302.86
23	Automobiles	931	2262.90	13452.69	6.81	83.39	344.78	1065.22	7218.78
30	Oil	260	35470.13	207681.14	0.28	37.43	605.17	3916.58	81458.87
31	Utilities	884	1277.88	2192.91	0.44	90.37	654.5	1655.20	4214.80
37	Chips	1257	3225.41	20695.54	0.33	21.49	145.23	862.40	9787.18
38	Lab Equipment	42	741.96	1727.98	0.01	6.32	148.59	313.86	5202.75
39	Business Supplies	567	5145.00	14184.77	0.20	44.52	401.60	3137.31	26560.33
42	Wholesale	281	3906.50	9246.83	5.85	66.69	320.58	2549.61	17913.59
				Panel B: Raw Emissions					
2	Food	274	5689565.32	22077021.89	300.00	54510.00	167708.00	1734460.00	33196255.00
9	Consumer Goods	502	6089111.37	20106480.42	5700.00	63648.00	635478.00	4023288.00	29109529.00
12	Medical Equipment	66	4193503.51	16562747.29	135.98	6251.60	121538.00	732969.38	5695430.44
13	Drugs	145	8167089.71	26955560.83	822.00	26142.00	124129.00	1573359.00	44682336.00
14	Chemicals	1083	44835106.31	198327087.50	2310.00	193225.00	1373778.00	14021622.73	162562347.00
15	Rubber and Plastic	21	899415.57	1558267.24	3189.00	17536.00	251600.00	762102.00	4163005.00
16	Textiles	21	1013173.24	2168216.62	10900.00	75170.00	150810.00	874763.00	4774493.00
17	Construction Materials	901	6531183.77	17932925.92	370.00	59177.00	409144.00	3376080.38	35591100.00
19	Construction	899	18146852.64	36890047.78	6319.00	261989.00	1963498.00	18120683.47	89512666.00
21	Machinery	1498	2971912.42	11930530.50	3087.16	51051.00	289070.00	1130734.74	17187158.85
22	Electrical Equipment	357	3902551.08	14317985.73	1015.00	17115.00	135297.00	2879014.00	21549813.00
23	Automobiles	931	5776111.22	28016557.68	9521.20	89921.00	421313.00	1832979.71	22561911.00
30	Oil	260	46528899.46	108925732.20	620.50	61117.50	536918.00	33588692.8	244184870.80
31	Utilities	884	22346642.21	41441172.80	9181.00	993036.00	4929587.00	18426788.00	140689392.30
37	Chips	1257	1814116.99	11851288.49	310.00	20556.00	154240.00	658659.00	4882617.20
38	Lab Equipment	42	332609.15	524839.03	18.67	5412.90	68725.80	455603.77	1036367.58
39	Business Supplies	567	13968064.23	34524463.37	180.00	50828.00	442948.00	6006225.06	92645715.52
42	Wholesale	281	5967050.55	29535851.95	2912.00	40690.00	224541.00	1644366.60	30078578.74

Table IA.9 Transition Matrix: Persistence of Emissions

This table presents transition frequency (%) across emission intensity quintiles from year t to year t+1 in Panel A and from year t to t+5 in Panel B. Emission intensity is measured as the sum of all emissions in pounds produced in all plants owned by a firm, scaled by total assets in million dollars. The emission quintiles in year t are sorted in the same way as in Tables III and IV. The sample period is 1991 to 2016.

	Panal A: One-Year					Panal B: Five-Year				
	L(t+1)	2(t+1)	3(t+1)	4(t+1)	H(t+1)	L(t+5)	2(t+5)	3(t+5)	4(t+5)	H(t+5)
L(t)	87.62	11.12	0.87	0.40	0.00	73.54	19.62	3.99	1.93	0.92
2(t)	14.28	73.98	10.81	0.61	0.32	25.90	56.91	13.85	2.44	0.90
3(t)	1.60	14.69	71.62	11.47	0.62	8.12	26.31	48.20	15.20	2.17
4(t)	0.39	1.23	15.05	76.46	6.86	2.05	6.22	29.45	51.76	10.52
H(t)	0.11	0.39	0.74	9.83	88.92	0.95	1.44	5.76	20.39	71.46

Table IA.10 Portfolio Sorted on Toxicity-Adjusted Emissions

This table shows the returns and risk-adjusted returns of five portfolios sorted on toxicity-adjusted emission intensity relative to their industry peers (and a high-minus-low portfolio "H-L"). At the end of September of year t, we rank firms by toxicity-adjusted emission intensity in year $t-1$ relative to their industry peers and assign portfolios to five groups from low to high within the corresponding Fama and French (1997) 49 industries. The left (right) panel uses toxicity-adjusted emission intensity estimated by a three(five)-year moving average of future mortality rates. In Panel A, we report average excess returns over the risk-free rate (E[R]-R_f), standard deviations (Std), and Sharpe ratios (SR). To adjust for risk exposure, we perform time-series regressions of emission-sorted portfolios' excess returns on the market factor (MKT) in the CAPM model in Panel B, on the Fama and French (1996) three factors (MKT, SMB, and HML) in Panel C, on the Fama and French (1996) three factors plus Carhart (1997) factor (MKT, SMB, HML, and UMD) in Panel D, on the Fama and French (2015) five factors (MKT, SMB, HML, RMW, and CMA) in Panel E, and on the Hou, Xue, and Zhang (2015) q-factors (MKT, SMB, I/A, and ROE) in Panel F, respectively. Data on the Fama-French five factors come from Kenneth French's website. Data on the I/A and ROE factors are provided by Kewei Hou, Chen Xue, and Lu Zhang. Average returns, alphas, and betas are all annualized. Standard errors are estimated in using the Newey-West correction. t-statistics are reported. The sample period is October 1996 to September 2018 in the left panel and October 1999 to September 2018 in the right panel.

	Toxidicity-Adj. Emissions 3-yr						Toxidicity-Adj. Emissions 5-yr					
	L	2	3	4	H	H-L	L	2	3	4	H	H-L
Panel A: Univariate Portfolio Sorts												
E[R]-R_f (%)	7.35	7.25	8.83	8.75	10.57	3.22	4.94	7.23	7.64	8.29	8.19	3.25
[t]	1.96	1.74	2.33	2.37	2.6	2.09	1.12	1.71	1.72	2.03	1.88	2.32
Std (%)	16.53	18.31	16.03	17.68	17.04	9.05	16.41	18.3	16.25	16.95	16.64	8.53
SR	0.44	0.4	0.55	0.49	0.62	0.36	0.3	0.39	0.47	0.49	0.49	0.38
Panel B: CAPM												
α_{CAPM}	-0.03	-0.82	2.07	1.42	3.07	3.10	-1.12	0.58	1.89	2.42	1.92	3.05
[t]	-0.02	-0.43	1.04	0.61	1.67	2.08	-0.69	0.21	0.83	0.95	1.16	2.22
MKT	0.95	1.04	0.87	0.94	0.97	0.02	0.96	1.05	0.91	0.92	0.99	0.03
[t]	13.02	16.82	10.57	11.59	23.79	0.35	11.17	12.90	9.21	8.66	24.16	0.57
Panel C: FF3												
α_{FF3}	-0.87	-1.10	1.54	0.49	2.70	3.57	-1.51	-0.35	1.35	1.77	1.45	2.96
[t]	-0.71	-0.60	0.89	0.29	1.67	2.51	-1.11	-0.16	0.67	0.97	0.94	2.41
MKT	0.98	1.08	0.89	0.98	0.99	0.01	0.98	1.07	0.91	0.96	0.99	0.01
[t]	25.60	23.19	14.99	21.95	32.27	0.21	19.82	20.39	12.00	15.42	29.18	0.20
SMB	0.01	-0.12	0.02	-0.02	-0.03	-0.04	-0.06	0.01	0.03	-0.05	0.03	0.09
[t]	0.13	-2.14	0.35	-0.24	-0.43	-0.68	-0.92	0.09	0.43	-0.50	0.41	1.19
HML	0.30	0.25	0.17	0.37	0.17	-0.13	0.27	0.35	0.16	0.35	0.13	-0.14
[t]	3.59	4.22	2.02	2.30	2.48	-2.22	3.19	6.18	1.55	2.11	1.87	-2.30
Panel D: FF4												
α_{FF3}	-0.41	-1.03	1.67	0.67	2.70	3.11	-1.26	-0.17	1.29	1.72	1.42	2.68
[t]	-0.31	-0.59	0.98	0.43	1.63	2.21	-0.89	-0.08	0.66	0.94	0.91	2.18
MKT	0.95	1.08	0.88	0.97	0.99	0.03	0.96	1.05	0.92	0.96	1.00	0.03
[t]	19.01	21.82	12.29	19.54	27.77	0.77	14.92	17.26	9.30	14.17	23.47	0.70
SMB	0.02	-0.12	0.02	-0.02	-0.03	-0.05	-0.04	0.02	0.02	-0.06	0.03	0.07
[t]	0.35	-1.94	0.41	-0.20	-0.42	-1.04	-0.66	0.23	0.31	-0.58	0.37	0.89
HML	0.27	0.24	0.17	0.36	0.16	-0.11	0.25	0.34	0.17	0.36	0.13	-0.12
[t]	4.14	3.79	2.02	2.27	2.79	-2.10	3.51	5.23	1.74	2.16	2.07	-2.00
UMD	-0.06	-0.01	-0.02	-0.02	-0.00	0.06	-0.05	-0.03	0.01	0.01	0.01	0.05
[t]	-1.28	-0.16	-0.32	-0.43	-0.00	1.57	-0.98	-0.72	0.18	0.18	0.17	1.59
Panel E: FF5												
α_{FF5}	-2.81	-2.38	-0.75	-3.11	0.23	3.04	-3.45	-2.05	-1.31	-2.48	-0.83	2.62
[t]	-1.93	-1.24	-0.38	-1.72	0.12	2.01	-2.24	-1.01	-0.74	-1.24	-0.48	2.15
MKT	1.06	1.13	0.98	1.13	1.09	0.03	1.06	1.14	1.02	1.13	1.08	0.02
[t]	21.07	19.56	12.68	25.60	24.34	0.88	15.59	16.38	9.45	19.07	22.07	0.38
SMB	0.08	-0.10	0.07	0.09	0.05	-0.03	-0.01	0.06	0.08	0.09	0.12	0.13
[t]	1.15	-1.76	1.40	1.44	0.70	-0.50	-0.14	0.73	1.28	1.51	1.88	1.70
HML	0.15	0.12	-0.03	0.08	-0.03	-0.19	0.11	0.22	-0.08	0.05	-0.02	-0.13
[t]	2.00	1.74	-0.35	0.63	-0.43	-2.23	1.69	2.85	-0.68	0.34	-0.21	-1.40
RMW	0.24	0.11	0.23	0.42	0.28	0.04	0.20	0.18	0.24	0.48	0.28	0.08
[t]	3.70	1.66	2.53	6.08	3.68	0.59	2.87	2.14	1.86	6.17	3.83	1.18
CMA	0.15	0.21	0.30	0.35	0.25	0.09	0.20	0.16	0.38	0.33	0.11	-0.08
[t]	2.20	1.91	2.45	3.45	2.11	0.83	2.68	1.42	2.50	2.98	1.05	-0.79
Panel F: HXZ												
α_{HXZ}	-1.51	-2.02	0.71	-1.90	1.82	3.33	-2.30	-0.57	0.46	-0.63	1.38	3.67
[t]	-1.11	-1.12	0.43	-0.94	1.24	2.24	-1.58	-0.29	0.34	-0.33	1.21	3.21
MKT	1.04	1.16	0.97	1.13	1.07	0.02	1.06	1.16	1.02	1.15	1.06	0.01
[t]	22.51	27.02	14.12	25.80	33.20	0.55	18.19	18.97	10.90	22.78	28.70	0.10
SMB	-0.01	-0.10	0.04	0.00	-0.02	-0.01	-0.07	-0.02	0.04	-0.03	-0.00	0.07
[t]	-0.13	-2.20	0.95	0.01	-0.34	-0.14	-1.30	-0.27	0.80	-0.37	-0.03	1.45
I/A	0.38	0.37	0.25	0.60	0.29	-0.08	0.41	0.46	0.32	0.53	0.17	-0.24
[t]	3.33	3.31	2.49	4.19	2.73	-0.75	3.37	3.76	2.23	3.31	2.14	-2.79
ROE	0.10	0.16	0.16	0.27	0.15	0.05	0.11	0.13	0.16	0.36	0.13	0.02
[t]	2.06	1.97	2.44	3.16	1.97	0.80	2.23	1.36	2.42	4.36	1.99	0.34

Table IA.11 Fama-Macbeth Regressions

This table reports Fama-Macbeth regressions of individual stock excess returns on the logarithm of their toxicity-adjusted emission intensity and other firm characteristics. The left (right) panel uses toxicity-adjusted intensity estimated as a three-year (five-year) moving average of mortality rates. We conduct cross-sectional regressions for each month from October of year t to September of year $t+1$. In each month, monthly returns of individual stock returns (annualized by multiplying by 12) are regressed on the logarithm of emission intensity in year $t-1$ (that is reported by the end of September of year t) on control variables known by the end of September of year t and on industry fixed effects. Control variables include the natural logarithm of market capitalization (Size), the natural logarithm of book-to-market ratio (B/M), investment rate (I/K), return on equity (ROE), tangibility (TANT), WW index, book leverage, and industry dummies based on Fama and French (1997) 49-industry classifications. All independent variables are normalized to zero mean and unit standard deviation after winsorization at the 1st and 99th percentiles to reduce the impact of outliers. Standard errors are estimated using the Newey-West correction. The sample period is October 1996 to September 2018 (October 1999 to September 2018) in the left (right) panel.

	Toxicity-Adj. Emissions 3yr			Toxicity-Adj. Emissions 5yr		
	(1)	(2)	(3)	(4)	(5)	(6)
Log Emissions	1.01	1.19	0.95	1.30	1.26	1.21
[t]	2.00	2.00	2.18	2.33	2.39	2.47
Log ME		6.29	31.81		5.63	29.15
[t]		5.63	10.59		4.49	9.93
Log B/M		5.96	13.04		5.94	12.04
[t]		5.36	10.42		4.80	9.72
I/K		0.57	-0.89		0.26	-1.07
[t]		0.69	-1.10		0.28	-1.27
ROE		1.90	4.34		2.57	3.94
[t]		1.55	3.58		1.74	2.89
TANT			-0.18			-0.22
[t]			-0.23			-0.25
WW			28.49			26.27
[t]			11.35			10.58
Lev			3.14			3.42
[t]			3.93			3.81
Observations	95,390	91,167	89,161	79,365	76,099	74,695
R-squared	0.10	0.14	0.17	0.10	0.14	0.17
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

Table IA.12 Portfolio Sorted on Environmental Scores from ASSET4

This table shows asset pricing tests for five portfolios sorted on environmental scores relative to their industry peers (and a low-minus-high portfolio "L-H"). We use environmental scores from the ASSET4 database and exclude financial industries. At the end of June of year t, we rank firms by environmental scores in year $t-1$ relative to their industry peers and assign portfolios to five groups from low to high within the corresponding Fama and French (1997) 49-industries. In Panel A, we report the time-series average of the cross-sectional mean, median, and standard deviation of the environmental score in each portfolio. We also report the pooled mean, median, and standard deviation of the environmental scores of the full sample in the column labeled "All." In Panel B, we report average excess returns over the risk-free rate (E[R]-R_f), standard deviations (Std), and Sharpe ratios (SR). To adjust for risk exposure, we perform time-series regressions of emission-sorted portfolios' excess returns on the market factor (MKT) in the CAPM model in Panel C, on the Fama and French (2015) five factors (MKT, SMB, HML, RMW, and CMA) in Panel D, and on the Hou, Xue, and Zhang (2015) q-factors (MKT, SMB, I/A, and ROE) in Panel E, respectively. Data on the Fama-French five factors come from Kenneth French's website. Data on the I/A and ROE factors are provided by Kewei Hou, Chen Xue, and Lu Zhang. Average returns, alphas, and betas are all annualized. Standard errors are estimated by using the Newey-West correction. t-statistics are also reported. The sample period is July 2003 to June 2014.

	L	2	3	4	H	All
			Panel A: Summary Statistics			
Num	45	65	52	53	52	6,600
Mean	14.13	21.62	42.56	68.47	88.37	45.01
Median	13.15	17.26	39.45	74.90	91.72	33.49
Std	3.09	9.97	18.47	18.47	9.64	31.46
	L	2	3	4	H	L-H
			Panel B: Portfolio Returns			
E[R]-R_f (%)	13.09	12.91	11.96	12.33	8.79	4.30
[t]	2.32	2.08	2.68	2.66	1.95	2.35
Std (%)	16.70	16.70	14.59	13.75	13.73	10.50
SR	0.78	0.77	0.82	0.90	0.64	0.41
			Panel C: CAPM			
α_{CAPM}	5.19	4.23	4.57	5.22	1.93	3.26
[t]	1.63	1.62	2.17	2.91	0.79	1.81
MKT	0.91	1.00	0.85	0.82	0.79	0.12
[t]	18.34	20.97	13.75	19.37	16.62	2.34
			Panel D: FF5			
α_{FF5}	4.53	2.92	4.17	4.47	0.05	4.49
[t]	1.69	1.07	1.95	2.76	0.02	2.97
MKT	1.00	1.09	0.92	0.90	0.96	0.04
[t]	13.87	13.99	15.79	16.92	20.41	0.65
SMB	0.01	0.12	-0.09	-0.16	-0.34	0.35
[t]	0.09	1.17	-0.86	-1.71	-5.03	2.39
HML	-0.22	-0.21	-0.03	0.06	0.04	-0.26
[t]	-0.95	-1.16	-0.20	0.47	0.37	-1.70
RMW	0.22	0.35	0.18	0.26	0.47	-0.25
[t]	1.35	2.66	1.37	1.87	4.21	-1.66
CMA	-0.32	-0.38	-0.27	-0.23	0.03	-0.35
[t]	-1.77	-1.91	-1.64	-1.83	0.22	-2.79
			Panel E: HXZ			
α_{HXZ}	5.03	5.18	4.48	4.78	1.41	3.63
[t]	2.59	2.65	2.04	2.44	0.53	1.75
MKT	0.99	1.00	0.91	0.91	0.95	0.04
[t]	15.14	18.44	15.14	18.84	21.1	0.54
SMB	-0.06	-0.03	-0.10	-0.18	-0.40	0.34
[t]	-0.40	-0.23	-0.92	-2.33	-5.36	2.03
I/A	-0.43	-0.52	-0.23	-0.07	0.12	-0.55
[t]	-2.29	-3.46	-1.98	-0.64	0.95	-2.36
ROE	0.21	-0.05	0.15	0.22	0.24	-0.04
[t]	1.44	-0.42	1.71	2.32	1.88	-0.16

Table IA.13 Event Studies

This table presents the cumulative abnormal returns around the appointment of the EPA head (the presidential election in 2004 and 2000) of stocks sorted into emissions-sorted portfolios in Panel A (Panel B and Panel C). The table reports daily and annualized cumulative returns over a 10-day window from one day after the event date to 10 days after the event date, which we refer to as a (0,10) window.

	Event Studies					
CAR (%)	L	2	3	4	H	H-L
	Panel A: Appointment of EPA Head					
Daily Ret.	-0.73	-0.39	-0.05	0.06	-0.14	0.59
Annualized Ret.	-18.15	-9.66	-1.36	1.45	-3.40	14.75
[t]	-1.69	-0.85	-0.95	-0.04	-0.15	1.35
	Panel B: Presidential Election in 2004					
Daily Ret.	-2.35	1.12	0.09	-1.93	1.16	3.52
Annualized Ret.	-58.75	28.00	2.25	-48.25	29.00	88.00
[t]	-3.95	4.29	0.19	-4.30	3.12	4.37
	Panel C: Presidential Election in 2000					
Daily Ret.	2.41	8.93	8.89	11.90	7.45	5.04
Annualized Ret.	60.25	223.25	222.25	297.50	186.25	126.00
[t]	2.97	7.91	6.34	15.57	9.49	3.61

Table IA.14 Aggregate Predictive Regressions for Emissions

This table reports time-series regressions of the growth rate of civil penalties and other macroeconomic fundamentals (see Section I.A of our main paper for variable definitions). The sample period is 1991 to 2016 at an annual frequency. Macroeconomic variables are normalized to zero mean and unit standard deviation. *t*-statistics based on Newey-West standard errors are reported.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Contemporaneous Regressions								
Unep	-3.69							-47.05
[t]	-0.28							-1.01
dy		-5.02						-33.05
[t]		-0.46						-0.89
EPU			5.76					41.25
[t]			0.94					1.09
P/D				-8.32				-109.97
[t]				-1.09				-1.80
CAPE					0.12			106.62
[t]					0.02			1.88
TED						-10.63		-42.81
[t]						-1.36		-2.62
DEF							2.68	5.49
[t]							0.46	0.25
Panel B: Predictive Regressions								
Unep	-3.32							-40.60
[t]	-0.29							-1.06
dy		-5.33						-22.61
[t]		-1.03						-1.20
EPU			1.99					26.05
[t]			0.17					1.23
P/D				-8.00				-75.16
[t]				-1.00				-1.19
CAPE					-2.83			68.50
[t]					-0.56			1.17
TED						-3.35		-29.16
[t]						-0.64		-0.91
DEF							7.83	10.87
[t]							0.51	0.32

Table IA.15 Calibrated Parameters

Description	Parameter	Value
General		
Risk Aversion	γ	3.5
Terminal Period	T	10
Timing of Regime Shifts	τ	5
Borrowing Rate	r	0.08
Profitability		
Maximum of ξ	ξ^{max}	2
Minimum of ξ	ξ^{min}	0
Unconditional Mean of ROA	μ	0.08
Conditional Mean under the Weak Regime	g^{W}	0.015
Conditional Mean under the Strong Regime	g^{S}	-0.025
Volatility to Aggregate Shocks	σ	0.085
Volatility to Idiosyncratic Shocks	σ_I	0.05
Learning		
Volatility of the Prior Distribution	σ_c	1.20
Leverage		
Debt to Equity Ratio	ι	0.30
Sensitivity to Debt Financing	θ	0.70

Table IA.16 Unconditional Aggregate Moments

This table reports aggregate asset prices and real quantities in the model and data. We consider the model with equity financing only as the benchmark model and the model with time-varying leverage as the extension. Aggregate asset price refers to the first and second moments of the equity premium ($E[R_m]-R_f$) in annual frequency, and real quantities refer to the first and second moments of aggregate ROA, book-to-market ratio, and leverage. In the benchmark and extended models, we show that the equity premium is attributed to fundamental and regime change shocks and the probability of regime shifts.

