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Environmental Regulatory Risk

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Environmental regulatory risk*

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Abstract

The aim of this paper is to determine from market expectations how firms are affected by risks arising from environmental regulation. We use a text-based measure of environmental regulatory stringency derived from U.S. EPA legal documents and industry-level relevance scores to capture time-varying regulatory stringency exposure. We find that environmental regulatory stringency carries a positive and statistically significant return compensation, especially for firms with high cash holdings. For firms with low cash holdings, the effect is highly volatile, showing investors are uncertain about a firm's future when faced with stricter regulation. Firms' environmental profiles further matter, as high-emission firms' returns are negatively affected when regulatory stringency increases. Because regulatory text is released infrequently, challenging real-time risk analysis, we utilise our studies insights to derive a high-frequency, market-expectation capturing Environmental Regulatory Risk Index (ERRI). We show that ERRI captures shifts in investors' expectations of environmental regulatory stringency and how ERRI reacts during environmental policy and political developments.

Keywords: Market Expectations, Asset Pricing, Regulatory Risk Modeling, Environmental Regulation

JEL classification: C55, C58, G12, Q50

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1 Introduction

In recent years, more and more environmental regulation was imposed, which was met by firms lobbying for less strict regulation so as not to affect their business models too much. That regulation impacts firms' business decisions and valuations is well established (Greenstone et al., 2012; Rajabi et al., 2024; Veith et al., 2009) as well as that the effects vary between firms and industries (OECD, 2021). Quantifying the expected impact of policies for a firm is challenging though. However, investors expectations of the long-term success of a firm are reflected in their stock price and that risks arising from regulation have great impact on asset portfolios is confirmed by institutional investor surveys (Krueger et al., 2020). Hence, from investors reactions to environmental regulation we can determine how strongly markets expect firms to be affected by it, and which of those are expected to weather stricter regulation better.

We study via market expectations the anticipated risks arising from firms' exposure to environmental regulation. This relationship is often studied by treating the announcement or news about a regulation as an event in an event study (Brouwers et al., 2016; Rajabi et al., 2024; Ramiah et al., 2013). However, regulation differs by the stringency it imposes upon businesses and the exposure of the firms to the regulation. Firms in some sectors are naturally exposed stronger to environmental regulation and hence at higher risk of being affected by it. Further, the exposure of firms can change over time, which an event study cannot measure. Hence, to study the effects from environmental regulation, we utilize the stringency of the legal text obtained from a quantification of the number of binding words in the regulatory text and firms' estimated exposure to environmental regulation (Al-Ubaydli and McLaughlin, 2017). Following stricter environmental regulation, firms are exposed to a different regulatory environment. They have to adapt to this new environment, which is met by costs (Kalmenovitz, 2023) and affects their business model (Greenstone, 2002). Indeed Becker and Henderson (2000) and Greenstone et al. (2012) show that stricter environmental regulation leads to changes in investment decisions of firms operating manufacturing plants in the U.S. and Ince and Ozsoylev (2024) show that stricter regulation leads to additional costs. Following standard asset pricing theory, investors adjust their expectations towards a firm's future cash flows when costs increase or the regulatory environment changes (Pástor and Veronesi, 2012). Hence, the change in the regulatory environment results in uncertainty among investors about the impact on firms' business models, which we term as 'risks arising from environmental regulation'.

We investigate this relationship by employing a firm-characteristics predictive regression, to study changes in environmental regulatory stringency and the cross-section of equity returns in the U.S. market. It is well established that the environmental profile of firms, often determined from their emissions, matters for investors' expectations about a firm's future evaluation (Bolton and Kacperczyk, 2021; Sankar et al., 2024). Considering this, we examine the exposure of equity returns to environmental regulatory stringency, while controlling for the firms' environmental profiles and other established predictors of equity returns from the literature. For firms with poor environmental profiles, stricter regulation has a negative relationship with the firms' returns. This shows that investors take environmental regulatory stringency into account. Building on this finding, we investigate firms' ability to react flexibly to the new regulatory environment. Naturally, firms' cash holdings provide financial flexibility, which is especially valuable when firms face the uncertain costs created by new regulations. Gulen and Ion (2016) find that policy uncertainty has a negative effect on corporate investment, but that this effect is much weaker for firms with high cash reserves. A natural explanation would be that high cash holdings allow firms to react flexibly to a new regulatory reality. Drawing on these findings, we investigate asset returns of high-cash firms versus all others subject to regulatory stringency. The analysis shows that the positive relationship between environmental regulatory stringency and firm returns is statistically significant and larger in magnitude for firms with high cash reserves. Firms with low cash holdings, however, have an insignificant but still positive coefficient. This implies, for firms with low cash holdings, there is much more volatility between the affected firms. Naturally, regulation can distort a business model so much, that it requires substantial investments which are tougher to shoulder for firms which have to increase their debt burden for this, resulting in uncertainty for investors about the firm's future. This shows that stricter environmental regulation is unproblematic for firms with high cash holdings as they adapt to the new corporate environment. Investors still consider high-cash firms to be exposed to the changed environmental regulatory environment, but they are in an advantageous situation over firms with low cash holdings when regulation becomes increasingly stringent. It also shows that regulators can impose stricter environmental regulation without hurting firms too much if it is affecting mainly high-cash firms or if suitable remedies for low-cash firms are introduced.

