The Journal of FINANCE
The Journal of THE AMERICAN FINANCE ASSOCIATION

THE JOURNAL OF FINANCE • VOL. LXXVIII, NO. 3 • JUNE 2023

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.

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

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DOI: 10.1111/jofi.13217

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.[2] 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 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 (H-L) 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 H-L 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.

[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.

[2] The Internet Appendix may be found in the online version of this article.

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.[3] 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.[4] Fama 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.[5] In our model, the

[3] 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 3-day CARs after Republican election victories.

[4] 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 institutional investors have preferences against firms with a poor social image, such as those that perform poorly with respect to corporate social responsibility (CSR) 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 et al. (2019), Pástor, Stambaugh, and Taylor (2021), Hartzmark and Sussman (2019), and Ramelli et al. (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 et al. (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.

[5] 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.

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 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.[6] 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 H-L 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 a substantial yet under explored part of policy uncertainty. More importantly, *JT* difference test results show that our measure of environmental policy

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.

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

change risk is distinct from *general* policy uncertainty, as adding our measure of environmental policy change risk to the 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.[7] 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, 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)).[8] Some studies suggest that high-CSR firms are less risky because their CSR reputation helps them survive financial downturns (Lins, Servaes, and Tamayo (2017), Hoepner et al. (2019), and Albuquerque, Koskinen, and Zhang (2019)).[9] In addition, investor under- or overreaction to news about pollution or climate change can result in return predictability (Krüger (2015), Chen, Kumar, and Zhang (2019), Hong, Li, and Xu (2019)),[10] 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.[11] Such preferences

[7] Acemoglu (2002) shows that two major forces bias technological change: price effects and market size effects. Acemoglu et al. (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 et al. (2016a) show that interventions, such as taxes and subsidies, can promote transitions to clean technology. In their study of the automobile industry, Aghion et al. (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 et al. (2015) investigate the impact of toxic emissions on housing value and infant health.

[8] 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.

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

[10] 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.

[11] 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 et al. (2019) find that institutional investors are reluctant to sell high-CSR stocks but are more

may also influence systematic risk exposure (Bansal, Wu, and Yaron (2019), Pástor, Stambaugh, and Taylor (2021)).[12] 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 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.[13] 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.[14]

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 et al. (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.

[12] 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.

[13] With respect to economic uncertainty, Brogaard and Detzel (2015) examine how stock returns relate to the economic policy uncertainty (EPU) 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 et al. (2012a), Croce, Nguyen, and Schmid (2012b), and Belo, Gala, and Li (2013)).

[14] A large number of theoretical and empirical papers relates 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 National Income and Product Accounts (NIPA) consumption data in matching the equity premium. The literature also explores

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 fourth 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 TRI database constructed and maintained by the EPA.[15] The TRI database contains detailed information on all

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. van 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).

[15] 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 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.

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.[16] 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 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.[17] We use the environmental score (ENVSCORE) and its components, which are assigned to a firm annually.

[16] We acknowledge that the TRI database is subject to some data limitations, such as a failure to report and reporting errors, as Currie et al. (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.

[17] 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.

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).[18]

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 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.[19] 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.[20] Below we conduct factor regressions, Fama-MacBeth regressions, and two-way portfolio sorts to

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

[19] 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 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.

[20] 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

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), 5th percentile (P5), 25th percentile (P25), median, 75th percentile (P75), and 95th 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	6,567.88	6,272.44	0.67	0.18	0.09	0.19	0.33	−0.35	0.99	0.23
Std	44,586.41	21,765.23	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	1,302.75	0.55	0.16	0.09	0.20	0.30	−0.35	0.90	0.26
P75	2,372.91	4,448.09	0.83	0.22	0.13	0.30	0.44	−0.29	1.25	0.37
P95	23,254.81	26,056.43	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

separate the pollution effect from the size effect. We consistently find that 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 postformation 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 an 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 H-L 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

(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), EPU index, 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 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.