Moments	Data	Benchmark Model	Extended Model
$E[R_m]-R_f$ (%)	5.71	5.74	8.14
Decomposition:			
Fundamental Shock (%)		3.29	4.27
Regime Change Shock (%)		2.45	3.86
$Std[R_m]$ (%)	17.61	14.55	16.97
ROA	0.09	0.096	0.096
Std[ROA]	0.08	0.085	0.085
B/M	0.67	0.56	0.69
Probability of Regime Shifts		0.41	0.30
Leverage	0.23		0.23

Table IA.17 Portfolios, Firm Characteristics, and Model Comparison

This table reports time-series averages of the cross-sectional averages of firm characteristics across five portfolios sorted on emissions. Panel A is based on quintile portfolios as we present in Table III. Current ROA responds to contemporaneous ROA, current Lev responds to the average of book leverage from the current year to year five, and future ROA (Lev) refers to the five-year average of ROA (book leverage) from years six to ten. Panel B reports quintile portfolios based on our model economy with equity financing only as the benchmark. Panel C reports quintile portfolios based on the model economy with time-varying leverage as the extension. The returns E[R]-R_f are annualized.

Moments	L	2	3	4	H	H-L
			Panel A: Data			
E[R]-R_f (%)	6.90	9.68	9.08	9.11	11.32	4.42
Current ROA	0.08	0.08	0.09	0.09	0.10	
Future ROA	0.09	0.09	0.09	0.09	0.08	
Current Lev	0.23	0.24	0.23	0.23	0.24	
Future Lev	0.20	0.22	0.22	0.22	0.23	
			Panel B: The Benchmark Model			
E[R]-R_f (%)	3.75	4.73	5.71	6.71	7.74	3.99
Current ROA	0.08	0.09	0.10	0.10	0.11	
Future ROA	0.08	0.08	0.08	0.08	0.08	
			Panel C: The Extended Model			
E[R]-R_f (%)	4.54	6.24	8.09	10.05	12.12	7.58
Current ROA	0.08	0.09	0.09	0.10	0.11	
Future ROA	0.08	0.08	0.08	0.08	0.08	
Current Lev	0.67	0.66	0.64	0.63	0.62	
Future Lev	0.20	0.22	0.23	0.25	0.26	

Table IA.18 Sensitivity Analysis

The table reports results of sensitivity analyses in which key parameters of the model are varied around the values from the benchmark calibration shown in Table IA.15.

Moments	Data	Model (Benchmark)	0.9*Parameter	1.1*Parameter
		Panel A: Risk Aversion (γ)		
E[R]-R_f (%)	5.71	8.14	7.00	9.18
E[R_H- R_L] (%)	4.42	7.58	6.15	8.79
Prob		0.30	0.36	0.25
		Panel B: Diff. in Conditional Mean of Profitability (g^W-g^S)		
E[R]-R_f (%)	5.71	8.14	7.20	9.17
Fundamental (Regime Change Shock (%)		3.86	2.94	4.90
E[R_H- R_L] (%)	4.42	7.58	5.78	9.37
Prob		0.30	0.34	0.26
		Panel C: Volatility of the Prior Dist. of the Envr. Cost (σ_c)		
E[R]-R_f (%)	5.71	8.14	7.30	9.05
Fundamental (%)		4.28	4.27	4.27
Regime Change Shock (%)		3.86	3.03	4.78
E[R_H- R_L] (%)	4.42	7.58	5.91	9.32
		Panel D: Sensitivity of Debt Financing to Regime Shifts (θ)		
E[R]-R_f (%)	5.71	8.14	8.14	8.14
Fundamental (Regime Change Shock (%)		3.86	3.86	3.86
E[R_H- R_L] (%)	4.42	7.58	7.44	7.65

III. Mathematical Details of the Benchmark Model

A. *Proof of Lemma IA.1*

We show the aggregate capital at time T in Lemma IA.1.

LEMMA IA.1: The aggregate capital at time T, $B_T = \int_0^1 B_T^i di$, is given by

$$B_T = B_\tau e^{\left(\mu+g-\frac{1}{2}\sigma^2\right)(T-\tau)+\sigma(Z_T-Z_\tau)}, \tag{IA.2}$$

where $g \equiv g^{\mathrm{W}}$ when there is no policy regime shift and $g \equiv g^{\mathrm{S}}$ when there is a policy regime shift.

We consider an economy with a finite horizon $[0, T]$. A regime shift occurs at time τ, where $\tau \in (0, T)$ and $\tau+$ denotes the timing right after a regime shift.

From the capital growth equation $dB_t^i = B_t^i d\Pi_t^i$, where the stochastic process of $d\Pi_t^i$ is given by equation (3), we obtain the following expression for firm i's capital at time T

$$B_T^i = B_\tau^i e^{\left(\mu+\xi^i g-\frac{1}{2}\sigma^2-\frac{1}{2}\sigma_1^2\right)(T-\tau)+\sigma(Z_T-Z_\tau)+\sigma_1(Z_T^i-Z_\tau^i)}, \tag{IA.3}$$

where $g \equiv g^{\mathrm{W}}$ when there is shift to a weak-regulation regime and $g \equiv g^{\mathrm{S}}$ when there is a shift to a strong-regulation regime. Aggregating across firms, we obtain

$$B_T = \int_0^1 B_T^i di = e^{\left(\mu-\frac{1}{2}\sigma^2-\frac{1}{2}\sigma_1^2\right)(T-\tau)+\sigma(Z_T-Z_\tau)} \int_0^1 B_\tau^i e^{\xi^i g(T-\tau)+\sigma_1(Z_T^i-Z_\tau^i)} di. \tag{IA.4}$$

The law of large numbers implies that

$$\begin{aligned}
\int_0^1 B_\tau^i e^{\xi^i g(T-\tau)+\sigma_1(Z_T^i-Z_\tau^i)} di &\rightarrow \mathrm{E}^i\left[B_\tau^i e^{g(T-\tau)+\sigma_1(Z_T^i-Z_\tau^i)}\right] \\
&= e^{g(T-\tau)}\mathrm{E}^i\left[B_\tau^i\right]\mathrm{E}^i\left[e^{\sigma_1(Z_T^i-Z_\tau^i)}\right] \\
&= B_\tau e^{g(T-\tau)+\frac{1}{2}\sigma_1^2(T-\tau)},
\end{aligned} \tag{IA.5}$$

where E^i is the cross-sectional expectation operator. The second equality in equation (IA.5) presents the independence of $B_{\tau_n}^i$ and $Z_T^i - Z_\tau^i$. In the last step, the cross-sectional expectation of B_τ^i is given by

$$\mathrm{E}^i\left[B_\tau^i\right] = \int_0^1 B_\tau^i di = B_\tau, \tag{IA.6}$$

and the expectation of $\mathrm{E}^i\left[e^{\sigma_1(Z_T^i-Z_\tau^i)}\right]$ implies the mean of lognormal distribution.

B. Proof of Proposition 1

Using the market-clearing condition $W_T = B_T$, we can use equation (IA.2) to compute the expected utility at time T conditional on a strict or weak regulatory regime. The expectation is conditional on the government's information set, which includes the realization of the environmental cost

$$\mathrm{E}_\tau\left[\frac{W_T^{1-\gamma}}{1-\gamma}\middle|\mathrm{S}\right] = \frac{B_\tau^{1-\gamma}}{1-\gamma}e^{(1-\gamma)\left(\mu+g^{\mathrm{S}}-\frac{1}{2}\sigma^2\right)(T-\tau)+\frac{1}{2}(1-\gamma)^2\sigma^2(T-\tau)} \tag{IA.7}$$

$$\mathrm{E}_\tau\left[\frac{W_T^{1-\gamma}}{1-\gamma}\middle|\mathrm{W}\right] = \frac{\Phi(c)B_\tau^{1-\gamma}}{1-\gamma}e^{(1-\gamma)\left(\mu+g^{\mathrm{W}}-\frac{1}{2}\sigma^2\right)(T-\tau)+\frac{1}{2}(1-\gamma)^2\sigma^2(T-\tau)}. \tag{IA.8}$$

The claim of the proposition follows immediately from the optimality condition,

$$\mathrm{E}_\tau\left[\frac{W_T^{1-\gamma}}{1-\gamma}\middle|\mathrm{S}\right] > \mathrm{E}_\tau\left[\frac{\Phi(c)W_T^{1-\gamma}}{1-\gamma}\middle|\mathrm{W}\right]. \tag{IA.9}$$

Therefore,

$$\frac{B_\tau^{1-\gamma}}{1-\gamma}e^{(1-\gamma)\left(\mu+g^{\mathrm{S}}-\frac{1}{2}\sigma^2\right)(T-\tau)+\frac{1}{2}(1-\gamma)^2\sigma^2(T-\tau)} > \frac{\Phi(c)B_\tau^{1-\gamma}}{1-\gamma}e^{(1-\gamma)\left(\mu+g^{\mathrm{W}}-\frac{1}{2}\sigma^2\right)(T-\tau)+\frac{1}{2}(1-\gamma)^2\sigma^2(T-\tau)}. \tag{IA.10}$$

We specify the functional form of $\Phi(c)$ as $1+e^c$ and further rearrange the inequality above to obtain

$$e^{(1-\gamma)g^{\mathrm{S}}(T-\tau)} < \Phi(c)e^{(1-\gamma)g^{\mathrm{W}}(T-\tau)} = (1+e^c)e^{(1-\gamma)g^{\mathrm{W}}(T-\tau)} \tag{IA.11}$$

$$\begin{aligned} e^{(\gamma-1)(g^{\mathrm{W}}-g^{\mathrm{S}})(T-\tau)} - 1 &< e^c \\ \log\left\{e^{(\gamma-1)(g^{\mathrm{W}}-g^{\mathrm{S}})(T-\tau)} - 1\right\} &< c. \end{aligned} \tag{IA.12}$$

The threshold for a policy regime shift is given as

$$\underline{c}(\tau) \equiv \log\left\{e^{(\gamma-1)(g^{\mathrm{W}}-g^{\mathrm{S}})(T-\tau)} - 1\right\}. \tag{IA.13}$$

As we can see, the government considers a regime shift if the true environmental cost, c, revealed at time τ, exceeds a given threshold, $\underline{c}(\tau)$. Two observations about the threshold stand out, as in equation (13). First, given $\gamma > 1$, a higher γ implies that households are more averse to a shift to the strong regulatory regime with negative g^{S}. As a result, the threshold $\underline{c}(\tau)$ becomes higher, suggesting a lower probability of shifting to the strong-regulation regime. Second, the threshold $\underline{c}(\tau)$ depends on the difference between g^{W} and g^{S}. A larger difference indicates a more costly transition from the weak- to the strong-regulation regime when aggregate profitability undergoes a permanent drop. Such an unfavorable economic consequence attenuates the government's incentive to switch to strong environmental regulation. We therefore expect a lower likelihood for an environmental policy regime shift.

Before time τ (i.e., $\tau-$), agents face uncertainty about the government's action at time τ because they do not observe the environment cost c. From Proposition 1, we derive the probabilities of switching to the strong regulation as perceived at any time $t < \tau$.

C. *Proof of Corollary 1*

We define $n(c; a, b)$ as the probability density function (p.d.f.) of a normal distribution with mean a and variance b. The p.d.f. conditional on information at time t, where $t \leq \tau-$, is given by

$$n(c; \hat{c}_t, \hat{\sigma}_t^2) = \int_{-\infty}^{\infty} n(c; \hat{c}_{\tau-}, \hat{\sigma}_{\tau-}^2) n(\hat{c}_{\tau-}; \hat{c}_t, \hat{\sigma}_t^2 - \hat{\sigma}_{\tau-}^2) d\hat{c}_{\tau-}. \tag{IA.14}$$

This follows from general properties of the normal distribution. Note that

$$\begin{aligned} c &= c - \hat{c}_{\tau-} + \hat{c}_{\tau-}, && \text{(IA.15)} \\ c - \hat{c}_{\tau-} \mid \mathcal{F}_{\tau-} &\sim Normal(0, \hat{\sigma}_{\tau-}^2), && \text{(IA.16)} \\ \hat{c}_{\tau-} \mid \mathcal{F}_t &\sim Normal(\hat{c}_t, \hat{\sigma}_t^2 - \hat{\sigma}_\tau^2), && \text{(IA.17)} \end{aligned}$$

where $\mathcal{F}$ denotes an information set. Conditional on information at time t (i.e., $\mathcal{F}_t$), $\hat{c}_{\tau-}$ also follows a normal distribution. According to the dynamics of a posterior mean in equation (10), the recursive expression is given by

$$\hat{c}_{\tau-} = \hat{c}_t + \int_t^{\tau-} \hat{\sigma}_s^2 dZ_s^c. \tag{IA.18}$$

Therefore, the conditional expectation based on information at time t is

$$\mathrm{E}_t[\hat{c}_{\tau-}] = \hat{c}_t, \tag{IA.19}$$

and the variance is

$$\begin{aligned} \mathrm{E}_t[(\hat{c}_{\tau-} - \hat{c}_t)^2] &= \int_t^{\tau-} \left(\hat{\sigma}_s^2\right)^2 ds \\ &= \left. \frac{1}{\frac{1}{\sigma_c^2} + s} \right|_t^{\tau-} = \hat{\sigma}_t^2 - \hat{\sigma}_{\tau-}^2. && \text{(IA.20)} \end{aligned}$$

Given the linearity of the expectation operator, we have

$$\begin{aligned} \mathrm{E}_t[c] &= \mathrm{E}_t[(c - \hat{c}_{\tau-}) + \hat{c}_{\tau-}] = \mathrm{E}_t[(c - \hat{c}_{\tau-})] + \mathrm{E}_t[\hat{c}_{\tau-}] \\ &= \mathrm{E}_t\big[\mathrm{E}_{\tau-}[(c - \hat{c}_{\tau-})]\big] + \mathrm{E}_t[\hat{c}_{\tau-}] \\ &= 0 + \hat{c}_t \\ &= \hat{c}_t. && \text{(IA.21)} \end{aligned}$$

We can also show that $c-\hat{c}_{\tau-}$ and $\hat{c}_{\tau-}$ are independent when two random variables are uncorrelated. The covariance is defined as

$$\mathrm{Cov}_t[(c-\hat{c}_{\tau-}),\hat{c}_{\tau-}] = \mathrm{E}_t[(c-\hat{c}_{\tau-})\hat{c}_{\tau-}] - \mathrm{E}_t[(c-\hat{c}_{\tau-})]\mathrm{E}_t[\hat{c}_{\tau-}]. \tag{IA.22}$$

By using the law of iterated expectations, the first term in the right-hand side (RHS) of equation (IA.22) is:

$$\begin{aligned}
\mathrm{E}_t[(c-\hat{c}_{\tau-})\hat{c}_{\tau-}] &= \mathrm{E}_t\left[\mathrm{E}_{\tau-}[(c-\hat{c}_{\tau-})\hat{c}_{\tau-}]\right] \\
&= \mathrm{E}_t\left[\mathrm{E}_{\tau-}[(c-\hat{c}_{\tau-})]\hat{c}_{\tau-}\right] \\
&= 0,
\end{aligned} \tag{IA.23}$$

and the second term in the RHS of equation (IA.22) is also equal to zero. Therefore, we verify the independence that implies $\mathrm{Cov}_t[(c-\hat{c}_{\tau-}),\hat{c}_{\tau-}] = 0$. As a result, the variance based on information at time t is

$$\begin{aligned}
\mathrm{Var}_t[c] &= \mathrm{Var}_t[(c-\hat{c}_{\tau-})+\hat{c}_{\tau-}] = \mathrm{Var}_t[c-\hat{c}_{\tau-}] + \mathrm{Var}_t[\hat{c}_{\tau-}] + 2\ \mathrm{Cov}_t[(c-\hat{c}_{\tau-}),\hat{c}_{\tau-}] \\
&= \hat{\sigma}^2_{\tau-} + (\hat{\sigma}^2_t - \hat{\sigma}^2_{\tau-}) + 0 \\
&= \hat{\sigma}^2_t.
\end{aligned} \tag{IA.24}$$

Therefore, c follows a normal distribution condition on information at time t,

$$c \sim Normal(\hat{c}_t, \hat{\sigma}^2_t), \tag{IA.25}$$

and the probability of a regime shift at $\tau-$ is

$$p_{\tau-|t} = 1 - Normal(\underline{c}(\tau); \hat{c}_t, \hat{\sigma}^2_t). \tag{IA.26}$$

D. Proof of Proposition IA.1

We determine the state price density in the following proposition.

PROPOSITION IA.1: Before the resolution of a regime shift, for $t < \tau$, the state price density is given by

$$\pi_t = B_t^{-\gamma}\Omega_t, \tag{IA.27}$$

where the functional form of Ω_t refers to equation (IA.47).

Before we prove Proposition IA.1, we need to prove the lemma below.

LEMMA IA.2: When a policy regime shift occurs at time τ, the market value of each firm i takes one of two values:

$$M_{\tau+}^{i}=\begin{cases}M_{\tau+}^{\mathrm{S},i}=B_{\tau}^{i}e^{(\mu-\gamma\sigma^{2}+\xi^{i}g^{\mathrm{S}})(T-\tau)} & \text{if a regime occurs}\\ M_{\tau+}^{\mathrm{W},i}=B_{\tau}^{i}e^{(\mu-\gamma\sigma^{2}+\xi^{i}g^{\mathrm{W}})(T-\tau)} & \text{if a regime shift does not occur,}\end{cases} \tag{IA.28}$$

where $\tau+$ is the timing immediately after a regime shift. Unconditionally, firm i's market value is

$$M_{\tau}^{i}=\mathrm{E}_{\tau}[M_{\tau+}^{i}]=p_{\tau}M_{\tau+}^{\mathrm{S},i}+(1-p_{\tau})M_{\tau+}^{\mathrm{W},i}. \tag{IA.29}$$

Proof of Lemma IA.2

The state price density is $\pi_t=\frac{1}{\kappa}\mathrm{E}_t\left[B_T^{-\gamma}\right]$. Its value when a regime shift occurs at time τ is given by

$$\begin{aligned}
\pi_{\tau+} &= \kappa^{-1}B_{\tau}^{-\gamma}\mathrm{E}_{\tau+}\left[e^{-\gamma(\mu+g-\frac{1}{2}\sigma^{2})(T-\tau)-\gamma\sigma(Z_T-Z_{\tau})}\right]\\
&= \begin{cases}\kappa^{-1}B_{\tau}^{-\gamma}\mathrm{E}_{\tau+}\left[e^{-\gamma(\mu+g^{\mathrm{S}}-\frac{1}{2}\sigma^{2})(T-\tau)-\gamma\sigma(Z_T-Z_{\tau})}\right] & \text{if a regime shift occurs}\\ \kappa^{-1}B_{\tau}^{-\gamma}\mathrm{E}_{\tau+}\left[e^{-\gamma(\mu+g^{\mathrm{W}}-\frac{1}{2}\sigma^{2})(T-\tau)-\gamma\sigma(Z_T-Z_{\tau})}\right] & \text{if a regime shit does not occur}\end{cases}\\
&= \begin{cases}\pi_{\tau+}^{\mathrm{S}}=\kappa^{-1}B_{\tau}^{-\gamma}e^{\left\{-\gamma(\mu+g^{\mathrm{S}})+\frac{1}{2}\gamma(\gamma+1)\sigma^{2}\right\}(T-\tau)} & \text{if a regime shit occurs}\\ \pi_{\tau+}^{\mathrm{W}}=\kappa^{-1}B_{\tau}^{-\gamma}e^{\left\{-\gamma(\mu+g^{\mathrm{W}})+\frac{1}{2}\gamma(\gamma+1)\sigma^{2}\right\}(T-\tau)} & \text{if a regime shit does not occur}\end{cases}
\end{aligned} \tag{IA.30}$$

where we use the definition of equation (IA.2). We can now infer the state price density at time τ:

$$\pi_{\tau}=\mathrm{E}_{\tau}[\pi_{\tau+}]=p_{\tau}\pi_{\tau+}^{\mathrm{S}}+(1-p_{\tau})\pi_{\tau+}^{\mathrm{W}}, \tag{IA.31}$$

where p_τ is the probability of a policy change from the perspective of an investor. The market value of stock i is given by

$$M_t^i=\mathrm{E}_t\left[\frac{\pi_T}{\pi_t}B_T^i\right]. \tag{IA.32}$$

After a policy regime changes at time τ, using the results of equations (IA.2) and (IA.30), we obtain

$$\begin{aligned}
\mathrm{E}_{\tau+}[\pi_T B_T^i\mid \mathrm{S}] &= \kappa^{-1}\mathrm{E}_{\tau+}[B_T^{-\gamma}B_T^i\mid \mathrm{S}]\\
&= \kappa^{-1}B_{\tau}^{-\gamma}B_{\tau}^{i}\mathrm{E}_{\tau+}\left[e^{(1-\gamma)(\mu-\frac{1}{2}\sigma^{2})(T-\tau)+(\xi^{i}-\gamma)g^{\mathrm{S}}(T-\tau)+(1-\gamma)\sigma(Z_T-Z_{\tau})}\mid \mathrm{S}\right]\\
&\quad\times\mathrm{E}_{\tau+}\left[e^{-\frac{1}{2}\sigma_I^{2}(T-\tau)+\sigma_I(Z_T^i-Z_{\tau}^i)}\right]\\
&= \kappa^{-1}B_{\tau}^{-\gamma}B_{\tau}^{i}\mathrm{E}_{\tau+}\left[e^{(1-\gamma)(\mu-\frac{1}{2}\sigma^{2})(T-\tau)+(\xi^{i}-\gamma)g^{\mathrm{S}}(T-\tau)+(1-\gamma)\sigma(Z_T-Z_{\tau})}\mid \mathrm{S}\right]\\
&= \kappa^{-1}B_{\tau}^{-\gamma}B_{\tau}^{i}\mathrm{E}_{\tau+}\left[e^{(1-\gamma)(\mu-\frac{1}{2}\sigma^{2})(T-\tau)+(\xi^{i}-\gamma)g^{\mathrm{S}}(T-\tau)+(1-\gamma)\sigma(Z_T-Z_{\tau})}\right]\\
&= \kappa^{-1}B_{\tau}^{-\gamma}B_{\tau}^{i}e^{(1-\gamma)(\mu-\frac{1}{2}\sigma^{2})(T-\tau)+(\xi^{i}-\gamma)g^{\mathrm{S}}(T-\tau)+\frac{1}{2}(1-\gamma)^{2}\sigma^{2}(T-\tau)},
\end{aligned} \tag{IA.33}$$

$$\mathrm{E}_{\tau+}[\pi_T B_T^i\mid \mathrm{S}]=\kappa^{-1}B_{\tau}^{-\gamma}B_{\tau}^{i}e^{(1-\gamma)(\mu-\frac{1}{2}\sigma^{2})(T-\tau)+(\xi^{i}-\gamma)g^{\mathrm{W}}(T-\tau)+\frac{1}{2}(1-\gamma)^{2}\sigma^{2}(T-\tau)}, \tag{IA.34}$$

where the derivations of $\mathrm{E}_{\tau+}[\pi_T B_T^i \mid \mathrm{S}]$ are analogous to those of $\mathrm{E}_{\tau+}[\pi_T B_T^i \mid \mathrm{S}]$. We can obtain firm i's stock price after a policy regime shift as follows:

$$M_{\tau+}^{\mathrm{S},i} = \mathrm{E}_{\tau+}\left[\frac{\pi_T}{\pi_{\tau+}^{\mathrm{S}}} B_T^i \middle| \mathrm{S}\right] = \frac{\mathrm{E}_{\tau+}[\pi_T B_T^i \mid \mathrm{S}]}{\pi_{\tau+}^{\mathrm{S}}} = B_{\tau+}^i e^{(\mu-\gamma\sigma^2+\xi^i g^{\mathrm{S}})(T-\tau)} \tag{IA.35}$$

and

$$M_{\tau+}^{\mathrm{W},i} = \mathrm{E}_{\tau+}\left[\frac{\pi_T}{\pi_{\tau+}^{\mathrm{W}}} B_T^i \middle| \mathrm{W}\right] = \frac{\mathrm{E}_{\tau+}[\pi_T B_T^i \mid \mathrm{W}]}{\pi_{\tau+}^{\mathrm{W}}} = B_{\tau+}^i e^{(\mu-\gamma\sigma^2+\xi^i g^{\mathrm{W}})(T-\tau)}. \tag{IA.36}$$