From an investor's viewpoint, risks arising from environmental regulation is something to hedge against. From a policy makers' perspective, we would like a measure to track the market's present perception of risk arising from environmental regulation. Regulation is only released infrequently which makes such tracking challenging. Following standard asset pricing theory, investors adjust their expectations towards a firm's future cash flows when the regulatory environment changes. Accounting for these stakeholders, we construct an index from low-minus-high exposure portfolios of regulatory stringency, which allows to determine risks arising from environmental regulation from market expectations at high frequency. For the construction of the exposure portfolios, we draw on the economic and financial literature which showed that firms are differently exposed to environmental regulation subject to their size (Becker and Henderson, 2000), cash holdings (Gulen and Ion, 2016), among others, and it affects investment decisions (Becker and Henderson, 2000) and costs (Ince and Ozsoylev, 2024; Kalmenovitz, 2023). We identify asset pricing clusters, obtained from Jensen et al. (2023), which contain factors related to these exposures and construct geometrically weighted averages over the factors in the four identified clusters. With the index construction methodology of Trimborn and Härdle (2018), we dynamically choose from the candidate exposure portfolios a representative subset, reflecting market expectations of risks arising from environmental regulation at high frequency. We find the index to experience its largest spike in 1987, when the U.S. introduced the Global Climate Protection Act. Apparently U.S. investors saw it as a sweeping change to the business environment. In 1997, markets considered risks arising from environmental regulation low, despite the Kyoto Protocol being discussed and later signed. This was due to the Byrd-Hagel Resolution, which prevented the U.S. senate from ratifying any policies which would harm the U.S. economy. Even though the U.S. did sign the Kyoto Protocol, it was never ratified, rendering this step as largely symbolic and therefore posing no risk to firms' business models. A large spike in risks arising from environmental regulation occurred though when Al Gore, who later received the Nobel Peace Prize for his efforts to put the climate crisis on policy makers agendas, ran for the U.S. presidency. The climate protests led by Greta Thunberg were evaluated by markets as a small risk given they took place during Donald Trump's first presidency, whose administration weakened environmental regulation.

Our results contribute to the literature in a number of dimensions. Firstly, we contribute to the literature on modeling risks arising from environmental regulation. Deng and Hao (2024) use the investment rate of firms into pollution abatement technologies as a proxy for firm reactions to environmental regulation in China. Dagestani et al. (2023) also use the introduction of stricter environmental regulation in China as a policy shock, showing that polluting firms were incentivized to become greener. Shi and Xu (2018) determine the impact the 11th 5-year plan of China has upon exports from China. These studies focus upon firm policy changes as a result of regulation, whereas we differ by focusing upon investors' expectations as to firms' success following stricter environmental regulation.

Secondly, we contribute to the literature on index construction, tracking policy and societal environmental actions and concerns. Kruse et al. (2022) propose a yearly index to measure environmental policy stringency in OECD countries, available up to and including 2020. The index was used by Zhou et al. (2025) to study costs of debt across countries. Engle et al. (2020) derive a monthly index of media-based climate change risk, while Ardia et al. (2023) develop a measure of climate change concerns from news sentiment. These indices measure policy stringency on a low frequency or focus upon climate attention. We differ by providing an index for market perception of risks arising from environmental regulation on a daily frequency, allowing to track and study changes in this risk at high frequencies.

Thirdly, we contribute to the literature on regulatory and political risk, and uncertainty derived from political action. Baker et al. (2016) develop an aggregate-level measure of policy uncertainty based on the frequency of news articles that contain terms related to economic policy uncertainty. Hassan et al. (2019) study firms' worries about political risk by identifying the share of earnings calls devoted to political discussions and their proximity to uncertainty-related words. Kaviani et al. (2020) investigate how policy uncertainty affects credit spreads. A theoretical model of policy uncertainty was suggested by Pástor and Veronesi (2013) and extended by Kelly et al. (2016), dissecting the effect of political uncertainty and economic uncertainty. We differ from this literature by focusing upon risks arising from environmental regulation, instead of the broader risk from the political environment.

Further, we contribute to the literature on pricing firm securities with respect to the environment and climate. We show that investors price exposure to environmental regulation in the cross-section of asset prices, even when controlling for firms' environmental profiles. The literature on the exposure of firms towards climate risk is still in its infancy, but rapidly expanding, see Giglio et al. (2021) for an overview. Bolton and Kacperczyk (2021) and Bolton and Kacperczyk (2023) show that firm emissions are priced in the cross-section of both U.S. and non-U.S. stock returns. Seltzer et al. (2022) study state-level law enforcements and its impact upon firms' cost of corporate debt. Fan and Wu (2022) focus on the role of governance and the impact of environmental regulations on firms' innovation. They find that stricter environmental regulation not only reduces pollution but also increases firm innovation. We also utilize the measure of regulatory stringency from Al-Ubaydli and McLaughlin (2017) but differ by investigating whether exposure to environmental regulation has an effect on equity returns rather than investigating firms' corporate reactions to a changing regulatory environment, as done in Fan and Wu (2022). As we are interested in industry- and firm-specific market reactions to new environmental regulation, we conduct a more granular investigation of exposure to environmental regulation and equity market reactions.