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

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

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	18,808.25	243,610.89	796,053.89	1,488,382.07	3,106,629.16
Emissions	15.52	134.09	487.54	1,501.08	8,146.43
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

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 B/M, I/K, 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 V, 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

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
[tt	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

(*Continued*)

Table IV
(Continued)

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		L	2	3	4	H	H-L
			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 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^2	0.13	0.16
Industry FE	Yes	Yes

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.[21] 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 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.[22] 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.[23] 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; we annualize portfolio returns by multiplying them by 12. In the high-

[21] 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 et al. (2019), Pástor, Stambaugh, and Taylor (2021), Hartzmark and Sussman (2019), Ramelli et al. (2021), and Goldstein et al. (2022), among others.

[22] 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 value-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 who hold the focal firm.

[23] 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 $t+1$.

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.

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.[24] 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, 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.[25] 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 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 significantly higher returns than low-pollution firms. Hence, the

[24] 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, 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)).

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

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 Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (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. 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 an industry. Panel C of Table IA.5 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 (Cheng, Hong, and Shue (2013), Masulis and Reza (2015), Glossner (2018), Hoepner et al. (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 who 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 columns (3) and (4) of Table IA.3. 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.[26] Panel A of Table IA.6 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.

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.[27] 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.[28] We control for political donations in our Fama-MacBeth regressions in columns (5) and (6) of Table IA.3. 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 shows that returns on the H-L portfolio sorted on emission intensity are statistically significant in

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

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

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

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 (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 I/K. 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 I/K in our Fama-MacBeth regressions in columns (7) and (8), respectively, of Table IA.3. We find that emission intensity significantly positively predicts future stock returns. We also implement two-way sorting. In Panel A of Table IA.7, 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 I/K 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 I/K 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 I/K 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 Size-Age (SA) index (Hadlock and Pierce (2010).)[29] 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. We find that emission intensity continues to significantly positively predict future stock returns. In Panel B of Table IA.7, 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).[30] 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. 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 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 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.

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

[30] 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).

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.[31] 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 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, 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.

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.[32] 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

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

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

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, B/M, I/K, current profitability, TANT, financial constraints, book leverage, and operating leverage in year t. We also include industry-year fixed effects.[33]

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 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, B/M, I/K, lagged profitability, TANT, financial constraints, Lev, and OL in year t, as well as industry-year fixed effects.[34] 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.

[33] 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.

[34] 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.

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 (B/M), investment rate (I/K), current profitability, tangibility (TANT), 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 1$^{\text{st}}$ and 99$^{\text{th}}$ 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) Poisson	(4) Probit	(5) NB	(6) Poisson
Log Emissions	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

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.[35] In Panel A of Table VIII, we find a significantly negative

[35] 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, 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.

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^2	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

(*Continued*)

Table VII—*Continued*

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 1 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

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 et al. (2021), Brown and Huang (2020), and Child et al. (2021).[36] To isolate the impact of new information on stock prices, we consider CARs calculated with respect to the CAPM.[37] 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

[36] Di Giuli and Kostovetsky (2014) also show that firms with low social responsibility scores provide significantly positive 3-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.

[37] 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 10 days after the event date, which we refer to as the (0,10) window.

the lowest and highest portfolios is sizable at 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.[38] 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 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.

[38] 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 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,

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

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].[39]

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.[40] As another piece of suggestive evidence, in Section V.B we show that, upon the arrival of policy change shocks that increase the perceived

[39] 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.

[40] 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

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.[41] For all $j \in [0, 1]$, investor j's utility function is given by

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

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.[42] 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 government 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*.

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.

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

[42] 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.

Due to the uncertainty about environmental costs before time τ, stock prices respond to environmental cost signals, as we show* in Section III.C.

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:

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

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 $B_T = \int_0^1 B_T^i di$.[43]

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 conditional 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 downward.

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

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.[44] 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

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

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 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.[45]

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

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

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 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:

(i) When $\bar{\xi} < \xi^{max}$, ξ^{i*} must exist and is smaller than $\bar{\xi}$.
(ii) ξ^{i*} is increasing in η^i, and $\lim_{\eta^i \to \infty} \xi^{i*} = \bar{\xi}$.
(iii) $\Psi_0^H < \Psi_0^L$ 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 microfoundation 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 microfoundation 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.[46] 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.[47] 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

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

[46] 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.