Finally, the stock price at time τ when the policy changes is equal to

$$\begin{aligned} M_\tau^i &= \mathrm{E}_\tau\left[\frac{\pi_T}{\pi_\tau} B_T^i\right] = \frac{1}{\pi_\tau}\mathrm{E}_\tau[\mathrm{E}_{\tau+}[\kappa^{-1} B_T^{-\gamma} B_T^i]] \\ &= \frac{p_\tau \mathrm{E}_{\tau+}[\kappa^{-1} B_T^{-\gamma} B_T^i \mid \mathrm{S}] + (1-p_\tau)\mathrm{E}_{\tau+}[\kappa^{-1} B_T^{-\gamma} B_T^i \mid \mathrm{W}]}{\pi_\tau} \\ &= \frac{p_\tau \pi_{\tau+}^{\mathrm{S}} M_{\tau+}^{\mathrm{S},i} + (1-p_\tau)\pi_{\tau+}^{\mathrm{W}} M_{\tau+}^{\mathrm{W},i}}{p_\tau \pi_{\tau+}^{\mathrm{S}} + (1-p_\tau)\pi_{\tau+}^{\mathrm{W}}} \\ &= \phi_\tau M_{\tau+}^{\mathrm{S},i} + (1-\phi_\tau) M_{\tau+}^{\mathrm{W},i}, \end{aligned} \tag{IA.37}$$

where

$$\begin{aligned} \phi_\tau &\equiv \frac{p_\tau \pi_{\tau+}^{\mathrm{S}}}{p_\tau \pi_{\tau+}^{\mathrm{S}} + (1-p_\tau)\pi_{\tau+}^{\mathrm{W}}} \\ &= \frac{p_\tau}{p_\tau + (1-p_\tau)\frac{\pi_{\tau+}^{\mathrm{W}}}{\pi_{\tau+}^{\mathrm{S}}}} \\ &= \frac{p_\tau}{p_\tau + (1-p_\tau)e^{-\gamma(g^{\mathrm{W}}-g^{\mathrm{S}})(T-\tau)}} \end{aligned} \tag{IA.38}$$

and

$$G_\tau^i \equiv \frac{M_{\tau+}^{\mathrm{W},i}}{M_{\tau+}^{\mathrm{S},i}} = e^{\xi^i(g^{\mathrm{W}}-g^{\mathrm{S}})(T-\tau)} > 1, \tag{IA.39}$$

given that $g^{\mathrm{W}} - g^{\mathrm{S}} > 0$ and $\xi^i > 0$. We now prove Proposition IA.1. The state price density is the expected value of the state price density when the environmental policy regime shifts. The state price density is the expected value of whether the policy regime shifts or not,

$$\begin{aligned} \pi_t &= \mathrm{E}_t[\pi_{\tau+}] \\ &= \mathrm{E}_t[p_\tau \pi_{\tau+}^{\mathrm{S}} + (1-p_\tau)\pi_{\tau+}^{\mathrm{W}}] \\ &= \mathrm{E}_t[p_\tau]\mathrm{E}_t\left[\pi_{\tau+}^{\mathrm{S}}\right] + \mathrm{E}_t[(1-p_\tau)]\mathrm{E}_t\left[\pi_{\tau+}^{\mathrm{W}}\right] \\ &= p_{\tau|t}\pi_t^{\mathrm{S}} + (1-p_{\tau|t})\pi_t^{\mathrm{W}}, \end{aligned} \tag{IA.40}$$

where

$$\pi_t^{\mathrm{S}} = \mathrm{E}_t\left[\pi_{\tau+}^{\mathrm{S}}\right], \quad \text{(IA.41)}$$

$$\pi_t^{\mathrm{W}} = \mathrm{E}_t\left[\pi_{\tau+}^{\mathrm{W}}\right], \quad \text{(IA.42)}$$

and $p_{\tau|t}$ refers to Corollary 1 in our main paper. We can show that

$$\begin{aligned} \mathrm{E}_t[p_\tau] &= \mathrm{E}_t\left[\int_{\underline{c}(\tau)}^{\infty} n(c;\hat{c}_\tau,\hat{\sigma}_\tau^2)dc\right] \\ &= \int_{-\infty}^{\infty}\left[\int_{\underline{c}(\tau)}^{\infty} n(c;\hat{c}_\tau,\hat{\sigma}_\tau^2)dc\right] n(\hat{c}_\tau;\hat{c}_t,\hat{\sigma}_t^2-\hat{\sigma}_\tau^2)d\hat{c}_\tau \\ &= \int_{\underline{c}(\tau)}^{\infty}\left[\int_{-\infty}^{\infty} n(c;\hat{c}_\tau,\hat{\sigma}_\tau^2)n(\hat{c}_\tau;\hat{c}_t,\hat{\sigma}_t^2-\hat{\sigma}_\tau^2)d\hat{c}_\tau\right]dc \\ &= \int_{\underline{c}(\tau)}^{\infty} n(c;\hat{c}_t,\hat{\sigma}_t^2)dc \\ &= 1-N(\underline{c}(\tau);\hat{c}_t,\hat{\sigma}_t^2) \\ &= p_{\tau|t}. \end{aligned} \quad \text{(IA.43)}$$

Recalling that equation (IA.30) is the state price density after the government decides whether to change its environmental policy or not, its value conditional on time $t \le \tau$ is characterized by

$$\begin{aligned} \pi_t^{\mathrm{S}} = \mathrm{E}_t\left[\pi_{\tau+}^{\mathrm{S}}\right] &= \mathrm{E}_t\left[\kappa^{-1}B_{\tau+}^{-\gamma}e^{\left\{-\gamma(\mu+g^{\mathrm{S}})+\frac{1}{2}\gamma(\gamma+1)\sigma^2\right\}(T-\tau)}\right] \\ &= e^{\left\{-\gamma(\mu+g^{\mathrm{S}})+\frac{1}{2}\gamma(\gamma+1)\sigma^2\right\}(T-\tau)}\mathrm{E}_t\left[B_{\tau+}^{-\gamma}\right] \\ &= e^{\left\{-\gamma(\mu+g^{\mathrm{S}})+\frac{1}{2}\gamma(\gamma+1)\sigma^2\right\}(T-\tau)} \times B_t^{-\gamma}e^{\left\{-\gamma(\mu+g^{\mathrm{W}})+\frac{1}{2}\gamma(\gamma+1)\sigma^2\right\}(\tau-t)} \\ &= B_t^{-\gamma}e^{\left\{-\gamma\mu+\frac{1}{2}\gamma(\gamma+1)\sigma^2\right\}(T-t)-\gamma g^{\mathrm{W}}(\tau-t)-\gamma g^{\mathrm{S}}(T-\tau)}, \end{aligned} \quad \text{(IA.44)}$$

where the capital at time t is given by

$$B_\tau = B_t e^{\mu(\tau-t)+g^{\mathrm{W}}(\tau-t)-\frac{1}{2}\sigma^2(\tau-t)+\sigma(Z_\tau-Z_t)}.$$

Given that the economy starts from the weak regulatory regime in equation (3), we solve the expectation problem by substituting the recursive expression of B_τ into the expectation. We can immediately obtain the state price density at time t given no regulatory regime shift:

$$\pi_t^{\mathrm{W}} = \mathrm{E}_t\left[\pi_{\tau+}^{\mathrm{W}}\right] = B_t^{-\gamma}e^{\left\{-\gamma(\mu+g^{\mathrm{W}})+\frac{1}{2}\gamma(\gamma+1)\sigma^2\right\}(T-t)}. \quad \text{(IA.45)}$$

Finally, we obtain the state price density at time t conditional on the government making a regulatory change. The unconditional state price density is

$$\begin{aligned}
\pi_t &= p_{\tau|t}\pi_t^{\mathrm{S}} + (1-p_{\tau|t})\pi_t^{\mathrm{W}} \\
&= p_{\tau|t}B_t^{-\gamma}e^{\left(-\gamma\mu+\frac{1}{2}\gamma(\gamma+1)\sigma^2\right)(T-t)-\gamma g^{\mathrm{W}}(\tau-t)-\gamma g^{\mathrm{S}}(T-\tau)} + (1-p_{\tau|t})B_t^{-\gamma}e^{\left(-\gamma(\mu+g^{\mathrm{W}})+\frac{1}{2}\gamma(\gamma+1)\sigma^2\right)(T-t)} \\
&= B_t^{-\gamma}e^{\left(-\gamma\mu+\frac{1}{2}\gamma(\gamma+1)\sigma^2\right)(T-t)-\gamma g^{\mathrm{W}}(\tau-t)}\left[p_{\tau|t}e^{-\gamma g^{\mathrm{S}}(T-\tau)} + (1-p_{\tau|t})e^{-\gamma g^{\mathrm{W}}(T-\tau)}\right] \\
&= B_t^{-\gamma}\Omega_t, \qquad \text{(IA.46)}
\end{aligned}$$

where

$$\Omega_t = e^{\left(-\gamma\mu+\frac{1}{2}\gamma(\gamma+1)\sigma^2\right)(T-t)-\gamma g^{\mathrm{W}}(\tau-t)}\left[p_{\tau|t}e^{-\gamma g^{\mathrm{S}}(T-\tau)} + (1-p_{\tau|t})e^{-\gamma g^{\mathrm{W}}(T-\tau)}\right]. \qquad \text{(IA.47)}$$

E. Proof of Proposition 2

The SDF dynamics stem from an application of Ito's Lemma to equation (IA.46):

$$\frac{d\pi_t}{\pi_t} = E_t\left[\frac{d\pi_t}{\pi_t}\right] - \lambda dZ_t - \lambda_{c,t}d\hat{Z}_t^c. \qquad \text{(IA.48)}$$

The price of fundamental shock risk is

$$\lambda = \gamma\sigma. \qquad \text{(IA.49)}$$

The price of uncertainty shock risk is

$$\begin{aligned}
\lambda_{c,t} &= -\frac{1}{\Omega_t}\frac{\partial\Omega_t}{\partial p_{\tau|t}}\frac{\partial p_{\tau|t}}{\partial\hat{c}_t}\hat{\sigma}_{c,t}^2\eta^{-1} \\
&= -\frac{e^{\left(-\gamma\mu+\frac{1}{2}\gamma(\gamma+1)\sigma^2\right)(T-t)-\gamma g^{\mathrm{W}}(\tau-t)}\left[e^{-\gamma g^{\mathrm{S}}(T-\tau)} - e^{-\gamma g^{\mathrm{W}}(T-\tau)}\right]}{e^{\left(-\gamma\mu+\frac{1}{2}\gamma(\gamma+1)\sigma^2\right)(T-t)-\gamma g^{\mathrm{W}}(\tau-t)}\left[p_{\tau|t}e^{-\gamma g^{\mathrm{S}}(T-\tau)} + (1-p_{\tau|t})e^{-\gamma g^{\mathrm{W}}(T-\tau)}\right]} \times n(\underline{c}(\tau);\hat{c}_t,\hat{\sigma}_{c,t}^2) \times \hat{\sigma}_{c,t}^2\eta^{-1} \\
&= -\left[\frac{(1-p_{\tau|t})(1-F_\tau)}{p_{\tau|t}+(1-p_{\tau|t})F_\tau}\right]n(\underline{c}(\tau);\hat{c}_t,\hat{\sigma}_{c,t}^2)\hat{\sigma}_{c,t}^2\eta^{-1}, \qquad \text{(IA.50)}
\end{aligned}$$

where

$$\begin{aligned}
F_\tau &= \frac{e^{-\gamma^{\mathrm{W}}(T-\tau)}}{e^{-\gamma^{\mathrm{S}}(T-\tau)}} \\
&= e^{-\gamma(g^{\mathrm{W}}-g^{\mathrm{S}})(T-\tau)} < 1. \qquad \text{(IA.51)}
\end{aligned}$$

Therefore, the first term in the last equality of equation (IA.50) is positive. Given that the rest of the terms are positive, we verify that the regime shift shock risk is negatively priced (i.e., $\lambda_{c,t} < 0$).

F. *Proof of Proposition 3*

First, we determine the analytical expression for the level of firm i's stock price.

PROPOSITION IA.2: For $t < \tau$, the stock price for firm i is given by

$$M_t^i = B_t^i \Theta_t^i, \tag{IA.52}$$

where the functional form of Θ_t^i refers to equation (IA.58).

Proof of Proposition IA.2

The proof is a continuation of Proposition 2. For $t < \tau$, market value satisfies $M_t^i = \mathrm{E}_t\left[\frac{\pi_T}{\pi_t} M_T^i\right]$. Firm i's stock price is then

$$M_t^{\mathrm{S},i} = \frac{\mathrm{E}_t\left[\pi_{\tau+}^{\mathrm{S}} M_{\tau+}^{\mathrm{S},i}\right]}{\pi_t^{\mathrm{S}}} = B_t^i e^{(\mu-\gamma\sigma^2)(T-t)+\xi^i g^{\mathrm{W}}(\tau-t)+\xi^i g^{\mathrm{S}}(T-\tau)} \tag{IA.53}$$

when a regime shift occurs at time τ, and

$$M_t^{\mathrm{W},i} = \frac{\mathrm{E}_t\left[\pi_{\tau+}^{\mathrm{W}} M_{\tau+}^{\mathrm{W},i}\right]}{\pi_t^{\mathrm{W}}} = B_t^i e^{(\mu-\gamma\sigma^2+\xi^i g^{\mathrm{W}})(T-t)} \tag{IA.54}$$

when a regime shift does not occur at time τ. Following Proposition 2, firm i's stock price is determined using the law of iterated expectations:

$$
\begin{aligned}
M_t^i &= \mathrm{E}_t\left[\frac{\pi_T}{\pi_t}B_T^i\right] = \frac{1}{\pi_t}\mathrm{E}_t[\mathrm{E}_\tau[\kappa^{-1}B_T^{-\gamma}B_T^i]] \\
&= \frac{\mathrm{E}_t\Big[p_\tau \mathrm{E}_{\tau+}[\kappa^{-1}B_T^{-\gamma}B_T^i \mid \mathrm{S}] + (1-p_\tau)\mathrm{E}_{\tau+}[\kappa^{-1}B_T^{-\gamma}B_T^i \mid \mathrm{W}]\Big]}{\pi_t} \\
&= \frac{p_{\tau|t}\mathrm{E}_t\Big[\kappa^{-1}B_\tau^{-\gamma}e^{\left(-\gamma(\mu+g^{\mathrm{S}})+\frac{1}{2}\gamma(\gamma+1)\sigma^2\right)(T-\tau)}B_\tau^i e^{(\mu-\gamma\sigma^2+\xi^i g^{\mathrm{S}})(T-\tau)}\Big]}{\pi_t} \\
&\quad + \frac{(1-p_{\tau|t})\mathrm{E}_t\Big[\kappa^{-1}B_\tau^{-\gamma}e^{\left(-\gamma(\mu+g^{\mathrm{W}})+\frac{1}{2}\gamma(\gamma+1)\sigma^2\right)(T-\tau)}B_\tau^i e^{(\mu-\gamma\sigma^2+\xi^i g^{\mathrm{W}})(T-\tau)}\Big]}{\pi_t} \\
&= \frac{\kappa^{-1}B_t^{-\gamma}B_t^i e^{(1-\gamma)\mu(T-t)+\frac{1}{2}\gamma(\gamma-1)\sigma^2(T-t)+(\xi^i-\gamma)g^{\mathrm{W}}(\tau-t)}\Big[p_{\tau|t}e^{(\xi^i-\gamma)g^{\mathrm{S}}(T-\tau)} + (1-p_{\tau|t})e^{(\xi^i-\gamma)g^{\mathrm{W}}(T-\tau)}\Big]}{\kappa^{-1}B_t^{-\gamma}e^{\left(-\gamma+\frac{1}{2}\gamma(\gamma-1)\sigma^2\right)(T-t)-\gamma g^{\mathrm{S}}(\tau-t)}\Big[p_{\tau|t}e^{-\gamma g^{\mathrm{S}}(T-\tau)} + (1-p_{\tau|t})e^{-\gamma g^{\mathrm{W}}(T-\tau)}\Big]} \\
&= \frac{p_{\tau|t}e^{-\gamma g^{\mathrm{S}}(T-\tau)}B_t^i e^{(\mu-\gamma\sigma^2)(T-t)+\xi^i g^{\mathrm{W}}(\tau-t)+\xi^i g^{\mathrm{S}}(T-\tau)} + (1-p_{\tau|t})e^{-\gamma g^{\mathrm{W}}(T-\tau)}B_t^i e^{(\mu-\gamma\sigma^2+\xi^i g^{\mathrm{W}})(T-t)}}{p_{\tau|t}e^{-\gamma g^{\mathrm{S}}(T-\tau)} + (1-p_{\tau|t})e^{-\gamma g^{\mathrm{W}}(T-\tau)}} \\
&= \frac{p_{\tau|t}e^{-\gamma g^{\mathrm{S}}(T-\tau)}M_t^{\mathrm{S},i} + (1-p_{\tau|t})e^{-\gamma g^{\mathrm{W}}(T-\tau)}M_t^{\mathrm{W},i}}{p_{\tau|t}e^{-\gamma g^{\mathrm{S}}(T-\tau)} + (1-p_{\tau|t})e^{-\gamma g^{\mathrm{W}}(T-\tau)}} \\
&= \frac{p_{\tau|t}M_t^{\mathrm{S},i} + (1-p_{\tau|t})\left(\frac{e^{-\gamma g^{\mathrm{W}}(T-\tau)}}{e^{-\gamma g^{\mathrm{S}}(T-\tau)}}\right)M_t^{\mathrm{W},i}}{p_{\tau|t} + (1-p_{\tau|t})\left(\frac{e^{-\gamma g^{\mathrm{W}}(T-\tau)}}{e^{-\gamma g^{\mathrm{S}}(T-\tau)}}\right)} \\
&= \frac{p_{\tau|t}M_t^{\mathrm{S},i} + (1-p_{\tau|t})e^{-\gamma(g^{\mathrm{W}}-g^{\mathrm{S}})(T-\tau)}M_t^{\mathrm{W},i}}{p_{\tau|t} + (1-p_{\tau|t})e^{-\gamma(g^{\mathrm{W}}-g^{\mathrm{S}})(T-\tau)}} \\
&= \phi_t M_t^{\mathrm{S},i} + (1-\phi_t)M_t^{\mathrm{W},i}, \qquad \text{(IA.55)}
\end{aligned}
$$

where

$$\phi_t \equiv \frac{p_{\tau|t}}{p_{\tau|t} + (1-p_{\tau|t})e^{-\gamma(g^{\mathrm{W}}-g^{\mathrm{S}})(T-\tau)}}. \qquad \text{(IA.56)}$$

We can obtain firm i's market valuation unconditionally by substituting equations (IA.53) and (IA.54) into the last equality in equation (IA.55),

$$
\begin{aligned}
M_t^i &= \phi_t M_t^{\mathrm{S},i} + (1-\phi_t)M_t^{\mathrm{W},i} \\
&= B_t^i e^{(\mu-\gamma\sigma^2)(T-t)+\xi^i g^{\mathrm{W}}(\tau-t)}\Big[\phi_t e^{\xi^i g^{\mathrm{S}}(T-\tau)} + (1-\phi_t)e^{\xi^i g^{\mathrm{W}}(T-\tau)}\Big] \\
&= B_t^i \Theta_t^i, \qquad \text{(IA.57)}
\end{aligned}
$$

where

$$\Theta_t^i = e^{(\mu-\gamma\sigma^2)(T-t)+\xi^i g^{\mathrm{W}}(\tau-t)}\Big[\phi_t e^{\xi^i g^{\mathrm{S}}(T-\tau)} + (1-\phi_t)e^{\xi^i g^{\mathrm{W}}(T-\tau)}\Big]. \qquad \text{(IA.58)}$$

Proof of Proposition 3:

An application of Ito's Lemma to equation (IA.52) characterizes the return dynamics as

$$\frac{dM_t^i}{M_t^i} = E_t\left[\frac{dM_t^i}{M_t^i}\right] + \sigma dZ_t + \sigma_I dZ_t^i + \beta_{M,t}^i d\hat{Z}_t^c, \tag{IA.59}$$

where $\sigma_{c,t}^i$ is the risk exposure to uncertainty shocks. The derivations of $\sigma_{c,t}^i$ are as follows:

$$\begin{aligned}
\beta_{M,t}^i &= \frac{1}{\Theta_t^i}\frac{\partial\Theta_t^i}{\partial\phi_t}\frac{\partial\phi_t}{\partial p_{\tau|t}}\frac{\partial p_{\tau|t}}{\partial\hat{c}_t}\hat{\sigma}_{c,t}^2 \\
&= \frac{e^{(\mu-\gamma\sigma^2)(T-t)+\xi^i g^{\mathrm{W}}(\tau-t)}\left[e^{\xi^i g^{\mathrm{S}}(T-\tau)} - e^{\xi^i g^{\mathrm{W}}(T-\tau)}\right]}{e^{(\mu-\gamma\sigma^2)(T-t)+\xi^i g^{\mathrm{W}}(\tau-t)}\left[\phi_t e^{\xi^i g^{\mathrm{S}}(T-\tau)} + (1-\phi_t)e^{\xi^i g^{\mathrm{W}}(T-\tau)}\right]} \times \\
&\quad \frac{\left[p_{\tau|t} + (1-p_{\tau|t})e^{-\gamma(g^{\mathrm{W}}-g^{\mathrm{S}})(T-\tau)}\right] - p_{\tau|t}(1-e^{-\gamma(g^{\mathrm{W}}-g^{\mathrm{S}})(T-\tau)})}{\left[p_{\tau|t} + (1-p_{\tau|t})e^{-\gamma(g^{\mathrm{W}}-g^{\mathrm{S}})(T-\tau)}\right]^2} n(\underline{c}(\tau);\hat{c}_t,\hat{\sigma}_{c,t}^2)\hat{\sigma}_{c,t}^2 \\
&= \left[\frac{1-e^{\xi^i(g^{\mathrm{W}}-g^{\mathrm{S}})(T-\tau)}}{\phi_t + (1-\phi_t)e^{\xi^i(g^{\mathrm{W}}-g^{\mathrm{S}})(T-\tau)}}\right]\left[\frac{e^{-\gamma(g^{\mathrm{W}}-g^{\mathrm{S}})(T-\tau)}}{\left(p_{\tau|t} + (1-p_{\tau|t})e^{-\gamma(g^{\mathrm{W}}-g^{\mathrm{S}})(T-\tau)}\right)^2}\right] \times \\
&\quad n(\underline{c}(\tau);\hat{c}_t,\hat{\sigma}_{c,t}^2),\hat{\sigma}_{c,t}^2 \\
&= \left[\frac{1-G_\tau^i}{\phi_t + (1-\phi_t)G_\tau^i}\right]\left[\frac{F_\tau}{\left(p_{\tau|t} + (1-p_{\tau|t})F_\tau\right)^2}\right] n(\underline{c}(\tau);\hat{c}_t,\hat{\sigma}_{c,t}^2),\hat{\sigma}_{c,t}^2 < 0,
\end{aligned} \tag{IA.60}$$

given that $G_\tau^i > 1$ in equation (IA.39).