The rest of the paper is organized as follows. Section 2 introduces the regulatory-text based measure for regulatory stringency and the data used in this study. In Section 3, we investigate the effect of exposure to environmental regulation on the cross-section of asset returns. In Section 4, we construct low-minus-high environmental regulatory stringency exposure portfolios and evaluate their performance. In Section 4.4 we construct the Environmental Regulatory Risk Index (ERRI) and study its performance over the market risk in relation to environmentally relevant policy developments. We find ERRI to be a suitable measure to evaluate environmental policies and regulations for the risks they pose. In Section 5 we discuss the policy implications and Section 6 concludes.

2 A legal-text based measure of regulatory stringency, the data, and their summary statistics

In this section we describe how the measure of environmental regulatory stringency, obtained from the Mercatus Center's RegData Database (Al-Ubaydli and McLaughlin, 2017), is constructed from the regulatory text, show how it performs across industries, and present the summary statistics associated with it. We control for the environmental profile of firms via their emissions. We introduce the Trucost database from which we obtain the emissions data and describe the methodologies by which they are measured. Lastly, we introduce the control variables used for the panel of firms.

2.1 Regulatory exposure and stringency

The Code of Federal Regulations (CFR) of the U.S. is the official record of all regulations created by the U.S. federal government and is revised yearly. The structure of the CFR is composed of Titles, that can be further subdivided into chapters and parts. Environmental laws passed by the Environmental Protection Agency (EPA) are contained in the Title 40 of the CFR, titled 'Protection of Environment', and updated annually. The legal literature found that, in the legal process, the choices of binding words are employed to impose a high degree of obligation on the addressee (Danet, 1980; Trosborg, 1995). This includes terms such as 'shall', 'must', 'may not', 'prohibited', and 'required'. This allows to quantify the restrictiveness of legal documents by the number of regulatory binding words. From the Mercatus Center's RegData Database (Al-Ubaydli and McLaughlin, 2017) we obtain the number of binding words over the total number of words in the regulatory documents. We term this measure 'restrictiveness ratio', denoted as the variable *RestRatio*. By its construction, this variable controls for the length of the documents and provides an estimate of the actual bindingness of the regulatory text. Since regulations impact firms differently, it is crucial to quantify the likelihood that newly published regulation impacts a firm. Motivated by earlier work by Fan and Wu (2022) and Kaviani et al. (2020) we employ an industry-based approach. The standard classification system used by U.S. Federal statistical agencies is the North American Industry Classification System (NAICS). Following this classification, we consider firms within the same NAICS industry to be subject to the same environmental regulatory stringency. The restrictiveness measure as well as the *Relevance* score to determine a legal text relevance to an industry are also obtained from the formerly referenced RegData database. They determine the relevance score with a classification model tailored to learn the patterns of text that relate strongest to a specific industry. The model is trained on the bills proposed by firms within a specific industry (McLaughlin and Nelson, 2021). A more detailed explanation of the model can be found in the technical appendix in Section A and in Al-Ubaydli and McLaughlin (2017). In order to obtain the stringency measure *RegStringency* at the industry level, we multiply the restrictiveness ratio of the regulatory documents, that is *RestRatio*, by the industry specific *Relevance* score. By this we obtain the stringency measure $RegStringency_{j,t}$ at the industry level: $RegStringency_{j,t} = \sum_p Relevance_{j,p,t} \times RestRatio_{p,t}$. Here p are the parts of the CFR legal text, t denotes time and j the industry. The resulting $RegStringency_{j,t}$ metric is an industry-level time-varying measure of environmental regulatory stringency that we are going to employ in our study. We obtain the measures at the 4-digit NAICS industry classification, which is available for the years 1973 through 2022.

2.2 Emissions and stock data

In the academic literature it has been shown that the emissions of a firm matter to investors (Bolton and Kacperczyk, 2021; Bolton and Kacperczyk, 2023; Chava, 2014). Following these findings, we will investigate if markets care about the regulatory stringency exposure of a firm relative to its environmental profile which we obtain from their emissions. To derive the environmental profile, we employ the firm-level green house gas (GHG) emission data from Trucost/Carbon Disclosure Project (CDP). The emissions are measured in three different ways, termed Scopes, and defined in the Greenhouse Gas Protocol. Scope 1 are the direct emissions, which comprise emissions of a firm and its subsidiaries. Scope 2 includes the indirect emissions generated during the production of energy purchased by the firm. Therefore, a firm relying mainly on renewable energy sources has a lower Scope 2 emissions score than one relying on coal or gas as energy sources. Scope 3 comprises of other indirect emissions, which are the ones from the firms' suppliers and the firms it supplies, among other contributing factors such as business travel. Each scope measures emissions in two different specifications, that is the absolute value of tonnes of CO_2 and the Intensity measure, which is obtained by scaling the absolute value by the firms' revenues. Typically the emission numbers are large and right-skewed, which is why we consider the log of the emission variable, both in the absolute and in the intensity specifications. We will consider each scope in the study as they provide a holistic overview of the firms' environmental profiles.