[47] 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.

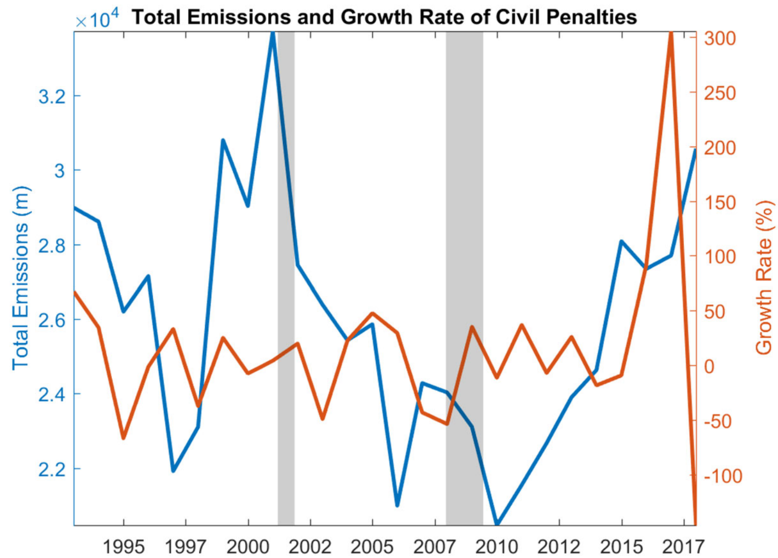

Figure 1. Time-series patterns of the number of civil cases. This figure plots the time series of total emissions in the EPA's TRI database (blue line on the left vertical axis) and the log growth in civil penalties (Δn_t) (orange line on the right vertical axis). The data are downloaded from the Enforcement 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. (Color figure can be viewed at wileyonlinelibrary.com)

$$+c\,Controls_{i,t} + \varepsilon_{i,t}, \tag{29}$$

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 changes. The vector $Controls$ includes control variables ROA, change in ROA, size, B/M, I/K, TANT, 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, pp. 236–239), we first specify the SDF as

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

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.[48] We then conduct GMM estimation for the following empirical approximation to equation (23) (e.g., Kogan and Papanikolaou (2014))

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

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

[48] This choice of test assets follows Lewellen, Nagel, and Shanken (2010), Belo et al. (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.

mean absolute percent errors (MAPE)—as well as the J-statistic of overidentifying model restrictions.[49] 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 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 EPU index of Bloom (2009), which reflects general EPU 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.[50] 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 further added to the SDF, we find that it is significantly negatively priced and reduces pricing

[49] Given the Euler equation $\mathrm{E}[\mathrm{SDF} \times R_i^e] = 0$, our SSQE and MAPE are based on each test asset i's moment error u_i as follows: $u_i = \frac{1}{T}\sum_{t=1}^{T}[\widehat{\mathrm{SDF}} \times R_{i,t}^e]$. 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.

[50] 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.

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: $u_i = \frac{1}{T}\sum_{t=1}^{T}[\widehat{\text{SDF}} \times R_{i,t}^e]$. 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_{MKT}^i and $\beta_{\Delta n}^i$) 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]		10.57	8.6	3.16	5.10	7.50	7.85
Δn	−1.66		−0.99		−0.81		−0.95
[t]	−6.23		−4.37		−5.42		−3.81
Uncertainty				−0.99	−0.64		
[t]				−8.43	−6.42		
GDP						0.48	0.18
[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

(*Continued*)

Table X—*Continued*

	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]	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]	−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]	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]	−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]	−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

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.[51] 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 Panels C to B and when we compare Panels E to 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 emission 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

[51] 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).

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.

Initial submission: December 1, 2018; Accepted: January 31, 2022
Editors: Stefan Nagel, Philip Bond, Amit Seru, and Wei Xiong

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix.
Replication Code.