As shown in equation (22), the partial derivative of ξ^i with respect to its dependence on $\beta_{M,t}^i$ is given as

$$\begin{aligned}
\frac{\partial\beta_{M,t}^i}{\partial\xi^i} &= \frac{\partial}{\partial\xi^i}\left\{\left[\frac{1-G_\tau^i}{\phi_t + (1-\phi_t)G_\tau^i}\right]\left[\frac{F_\tau}{\left(p_{\tau|t} + (1-p_{\tau|t})F_\tau\right)^2}\right] n(\underline{c}(\tau);\hat{c}_t,\hat{\sigma}_{c,t}^2),\hat{\sigma}_{c,t}^2\eta^{-1}\right\} \\
&= \left[\frac{F_\tau}{\left(p_{\tau|t} + (1-p_{\tau|t})F_\tau\right)^2}\right] n(\underline{c}(\tau);\hat{c}_t,\hat{\sigma}_{c,t}^2),\hat{\sigma}_{c,t}^2\eta^{-1} \times \frac{\partial}{\partial\xi^i}\left\{\left[\frac{1-G_\tau^i}{\phi_t + (1-\phi_t)G_\tau^i}\right]\right\}
\end{aligned} \tag{IA.61}$$

Since only G_τ^i depends on ξ^i, our analysis focuses on terms related to G_τ^i,

$$\frac{\partial}{\partial\xi^i}\left\{\left[\frac{1-G_\tau^i}{\phi_t + (1-\phi_t)G_\tau^i}\right]\right\} = \frac{-\frac{\partial G_\tau^i}{\partial\xi^i}[\phi_t + (1-\phi_t)G_\tau^i] - \left(-\phi_t\frac{\partial G_\tau^i}{\partial\xi^i}\right)(1-G_\tau^i)}{\left[\phi_t + (1-\phi_t)G_\tau^i\right]^2} < 0, \tag{IA.62}$$

where $G_\tau^i > 1$ and $\partial G_\tau^i/\partial\xi^i > 0$ according to equation (IA.39).

G. Proof of Proposition 4

We implement a second-order Taylor expansion around the average ξ_o and obtain

$$M_0^i \approx M_0^i\big|_{\xi^i=\xi_0} + \frac{\partial M_0^i}{\partial \xi}\big|_{\xi^i=\xi_0} \times (\xi^i - \xi_0) + \frac{1}{2}\frac{\partial^2 M_0^i}{\partial \xi^2}\big|_{\xi^i=\xi_0} \times (\xi^i - \xi_0)^2. \tag{IA.63}$$

Next, we take the partial derivative with respect to ξi,

$$\frac{\partial M_0^i}{\partial \xi^i} = \underbrace{\left(\frac{\partial M_0^i}{\partial \xi}\big|_{\xi^i=\xi_0} - \frac{\partial^2 M_0^i}{\partial \xi^2}\big|_{\xi^i=\xi_0} \times \xi_0\right)}_{-\omega_0} + \underbrace{\frac{\partial^2 M_0^i}{\partial \xi^2}\big|_{\xi^i=\xi_0}}_{\omega_1} \times \xi^i, \tag{IA.64}$$

where $\omega_0 > 0$ and $\omega_1 > 0$ are the Taylor expansion parameters evaluated at ξ_0.

In equilibrium, the optimal emission intensity is determined by taking the first-order derivative with respect to ξ^i to solve the optimal problem in equation (26). In this regard, the first-order optimality condition holds when the marginal benefit is equal to the marginal cost as in equation (2). We solve for the optimal ξ^{i*} by equating firm i's marginal benefit in equation (24) to marginal cost in equation (25). We then obtain the optimal emission intensity ξ^{i*},

$$\xi^{i*} = \bar{\xi} + \frac{\overbrace{-\omega_0 + \omega_1\bar{\xi}}^{-}}{\underbrace{\omega_1}_{+}\underbrace{(\eta^i - 1)}_{+}}, \tag{IA.65}$$

where $\eta^i > 1$, $\omega_1 > 0$, and $\bar{\xi} < \frac{\omega_0}{\omega_1}$. Therefore, it is trivial to prove that $\xi^{i*} < \bar{\xi}$. As η^i goes to infinity, the second component on the RHS in equation (IA.65) converges to zero, and therefore ξ^{i*} converges to $\bar{\xi}$.

By taking the partial derivative with respect to η, we obtain

$$\frac{\partial \xi^{i*}}{\partial \eta^i} = \Big(\frac{-\omega_0 + \omega_1\bar{\xi}}{\omega_1}\Big)\left[\frac{-1}{(\eta^i - 1)^2}\right] > 0. \tag{IA.66}$$

Finally, we show that a high-emission firm incurs lower abatement costs than a low-emission firm. Given the marginal abatement costs in equation (25), we can obtain firm i's abatement cost by integrating over ξ:

$$\Psi_0^i \equiv \int \frac{\partial \Psi_0^i}{\partial \xi^i} d\xi^i. \tag{IA.67}$$

The difference in abatement costs between a high- and low-emission firm is given by $\Psi_0^H - \Psi_0^L$. Applying the Mean Value Theorem, there exists a $\widetilde{\xi} \in (\xi^L, \xi^H)$ such that

$$\Psi_0^H - \Psi_0^L = \frac{\partial \Psi_0}{\partial \xi}\Big|_{\xi=\widetilde{\xi}} \times (\xi^H - \xi^L). \tag{IA.68}$$

Given equation (IA.65) in equilibrium and the parameter restriction for $\eta^i > 1$, we can find a $\widetilde{\eta}$ with respect to $\widetilde{\xi}$ and show that

$$\begin{aligned} \frac{\partial \Psi_0}{\partial \xi}\Big|_{\xi=\widetilde{\xi}} &= \omega_1 \widetilde{\eta}(\widetilde{\xi} - \bar{\xi}) \\ &= \omega_1 \widetilde{\eta} \left[\frac{-\omega_0 + \omega_1 \bar{\xi}}{\omega_1(\widetilde{\eta} - 1)} \right] < 0. \end{aligned} \tag{IA.69}$$

Therefore, $\Psi_0^H - \Psi_0^L < 0$.

H. *Proof of Corollary 2*

We ignore subscripts again for the notational brevity. Suppose that η^i follows an inverse uniform distribution that takes values between η^{min} and η^{max},

$$(\eta^{min}, \eta^{max}) = \left(\frac{-\omega_0 + \omega_1 \bar{\xi}}{\omega_1(\xi^{max} - \bar{\xi})} + 1, \frac{-\omega_0 + \omega_1 \bar{\xi}}{\omega_1(\xi^{min} - \bar{\xi})} + 1 \right), \tag{IA.70}$$

and the probability density function $h(\eta)$ is given by

$$h(\eta) = \frac{1}{(\eta - 1)^2} \left(\frac{\frac{-\omega_0 + \omega_1 \bar{\xi}}{\omega_1}}{\xi^{min} - \xi^{max}} \right). \tag{IA.71}$$

Suppose further that there is a transformation such that $\hat{\eta} = \eta - 1$. Then $\hat{\eta}$ also follows an inverse uniform distribution that takes values in the range

$$\left(\frac{-\omega_0 + \omega_1 \bar{\xi}}{\omega_1(\xi^{max} - \bar{\xi})}, \frac{-\omega_0 + \omega_1 \bar{\xi}}{\omega_1(\xi^{min} - \bar{\xi})} \right), \tag{IA.72}$$

and the probability density function of $\hat{\eta}$,

$$h(\hat{\eta}) = \frac{1}{\hat{\eta}^2} \left(\frac{\frac{-\omega_0 + \omega_1 \bar{\xi}}{\omega_1}}{\xi^{min} - \xi^{max}} \right). \tag{IA.73}$$

We rearrange equation (IA.65) to obtain

$$\xi - \bar{\xi} = \frac{-\omega_0 + \omega_1 \bar{\xi}}{\omega_1(\eta - 1)}. \tag{IA.74}$$

Let $\hat{\xi} \equiv \xi - \bar{\xi}$ and recall that $\hat{\eta} \equiv \eta - 1$. The equality above becomes

$$\hat{\xi} = \left(\frac{-\omega_0 + \omega_1 \bar{\xi}}{\omega_1} \right) \left(\frac{1}{\hat{\eta}} \right). \tag{IA.75}$$

Clearly, there exists a transformation from $\hat{\eta}$ to $\hat{\xi}$, and the probability density function of $\hat{\xi}$ is

$$
\begin{aligned}
l(\hat{\xi}) &= h(\hat{\eta}(\hat{\xi}))\left|\frac{\mathrm{d}\hat{\eta}}{\mathrm{d}\hat{\xi}}\right| \\
&= \hat{\xi}^2\left(\frac{-\omega_0+\omega_1\bar{\xi}}{\omega_1}\right)^{-2} \times \left(\frac{\frac{-\omega_0+\omega_1\bar{\xi}}{\omega_1}}{\xi^{min}-\xi^{max}}\right) \times \left|\frac{-1}{\hat{\xi}^2} \times \left(\frac{-\omega_0+\omega_1\bar{\xi}}{\omega_1}\right)\right| \\
&= \hat{\xi}^2\left(\frac{-\omega_0+\omega_1\bar{\xi}}{\omega_1}\right)^{-2} \times \left(\frac{\frac{-\omega_0+\omega_1\bar{\xi}}{\omega_1}}{\xi^{min}-\xi^{max}}\right) \times \left(\frac{-1}{\hat{\xi}^2}\right) \times \left(\frac{-\omega_0+\omega_1\bar{\xi}}{\omega_1}\right) \\
&= \frac{-1}{\xi^{min}-\xi^{max}} \\
&= \frac{1}{\xi^{max}-\xi^{min}}. \qquad \text{(IA.76)}
\end{aligned}
$$

Apparently, both $\hat{\xi}$ and ξ follow uniform distributions. Moreover, as a mean-shifting distribution of $\hat{\xi}$, ξ takes values in the range between ξ^{min} and ξ^{max}: $\xi \in [\xi^{min}, \xi^{max}]$.

IV. The Extended Model

In this section, we extend our benchmark model by explicitly allowing for debt financing associated with a regime shift, and we show that this channel amplifies the emission-return relation.

A. *The Model Economy*

Production. We consider an economy with a finite horizon $[0, T]$ and a continuum of firms $i \in [0, 1]$. Each firm i issues both equity and debt to acquire capital. Let B_t^i and D_t^i denote firm i's book value of equity and debt, respectively, at time t. Therefore, firm i's total capital equals $B_t^i + D_t^i$. At time 0, all firms are endowed with the same amount of capital, which we normalize to $B_0^i + D_0^i = 1$, and start from the same debt-to-equity ratio, denoted by $\iota = \frac{D_0^i}{B_0^i}$. Firm i invests its capital in a linear production technology with a stochastic rate of return denoted by $d\Pi_t^i$. Given that $d\Pi_t^i$ equals profits over capital, we refer to it as firm i's profitability or return on assets (ROA). For all $t \in [0, T]$, firm i's profitability follows the process

$$d\Pi_t^i = (\mu + \xi^i g)dt + \sigma dZ_t + \sigma_I dZ_t^i, \qquad \text{(IA.77)}$$

where $(\mu, g, \sigma, \sigma_I)$ are observable and constant parameters, Z_t is a Brownian motion, and Z_t^i is an independent Brownian motion that is specific to firm i. The parameter g denotes the impact of different environmental policy regimes (i.e., weak or strong environmental regulation regime) on the mean of the profitability process among firms. When $g = 0$, the environmental policy regime is "neutral" with zero impact on firm i's profitability.

The impact of an environmental policy change, g, is constant when the regime is not changed.

At time τ (i.e., $0 < \tau < T$), the government makes an irreversible decision as to whether to change its environmental policy from the weak- to the strong-regulatory regime. As a result, g is a simple step function over time:

$$g = \begin{cases} g^{\mathrm{W}} & \text{for } t \leq \tau \\ g^{\mathrm{W}} & \text{for } t > \tau \text{ if there is no policy regime shift} \\ g^{\mathrm{S}} & \text{for } t > \tau \text{ if there is a policy regime shift,} \end{cases} \tag{IA.78}$$

where g^{W} denotes the impact of environmental policy under the weak regulation at the beginning. An environmental policy change replaces weak regulation, denoted by W, by strong regulation, denoted by S. Such a policy decision replaces g^{W} by g^{S}, thereby inducing a permanent change in firms' average profitability. We further assume that firms with different emission intensity have heterogeneous levels of exposure to the environmental policy change, as captured by the parameter ξ^i. We assume that ξ^is are positively proportional to firms' emission intensity and ξ^is are drawn from a uniform distribution on the interval $[\xi^{min}, \xi^{max}]$ at time 0 and then remain unchanged. Without loss of generality, we normalize the distribution of ξ^i, which has mean equal to one. As we detail in Section V.A, we calibrate the parameters as $g^{\mathrm{S}} < 0 < g^{\mathrm{W}}$, and the interval of ξ as [0,2]. Such calibration allows our model to reproduce a monotonically increasing pattern of firms' current profitability (ROA) and a flat pattern of firms' future ROA, consistent with our data.

Our setup together with its calibrated parameters has two implications. First, because $g^{\mathrm{S}} < g^{\mathrm{W}}$ and ξ^i has unit mean, an environmental policy change from the weak- to the strong-regulation regime triggers an adverse effect on average profitability in the economy.

Second, the parameter ξ^i governs the heterogeneous levels of exposure of firms' profitability with respect to regime change risks across firms with different levels of emission intensity. Suppose that there are two firms: a high-emission firm (i.e., ξ^H) and a low-emission firm (i.e., ξ^L, such that $\xi^L < \xi^H$). Owing to lower abatement costs under the weak regime, a high-emission firm's average profitability is higher than that of a low-emission firm by the magnitude of $g^{\mathrm{W}}(\xi^H - \xi^L)$. This assumption is consistent with the empirical evidence we present in Section III.B of our main paper: high-emission firms enjoy higher current ROA than their low-emission counterparts, as they take on fewer costs of pollution abatement and environmental recovery. In stark contrast, because $g^{\mathrm{S}} < 0$, high-emission firms' average profitability drops more than that of low-emission firms under the strong-regulation regime. We present supportive evidence for this assumption in Section V.B of our main paper. In particular, we show that although high-emission firms' current ROA is higher, their average future ROA is almost the same as that of their low-emission counterparts. This implies that high-emission firms' ROA tends to be more negatively affected than the ROA of low-emission firms when the strong -regulation regime is enacted with some positive probability. As another piece of suggestive evidence, in Section V.B of our main paper, we show that upon the arrival of a policy change shock that increases the perceived likelihood of a regime shift, high-emission firms' future ROA drops more than the ROA of low-emission firms. As we discuss below, the cross-sectional dispersion in firms' emission intensity, ξ^is, by the above assumption, serves as a crucial force driving heterogeneous firms' exposure to aggregate regime changes and therefore determining different risk premia across emission-sorted portfolios in equilibrium.

Debt Financing and Leverage. In this economy, we allow firm i to raise debt financing D_t^i. For parsimony, we assume that firm i's debt-to-equity ratio is $\iota_{i,t} = \nu_i \iota$, where ι denotes a constant aggregate debt-to-equity ratio while ν_i captures firm heterogeneity in debt financing. To capture the impact of an environmental policy change on firms' debt financing, we assume that ν_i follows

$$\nu_i = \begin{cases} 1 & \text{for } t \leq \tau \\ 1 & \text{for } t > \tau \text{ if no policy regime shift occurs} \\ f(\xi_i) & \text{for } t > \tau \text{ if a policy regime shift occurs.} \end{cases} \tag{IA.79}$$

Before a change in environmental regulatory regime, all firms' debt-to-equity ratios are the same and equal to their aggregate counterpart. However, firms with different emission intensity exhibit different sensitivities of debt financing with respect to a regime shift, as characterized by $f(\xi_i)$. We assume that

$$f(\xi_i) = (1 - \theta) + \theta \xi_i, 0 < \theta \leq 1. \tag{IA.80}$$

Note that ξ_i follows a uniform distribution on the interval $[0, 2]$ with unit mean. Therefore, it is easy to prove that according to equation (IA.80), ν_i also follows a uniform distribution over the interval $[1 - \theta, 1 + \theta]$ with the same unit mean. This implies that policy regime switches do not change the average debt-to-equity ratio of the economy. However, the dependence of $f(\xi_i)$ on ξ_i with a coefficient of θ captures heterogeneous sensitivities of debt financing to a regime shift across firms with different emission intensity. In particular, a positive θ implies that high-emission (i.e., $\xi_i > 1$) firms' debt-to-equity ratio increases (i.e., $\nu_i > 1$), while the ratio of low-emission firms (i.e., $\xi_i < 1$) decreases (i.e., $\nu_i < 1$) after a shift to the strong-regulation regime. The intuition for this setting is that high-emission firms perceive a higher need for cash due to the regime change and therefore use more debt as precautionary savings. The setup in equation (IA.80) is consistent with our empirical evidence that there is a monotonically increasing pattern of firms' future leverage across emission-sorted portfolios, which we show in Section IV.V.[28]

We further assume that an all-equity payout, which is equal to the profit net of the payout to debt holders, is retained and reinvested, so that firm i's book equity dynamics dB_t^i evolve according to

[28]Besides the quantity of debt financing, Chava (2014) and Heinkel, Kraus, and Zechner (2001) show a negative impact of environmental concerns on a firm's cost of capital with respect to both equity and debt financing, which we do not model here.

$$
\begin{aligned}
dB_t^i &= \underbrace{(B_t^i + D_t^i)d\Pi_t^i}_{\text{Profit}} - \underbrace{\Big[\overbrace{e^{\int_{t-\Delta}^t rds} D_{t-\Delta}^i}^{\text{Existing debt repayment}} - \overbrace{D_t^i}^{\text{New debt issuance}}\Big]}_{\text{Net debt payout}}, \\
&\approx B_t^i\big[(1+\nu_i\iota)d\Pi_t^i - r\nu_i\iota dt\big], \\
&= B_t^i d\Psi_t^i, \qquad \text{(IA.81)}
\end{aligned}
$$

where $d\Psi_t^i$ is firm i's payout over book equity by subtracting firm i's profit by its payout to debt holders.[29] That is, the last equality implies that the equity payout ratio is

$$d\Psi_t^i = (1+\nu_i\iota)d\Pi_t^i - r\nu_i\iota dt. \qquad \text{(IA.82)}$$

The firms are owned by a continuum of identical households who maximize expected utility derived from their terminal wealth. For all $j \in [0,1]$, investor j's utility function is given by

$$U(W_T^j) = \frac{(W_T^j)^{1-\gamma}}{1-\gamma}, \qquad \text{(IA.83)}$$

where W_T^j is investor j's wealth at time T, and $\gamma > 1$ is the coefficient of relative risk aversion. At time 0, all investors are equally endowed with the same shares of firm stocks. Stocks pay dividends at time T.[30] Households observe whether a regime shift occurs at time τ.

When making its policy decision at time τ, the government maximizes the same objective function as households, except that it internalizes the negative externalities of pollution as the environmental cost $\Phi(c)$ if the economy is under the weak environmental regulation regime. The government commits to a change in environmental policy only if the government's expected utility under the strong-regulation regime is higher than when under the weak-regulation regime. Specifically, the government solves the optimization problem

$$\max\left\{ \mathrm{E}_\tau\left[\frac{\Phi(c)W_T^{1-\gamma}}{1-\gamma}\middle|\mathrm{W}\right], \mathrm{E}_\tau\left[\frac{W_T^{1-\gamma}}{1-\gamma}\middle|\mathrm{S}\right]\right\}, \qquad \text{(IA.84)}$$

where $W_T = B_T = \int_0^1 B_T^i di$ is the final value of aggregate book equity, and $\Phi(c) = 1 + e^c$ is the *environmental cost* if the weak-regulation regime is retained. We refer to $\Phi(c) > 1$ as the cost to society, since, given $\gamma > 1$, a higher value of $\Phi(c)$ translates into lower utility since $W_T^{1-\gamma}/(1-\gamma) < 0$. The value of c is randomly drawn at time τ from a normal distribution as below, which implies that

[29] We allow firms to borrow at a constant interest rate r.

[30] No dividends are paid before time T because households' preferences do not involve intermediate consumption. Firms in our model reinvest all of their earnings net of payout to debt holders, as mentioned earlier.

$E[e^c] = 1$,

$$c \sim Normal\left(-\frac{1}{2}\sigma_c^2, \sigma_c^2\right), \tag{IA.85}$$

where c is independent of the Brownian motions in equation (IA.77). As soon as the value of c is revealed to all agents at time τ, the government uses this value to make its environmental policy decision. We refer to σ_c as *regime shift uncertainty*. Due to the uncertainty about environment costs before time τ, stock prices respond to environmental cost signals, as we show in Section III.C of our main paper.