We obtain the monthly stock prices of the firms from CRSP for the years 1973 through 2022, which matches the availability of the regulatory stringency data. We further extend the dataset with the set of control variables used in Garel et al. (2024), which we obtain from the Compustat database. They consist of Total Assets, Market Capitalization, Book-to-market Ratio, Leverage, Capex/Total Assets, PPE/Total Assets, ROA, Asset Growth, Sales Growth, Volatility and Momentum. We match these data with the emissions data from Trucost and the environmental regulatory stringency measures. The Trucost emissions data are available at yearly frequency from 2002 through 2022.

In the first part of this study, we control for the environmental profile of firms, including only those with more than 90% of emission data availability over the 2002–2022 period. That leads to a monthly dataset spanning the years 2002–2022, covering 210,672 firm-month observations. In the second part of this study, we construct long-short portfolios to track risks arising from environmental regulation at any given frequency and map them into a daily index. As this part of the study does not rely on firms' environmental profiles, we construct the portfolios on the full dataset from 1973 to 2022, covering 25,058 firms and 14,734,104 firm-month observations.

Figure 1 shows the granularity of the 4-digit NAICS industries. We observe that most industries are so specific at this level of granularity, that they only contain one or two firms. Only a selected few reach higher numbers of constituents, with two peaking in the double digits. This shows that for many industries, the measured environmental regulatory stringency is entirely or almost fully firm-specific. Given the huge number of industries, we display in Figure 2 the time series of the regulatory stringency for two representative industries. The regulatory stringency measure increases over time in both industries. In both cases, it reaches

Figure 1: Number of firms in 4-digit NAICS industries. We observe that the environmental regulatory stringency measure is firm specific in many industries.

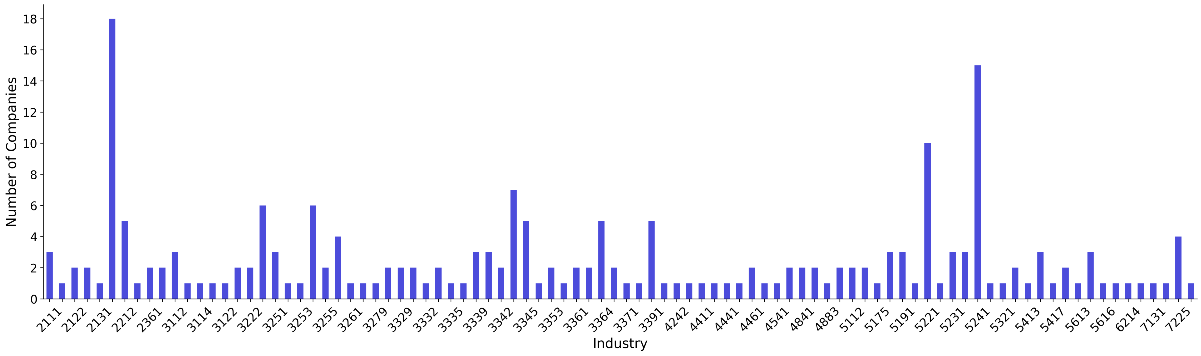
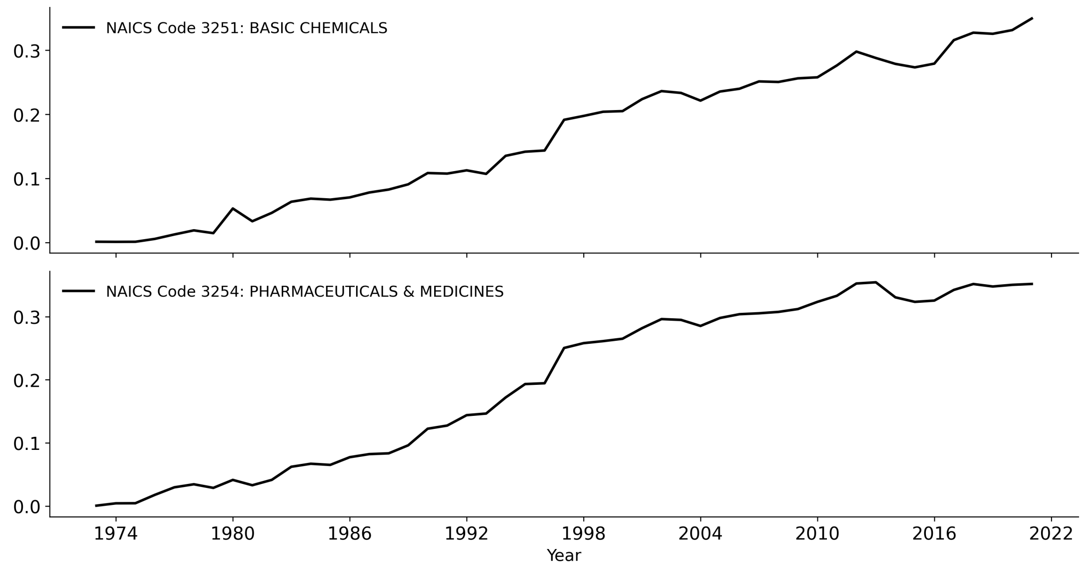


Figure 2: Time series of the $RegStringency_{j,t}$ measure for selected industries. We observe that the regulatory stringency measure is correlated across time, motivating the need for the Hjalmarsson (2010) estimator.



an intermediary peak in 2012/2013, declines for a few years, and then rises toward the end of the sample. The upward trend was to be expected as environmental protection received increasing attention in the past two decades, which should also be reflected in environmental regulation. It further illustrates that the environmental regulatory stringency across industries and firms is highly correlated across time, which would lead to an estimation bias if not accounted for. Therefore, the panel estimation in Section 3 relies on the estimator by Hjalmarsson (2010), which controls for the effects of common factors driving correlation in the regulatory stringency measure across industries.