B. *Learning about Environmental Costs*

The environmental cost c is unknown to all agents until time τ. At time $t < \tau$, agents start to learn about c by observing unbiased signals. We model these signals as the true value of signals plus noise, which takes the following form in continuous time:

$$ds_t = cdt + \eta dZ_t^c. \tag{IA.86}$$

The signal ds_t is assumed to be independent of other shocks in the economy. We refer to these shocks as environmental cost signals, and note that they capture the steady flow of news related to environmental issues that are of concern to both the public media and regulatory authorities. Combining the signals in equation (IA.86) with the prior distribution in equation (IA.85), we obtain the posterior distribution of c at any time $t < \tau$,

$$c \sim Normal(\hat{c}_t, \hat{\sigma}_{c,t}^2), \tag{IA.87}$$

where the posterior mean and variance evolve according to

$$d\hat{c}_t = \hat{\sigma}_{c,t}^2 d\hat{Z}_t^c, \tag{IA.88}$$

$$\hat{\sigma}_{c,t}^2 = \frac{1}{\frac{1}{\sigma_c^2} + t}. \tag{IA.89}$$

Equation (IA.86) shows that agents' beliefs about c are driven by the Brownian motion shocks $d\hat{Z}_t^c$, which reflect the differences between the cost signals ds_t and their expectations ($d\hat{Z}_t^c = ds_t - \mathrm{E}_t[ds_t]$). Since the cost signals are independent of all *fundamental* shocks in the economy (i.e., dZ_t and dZ_t^i), the innovations $d\hat{Z}_t^c$ represent signal shocks to the true value of environmental costs. These shocks shape agents' beliefs about which environmental policy is likely to be adopted in the future, above and beyond the effect of fundamental economic shocks. We refer to such signal shocks as *regime change risks*. Below, we emphasize that these shocks command a risk premium in equilibrium. Moreover, since firms with different emission intensity have heterogeneous levels of exposure to a regime shift, they exhibit different risk compensations with respect to regime change risks.

From the modelling perspective, although our model builds on Pástor and Veronesi (2012, 2013) in specifying the change of policy regimes, it also exhibits three major differences. The most prominent difference is the role of debt financing, which is absent in Pástor and Veronesi (2012, 2013). As we further show in Corollaries IA.2 and IA.3, the regime-shift channel in debt financing amplifies the emission-return relation.

Second, we do not introduce policy impact uncertainty, while Pástor and Veronesi (2012, 2013) explicitly assume that agents must learn about the policy impact g. In our model, we assume that the policy impacts g^W and g^S for two policy regimes are known to all agents, and we calibrate them based on empirical relations between firms' emission intensity and their current and future profitability (ROA), as we show in Table VII of our main paper and discuss in Section IV.V. Whether to include impact uncertainty plays a crucial role in determining the sign on the market price of policy regime shift risk. In our model, we assume $g^S < 0 < g^W$, which implies that, due to higher abatement costs, a policy change from the weak- to the strong-regulatory regime has an adverse effect on average profitability in the economy. This effect corresponds to a high-marginal utility state of a representative household. That is, the market price of a positive regime change shock, which increases agents' perceived probability that a strong regime is adopted, is negative. In contrast, the market price of policy uncertainty risk can switch signs in Pástor and Veronesi (2012, 2013), depending on the relative magnitudes of the posterior $\hat{g}_t$ for old versus new policies.

Third, we allow agents to learn about the environmental cost c before time τ. Learning about c introduces policy regime change shocks to the economy, which plays a critical role in explaining the pollution premium in the cross-section. Pástor and Veronesi (2012) do not have this channel. Although Pástor and Veronesi (2013) introduce a "seemingly" observationally equivalent learning channel for c, which they use to capture random political costs, we emphasize that, from an economics perspective, these two costs are very different. In our setup, the government is benevolent and acts as a social planner, considering environment costs in the form of negative externalities of emissions when making policy choices. In Pástor and Veronesi (2013), in contrast, such political costs create a wedge between a "quasi-benevolent" government and the social planner.

In addition to these modelling differences, the focus of our paper differs significantly from Pástor and Veronesi (2012, 2013). Pástor and Veronesi (2012) emphasize the announcement returns associated with policy changes, whereas Pástor and Veronesi (2013) analyze the risk premium of the aggregate equity market and its time-series fluctuation induced by political uncertainty. Our work is distinct, because, with both our model and empirical tests, we emphasize that firms' heterogeneous levels of exposure to regime change risks translate into cross-sectional dispersion in expected returns across firms with different levels of emission intensity.

C. Optimal Changes in Environmental Regime Changes

After a period of learning about c, the government decides whether to change policy regime at time τ. If the government changes regime, then the value of g changes from g^{W} to g^{S}, and firms' debt-to-equity ratios change from ι to $f(\xi_i)\iota$. According to equation (IA.82), the government changes policy regime if and only if

$$\mathrm{E}_\tau\left[\frac{W_T^{1-\gamma}}{1-\gamma}\middle|\mathrm{S}\right] > \mathrm{E}_\tau\left[\frac{\Phi(c)W_T^{1-\gamma}}{1-\gamma}\middle|\mathrm{W}\right]. \tag{IA.90}$$

Since the regime shift permanently affects future profitability and leverage ratios, the two expectations in equation (IA.90) are determined by different stochastic processes for aggregate capital $B_T = \int_0^1 B_T^i di$.[31] We show the aggregate capital at time T in the following lemma.

LEMMA IA.3: The aggregate capital at time T, $B_T = \int_0^1 B_T^i di$, is given by

$$B_T = \begin{cases} B_\tau e^{[(1+\iota)(\mu+g^{\mathrm{S}})-r\iota](T-\tau)-\frac{1}{2}(1+\iota)^2\sigma^2(T-\tau)+(1+\iota)\sigma(Z_T-Z_\tau)} & \text{if a regime occurs} \\ B_\tau e^{[(1+\iota)(\mu+g^{\mathrm{W}})-r\iota](T-\tau)-\frac{1}{2}(1+\iota)^2\sigma^2(T-\tau)+(1+\iota)\sigma(Z_T-Z_\tau)} & \text{if a regime does not occur.} \end{cases} \tag{IA.91}$$

Proof: See the Proof of Lemma IA.3 in Section VI.A.

Plugging aggregate capital in equation (IA.91) into equation (IA.90), the inequality can be further simplified and provides a rule for the policy regime shift, as we show in the following proposition.

PROPOSITION IA.3: A regulation regime shift occurs at time τ if and only if

$$\underline{c}(\tau) < c, \tag{IA.92}$$

where

$$\underline{c}(\tau) \equiv \log\left\{e^{(\gamma-1)(1+\iota)(g^{\mathrm{W}}-g^{\mathrm{S}})(T-\tau)} - 1\right\}. \tag{IA.93}$$

The probability of the policy regime shift at $\tau-$, $p_{\tau-}$, is given by

$$p_{\tau-} = 1 - Normal(\underline{c}(\tau); \hat{c}_{\tau-}, \hat{\sigma}^2_{c,\tau-}), \tag{IA.94}$$

where $Normal(x; \hat{c}_{\tau-}, \hat{\sigma}^2_{c,\tau-})$ denotes the cumulative density function (c.d.f.) of a normal distribution with mean $\hat{c}_{\tau-}$ and variance $\hat{\sigma}^2_{c,\tau-}$.
Proof: See the Proof of Proposition IA.3 in Section VI.B.

The decision with respect to a policy regime shift follows a simple cutoff rule: the government considers a regime change if the true environmental cost, c, revealed at time τ, exceeds a given threshold, $\underline{c}(\tau)$. Two observations on the threshold stand out, as in equation (IA.93). First, given $\gamma > 1$, a higher γ implies that households are more averse to a change to the strong-regulation regime

[31] At the terminal time T, firms no longer borrow, and hence, a firm's book value of equity is equal to the amount of capital.

with negative g^{S}. As a result, the threshold $\underline{c}(\tau)$ becomes higher, suggesting a lower probability of shifting to the strong regime. Second, the threshold $\underline{c}(\tau)$ depends on the difference between g^{W} and g^{S}. A larger difference indicates a more costly transition from the weak to the strong regulatory regime when aggregate profitability suffers a permanent decrease. Such an unfavorable economic consequence attenuates the government's incentive to switch to the strong environmental regime. We therefore expect a lower likelihood for an environmental policy regime shift.

Before time τ (i.e., $\tau-$), agents face uncertainty about the government's action at time τ because they do not observe the environment cost c. From Proposition IA.3, we derive the probabilities of switching to the strong-regulation regime as perceived at any time $t < \tau$.

COROLLARY IA.1: $p_{\tau|t}$ denotes agents' time-t perceived probability of the policy regime shift at time τ conditional on information at time t:

$$p_{\tau-|t} = 1 - Normal(\underline{c}(\tau); \hat{c}_t, \hat{\sigma}^2_{c,t}), \tag{IA.95}$$

where $Normal(x; \hat{c}_t, \hat{\sigma}^2_{c,t})$ denotes the c.d.f. of a normal distribution with mean $\hat{c}_t$ and variance $\hat{\sigma}^2_{c,t}$.
Proof: See the Proof of Corollary IA.1 in Section VI.C.

The intuition behind Corollary IA.1 is as follows. The arrival of a positive regime change shock $d\hat{Z}^c_t$ updates agents' beliefs in terms of the environmental cost (i.e., the posterior mean $\hat{c}_t$) and in turn affects the perceived probability of a policy regime shift from the weak to the strong regulatory regime. Corollary IA.1 provides testable implications for our empirical analysis in Section IV of our main paper, where we use the growth in civil litigation as a proxy for regime shift shocks, and we show that such shocks increase the perceived probability of a regime shift and lead to a negative change in asset prices. However, Corollary IA.1 is consistent with Section III.C of our main paper: upon Trump's U.S. presidential election victory that serves as a negative regime change shock, the perceived probability is revised downwards. Consistent with our model, we show that high-emission firms' stock prices react more positively to these events than do price of low-emission firms.

D. Asset Pricing Implications

In this section, we study the asset pricing implications of regime change risk. First, we show the impact of regime change risk on the state price density. Second, we show how stock prices depend on fundamental shocks and regime change shocks. Finally, we decompose firms' risk premia into risk compensations to fundamental shocks and regime change shocks, and note that the heterogeneity in firms' emission intensity translates into the cross-sectional difference in expected stock returns with respect to regime change risk.

Firm i's stock represents a claim on firm i's liquidating dividend at time T, which is equal to B^i_T. Investors' total wealth at time T is equal to $B_T = \int_0^1 B^i_T di$. Stock prices adjust such that households hold all of a firm's stock. In addition to stocks, there is a zero-coupon bond in zero net supply, which yields unit payoff at time T with certainty. We use this risk-free bond as the numeraire.[32] Under the assumption of market completeness, standard arguments imply that the state price density is uniquely given by

$$\pi_t = \frac{1}{\kappa}\mathrm{E}_t\big[B_T^{-\gamma}\big], \tag{IA.96}$$

where κ is the Lagrange multiplier from the utility maximization problem of the representative household. The market value of stock i is given by the present value of firm i's terminal book equity at T:

$$M_t^i = \mathrm{E}_t\Big[\frac{\pi_T}{\pi_t}B_T^i\Big]. \tag{IA.97}$$

D.1. State Price Density

Our main focus is on the response of stock prices before the regime shift uncertainty is resolved at time τ. Before time τ, agents learn about the environmental cost under the weak regulation. This learning generates stochastic variations in the posterior mean of c, according to equation (IA.88), and the posterior mean represents a stochastic state variable that affects asset prices before time τ. In contrast, the posterior variance of c varies deterministically over time as in equation (IA.89). We first determine the state price density in the following proposition.

PROPOSITION IA.4: Before the resolution of the regime shift (i.e., $t < \tau$), the state price density is given by:

$$\pi_t = B_t^{-\gamma}\Omega_t, \tag{IA.98}$$

where the functional form of Ω_t refers to equation (IA.153).
Proof: See the Proof of Proposition IA.4 in Section VI.D.

The dynamics of the state price density π_t are essential for understanding the source of risks in this economy. An application of Ito's Lemma to π_t determines the SDF in Proposition IA.5.

PROPOSITION IA.5: The SDF follows the process

$$\frac{d\pi_t}{\pi_t} - E_t\left[\frac{d\pi_t}{\pi_t}\right] = -\lambda dZ_t - \lambda_{c,t}d\hat{Z}_t^c, \tag{IA.99}$$

where the price of risk for fundamental shocks is given by

$$\lambda = (1+\iota)\gamma\sigma, \tag{IA.100}$$

and the price of risk for regime change shocks is given by

$$\lambda_{c,t} = \frac{1}{\Omega_t}\frac{\partial\Omega_t}{\partial\hat{c}_t}\hat{\sigma}_{c,t}^2 < 0. \tag{IA.101}$$

[32] This assumption is equivalent to assuming a risk-free rate of zero. Such an assumption is innocuous because, without intermediate consumption, there is no intertemporal consumption choice that would clearly identify the interest rate. This modeling choice ensures that interest rate fluctuations do not drive our results.

Proof: See the Proof of Proposition IA.5 in Section VI.E.

Equation (IA.99) shows that the prices of risk λ and $\lambda_{c,t}$ measure the sensitivity of the SDF with respect to fundamental shocks and regime change shocks. Fundamental shocks are represented by the Brownian motion dZ_t, which drives the aggregate fundamentals (profitability) of the economy. The first term of the SDF shows that fundamental shocks amplify the SDF due to the financial leverage effect. The second type of shock consists of regime change shocks. Although unrelated to fundamental shocks (i.e., $dZ_t \cdot d\hat{Z}_{c,t} = 0$), policy change shocks affect expected utility by affecting the perceived probability of a regime shift. These shocks are thus priced. Equation (IA.101) indicates that regime change shocks trigger a larger effect on the SDF when the sensitivity of marginal utility to variation in $\hat{c}_t$ is larger (i.e., $\partial\Omega_t/\partial\hat{c}_t$ is larger) and when the posterior variance $\hat{\sigma}_{c,t}$ is larger. As we prove in Section VI.E, the sign of $\lambda_{c,t}$ is negative. Upon a positive regime change shock, both the marginal value of wealth and the state price of density increase. Regime change shocks therefore carry a negative price of risk.

D.2. Stock Prices and Risk Premia

In this section, we present analytical expressions for the level and dynamics of firm i's stock prices, respectively.

PROPOSITION IA.6: For time $t < \tau$, the stock price of firm i is given by

$$M_t^i = B_t^i \Theta_t^i, \tag{IA.102}$$

where the functional form of Θ_t^i refers to equation (IA.163).
Proof: See the Proof of Proposition IA.6 in Section VI.F.

The dynamics of firm i's stock prices are presented in the following proposition.

PROPOSITION IA.7: Firm i's realized stock returns at $t < \tau$ follow the process

$$\frac{dM_t^i}{M_t^i} - E_t\left[\frac{dM_t^i}{M_t^i}\right] = \sigma(1+\iota)dZ_t + \sigma_I(1+\iota)dZ_t^i + \beta_{M,t}^i d\hat{Z}_t^c, \tag{IA.103}$$

where firm i's risk exposures to fundamental and firm-specific shocks are $\sigma(1+\iota)$ and $\sigma_I(1+\iota)$, respectively, and the risk exposure to policy regime shift shocks is

$$\beta_{M,t}^i \equiv \frac{1}{\Theta_t^i}\frac{\partial\Theta_t^i}{\partial\hat{c}_t}\hat{\sigma}_{c,t}^2, \tag{IA.104}$$

where the functional form of $\beta_{M,t}^i$ refers to equation (IA.165).
Proof. See the Proof of Proposition IA.7 in Section VI.G.

In equation (IA.103), we show that firm i's realized stock return contains risk exposure to fundamental shocks, $\sigma(1+\iota)$, firm-specific shocks, $\sigma_I(1+\iota)$, and policy regime change shocks,

$\beta^i_{M,t}$. In these return exposures, the multiplier $(1+\iota)$ reflects the financial leverage effect. The first term on the RHS of equation (IA.103) shows that all firms in the economy face the same exposure $\sigma(1+\iota)$ to fundamental shocks. The second term in equation (IA.103) determines firm i's exposure to firm-specific shocks and is homogeneous to a constant $\sigma_I(1+\iota)$. More importantly, the third term $\beta^i_{M,t}$ captures firm i's exposure to regime change shocks, which alters the perceived likelihood of the government choosing to shift to the strong regulatory regime. Since firms' exposure to fundamental shocks are homogeneous, the emission-sorted portfolios' return spread in the cross-section is determined only by heterogeneous levels of exposure to regime change shocks, $\beta^i_{M,t}$, the properties of which are summarized by Corollary IA.2 below.

COROLLARY IA.2: If $\mu - r - \gamma(1+\iota)\sigma^2 \leq 0$, we can prove that firm i's exposure to policy regime shift shocks (i.e., the sensitivity of its stock market return to policy regime changes) has the following properties:

1. Level: There must exist a $\xi^* \in [0,1)$ such that $\beta^i_{M,t} < 0$ for $\xi^i > \xi^*$, and $\beta^i_{M,t} \geq 0$ for $0 \leq \xi^i \leq \xi^*$.
2. Slope: $\frac{\partial \beta^i_{M,t}}{\partial \xi^i} < 0$ for $\xi^i \geq 0$.

Proof: See the Proof or Proposition IA.2 in Section VI.H.

Corollary IA.2 gives two important implications regarding the level and slope of $\beta^i_{M,t}$ with respect to emission intensity ξ^i. First, for firms with emission intensity $\xi^i > \xi^*$, their valuations and stock returns respond negatively to regime change shocks (i.e. , $\beta^i_{M,t} < 0$), while for firms with low emission intensity (i,e.,$\xi^i \leq \xi^*$), their risk exposure turns out to be positive (i.e., $\beta^i_{M,t} \geq 0$). The intuition is as follows. For high-emission firms with ξ^i above their mean of one, two effects negatively impact firm valuations upon a change to the strong-regulation regime: a permanent drop in profitability and an increase in the leverage ratio that leads to higher borrowing costs and a higher discount rate. Therefore, an increase in the perceived probability of the regime shift adversely impacts firm valuations. In contrast, for low-emission firms with ξ^i below their mean, they tend to use less debt upon the regime shift, which lowers both their borrowing costs and their discount rates. This result therefore creates a dampening effect as opposed to a permanent drop in profitability. In particular, for firms with emission intensity lower than ξ^*, the dampening effect starts to dominate and even makes the regime shift value-enhancing (i.e., $\beta^i_{M,t} \geq 0$). In summary, our model can generate the intuitive implication that a change to the strong-regulation regime decreases valuations among high-emission firms but increases valuations among low-emission firms.

Second, we show that firm i's exposure to regime change risk, $\beta^i_{M,t}$, monotonically decreases in their emission intensity ξ^i for $\xi^i > 0$. This underlying difference in ξ^i plays an essential role in determining heterogeneous responses of stock returns to regime change shocks and in formalizing the cross-sectional difference in expected stock returns.

In equilibrium, risk premia are determined by the Euler equation that characterizes the co-variance of a firm's returns with the SDF. To characterize the risk compensation for fundamental shocks and regime change shocks, we derive the expressions for the conditional risk premium. In particular, firm i's expected stock return equals its risk premia

$$\begin{aligned} \mathrm{E}_t\left[\frac{dM_t^i}{M_t^i}\right] &= -\mathrm{Cov}_t\left(\frac{dM_t^i}{M_t^i}, \frac{d\pi_t}{\pi_t}\right) \\ &= \sigma(1+\iota)\lambda dt + \beta_{M,t}^i \lambda_{c,t} dt. \end{aligned} \tag{IA.105}$$

In equation (IA.105), we show that firm i's risk premia are determined by its exposure to fundamental shocks and regime change shocks. The first term captures the risk premium of fundamental shocks and is homogeneous across firms. The risk premium of regime change shocks is in the second term of equation (IA.105). As we show in Proposition IA.5 and Proposition IA.7, upon a positive regime change shock, stock prices decrease precisely when the marginal utility and thus the SDF is high. Taken together, agents demand positive compensation for their exposure to a regime change shock.

More importantly, the heterogeneous risk compensation for regime change risks is responsible for the cross-sectional difference in expected returns across firms with different levels of emission intensity. As shown in Corollary IA.2, firm i's risk exposure to the regime change shock (i.e., $\beta_{M,t}^i$) negatively depends on its emission intensity ξ_i. When the regulatory regime changes, stock valuations of high-emission firms with high ξ drop more than do those of low-emission firms. Heterogeneous levels of exposure to regime change risks translate into cross-sectional differences in expected stock returns. Our model predicts that high-emission firms require a higher expected return than do low-emission firms. This prediction is strongly supported by a statistically significant H-L return spread among emission-sorted portfolios. We refer to this return spread as the pollution premium.

E. Amplification Effect on Risk Premia

One prominent departure of our model from Pástor and Veronesi (2012, 2013) is that we explicitly allow firms to obtain debt financing, and, moreover, leverage ratios of firms with different levels of emission intensity are affected differently upon a change to the strong regulatory regime. In this section, we show that this additional channel of regime-shifting behavior of debt financing amplifies the pollution premium in the cross-section. To highlight this effect, we compare our benchmark model with an alternative economy in which firms' leverage ratios remain unchanged around a regime shift, which we refer to as a constant leverage economy.

COROLLARY IA.3: We compare our benchmark economy to the constant leverage economy. In the latter economy, firm i's exposure to policy regime shift shocks is denoted by $\overline{\beta}_{M,t}^i$ and the cross-sectional difference in exposures to policy regime shift shocks is denoted by $\frac{\partial \overline{\beta}_{M,t}^i}{\partial \xi^i}$. Comparison shows that if $\mu - r - \gamma(1+\iota)\sigma^2 \leq 0$, we have

$$\beta_{M,t}^i < \overline{\beta}_{M,t}^i < 0 \tag{IA.106}$$

for high-emission firms (i.e., $\xi^i > 1$) and

$$\overline{\beta}^i_{M,t} > \beta^i_{M,t} \tag{IA.107}$$

for low-emission firms (i.e., $\xi^i \leq 1$).
Proof: See the Proof of Corollary IA.3 in Section VI.I.

The interpretation of the proposition above is as follows. In our benchmark economy, upon a switch to the strong regulatory regime, high-emission firms immediately increase their leverage ratio while their low-emission counterparts reduce their leverage ratio. Higher leverage leads to an amplification effect that makes high-emission firms' valuations become more sensitive to regime change shocks, as reflected by a higher return beta elasticity in equation (IA.106). More importantly, the dispersion in risk exposure to regime change shocks between high- and low-emission firms (i.e., $\xi^H > 1$ and $\xi^L \leq 1$) is larger in our benchmark economy than that in the constant-leverage economy (i.e., $\beta^H_{M,t} - \beta^L_{M,t} < \overline{\beta}^H_{M,t} - \overline{\beta}^L_{M,t} < 0$).

V. Calibration and Quantitative Model Predictions

In this section, we calibrate our model at an annual frequency and evaluate its ability to replicate key moments of both real quantities and asset prices at the aggregate level. More importantly, we investigate its performance in terms of quantitatively accounting for key features of firm characteristics and producing a pollution premium in the cross-section. Finally, we discuss quantitative implications of key parameters through sensitivity analysis.