To provide an overview how the variables compare against one another, we provide their descriptive statistics over the period 2002–2022, as this matches the availability of the emissions data, in Table 1. We observe that the emissions data of the various scopes are on a profoundly different scale than *RegStringency*, rationalising why we rely on their log scale throughout the

Table 1: The Table shows the summary statistics for the regulatory stringency measure and the emissions measures under the three different scope specifications.

	mean	std	median
RegStringency	0.061	0.112	0.006
log(Intensity: GHG Scope 1)	3.160	2.582	2.919
log(Intensity: GHG Scope 2 Location-based)	2.826	1.452	2.884
log(Intensity: GHG Scope 3 Upstream)	4.885	1.000	4.982
log(Absolute: GHG Scope 1)	12.206	2.845	12.264
log(Absolute: GHG Scope 2 Location-based)	11.854	2.058	12.028
log(Absolute: GHG Scope 3 Upstream Total)	13.940	1.696	14.089

analysis.

3 Environmental regulatory stringency and the cross section of asset returns

Within the framework of climate risks, it is well established that firm emissions matter in the cross-section of asset returns. The emissions are naturally linked to regulation, given that stricter environmental regulation sets incentives to decrease emissions. This raises the question how strongly, and in which direction, firms, relative to their environmental profile, are affected by stricter environmental regulation. We find that investors demand a return compensation for firms' exposure to regulatory stringency, but also that high emitting firms' asset returns are negatively affected by stricter environmental regulation, which shows that investors worry about a firm's future when it is strongly exposed to environmental regulation via its business model. But we also find that investors go long in firms with high cash holdings when regulation becomes tighter showing that the market expects them to weather the changing regulatory environment well.

3.1 Model Specification

We first examine the relationship between environmental regulatory stringency and asset returns. We expect a significant relationship between the environmental regulatory stringency at time $t-1$ and the stock returns at time t. We study the link in panel predictive regressions relating individual firms' returns to their regulatory stringency $RegStringency_{i,t}$. We regress the monthly stock returns on the lagged $RegStringency_{i,t}$ and a set of controls, composed of firm characteristics. We opt to use a firm characteristics regression because, unlike a traditional factor model, it does not rely on the assumption of an existing asset pricing model. This approach is suitable given that there is no consensus regarding the effect of environmental regulation on firm performance. Bolton and Kacperczyk (2023) discuss the use of a firm-characteristics regression extensively. A similar approach has also been used in Garel et al. (2024) to study the impact on asset prices of biodiversity risk. The first regression we estimate has the form

$$r_{i,t} = \beta_1 RegStringency_{i,t-1} + \beta_2 \mathbf{X}_{i,t-1} + \alpha_{i,t} + \varepsilon_{i,t}, \tag{1}$$

where the vector $\mathbf{X}_{i,t-1}$ represent a set of control variables that capture various firm-level characteristics, such as Debt-to-Equity Ratio (leverage), PPE/Total Assets (asset structure), ROA (profitability), and Asset Growth, which are measured annually, alongside with the Book-to-Market Ratio, Volatility, and Momentum, that are measured monthly. We also considered log(sales), Capex/Total Assets, Sales Turnover, and Capex, as used in Garel et al. (2024), but their Variance Inflation Factors (VIFs) were very large, hence they are already represented by the other retained control variables. In Eq. (1), $\alpha_{i,t}$ represents interactive fixed effects, allowing for a combination of common factors and individual effects, and $\varepsilon_{i,t}$ denotes the regression error. Note the frequency mismatch between annual regressors and monthly returns in our specification. We treat this by regressing monthly returns on the last observed values of the annual regressors, which leads to additional persistence of the regressors. However, the effect of this on inference is limited since we use an estimation procedure that is specifically designed to handle persistent regressors. We provide details in this regard in Appendix A.2.

Naturally, the environmental profile of a firm and its exposure to environmental regulation are intertwined. In light of this we examine whether a firm's environmental profile, combined with regulatory stringency, affects its financial returns. The definition of environmental profile that we employ rests on the firm's greenhouse gas emissions. Specifically, we use the logarithm of the number of tonnes of GHG gas produced directly by the firm, which are the Scope 1 emissions. The regression we estimate then, is

$$\begin{aligned} r_{i,t} = &\beta_1 RegStringency_{i,t-1} + \beta_2 EM_{i,t-1} + \beta_3 EM_{i,t-1} \times RegStringency_{i,t-1} \\ &+ \beta_4 \mathbf{X}_{i,t-1} + \alpha_{i,t} + \varepsilon_{i,t}, \end{aligned} \tag{2}$$