A. Calibration

In this section, we provide quantitative implications of two models. The benchmark model refers to the equity financing economy without debt financing in Section IV of our main paper. To highlight the role of the debt financing channel as an additional channel of the pollution-return relation, we also report the moments of the economy with regime-switching leverage in the extended model as described in Section VI.E.

Our benchmark model refers to the equity financing economy without debt financing. To highlight the role of the debt financing channel, we also report the moments of the economy with time-varying leverage in the extended model.

We present all parameters, which are grouped into four categories, in Table IA.15. We adopt the following calibration procedure to determine a set of sensible parameters. Parameters in the first category are based on either prior literature or a normalization argument. In particular, we set relative risk aversion γ to 3.5. The terminal time T is calibrated to be 10, roughly matching average Compustat firm age of 10 years in our sample. The sample path can be evenly split into two parts when regime shifts occur at the middle $\tau = 5$ between 0 and T, without a loss of generality. The borrowing rate r is set to 0.08, the Baa corporate bond yield.

The second category of parameters include those that determine the first and second moments of firm profitability. In our model, ξ^i measures the sensitivities of the firm i's profitability and leverage ratio to the environmental regulation regime, which depends linearly on firms' emission intensity. We assume that ξ^i follows a uniform distribution on the interval $[\xi^{min}, \xi^{max}]$. Without loss of generality, we normalize the mean of ξ^i to one, which implies that $\frac{\xi^{min}+\xi^{max}}{2} = 1$. Together with this condition, we use three moments with respect to firms' current profitability (ROA) to jointly determine four parameters regarding firms' profitability, $\{\xi^{min}, \xi^{max}, \mu, g^W\}$. In particular, we use $\mu+g^W$, $\mu+\xi^{min}g^W$, and $\mu+\xi^{max}g^W$ to match the average ROA of all firms and of firms in the lowest and highest emission-intensity quintiles, respectively. Furthermore, since the parameter g^S governs the impact of environment policy under the strong regulation, we use the difference in average future ROA between high-emission and low-emission firms, denoted by $j = H, L$, respectively, to identify this parameter. Given an unconditional probability of a regime shift, p, calibrated separately below, the model-implied average future (or long-term) ROA can be calculated as

$$ROA_j^{LT} = p(\mu + \xi^j g^S) + (1 - p)(\mu + \xi^j g^W), j = H, L, \quad \text{(IA.108)}$$

where $\xi^H = \xi^{max}$ and $\xi^L = \xi^{min}$. In the data, we calculate firms' future ROA as the average ROA from year $t + 6$ to $t + 10$, consistent with our model.

Panel A of Table IA.17 reports the empirical moments of firm characteristics for emission-sorted portfolios. The calibration procedure above results in the following parameter values: $\xi^{min} = 0$, $\xi^{max} = 2$, $\mu = 0.08$, $g^W = 0.015$, and $g^S = -0.025$. Two observations stand out. First, we empirically show a monotonically increasing pattern of current ROA among emission-sorted portfolios, which leads us to calibrate a positive g^W. This confirms our model assumption that, under weak regulation, the current profitability of high-emission firms is higher than that of low-emission firms, due to cost savings from not investing in emission abatement and environmental recovery in the short run. This assumption is also supported by regression-based evidence that we discuss in Section III.B of our main paper. Second, we find that, despite an increasing pattern of current ROA, firms' future ROA displays an almost flat pattern across emission-sorted portfolios. Mathematically, given $ROA_H^{LT} = ROA_L^{LT}$, from equation (IA.109), we can infer the parameter g^S to be negative, since $g^S = -\frac{(1-p)g^W}{p}$. The implied negative g^S again supports our assumption that, upon switching to strong regulation, firms' average profitability declines permanently, and high-emission firms' profitability decreases more than that of low-emission firms due to higher abatement costs.

We further calibrate parameters σ and σ_I, which corresponds to the second moments of firm profitability. The volatility of aggregate shocks to firms' ROA, σ, is set to match its empirical counterpart of 0.085. The volatility of firm-specific profitability shocks σ_I is calibrated to 0.05, in line with Pástor and Veronesi (2012, 2013).

The next parameter of interest is the learning parameter (i.e., the volatility of the prior distribution of environmental costs, σ_c). This parameter is critical for determining the unconditional probability of regime shifts, and is referred to as capturing regime shift uncertainty. We calibrate this parameter to generate an unconditional probability of a regime switch of 1/3 in the benchmark model (i.e., $p = 1/3$).[33]

The last set of parameters comprises those that determine firms' leverage ratio for the extended model.[34] We calibrate the parameter ι to broadly match firms' average leverage ratio of 0.23 in our sample. Since the parameter θ governs the heterogeneous effect on the leverage ratios of firms with different levels of emission intensity upon a change to the strong regulatory regime, we use the difference in average future (or long-term) leverage between high-emission and low-emission firms to identify this parameter. Given an unconditional probability of a regime shift, p, calibrated separately as above, the model-implied average future debt-to-equity ratio can be calculated as

$$\left(\frac{D}{B}\right)_j^{LT} = pf(\xi^j)\iota + (1-p)\iota, j = H, L, \tag{IA.109}$$

where $\xi^H = \xi^{max}$ and $\xi^L = \xi^{min}$.

From Panel A of Table IA.17, we find that firms' long-term leverage, calculated as the average leverage from year $t+6$ to $t+10$ consistent with our model, displays a monotonically increasing pattern across emission-sorted portfolios. Mathematically, based on equation (IA.109), we can infer the parameter θ using $\theta = \frac{(\frac{D}{B})_H^{LT} - (\frac{D}{B})_L^{LT}}{p(\xi^H - \xi^L)\iota}$. Calibrated in this way, we determine $\theta = 0.7$. A positive θ strongly supports our model assumption that the financial leverage of high-emission firms increases more than that of low-emission firms, upon a change to the strong regulatory regime. As we emphasize in Section IV.E, this regime-shift channel in firms' debt financing has an amplification effect on the pollution premium, and represents a prominent departure of our model from Pástor and Veronesi (2012, 2013).

B. *Model Quantitative Performance*

We now turn to the quantitative performance of the model at the aggregate level. We show that our benchmark model is broadly consistent with key empirical features of real quantities (i.e., profitability and the leverage ratio) and asset prices (i.e., the book-to-market ratio and stock returns). Table IA.16 reports the model-simulated moments and compares them with their counterparts in the data.

Three observations are worth noting. First, our benchmark model well matches both first and second moments of ROA at the aggregate level, features a high equity premium (5.74%) and associated volatility (14.55%), and generates an average book-to-market ratio in line with its data

[33] In the model, the conditional probability corresponds to $p_{\tau|0}$ as defined in Corollary IA.1.
[34] Note that, in our model, we use ι to denote the debt-to-equity ratio. Financial leverage, defined as $\iota/(1+\iota)$, is monotonically increasing in the debt-to-equity ratio, ι.

counterpart.[35] Second, considering time-varying leverage as in the extended model, the debt financing economy produces a higher equity premium (8.14%) and stock market volatility (16.97%). Lastly, we decompose the equity risk premium into risk compensation to fundamental shocks and to regime change shocks. In the benchmark model, out of a total equity premium of 5.74%, these two shocks contribute 3.29% and 2.45%, respectively. That is, the fundamental shocks still contribute the majority of the overall equity premium (57%). However, as we show in the next table, regime change risk is responsible for the pollution premium in the cross-section.

Next, we study the implications of our model for the cross-section of emission-sorted portfolios. We simulate firms from the model and conduct the same emission-based portfolio sorting procedure based on emission intensity ξ^i. Table IA.17 reports the average returns of the sorted portfolios along with several other characteristics from the data (Panel A) and from simulations based on the benchmark model (Panel B) and the extended model (Panel C) .

We first find that our benchmark model (Panel B) generates a pollution premium (i.e., the return spread in the H-L portfolio) as sizable as 3.99%, which is comparable to the 4.42% that we obtain from our data in Panel A. Our benchmark model generates an upward-sloping pattern of current ROA but a flat pattern of future ROA, consistent with the data. As we discuss in our calibration, this implication is a result of our model assumptions that $g^W > 0$ and $g^S < 0$, and is strongly supported by the evidence. Furthermore, our extended model produces a flat pattern of current leverage but a monotonically increasing pattern of the long-term leverage ratio. Our key model assumption on the regime-shift behavior of firms' debt financing (i.e., $\theta > 0$) is responsible for this model implication, which is consistent with our data.

Moreover, as noted in results of Panel B, we observe a significant increase of our model's predicted pollution premium by about 90% as compared with our benchmark model, from 3.99% to 7.58%. This highlights the importance of a regime-shift behavior in firms' debt financing as an amplification channel on the pollution premium, which highlights a prominent difference of our model with respect to Pástor and Veronesi (2012, 2013).

C. Sensitivity Analysis

In this section, we discuss the sensitivity of our quantitative results to several vital parameters in the extended model. In the interest of space, we only discuss the moments that are sensitive to the respective parameter in Table IA.18.

Risk Aversion (γ). The parameter γ determines the price of risk for fundamental shocks and the probability of the policy regime shift. We vary this parameter by $\pm 10\%$ around the benchmark value of 3.5 from Table IA.15 and make the following observations.

[35] In the benchmark model, asset prices reported in Tables IA.16 and IA.17 are levered with a constant leverage ratio equal to the average leverage ratio in the extended model following the standard asset pricing literature (e.g., Bansal and Yaron (2004)), so that quantitative results are comparable to the extended model with debt financing.

First, according to equation (IA.100), the price of risk for fundamental shocks is constant and depends only on the risk aversion γ and the volatility of fundamental shocks σ. As Panel A of Table IA.18 shows, higher risk aversion increases the equity risk premium attributed to fundamental shocks. Second, an increase in risk aversion raises the threshold for the government to change the regulatory regime and leads to a lower probability of a policy regime change. Finally, higher risk aversion amplifies both the price of risk for and risk exposure to signal shocks, which indirectly increases the equity risk premium attributed to signal shocks and the H-L return spread in the cross-section.

Difference in the Conditional Mean of Profitability (g^W-g^S). We vary the difference in the conditional mean of profitability (g^{W}-g^{S}) by $\pm 10\%$. A larger g^{W}-g^{S} implies a substantial drop in aggregate wealth when the regulation shifts from the weak to the strong regime, and therefore implies a more negative impact on the price of risk λ_c for signal shocks. According to equation (IA.101), the price of risk λ_c for signal shocks is negative when signal shocks are positively correlated with households' marginal wealth. Therefore, a higher value of g^{W}-g^{S} eventually increases the equity risk premium attributed to signal shocks. In contrast, the equity risk premium attributed to fundamental shocks remains unchanged in the third and fourth columns of Panel B. Second, a lower probability of a policy regime change is triggered by an increase in the difference in the conditional mean of profitability when the government decides whether to change the regulatory regime. Moreover, a larger difference leads to a larger dispersion in risk exposures to signal shocks across firms with different emission intensities. Hence, it amplifies the H-L return spread in the cross-section.

Volatility of the Prior Distribution of the Environmental Cost (σ_c). As shown in equation (IA.101), an increase in the value of σ_c generates the higher equity risk premium attributed to signal shocks by magnifying the price of risk λ_c. In contrast, the equity risk premium for fundamental shocks is totally unaffected as fundamental shocks are orthogonal to signal shocks. Moreover, a higher σ_c leads to higher risk exposure to signal shocks in the cross-section and increases the long-short portfolio sorted on emission intensity ξ^i.

Sensitivity of Debt Financing to Regime Shifts (θ). According to equation (IA.80), the parameter θ captures the impact of environmental regime changes on firms' debt financing distribution ν^i: $\nu^i \in [1-\theta, 1+\theta]$. Apparently, the distribution of ν^i has the same mean of one. The variation in θ leads to changes in the cross-sectional dispersion of ν^i but leaves the aggregate moments unchanged. As we can see in Panel D of Table IA.18, the first two moments in the aggregate equity premium remain unchanged when we vary the difference in θ. In contrast, larger variation in θ triggers larger dispersion in risk exposures to both fundamental and signal shocks across firms with different emission intensities. This result suggests an amplified H-L return spread in the cross-section. However, we document a marginal effect on the quantitative magnitude with respect to changes in the parameter θ.

VI. Mathematical Details of the Extended Model

A. Proof of Proposition Lemma IA.3

We consider an economy with a finite horizon $[0, T]$. A regime shift occurs at time τ, where $\tau \in (0, T)$, and where $\tau+$ denotes the timing immediately after a regime shift.

According to Lemma IA.3, the aggregate capital at time T, $B_T = \int_0^1 B_T^i di$, is given by

$$B_T = \begin{cases} B_\tau e^{[(1+\iota)(\mu+g^{\mathrm{S}})-r\iota](T-\tau)-\frac{1}{2}(1+\iota)^2\sigma^2(T-\tau)+(1+\iota)\sigma(Z_T-Z_\tau)} & \text{if a regime occurs} \\ B_\tau e^{[(1+\iota)(\mu+g^{\mathrm{W}})-r\iota](T-\tau)-\frac{1}{2}(1+\iota)^2\sigma^2(T-\tau)+(1+\iota)\sigma(Z_T-Z_\tau)} & \text{if a regime does not occur,} \end{cases} \tag{IA.110}$$

where $g \equiv g^{\mathrm{W}}$ when no policy regime shift occurs and $g \equiv g^{\mathrm{S}}$ when a policy regime shift does not occur.

From the capital growth equation $dB_t^i = B_t^i d\Psi_t^i$, where the stochastic process $d\Psi_t^i$ is given by equation (IA.82), we obtain the following expression for firm i's capital at time T:

$$B_T^i = \begin{cases} B_\tau^i e^{[(1+\nu^i\iota)(\mu+\xi^i g^{\mathrm{S}})-r\nu^i\iota](T-\tau)-\frac{1}{2}(1+\nu^i\iota)^2\sigma^2(T-\tau)-\frac{1}{2}(1+\nu^i\iota)^2\sigma_I^2(T-\tau)+(1+\nu^i\iota)\sigma(Z_T-Z_\tau)+(1+\nu^i\iota)\sigma_I(Z_T^i-Z_\tau^i)} \\ B_\tau^i e^{[(1+\iota)(\mu+\xi^i g^{\mathrm{W}})-r\iota](T-\tau)-\frac{1}{2}(1+\iota)^2\sigma^2(T-\tau)-\frac{1}{2}(1+\iota)^2\sigma_I^2(T-\tau)+(1+\iota)\sigma(Z_T-Z_\tau)+(1+\iota)\sigma_I(Z_T^i-Z_\tau^i)}, \end{cases} \tag{IA.111}$$

where $g \equiv g^{\mathrm{W}}$ when there is no policy regime shift and $g \equiv g^{\mathrm{S}}$ when there is a policy regime shift. When we aggregate capital across all firms, an application of the law of large numbers implies that ν^i and ξ^i converge to their cross-sectional mean of one. Therefore,

$$\begin{aligned} B_T &= \int B_T^i di \\ &= \begin{cases} \int B_\tau^i e^{[(1+\nu^i\iota)(\mu+\xi^i g^{\mathrm{S}})-r\nu^i\iota](T-\tau)-\frac{1}{2}(1+\nu^i\iota)^2\sigma^2(T-\tau)-\frac{1}{2}(1+\nu^i\iota)^2\sigma_I^2(T-\tau)+(1+\nu^i\iota)\sigma(Z_T-Z_\tau)+(1+\nu^i\iota)\sigma_I(Z_T^i-Z_\tau^i)} di \\ \int B_\tau^i e^{[(1+\iota)(\mu+\xi^i g^{\mathrm{W}})-r\iota](T-\tau)-\frac{1}{2}(1+\iota)^2\sigma^2(T-\tau)-\frac{1}{2}(1+\iota)^2\sigma_I^2(T-\tau)+(1+\iota)\sigma(Z_T-Z_\tau)+(1+\iota)\sigma_I(Z_T^i-Z_\tau^i)} di, \end{cases} \\ &\to \begin{cases} B_\tau e^{[(1+\iota)(\mu+g^{\mathrm{S}})-r\iota](T-\tau)-\frac{1}{2}(1+\iota)^2\sigma^2(T-\tau)+(1+\iota)\sigma(Z_T-Z_\tau)} \mathrm{E}^i\left[e^{-\frac{1}{2}(1+\iota)^2\sigma_I^2(T-\tau)+(1+\iota)\sigma_I(Z_T^i-Z_\tau^i)}\right] \\ B_\tau e^{[(1+\iota)(\mu+g^{\mathrm{W}})-r\iota](T-\tau)-\frac{1}{2}(1+\iota)^2\sigma^2(T-\tau)+(1+\iota)\sigma(Z_T-Z_\tau)} \mathrm{E}^i\left[e^{-\frac{1}{2}(1+\iota)^2\sigma_I^2(T-\tau)+(1+\iota)\sigma_I(Z_T^i-Z_\tau^i)}\right] \end{cases} \\ &= \begin{cases} B_\tau e^{[(1+\iota)(\mu+g^{\mathrm{S}})-r\iota](T-\tau)-\frac{1}{2}(1+\iota)^2\sigma^2(T-\tau)+(1+\iota)\sigma(Z_T-Z_\tau)} \\ B_\tau e^{[(1+\iota)(\mu+g^{\mathrm{W}})-r\iota](T-\tau)-\frac{1}{2}(1+\iota)^2\sigma^2(T-\tau)+(1+\iota)\sigma(Z_T-Z_\tau)} \end{cases} \end{aligned} \tag{IA.112}$$

where $\mathrm{E}^i[\cdot] = \int di$ is the cross-sectional expectation operator. The third equality in equation (IA.112) presents the independence of B_τ^i and $Z_T^i - Z_\tau^i$. The summation of B_τ^i is given by

$$\int B_\tau^i di = B_\tau, \tag{IA.113}$$

and the expectation $\mathrm{E}^i\left[e^{\sigma_1(Z^i_T - Z^i_\tau)}\right]$ follows the lognormal distribution.

B. Proof of Proposition IA.3

Using the market-clearing condition $W_T = B_T$, we can use equation (IA.91) to compute the expected utility at time T conditional on strong or weak regulation. The expectation under the weak-regulation regime includes the realization of the environmental cost,

$$\mathrm{E}_\tau\left[\frac{W_T^{1-\gamma}}{1-\gamma}\middle|\mathrm{S}\right] = \frac{B_\tau^{1-\gamma}}{1-\gamma} e^{(1-\gamma)[(1+\iota)(\mu+g^{\mathrm{S}})-r\iota](T-\tau)+\frac{1}{2}\gamma(\gamma+1)\sigma^2(T-\tau)} \tag{IA.114}$$

$$\mathrm{E}_\tau\left[\frac{W_T^{1-\gamma}}{1-\gamma}\middle|\mathrm{W}\right] = \frac{\Phi(c)B_\tau^{1-\gamma}}{1-\gamma} e^{(1-\gamma)[(1+\iota)(\mu+g^{\mathrm{W}})-r\iota](T-\tau)+\frac{1}{2}\gamma(\gamma+1)\sigma^2(T-\tau)}. \tag{IA.115}$$

The claim of the proposition follows immediately from the optimality condition,

$$\mathrm{E}_\tau\left[\frac{W_T^{1-\gamma}}{1-\gamma}\middle|\mathrm{S}\right] > \mathrm{E}_\tau\left[\frac{\Phi(c)W_T^{1-\gamma}}{1-\gamma}\middle|\mathrm{W}\right]. \tag{IA.116}$$

Therefore,

$$\frac{B_\tau^{1-\gamma}}{1-\gamma} e^{(1-\gamma)[(1+\iota)(\mu+g^{\mathrm{S}})-r\iota](T-\tau)+\frac{1}{2}\gamma(\gamma+1)\sigma^2(T-\tau)} > \frac{\Phi(c)B_\tau^{1-\gamma}}{1-\gamma} e^{(1-\gamma)[(1+\iota)(\mu+g^{\mathrm{W}})-r\iota](T-\tau)+\frac{1}{2}\gamma(\gamma+1)\sigma^2(T-\tau)}. \tag{IA.117}$$

We specify the functional form of $\Phi(c)$ as $1 + e^c$, and rearrange the inequality above to obtain

$$e^{(1-\gamma)(1+\iota)g^{\mathrm{S}}(T-\tau)} < \Phi(c)e^{(1-\gamma)(1+\iota)g^{\mathrm{W}}(T-\tau)} = (1+e^c)e^{(1-\gamma)(1+\iota)g^{\mathrm{W}}(T-\tau)} \tag{IA.118}$$

$$\begin{aligned} e^{(\gamma-1)(1+\iota)(g^{\mathrm{W}}-g^{\mathrm{S}})(T-\tau)} - 1 &< e^c \\ \log\left\{e^{(\gamma-1)(1+\iota)(g^{\mathrm{W}}-g^{\mathrm{S}})(T-\tau)} - 1\right\} &< c. \end{aligned} \tag{IA.119}$$

The threshold for a policy regime shift is then given by

$$\underline{c}(\tau) \equiv \log\left\{e^{(\gamma-1)(1+\iota)(g^{\mathrm{W}}-g^{\mathrm{S}})(T-\tau)} - 1\right\}. \tag{IA.120}$$

C. Proof of Corollary IA.1

We define $n(c; a, b)$ as the p.d.f. of a normal distribution with mean a and variance b. The p.d.f. conditional on information at time t, where $t \leq \tau-$, is given by

$$n(c; \hat{c}_t, \hat{\sigma}_t^2) = \int_{-\infty}^{\infty} n(c; \hat{c}_{\tau-}, \hat{\sigma}_{\tau-}^2)\, n(\hat{c}_{\tau-}; \hat{c}_t, \hat{\sigma}_t^2 - \hat{\sigma}_{\tau-}^2)\, d\hat{c}_{\tau-}. \tag{IA.121}$$

This follows from general properties of the normal distribution. Note that

$$
\begin{aligned}
c &= c - \hat{c}_{\tau-} + \hat{c}_{\tau-}, && \text{(IA.122)}\\
c - \hat{c}_{\tau-} \mid \mathcal{F}_{\tau-} &\sim Normal(0, \hat{\sigma}^2_{\tau-}), && \text{(IA.123)}\\
\hat{c}_{\tau-} \mid \mathcal{F}_t &\sim Normal(\hat{c}_t, \hat{\sigma}^2_t - \hat{\sigma}^2_\tau), && \text{(IA.124)}
\end{aligned}
$$

where $\mathcal{F}$ denotes the information set. Conditional on information at time t (i.e., $\mathcal{F}_t$), $\hat{c}_{\tau-}$ also follows a normal distribution. According to the dynamics of the posterior mean in equation (IA.88), the recursive expression is given by

$$
\hat{c}_{\tau-} = \hat{c}_t + \int_t^{\tau-} \hat{\sigma}^2_s dZ^c_s. \tag{IA.125}
$$