where $\mathbf{X}_{i,t-1}$, $\alpha_{i,t}$ and $\varepsilon_{i,t}$ are defined as above. The coefficients of particular interest are β_1, β_2 and β_3. The coefficient β_1 represents the effect of an increase in regulatory stringency on a firm's return. Likewise, the coefficient β_2 captures the effect of an increase in firms' emissions on firms' returns. Higher emissions signify a worse environmental profile; therefore, a positive value of β_2 means that firms with worse environmental profiles (i.e., higher emissions) experience higher returns. Conversely, a negative value of β_2 would indicate that firms with worse environmental profiles suffer lower returns, suggesting that higher emissions may negatively impact returns. The coefficient β_3 represents the interaction effect between a firm's emissions and regulatory stringency on the firm's returns. A positive value of β_3 would indicate that as regulatory stringency increases, the positive (or negative) effect of emissions on returns is amplified. Conversely, a negative β_3 would imply that as regulatory stringency increases (decreases), the positive (negative) effect of emissions on returns diminishes. The vector β_4 contains the parameters associated with the control variables. We detail the estimation procedure in the following section.

3.2 Model estimation

For the predictability of stock returns using financial characteristics, it is well documented that in the presence of persistent variables, estimation will be biased. For panel data, the issue of persistent predictors is documented by Campbell and Yogo (2006). Furthermore, the overall out-of-sample reliability of these predictive relationships has been challenged by Welch and Goyal (2008). Inference can be made only when the time-series properties are correctly specified; therefore, we employ the estimator proposed by Hjalmarsson (2010), which is based on the projection method introduced by Pesaran (2006).

The idea behind the estimator is to remove the influence of common factors, in line with what fixed effects would do, by projecting the data onto the space orthogonal to unobserved common factors, therefore removing their effect from the estimation. The cross-sectional averages are used as a proxy of unobservable common factors. In addition, the method allows for individual fixed effects. The proposed estimator has the form

$$\hat{\beta} = \left(\sum_{i=1}^{n} \hat{\mathbf{X}}'_{i,-1} \hat{\mathbf{X}}^{dd}_{i,-1} \right)^{-1} \left(\sum_{i=1}^{n} \hat{\mathbf{X}}'_{i,-1} \hat{\mathbf{Y}}^{dd}_{i} \right),$$

where $\hat{\mathbf{X}}^{dd}_{i,-1}$ and $\hat{\mathbf{Y}}^{dd}_{i}$ represent the forward demeaned and projected lagged regressors and dependent variables. The lagged regressors $\hat{\mathbf{X}}_{i,-1}$ and dependent variables $\hat{\mathbf{Y}}_{i}$ are obtained from projecting the observations onto the space orthogonal to the common factors, by premultiplying with the orthogonal projection matrix $\mathbf{M_H}$, with $\mathbf{H}$ containing the cross-sectional averages of the regressors. Hence, $\hat{\mathbf{X}}_{i,-1} = \mathbf{M_H}\mathbf{X}_{i,-1}$ and $\hat{\mathbf{Y}}_{i} = \mathbf{M_H}\mathbf{Y}_{i}$. In addition, the forward demeaning in $\hat{\mathbf{X}}^{dd}_{i,-1}$ and $\hat{\mathbf{Y}}^{dd}_{i}$ corrects for the individual fixed effects. For the sake of brevity, the asymptotic distribution and a more detailed description of the estimator is provided in Appendix A. Standard errors are constructed using the firm-level sandwich estimator embedded in the asymptotic variance-covariance matrix of Hjalmarsson (2010).

3.3 Environmental regulatory stringency & firm agility

We look at the effect of environmental regulatory stringency upon firm returns, see Table 2. The estimated coefficient of interest in equation (1) is β_1 as it captures the effect of environmental regulatory stringency on stock returns after controlling for firm characteristics. We find that the effect of environmental regulatory stringency is positive and significant, showing that investors expect a return compensation for exposure to it.[1] For the cross-sectional pricing of carbon emissions, a similar finding has been made by Bolton and Kacperczyk (2021).

Building on this finding, we investigate firms' ability to react flexibly to the new regulatory environment. Naturally, firms' cash holdings provide financial flexibility, which is especially valuable when firms face the uncertain costs created by new regulations. Indeed Gulen and Ion (2016) find that policy uncertainty has a negative effect on corporate investment, but this effect is much weaker for firms with high cash reserves.

Consequently, we analyze the role of corporate cash holdings on the return compensation investors expect when firms are presented with stricter regulatory requirements. We do so by constructing subsets of firms above the median of the cash holdings distribution and below. The result is also presented in Table 2. The analysis shows that the positive relationship between environmental regulatory stringency and firm returns is statistically significant and larger in magnitude for firms with high cash reserves. Firms with low cash holdings, however, have an insignificant but still positive coefficient. This implies for firms with low cash holdings, there is much more volatility between the affected firms. Naturally, regulation can distort a business model enough to require substantial investments. These are tougher to shoulder for firms which have to increase their debt burden for this, resulting in uncertainty for investors about the firms' future. This shows that stricter environmental regulation is unproblematic for firms with high cash holdings as they adapt to the new corporate environment. Investors require a higher return compensation though but high cash firms are still in an advantageous situation over firms with low cash holdings when regulation becomes increasingly stringent.

A natural concern is endogeneity and we address it partly through our modeling setup and also conduct an investigation if our results are driven by industry-level growth dynamics instead of regulatory exposure. All regressors are lagged by 12 months, ensuring *RegStringency* is predetermined with respect to returns and avoids reverse causality by construction. Also, *RegStringency* is constructed from the number of binding words relative to the total number of words in EPA legal documents and an industry relevance score derived from the regulatory text itself, so no firm-level behavior enters the variable construction. Lastly, we investigate the possibility of an industry-specific omitted variable. The most plausible candidate is an industry measure that attracts regulatory attention and affects firms' returns. We assess this by adding the AR(1) innovation of the Federal Reserve's industrial production index matched to each firm's 3-digit NAICS industry as a variable to Equation 1. The coefficient on *RegStringency* changes only marginally, remains positive and statistically significant, while the innovation itself enters with the expected positive sign, see Table 8 in the Appendix. This result supports the reliability of the interpretation of $\hat{\beta}_1$.

[1] Breusch-Pagan tests (Breusch and Pagan, 1979) strongly reject homoskedasticity across all specifications (LM statistics ranging from 444 to 5793, $p < 0.001$ in all cases), confirming that firm-level heteroskedasticity is present. Serial correlation is absent at all horizons: Durbin-Watson statistics are close to 2 and Ljung-Box mean p-values exceed 0.40 at lag 1 across all specifications. Full diagnostic results are reported in Table 7 in the Appendix.

Table 2: We report the estimated parameters and standard errors of the predictive regressions relating monthly stock returns to firms' exposure to environmental regulatory stringency, for the full sample and for subsamples split by cash holdings. We find a positive and statistically significant relationship between environmental regulatory stringency and stock returns in the full sample. Splitting firms by cash holdings, shows that the parameter remains positive and statistically significant for firms with high cash holdings, showing that investors expect them to weather the stringent regulation better. For firms with low cash holdings, the relationship is much more volatile, but still positive. This implies investors are more uncertain about firms' abilities to weather stricter regulation when they, potentially, have to increase their debt burden to comply with the regulation. Standard errors are clustered at the 3-Digit industry level. $^{\dagger}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

	Dependent variable, monthly returns		
	(1)	(2)	(3)
Sample	Full Sample	High Cash Subsample	Low Cash Subsample
RegStringency	0.425***	0.496***	$0.300^{\dagger}$
	(0.0894)	(0.1242)	(0.1713)
Controls	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Number of firms	217	108	109
Observations	52080	25920	26160
R^2	0.050	0.015	0.051

3.4 Environmental regulatory stringency & firms' environmental profile

We turn to study the effect of a firm's regulatory stringency exposure subject to its environmental profile. We analyze the joint effect of environmental regulation and environmental profile in equation (2), represented by the coefficients β_2 and β_3, and summarised in Table 3. We employ different emissions specifications to measure the environmental profile: Scope 1, Scope 1+2, and Scope 1+2+3 GHG emissions. For each scope, we consider both 'Intensity' and 'Absolute' measures of emissions. Across all the specifications reported in Table 3, the effect of emissions on returns is positive and significant, with the exception of Scope 1+2+3 (Absolute). Scope 3 expands the definition of a firm's emissions profile to include indirect emissions from its suppliers and firms it supplies. While crucial to obtain a full overview of a firm's emissions footprint, Scope 3 is not directly firm related. The Scope adds by its construction variation to the emissions profile, which is beyond the firm's control. We attribute the insignificance of the parameter to this non-firm-specific variation. Scope 1, however, are the direct emissions generated by the firm. Also Scope 2, which is the emissions generated from the firms energy consumption mix, is to some extend in the firms control, given it can choose its energy supply. Beyond significance, all parameters are positive. This implies that higher absolute and intensity emissions are associated with higher equity returns, since investors require a return compensation, which is consistent with findings in other studies (Bolton and Kacperczyk, 2021; Bolton and Kacperczyk, 2023; Sankar et al., 2024). The interaction term coefficient is consistently negative and statistically significant in five of six specifications. This is a crucial finding: firms with a 'bad' environmental profile (higher emissions) experience a negative impact of regulatory stringency on their returns since investors have to be uncertain about the firm's future in light of the stricter regulation. Vice versa, firms with a 'good' environmental profile are rewarded by investors for this when faced with stricter environmental regulation.

Table 3: We report the estimated parameters and corresponding standard errors of the predictive regression in equation (2), examining the joint effect of environmental regulatory stringency and firms' environmental profiles on monthly stock returns, using alternative emission measures across scopes and specifications. We find that emissions are positively related to returns, consistent with higher returns for firms with weaker environmental profiles. At the same time, the interaction between emissions and regulatory stringency is negative and statistically significant across specifications, indicating that firms with higher emissions experience lower returns when regulatory stringency increases, while firms with cleaner environmental profiles are comparatively less affected. Standard errors are clustered at the 3-Digit industry level. $^{\dagger}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