Therefore, the conditional expectation based on information at time t is given by

$$
\mathrm{E}_t[\hat{c}_{\tau-}] = \hat{c}_t, \tag{IA.126}
$$

and the variance by

$$
\begin{aligned}
\mathrm{E}_t[(\hat{c}_{\tau-} - \hat{c}_t)^2] &= \int_t^{\tau-} \left(\hat{\sigma}^2_s\right)^2 ds\\
&= \left.\frac{1}{\frac{1}{\sigma_c^2} + s}\right|_t^{\tau-} = \hat{\sigma}^2_t - \hat{\sigma}^2_{\tau-}. && \text{(IA.127)}
\end{aligned}
$$

Given the linearity of the expectation operator,

$$
\begin{aligned}
\mathrm{E}_t[c] &= \mathrm{E}_t[(c - \hat{c}_{\tau-}) + \hat{c}_{\tau-}] = \mathrm{E}_t[(c - \hat{c}_{\tau-})] + \mathrm{E}_t[\hat{c}_{\tau-}]\\
&= \mathrm{E}_t\big[\mathrm{E}_{\tau-}[(c - \hat{c}_{\tau-})]\big] + \mathrm{E}_t[\hat{c}_{\tau-}]\\
&= 0 + \hat{c}_t\\
&= \hat{c}_t. && \text{(IA.128)}
\end{aligned}
$$

We can also show that $c - \hat{c}_{\tau-}$ and $\hat{c}_{\tau-}$ are independent when two random variables are uncorrelated. The covariance is defined as

$$
\mathrm{Cov}_t[(c - \hat{c}_{\tau-}), \hat{c}_{\tau-}] = \mathrm{E}_t[(c - \hat{c}_{\tau-})\hat{c}_{\tau-}] - \mathrm{E}_t[(c - \hat{c}_{\tau-})]\mathrm{E}_t[\hat{c}_{\tau-}]. \tag{IA.129}
$$

Using the law of iterated expectations, the first term in the RHS of equation (IA.21) is

$$
\begin{aligned}
\mathrm{E}_t[(c - \hat{c}_{\tau-})\hat{c}_{\tau-}] &= \mathrm{E}_t\big[\mathrm{E}_{\tau-}[(c - \hat{c}_{\tau-})\hat{c}_{\tau-}]\big]\\
&= \mathrm{E}_t\big[\mathrm{E}_{\tau-}[(c - \hat{c}_{\tau-})]\hat{c}_{\tau-}\big]\\
&= 0, && \text{(IA.130)}
\end{aligned}
$$

and the second term in the RHS of equation (IA.21) is also equal to zero. Therefore, independence implies $\mathrm{Cov}_t[(c-\hat{c}_{\tau-}),\hat{c}_{\tau-}]=0$. As a result, the variance based on information at time t is given by

$$\begin{aligned}\mathrm{Var}_t[c] &= \mathrm{Var}_t[(c-\hat{c}_{\tau-})+\hat{c}_{\tau-}] = \mathrm{Var}_t[c-\hat{c}_{\tau-}]+\mathrm{Var}_t[\hat{c}_{\tau-}]+2\,\mathrm{Cov}_t[(c-\hat{c}_{\tau-}),\hat{c}_{\tau-}] \\ &= \hat{\sigma}^2_{\tau-}+(\hat{\sigma}^2_t-\hat{\sigma}^2_{\tau-})+0 \\ &= \hat{\sigma}^2_t. \end{aligned} \tag{IA.131}$$

Therefore, c follows a normal distribution conditional on information at time t

$$c \sim Normal(\hat{c}_t,\hat{\sigma}^2_t), \tag{IA.132}$$

and the probability of a regime shift at $\tau-$ is

$$p_{\tau-|t}=1-Normal(\underline{c}(\tau);\hat{c}_t,\hat{\sigma}^2_t). \tag{IA.133}$$

D. Proof of Proposition IA.4

Before turning to the proof of Proposition IA.4, we must prove the lemma below.

LEMMA IA.4: When a policy regime shift occurs at time τ, the market value of each firm i takes one of two values:

$$M^i_{\tau+}=\begin{cases} M^{\mathrm{S},i}_{\tau+}=B^i_\tau e^{[(1+\nu^i\iota)(\mu+\xi^i g^{\mathrm{S}})-r\nu^i\iota](T-\tau)-\gamma(1+\nu^i\iota)(1+\iota)\sigma^2(T-\tau)} & \text{if a regime shift occurs} \\ M^{\mathrm{W},i}_{\tau+}=B^i_\tau e^{[(1+\iota)(\mu+\xi^i g^{\mathrm{W}})-r\iota](T-\tau)-\gamma(1+\iota)^2\sigma^2(T-\tau)} & \text{if a regime shift does not occur,} \end{cases} \tag{IA.134}$$

where $\tau+$ is the timing immediately after a regime shift. Unconditionally, firm i's market value is given by

$$M^i_\tau=\mathrm{E}_\tau[M^i_{\tau+}]=p_\tau M^{\mathrm{S},i}_{\tau+}+(1-p_\tau)M^{\mathrm{W},i}_{\tau+}. \tag{IA.135}$$

Proof of Lemma IA.4:
The state price density is $\pi_t=\frac{1}{\kappa}\mathrm{E}_t\left[B_T^{-\gamma}\right]$. Its value, when a policy regime shift occurs at time τ, is given by

$$\begin{aligned}\pi_{\tau+} &= \kappa^{-1}B_\tau^{-\gamma}\mathrm{E}_{\tau+}\left[e^{-\gamma[(1+\iota)(\mu+g)-r\iota](T-\tau)+\frac{\gamma}{2}(1+\iota)^2\sigma^2(T-\tau)-\gamma(1+\iota)\sigma(Z_T-Z_\tau)}\right] \\ &= \begin{cases}\kappa^{-1}B_\tau^{-\gamma}\mathrm{E}_{\tau+}\left[e^{-\gamma[(1+\iota)(\mu+g^{\mathrm{S}})-r\iota](T-\tau)+\frac{\gamma}{2}(1+\iota)^2\sigma^2(T-\tau)-\gamma(1+\iota)\sigma(Z_T-Z_\tau)}\right] & \text{if a regime shift occurs} \\ \kappa^{-1}B_\tau^{-\gamma}\mathrm{E}_{\tau+}\left[e^{-\gamma[(1+\iota)(\mu+g^{\mathrm{W}})-r\iota](T-\tau)+\frac{\gamma}{2}(1+\iota)^2\sigma^2(T-\tau)-\gamma(1+\iota)\sigma(Z_T-Z_\tau)}\right] & \text{if a regime shift does not occurs}\end{cases} \\ &= \begin{cases}\pi^{\mathrm{S}}_{\tau+}=\kappa^{-1}B_\tau^{-\gamma}e^{-\gamma[(1+\iota)(\mu+g^{\mathrm{S}})-r\iota](T-\tau)+\frac{1}{2}\gamma(\gamma+1)(1+\iota)^2\sigma^2(T-\tau)} & \text{if a regime shift occurs} \\ \pi^{\mathrm{W}}_{\tau+}=\kappa^{-1}B_\tau^{-\gamma}e^{-\gamma[(1+\iota)(\mu+g^{\mathrm{W}})-r\iota](T-\tau)+\frac{1}{2}\gamma(\gamma+1)(1+\iota)^2\sigma^2(T-\tau)} & \text{if a regime shift does not occur,}\end{cases}\end{aligned} \tag{IA.136}$$

where we use the definition of equation (IA.91). We can infer the state price density at time τ,

$$\pi_\tau = \mathrm{E}_\tau[\pi_{\tau+}] = p_\tau \pi^{\mathrm{S}}_{\tau+} + (1-p_\tau)\pi^{\mathrm{W}}_{\tau+}, \tag{IA.137}$$

where p_τ is the probability of a policy change. Firm i's market value is given by

$$M^i_t = \mathrm{E}_t\left[\frac{\pi_T}{\pi_t} B^i_T\right]. \tag{IA.138}$$

After a policy regime shift at time τ, using the results of equation (IA.110) and (IA.136), we obtain

$$\begin{aligned}
\mathrm{E}_{\tau+}[\pi_T B^i_T \mid \mathrm{S}] &= \kappa^{-1}\mathrm{E}_{\tau+}[B_T^{-\gamma} B^i_T \mid \mathrm{S}], \\
&= \kappa^{-1} B_\tau^{-\gamma} B^i_\tau \\
&\quad \times \exp\left\{\begin{array}{l} -\gamma[(1+\iota)(\mu+g^{\mathrm{S}}) - r\iota](T-\tau) + [(1+\nu^i\iota)(\mu+\xi^i g^{\mathrm{S}}) - r\nu^i\iota](T-\tau) \\ +\frac{\gamma}{2}(1+\iota)^2\sigma^2(T-\tau) - \frac{1}{2}(1+\nu^i\iota)^2\sigma^2(T-\tau) \\ +\frac{1}{2}[(1+\nu^i\iota) - \gamma(1+\iota)]^2\sigma^2(T-\tau) \end{array}\right\}
\end{aligned} \tag{IA.139}$$

and

$$\begin{aligned}
\mathrm{E}_{\tau+}[\pi_T B^i_T \mid \mathrm{W}] &= \kappa^{-1} B_\tau^{-\gamma} B^i_\tau \\
&\quad \times \exp\left\{\begin{array}{l} -\gamma[(1+\iota)(\mu+g^{\mathrm{W}}) - r\iota](T-\tau) + [(1+\iota)(\mu+\xi^i g^{\mathrm{W}}) - r\iota](T-\tau) \\ +\frac{\gamma}{2}(1+\iota)^2\sigma^2(T-\tau) - \frac{1}{2}(1+\iota)^2\sigma^2(T-\tau) \\ +\frac{1}{2}[(1+\iota) - \gamma(1+\iota)]^2\sigma^2(T-\tau) \end{array}\right\},
\end{aligned} \tag{IA.140}$$

where the derivations of $\mathrm{E}_{\tau+}[\pi_T B^i_T \mid \mathrm{W}]$ are analogous to those of $\mathrm{E}_{\tau+}[\pi_T B^i_T \mid \mathrm{S}]$. We can obtain firm i's stock price after a policy regime shift as

$$\begin{aligned}
M^{\mathrm{S},i}_{\tau+} &= \mathrm{E}_{\tau+}\left[\frac{\pi_T}{\pi^{\mathrm{S}}_{\tau+}} B^i_T \middle| \mathrm{S}\right] = \frac{\mathrm{E}_{\tau+}[\pi_T B^i_T \mid \mathrm{S}]}{\pi^{\mathrm{S}}_{\tau+}}, \\
&= B^i_\tau e^{[(1+\nu^i\iota)(\mu+\xi^i g^{\mathrm{S}}) - r\nu^i\iota](T-\tau) - \gamma(1+\nu^i\iota)(1+\iota)\sigma^2(T-\tau)}
\end{aligned} \tag{IA.141}$$

and

$$\begin{aligned}
M^{\mathrm{W},i}_{\tau+} &= \mathrm{E}_{\tau+}\left[\frac{\pi_T}{\pi^{\mathrm{W}}_{\tau+}} B^i_T \middle| \mathrm{W}\right] = \frac{\mathrm{E}_{\tau+}[\pi_T B^i_T \mid \mathrm{W}]}{\pi^{\mathrm{W}}_{\tau+}}, \\
&= B^i_\tau e^{[(1+\iota)(\mu+\xi^i g^{\mathrm{W}}) - r\iota](T-\tau) - \gamma(1+\iota)^2\sigma^2(T-\tau)}.
\end{aligned} \tag{IA.142}$$

Finally, the stock price at time τ when the policy regime shifts is equal to

$$
\begin{aligned}
M_\tau^i &= \mathrm{E}_\tau\left[\frac{\pi_T}{\pi_\tau} B_T^i\right] = \frac{1}{\pi_\tau}\mathrm{E}_\tau[\mathrm{E}_{\tau+}[\kappa^{-1} B_T^{-\gamma} B_T^i]], \\
&= \frac{p_\tau \mathrm{E}_{\tau+}[\kappa^{-1} B_T^{-\gamma} B_T^i \mid \mathrm{S}] + (1-p_\tau)\mathrm{E}_{\tau+}[\kappa^{-1} B_T^{-\gamma} B_T^i \mid \mathrm{W}]}{\pi_\tau}, \\
&= \frac{p_\tau \pi_{\tau+}^{\mathrm{S}} M_{\tau+}^{\mathrm{S},i} + (1-p_\tau)\pi_{\tau+}^{\mathrm{W}} M_{\tau+}^{\mathrm{W},i}}{p_\tau \pi_{\tau+}^{\mathrm{S}} + (1-p_\tau)\pi_{\tau+}^{\mathrm{W}}}, \\
&= \phi_\tau M_{\tau+}^{\mathrm{S},i} + (1-\phi_\tau) M_{\tau+}^{\mathrm{W},i},
\end{aligned} \tag{IA.143}
$$

where

$$
\begin{aligned}
\phi_\tau &\equiv \frac{p_\tau \pi_{\tau+}^{\mathrm{S}}}{p_\tau \pi_{\tau+}^{\mathrm{S}} + (1-p_\tau)\pi_{\tau+}^{\mathrm{W}}}, \\
&= \frac{p_\tau}{p_\tau + (1-p_\tau)\frac{\pi_{\tau+}^{\mathrm{W}}}{\pi_{\tau+}^{\mathrm{S}}}}, \\
&= \frac{p_\tau}{p_\tau + (1-p_\tau)e^{-\gamma(1+\iota)(g^{\mathrm{W}}-g^{\mathrm{S}})(T-\tau)}}
\end{aligned} \tag{IA.144}
$$

and

$$
\begin{aligned}
G_\tau^i &\equiv \frac{M_{\tau+}^{\mathrm{W},i}}{M_{\tau+}^{\mathrm{S},i}}, \\
&= e^{[(1+\iota)\xi^i(g^{\mathrm{W}}-g^{\mathrm{S}})-\iota(\nu^i-1)(\mu+\xi^i g^{\mathrm{S}})+r(\nu^i-1)\iota+\gamma(\nu^i-1)\iota(1+\iota)\sigma^2](T-\tau)}.
\end{aligned} \tag{IA.145}
$$

According to exponential terms in equation (IA.145), we can characterize three channels to account for changes in firm i's valuation upon a change from the weak to strong regulatory regime as follows:

$$
\overbrace{(1+\iota)\xi^i(g^{\mathrm{W}}-g^{\mathrm{S}}) + \iota(1-\nu^i)(\mu+\xi^i g^{\mathrm{S}})}^{\text{Profitability}} - \underbrace{r(1-\nu^i)\iota}_{\text{Borrowing Cost}} - \underbrace{\gamma(1-\nu^i)\iota(1+\iota)\sigma^2}_{\text{Discount Rate}}.
$$

Recalling equation (IA.82), we analyze high-emission (i.e., $\nu^i > 1$) and low-emission (i.e., $\nu^i \leq 1$) firms upon a regime shift. Looking first at the profitability channel, the first term, $(1+\iota)\xi^i(g^{\mathrm{W}}-g^{\mathrm{S}})$, is the difference in profitability between two regimes given that ι remains constant and unchanged. The second term, $\iota(1-\nu^i)(\mu+\xi^i g^{\mathrm{S}}))$, captures the difference in profitability driven by the regime-shift behavior in debt financing. This additional effect is positive among low-emission firms but negative among high-emission firms. Overall, firm profitability faces a permanent drop upon a regime shift, with the net effect negative and increasing in leverage for all firms. Turning next to the borrowing cost channel, the borrowing cost rises among high-emission firms with an increase in the use of debt financing, but the borrowing cost falls among low-emission firms. Third, the effect of an increase (decrease) in the borrowing cost is to amplify (attenuate) the discount rate among high- (low-) emission firms. Taken together, the three channels increase the difference in valuations between the two regimes among high-emission firms (i.e., $\nu^i > 1$). The net effect of these channels on the difference in valuations between the two regimes is dampened when the second and third channels are offset against the first channel among low-emission firms (i.e., $\nu^i \leq 1$).

We now prove Proposition IA.4. The state price density is the expected value of the state price density when the regime shifts:

$$\begin{aligned}
\pi_t &\equiv \mathrm{E}_t[\pi_{\tau+}], \\
&= \mathrm{E}_t[p_\tau \pi^{\mathrm{S}}_{\tau+} + (1-p_\tau)\pi^{\mathrm{W}}_{\tau+}], \\
&= \mathrm{E}_t[p_\tau]\mathrm{E}_t\left[\pi^{\mathrm{S}}_{\tau+}\right] + \mathrm{E}_t[(1-p_\tau)]\mathrm{E}_t\left[\pi^{\mathrm{W}}_{\tau+}\right], \\
&= p_{\tau|t}\pi^{\mathrm{S}}_t + (1-p_{\tau|t})\pi^{\mathrm{W}}_t, \qquad \text{(IA.146)}
\end{aligned}$$

where

$$\pi^{\mathrm{S}}_t = \mathrm{E}_t\left[\pi^{\mathrm{S}}_{\tau+}\right], \qquad \text{(IA.147)}$$

$$\pi^{\mathrm{W}}_t = \mathrm{E}_t\left[\pi^{\mathrm{W}}_{\tau+}\right], \qquad \text{(IA.148)}$$

and $p_{\tau|t}$ is defined in Corollary IA.1. We can show that

$$\begin{aligned}
p_{\tau|t} = \mathrm{E}_t[p_\tau] &= \mathrm{E}_t\left[\int_{\underline{c}(\tau)}^{\infty} n(c;\hat{c}_\tau,\hat{\sigma}^2_\tau)dc\right], \\
&= \int_{-\infty}^{\infty}\left[\int_{\underline{c}(\tau)}^{\infty} n(c;\hat{c}_\tau,\hat{\sigma}^2_\tau)dc\right] n(\hat{c}_\tau;\hat{c}_t,\hat{\sigma}^2_t-\hat{\sigma}^2_\tau)d\hat{c}_\tau, \\
&= \int_{\underline{c}(\tau)}^{\infty}\left[\int_{-\infty}^{\infty} n(c;\hat{c}_\tau,\hat{\sigma}^2_\tau) n(\hat{c}_\tau;\hat{c}_t,\hat{\sigma}^2_t-\hat{\sigma}^2_\tau)d\hat{c}_\tau\right]dc, \\
&= \int_{\underline{c}(\tau)}^{\infty} n(c;\hat{c}_t,\hat{\sigma}^2_t)dc, \\
&= 1 - Normal(\underline{c}(\tau);\hat{c}_t,\hat{\sigma}^2_t). \qquad \text{(IA.149)}
\end{aligned}$$

When the government decides to change the regulatory regime, the state price density conditional on information at time t is characterized as

$$\begin{aligned}
\pi^{\mathrm{S}}_t &= \mathrm{E}_t\left[\pi^{\mathrm{S}}_{\tau+}\right] \\
&= \mathrm{E}_t\left[\kappa^{-1}B_\tau^{-\gamma}e^{-\gamma[(1+\iota)(\mu+g^{\mathrm{S}})-r\iota](T-\tau)+\frac{1}{2}\gamma(\gamma+1)(1+\iota)^2\sigma^2(T-\tau)}\right] \\
&= \kappa^{-1}B_t^{-\gamma}e^{-\gamma[(1+\iota)(\mu+g^{\mathrm{W}})-r\iota](\tau-t)-\gamma[(1+\iota)(\mu+g^{\mathrm{S}})-r\iota](T-\tau)+\frac{1}{2}\gamma(\gamma+1)(1+\iota)^2\sigma^2(T-t)}, \qquad \text{(IA.150)}
\end{aligned}$$

where the capital at time t is given by

$$B_\tau = B_t e^{[(1+\iota)(\mu+g^{\mathrm{W}})-r\iota](\tau-t)-\frac{1}{2}(1+\iota)^2\sigma^2(\tau-t)+(1+\iota)\sigma(Z_\tau-Z_t)}.$$

We note that the economy starts from the weak-regulation regime, according to equation (IA.78). We solve the expectation problem by substituting the recursive expression of B_τ into the expectation. We can immediately obtain the state price density at time t, given no change in regulatory regime.

$$\pi_t^{\mathrm{W}} = \mathrm{E}_t\left[\pi_{\tau+}^{\mathrm{W}}\right] = \kappa^{-1} B_t^{-\gamma} e^{-\gamma[(1+\iota)(\mu+g^{\mathrm{W}})-r\iota](T-t)+\frac{1}{2}\gamma(\gamma+1)(1+\iota)^2\sigma^2(T-t)}. \tag{IA.151}$$

Finally, the unconditional state price density is given by

$$\begin{aligned}
\pi_t &= p_{\tau|t}\pi_t^{\mathrm{S}} + (1-p_{\tau|t})\pi_t^{\mathrm{W}}, \\
&= p_{\tau|t}\kappa^{-1}B_t^{-\gamma} e^{-\gamma[(1+\iota)(\mu+g^{\mathrm{W}})-r\iota](\tau-t)-\gamma[(1+\iota)(\mu+g^{\mathrm{S}})-r\iota](T-\tau)+\frac{1}{2}\gamma(\gamma+1)(1+\iota)^2\sigma^2(T-t)} \\
&\quad +(1-p_{\tau|t})\kappa^{-1}B_t^{-\gamma} e^{-\gamma[(1+\iota)(\mu+g^{\mathrm{W}})-r\iota](T-t)+\frac{1}{2}\gamma(\gamma+1)(1+\iota)^2\sigma^2(T-t)}, \\
&= \kappa^{-1}B_t^{-\gamma} e^{-\gamma[(1+\iota)(\mu+g^{\mathrm{W}})-r\iota](\tau-t)+\frac{1}{2}\gamma(\gamma+1)(1+\iota)^2\sigma^2(\tau-t)} \\
&\quad \times \left[\begin{array}{l} p_{\tau|t} \times e^{-\gamma[(1+\iota)(\mu+g^{\mathrm{S}})-r\iota](T-\tau)+\frac{1}{2}\gamma(\gamma+1)(1+\iota)^2\sigma^2(T-\tau)} \\ +(1-p_{\tau|t}) \times e^{-\gamma[(1+\iota)(\mu+g^{\mathrm{W}})-r\iota](T-\tau)+\frac{1}{2}\gamma(\gamma+1)(1+\iota)^2\sigma^2(T-\tau)} \end{array}\right], \\
&= \kappa^{-1}B_t^{-\gamma}\Omega_t,
\end{aligned} \tag{IA.152}$$

where

$$\begin{aligned}
\Omega_t &= e^{-\gamma[(1+\iota)(\mu+g^{\mathrm{W}})-r\iota](\tau-t)+\frac{1}{2}\gamma(\gamma+1)(1+\iota)^2\sigma^2(\tau-t)} \\
&\quad \times \left[\begin{array}{l} p_{\tau|t} \times e^{-\gamma[(1+\iota)(\mu+g^{\mathrm{S}})-r\iota](T-\tau)+\frac{1}{2}\gamma(\gamma+1)(1+\iota)^2\sigma^2(T-\tau)} \\ +(1-p_{\tau|t}) \times e^{-\gamma[(1+\iota)(\mu+g^{\mathrm{W}})-r\iota](T-\tau)+\frac{1}{2}\gamma(\gamma+1)(1+\iota)^2\sigma^2(T-\tau)} \end{array}\right].
\end{aligned} \tag{IA.153}$$

E. Proof of Proposition IA.5

The SDF dynamics stem from an application of Ito's Lemma to equation (IA.98),

$$\frac{d\pi_t}{\pi_t} - E_t\left[\frac{d\pi_t}{\pi_t}\right] = -\lambda dZ_t - \lambda_{c,t} d\hat{Z}_t^c. \tag{IA.154}$$

The price of fundamental shock risk is given by

$$\lambda = \gamma\sigma(1+\iota), \tag{IA.155}$$

The price of uncertainty shock risk is given by

$$
\begin{aligned}
\lambda_{c,t} &= -\frac{1}{\Omega_t}\frac{\partial \Omega_t}{\partial p_{\tau|t}}\frac{\partial p_{\tau|t}}{\partial \hat{c}_t}\hat{\sigma}^2_{c,t}, \\
&= -\frac{e^{-\gamma[(1+\iota)(\mu+g^{\mathrm{S}})-r\iota](T-\tau)+\frac{1}{2}\gamma(\gamma+1)(1+\iota)^2\sigma^2(T-\tau)} - e^{-\gamma[(1+\iota)(\mu+g^{\mathrm{W}})-r\iota](T-\tau)+\frac{1}{2}\gamma(\gamma+1)(1+\iota)^2\sigma^2(T-\tau)}}{\left[\begin{array}{l} p_{\tau|t}\times e^{-\gamma[(1+\iota)(\mu+g^{\mathrm{S}})-r\iota](T-\tau)+\frac{1}{2}\gamma(\gamma+1)(1+\iota)^2\sigma^2(T-\tau)} \\ +(1-p_{\tau|t})\times e^{-\gamma[(1+\iota)(\mu+g^{\mathrm{W}})-r\iota](T-\tau)+\frac{1}{2}\gamma(\gamma+1)(1+\iota)^2\sigma^2(T-\tau)} \end{array}\right]} \\
&\quad \times n(\underline{c}(\tau);\hat{c}_t,\hat{\sigma}^2_{c,t})\times\hat{\sigma}^2_{c,t}, \\
&= -\left[\frac{(1-p_{\tau|t})(1-F_\tau)}{p_{\tau|t}+(1-p_{\tau|t})F_\tau}\right] n(\underline{c}(\tau);\hat{c}_t,\hat{\sigma}^2_{c,t})\hat{\sigma}^2_{c,t}, \qquad \text{(IA.156)}
\end{aligned}
$$

where

$$
\begin{aligned}
F_\tau &= \frac{e^{-\gamma[(1+\iota)(\mu+g^{\mathrm{W}})-r\iota](T-\tau)+\frac{1}{2}\gamma(\gamma+1)(1+\iota)^2\sigma^2(T-\tau)}}{e^{-\gamma[(1+\iota)(\mu+g^{\mathrm{S}})-r\iota](T-\tau)+\frac{1}{2}\gamma(\gamma+1)(1+\iota)^2\sigma^2(T-\tau)}}, \\
&= e^{-\gamma(1+\iota)(g^{\mathrm{W}}-g^{\mathrm{S}})(T-\tau)} < 1. \qquad \text{(IA.157)}
\end{aligned}
$$

As a result, the first term in the last equality of equation (IA.156) is positive. Given that the rest of the terms are positive, we can show that the price of regime shift shock risk is negatively priced (i.e., $\lambda_{c,t} < 0$).

F. *Proof of Proposition IA.6*

This proof is a continuation of Proposition IA.5. For $t < \tau$, market value satisfies $M^i_t = \mathrm{E}_t\left[\frac{\pi_T}{\pi_t}M^i_T\right]$. Firm i's stock price can be derived as

$$
\begin{aligned}
M^{\mathrm{S},i}_t &= \frac{\mathrm{E}_t\left[\pi^{\mathrm{S}}_{\tau+}M^{\mathrm{S},i}_{\tau+}\right]}{\pi^{\mathrm{S}}_t}, \\
&= B^i_t e^{[(1+\iota)(\mu+\xi^i g^{\mathrm{W}})-r\iota](\tau-t)-\gamma(1+\iota)^2\sigma^2(\tau-t)+[(1+\nu^i\iota)(\mu+\xi^i g^{\mathrm{S}})-r\nu^i\iota](T-\tau)-\gamma(1+\nu^i\iota)(1+\iota)\sigma^2(T-\tau)} \qquad \text{(IA.158)}
\end{aligned}
$$

when the government changes the regime at time τ, while firm i's stock price can be derived as

$$
\begin{aligned}
M^{\mathrm{W},i}_t &= \frac{\mathrm{E}_t\left[\pi^{\mathrm{W}}_{\tau+}M^{\mathrm{W},i}_{\tau+}\right]}{\pi^{\mathrm{W}}_t}, \\
&= B^i_t e^{[(1+\iota)(\mu+\xi^i g^{\mathrm{W}})-r\iota](T-t)-\gamma(1+\iota)^2\sigma^2(T-t)} \qquad \text{(IA.159)}
\end{aligned}
$$

when the government does not change the regime at time τ. Following Proposition IA.5, firm i's stock price is determined using the law of iterated expectations as follows:

$$\begin{aligned} M_t^i &= \mathrm{E}_t\left[\frac{\pi_T}{\pi_\tau} B_T^i\right] = \frac{1}{\pi_t}\mathrm{E}_t[\mathrm{E}_{\tau+}[\kappa^{-1}B_T^{-\gamma}B_T^i]], \\ &= \frac{p_{\tau|t}\mathrm{E}_t[\kappa^{-1}B_T^{-\gamma}B_T^i \mid \mathrm{S}] + (1-p_{\tau|t})\mathrm{E}_t[\kappa^{-1}B_T^{-\gamma}B_T^i \mid \mathrm{W}]}{\pi_t}, \\ &= \frac{p_{\tau|t}\pi_t^{\mathrm{S}} M_t^{\mathrm{S},i} + (1-p_{\tau|t})\pi_t^{\mathrm{W}} M_t^{\mathrm{W},i}}{p_{\tau|t}\pi_t^{\mathrm{S}} + (1-p_{\tau|t})\pi_t^{\mathrm{W}}}, \\ &= \phi_{\tau|t} M_t^{\mathrm{S},i} + (1-\phi_{\tau|t}) M_t^{\mathrm{W},i}, \end{aligned} \tag{IA.160}$$

where

$$\begin{aligned} \phi_{\tau|t} &\equiv \frac{p_{\tau|t}\pi_t^{\mathrm{S}}}{p_{\tau|t}\pi_t^{\mathrm{S}} + (1-p_{\tau|t})\pi_t^{\mathrm{W}}}, \\ &= \frac{p_{\tau|t}}{p_{\tau|t} + (1-p_{\tau|t})\frac{\pi_t^{\mathrm{W}}}{\pi_t^{\mathrm{S}}}}, \\ &= \frac{p_{\tau|t}}{p_{\tau|t} + (1-p_{\tau|t})e^{-\gamma(1+\iota)(g^{\mathrm{W}}-g^{\mathrm{S}})(T-\tau)}}, \\ &= \frac{p_{\tau|t}}{p_{\tau|t} + (1-p_{\tau|t})F_\tau}. \end{aligned} \tag{IA.161}$$

We can obtain firm i's market valuation unconditionally by substituting equations (IA.158) and (IA.159) into the last equity in equation (IA.160):

$$\begin{aligned} M_t^i &= \phi_{\tau|t} M_t^{\mathrm{S},i} + (1-\phi_{\tau|t}) M_t^{\mathrm{W},i}, \\ &= B_t^i e^{[(1+\iota)(\mu+\xi^i g^{\mathrm{W}})-r\iota](\tau-t)-\gamma(1+\iota)^2\sigma^2(\tau-t)} \\ &\quad \times \left[\begin{array}{l} \phi_{\tau|t} \times e^{[(1+\nu^i\iota)(\mu+\xi^i g^{\mathrm{S}})-r\nu^i\iota](T-\tau)-\gamma(1+\nu^i\iota)(1+\iota)\sigma^2(T-\tau)} \\ +(1-\phi_{\tau|t}) \times e^{[(1+\iota)(\mu+\xi^i g^{\mathrm{W}})-r\iota](T-\tau)-\gamma(1+\iota)^2\sigma^2(T-\tau)} \end{array}\right], \\ &= B_t^i \Theta_t^i, \end{aligned} \tag{IA.162}$$

where

$$\Theta_t^i = e^{[(1+\iota)(\mu+\xi^i g^{\mathrm{W}})-r\iota](\tau-t)-\gamma(1+\iota)^2\sigma^2(\tau-t)} \times \left[\begin{array}{l} \phi_{\tau|t} \times e^{[(1+\nu^i\iota)(\mu+\xi^i g^{\mathrm{S}})-r\nu^i\iota](T-\tau)-\gamma(1+\nu^i\iota)(1+\iota)\sigma^2(T-\tau)} \\ +(1-\phi_{\tau|t}) \times e^{[(1+\iota)(\mu+\xi^i g^{\mathrm{W}})-r\iota](T-\tau)-\gamma(1+\iota)^2\sigma^2(T-\tau)} \end{array}\right]. \tag{IA.163}$$

G. *Proof of Proposition IA.7*

An application of Ito's Lemma to equation (IA.162) characterizes the return dynamics

$$\frac{dM_t^i}{M_t^i} - E_t\left[\frac{dM_t^i}{M_t^i}\right] = \sigma dZ_t + \sigma_I dZ_t^i + \beta_{M,t}^i d\hat{Z}_t^c, \tag{IA.164}$$

where $\beta_{M,t}^i$ is the risk exposure to uncertainty shocks. The derivations of $\beta_{M,t}^i$ are

$$\begin{aligned}
\beta_{M,t}^i &= \frac{1}{\Theta_t^i}\frac{\partial \Theta_t^i}{\partial \phi_t}\frac{\partial \phi_t}{\partial p_{\tau|t}}\frac{\partial p_{\tau|t}}{\partial \hat{c}_t}\hat{\sigma}_{c,t}^2, \\
&= \frac{e^{[(1+\nu^i\iota)(\mu+\xi^i g^{\mathrm{S}})-r\nu^i\iota](T-\tau)-\gamma(1+\nu^i\iota)(1+\iota)\sigma^2(T-\tau)} - e^{[(1+\iota)(\mu+\xi^i g^{\mathrm{W}})-r\iota](T-\tau)-\gamma(1+\iota)^2\sigma^2(T-\tau)}}{\left[\begin{array}{c} \phi_t \times e^{[(1+\nu^i\iota)(\mu+\xi^i g^{\mathrm{S}})-r\nu^i\iota](T-\tau)-\gamma(1+\nu^i\iota)(1+\iota)\sigma^2(T-\tau)} \\ +(1-\phi_t)\times e^{[(1+\iota)(\mu+\xi^i g^{\mathrm{W}})-r\iota](T-\tau)-\gamma(1+\iota)^2\sigma^2(T-\tau)} \end{array}\right]} \times \\
&\quad \frac{\left[p_{\tau|t} + (1-p_{\tau|t})F_\tau\right] - p_{\tau|t}(1-F_\tau)}{\left[p_{\tau|t} + (1-p_{\tau|t})F_\tau\right]^2} n(\underline{c}(\tau);\hat{c}_t,\hat{\sigma}_{c,t}^2)\hat{\sigma}_{c,t}^2, \\
&= \left[\frac{1-G_\tau^i}{\phi_t + (1-\phi_t)G_\tau^i}\right]\left[\frac{F_\tau}{\left(p_{\tau|t}+(1-p_{\tau|t})F_\tau\right)^2}\right] n(\underline{c}(\tau);\hat{c}_t,\hat{\sigma}_{c,t}^2),\hat{\sigma}_{c,t}^2,
\end{aligned} \tag{IA.165}$$

where $G_\tau^i = M_{\tau+}^{\mathrm{W},i}/M_{\tau+}^{\mathrm{S},i}$, according to equation (IA.145).

H. *Proof of Corollary IA.2*

The partial derivative of $\beta_{M,t}^i$ with respect to its dependence on ξ^i is

$$\begin{aligned}
\frac{\partial \beta_{M,t}^i}{\partial \xi^i} &= \frac{\partial}{\partial \xi^i}\left\{\left[\frac{1-G_\tau^i}{\phi_t+(1-\phi_t)G_\tau^i}\right]\left[\frac{F_\tau}{\left(p_{\tau|t}+(1-p_{\tau|t})F_\tau\right)^2}\right] n(\underline{c}(\tau);\hat{c}_t,\hat{\sigma}_{c,t}^2),\hat{\sigma}_{c,t}^2\right\}, \\
&= \left[\frac{F_\tau}{\left(p_{\tau|t}+(1-p_{\tau|t})F_\tau\right)^2}\right] n(\underline{c}(\tau);\hat{c}_t,\hat{\sigma}_{c,t}^2)\hat{\sigma}_{c,t}^2 \times \frac{\partial}{\partial \xi^i}\left\{\frac{1-G_\tau^i}{\phi_t+(1-\phi_t)G_\tau^i}\right\}.
\end{aligned} \tag{IA.166}$$

Since only G^i_τ depends on ξ^i, our analysis focuses on terms related to G^i_τ:

$$\begin{aligned}
\frac{\partial}{\partial \xi^i}\left\{\frac{1-G^i_\tau}{\phi_t+(1-\phi_t)G^i_\tau}\right\} &= \frac{-\frac{\partial G^i_\tau}{\partial \xi^i}[\phi_t+(1-\phi_t)G^i_\tau]-\Big(-\phi_t\frac{\partial G^i_\tau}{\partial \xi^i}\Big)(1-G^i_\tau)}{\big[\phi_t+(1-\phi_t)G^i_\tau\big]^2}, \\
&= \frac{-\frac{\partial G^i_\tau}{\partial \xi^i}G^i_\tau}{\big[\phi_t+(1-\phi_t)G^i_\tau\big]^2}, \\
&= \frac{-\frac{\partial \log G^i_\tau}{\partial \xi^i}(G^i_\tau)^2}{\big[\phi_t+(1-\phi_t)G^i_\tau\big]^2}, \\
&= \frac{-\frac{\partial \log G^i_\tau}{\partial \xi^i}}{\big[\phi_t(\frac{1}{G^i_\tau})^2+(1-\phi_t)\big]^2}, \qquad \text{(IA.167)}
\end{aligned}$$

where the sign of equation (IA.167) depends on $\frac{\partial \log G^i_\tau}{\partial \xi^i}$. Before we analyze the property of $\frac{\partial \beta^i_{M,t}}{\partial \xi^i}$. It is essential that we understand the functional form of G^i_τ, according to equation (IA.145). Focus on the exponential terms of G^i_τ. For notational brevity, we ignore subscripts and write

$$\begin{aligned}
\Gamma(\xi) &\equiv (1+\iota)\xi(g^{\mathrm{W}}-g^{\mathrm{S}})-\iota(\nu-1)(\mu+\xi g^{\mathrm{S}})+r(\nu-1)\iota+\gamma(\nu-1)\iota(1+\iota)\sigma^2 \\
&= -\iota\theta g^{\mathrm{S}}\xi^2+\big[(1+\iota)(g^{\mathrm{W}}-g^{\mathrm{S}})-\iota\theta(\mu-g^{\mathrm{S}})+r\iota\theta+\gamma\iota\theta(1+\iota)\sigma^2\big]\xi \\
&\quad +\big[\iota\theta\mu-r\iota\theta-\gamma\iota\theta(1+\iota)\sigma^2\big] \\
&= -\iota\theta g^{\mathrm{S}}\xi^2+[(1+\iota(1-\theta))(g^{\mathrm{W}}-g^{\mathrm{S}})+\iota\theta g^{\mathrm{W}}+\iota\theta(-\mu+r+\gamma(1+\iota)\sigma^2)]\xi \\
&\quad +\big[\iota\theta(\mu-r-\gamma(1+\iota)\sigma^2)\big], \qquad \text{(IA.168)}
\end{aligned}$$

where we replace $\nu-1$ by $\theta(\xi-1)$ based on equation (IA.80) and rearrange terms. The partial derivative $\frac{\partial G^i_\tau}{\partial \xi^i}$ depends on the sign of $\Gamma'(\xi)$, which is equal to

$$\Gamma'(\xi) = -2\iota\theta g^{\mathrm{S}}\xi+[(1+\iota(1-\theta))(g^{\mathrm{W}}-g^{\mathrm{S}})+\iota\theta g^{\mathrm{W}}+\iota\theta(-\mu+r+\gamma(1+\iota)\sigma^2)]. \qquad \text{(IA.169)}$$

For positive g^{W} and negative g^{S}, we know that $\Gamma'(\xi)$ is positive for any positive ξ when the sufficient condition

$$-\mu+r+\gamma(1+\iota)\sigma^2 \geq 0 \qquad \text{(IA.170)}$$

holds. Therefore, the partial derivative of $\log G^i_\tau$ is positive since

$$\frac{\partial \log G^i_\tau}{\partial \xi^i} = \Big\{\underbrace{-2\iota\theta g^{\mathrm{S}}\xi^i}_{+}+\big[\underbrace{(1+\iota(1-\theta))(g^{\mathrm{W}}-g^{\mathrm{S}})+\iota\theta g^{\mathrm{W}}}_{+}+\iota\theta(\underbrace{-\mu+r+\gamma(1+\iota)\sigma^2}_{+})\big]\Big\}(T-\tau)>0. \qquad \text{(IA.171)}$$

Finally, $\frac{\partial \log G^i_\tau}{\partial \xi^i}>0$ implies $\frac{\partial \beta^i_{M,t}}{\partial \xi^i}<0$ in equation (IA.166).

To understand the amplification effect, we must analyze the quadratic polynomial function $\Gamma(\xi)$.

Suppose there exists two real roots ξ_1 and ξ_2 for $\Gamma(\xi)$. Then the summation of two roots gives

$$\xi_1 + \xi_2 = \underbrace{\frac{(1+\iota(1-\theta))(g^{\mathrm{W}} - g^{\mathrm{S}}) + \iota\theta g^{\mathrm{W}}}{\iota\theta g^{\mathrm{S}}}}_{-} + \underbrace{\frac{\iota\theta(-\mu + r + \gamma(1+\iota)\sigma^2)}{\iota\theta g^{\mathrm{S}}}}_{-} < 0, \tag{IA.172}$$

and the multiplication of two roots gives

$$\xi_1\xi_2 = -\frac{\mu - r - \gamma(1+\iota)\sigma^2}{g^{\mathrm{S}}} \leq 0, \tag{IA.173}$$

according to the sufficient condition in equation (IA.170). The negative summation and the multiplication of two roots imply both a positive and negative root. Moreover, we know that

$$\Gamma(0) = \iota\theta(\mu - r - \gamma(1+\iota)\sigma^2) \leq 0, \tag{IA.174}$$

and

$$\Gamma(1) = (1+\iota)(g^{\mathrm{W}} - g^{\mathrm{S}}) > 0. \tag{IA.175}$$

As a result, the positive root, which we denote by ξ^*, must fall between zero and one. The discriminant Δ_D is given as

$$\begin{aligned} \Delta_D \;\; = \;\; & [(1+\iota(1-\theta))(g^{\mathrm{W}} - g^{\mathrm{S}}) + \iota\theta g^{\mathrm{W}} + \iota\theta(-\mu + r + \gamma(1+\iota)\sigma^2)]^2 \\ & -4(-2\iota\theta g^{\mathrm{S}})[\iota\theta(-\mu + r + \gamma(1+\iota)\sigma^2)], \end{aligned} \tag{IA.176}$$

and we can obtain the positive root as

$$\xi^* = -\frac{(1+\iota(1-\theta))(g^{\mathrm{W}} - g^{\mathrm{S}}) + \iota\theta g^{\mathrm{W}}}{-2\iota\theta g^{\mathrm{S}}} - \frac{\iota\theta(-\mu + r + \gamma(1+\iota)\sigma^2)}{-2\iota\theta g^{\mathrm{S}}} + \Big(\frac{\sqrt{\Delta_D}}{-2\iota\theta g^{\mathrm{S}}}\Big). \tag{IA.177}$$

The strictly positive $\Gamma'(\xi)$ for any positive ξ suggests $\Gamma(2) > \Gamma(1) > \Gamma(\xi^*) = 0 > \Gamma(0)$ when $\xi^{max} = 2$. The positive $\Gamma(2)$ suggests negative risk exposure (i.e., $\beta^{max}_{M,t} < 0$), while the negative $\Gamma(0)$ suggests positive risk exposure (i.e., $\beta^{min}_{M,t} < 0$) when $\xi^{min} = 0$.

I. Proof of Corollary IA.3

In the economy with constant leverage, firm i's exposure to signal shocks is a special case with $\nu^i = 1$. Its risk exposure $\overline{\beta}^i_{M,t}$ can be derived as

$$\overline{\beta}^i_{M,t} \;\; = \;\; \left[\frac{1 - \overline{G}^i_\tau}{\phi_t + (1-\phi_t)\overline{G}^i_\tau}\right]\left[\frac{F_\tau}{\left(p_{\tau|t} + (1-p_{\tau|t})F_\tau\right)^2}\right] n(\underline{c}(\tau); \hat{c}_t, \hat{\sigma}^2_{c,t}), \hat{\sigma}^2_{c,t}, \tag{IA.178}$$

where

$$\overline{G}^i_\tau = e^{\overline{\Gamma}(\xi^i)(T-\tau)}, \tag{IA.179}$$

and

$$\overline{\Gamma}(\xi) = (1+\iota)\xi(g^{\mathrm{W}} - g^{\mathrm{S}}). \tag{IA.180}$$

As above, we suppress subscripts for notational brevity. By setting ξ equal to zero and one, we obtain

$$\overline{\Gamma}(0) = 0, \tag{IA.181}$$

and

$$\overline{\Gamma}(1) = (1+\iota)(g^{\mathrm{W}} - g^{\mathrm{S}}). \tag{IA.182}$$

When ξ is equal to one, we have an intersection such that $\overline{\Gamma}(1) = \Gamma(1)$. Therefore, we obtain $\Gamma(\xi) > \overline{\Gamma}(\xi)$ and $G^i_\tau > \overline{G}^i_\tau > 1$ when ξ is larger than one and $\Gamma(\xi) \leq \overline{\Gamma}(\xi)$ and $G^i_\tau \leq \overline{G}^i_\tau$ when ξ is between zero and one. We thus obtain the relation

$$\beta^i_{M,t} < \overline{\beta}^i_{M,t} < 0 \tag{IA.183}$$

for high-emission firms (i.e., $\xi^i > 1$) and

$$\beta^i_{M,t} > \overline{\beta}^i_{M,t} \tag{IA.184}$$

for low-emission firms (i.e., $0 \leq \xi^i \leq 1$).

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