	Scope 1		Scope 1+2		Scope 1+2+3	
	Intensity	Absolute	Intensity	Absolute	Intensity	Absolute
RegStringency	0.8025***	0.7657***	0.8845***	0.8113***	0.8143***	0.6003***
	(0.2225)	(0.1300)	(0.2056)	(0.1633)	(0.1939)	(0.1628)
RegStringency × *Emissions*	-0.0480***	-0.0169**	-0.0277***	-0.0134**	-0.0172***	-0.0047
	(0.0076)	(0.0064)	(0.0060)	(0.0042)	(0.0050)	(0.0039)
Emissions Scope 1 (Intensity)	0.0047**					
	(0.0014)					
Emissions Scope 1 (Absolute)		0.0023*				
		(0.0012)				
Emissions Scope 1+2 (Intensity)			0.0045**			
			(0.0016)			
Emissions Scope 1+2 (Absolute)				0.0017*		
				(0.0008)		
Emissions Scope 1+2+3 (Intensity)					0.0036**	
					(0.0014)	
Emissions Scope 1+2+3 (Absolute)						0.0018†
						(0.0010)
Controls:	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of firms	217	217	217	217	217	217
Observations	52080	52080	52080	52080	52080	52080
R^2	0.051	0.060	0.051	0.063	0.054	0.066

4 A market-expectation index for risks arising from environmental regulation

We established that environmental regulatory stringency is a statistically significant predictor for asset returns in the cross-section of asset prices. Regulation of any kind is by construction only released infrequently. The EPA releases the environmental regulatory text once a year, which is too infrequent for active risk management and analysis. Therefore, we construct a high-frequency market-expectation index for risks arising from environmental regulation. To this end, we first construct yearly low-minus-high portfolios sorted by firms' exposure to environmental regulatory stringency. Although *RegStringency* is an annual measure, market expectations of future regulatory stringency evolve continuously, subject to e.g. congressional debates or election outcomes (Baker et al., 2016). Following standard asset pricing theory, investors adjust their expectations towards a firm's future cash flows when their expectations about the regulatory environment changes. Indeed it has been shown that changes in the regulatory environment affects firms costs (Ince and Ozsoylev, 2024; Kalmenovitz, 2023), firms investment decisions (Becker and Henderson, 2000; Greenstone et al., 2012) and affects their business model (Greenstone, 2002). The literature proposed a plethora of asset pricing factors which represent these firm characteristics at a daily frequency. The mimicking portfolio methodology of Lamont (2001) allows us to construct then a measure of regulatory stringency at higher frequency by determining the asset pricing factors that proxy the dynamics of the yearly signal. The methodology of Lamont (2001) has also been applied to climate risk by Engle et al. (2020) and De Nard et al. (2024), where they construct hedging portfolios against climate risk and climate change news.

The chosen asset pricing factors should have an economically or financially backed relationship with environmental regulation. As stated above, the literature showed that a change in regulation is met by costs, affects investment decisions, and firms' business models (Becker and Henderson, 2000; Greenstone, 2002; Greenstone et al., 2012; Ince and Ozsoylev, 2024; Kalmenovitz, 2023). We therefore identify asset pricing factors which are related to the firm characteristics that the literature identified as affected by environmental regulation.

We first introduce the construction of the environmental regulatory stringency portfolios and validate their ability to track environmental regulatory stringency. Based on these portfolios, we then create a market-expectation-based index termed Environmental Regulatory Risk Index (ERRI) with the dynamic index construction methodology of Trimborn and Härdle (2018).

4.1 Environmental regulatory risk portfolio construction

To construct the market-expectation index, we construct a factor-mimicking portfolio following the methodology of Lamont (2001) using a characteristics-based approach. The factors are drawn from the comprehensive library of Jensen et al. (2023) (henceforth JPK), organized into thirteen thematic clusters.[2] After identifying firm-characteristics affected by changes in regulation, we determine the clusters these asset pricing factors are associated with in the JPK taxonomy. Since *RegStringency* is a yearly measure, we have to keep the candidate set of factors low, whereas the factor zoo is sizable. To avoid cherry-picking of factors, we instead obtain the geometric mean across the factors in the identified clusters. Four clusters, namely *Debt Issuance*, *Profit Growth*, *Low Leverage*, and *Investment* are included on the basis of theoretical and empirical evidence linking regulation to the underlying firm characteristic.

The four selected clusters are motivated as follows. *Debt Issuance:* Kalmenovitz (2023) documents that a one-standard-deviation increase in regulatory intensity raises the probability of issuing new debt by approximately 1.8 percentage points, equivalent to around 7% of the cross-sectional mean. *Profit Growth:* Greenstone et al. (2012) estimate that nonattainment regulation reduces total factor productivity by 2.6% among surviving plants (4.8% after correcting for survivorship and output-price bias), generating a step-change in earnings dynamics. Ryan (2012) documents that the 1990 Clean Air Act Amendments raised entry costs and reduced product market surplus in the cement industry by \$0.8–3.2bn. *Low Leverage:* Kalmenovitz (2023) shows that regulatory intensity raises market leverage substantially, as firms deplete cash holdings to meet compliance costs and turn to debt financing. Ince and Ozsoylev (2024) further documents that regulatory exposure amplifies cash-flow volatility for high-leverage firms. *Investment:* Becker and Henderson (2000) and Greenstone et al. (2012) show that stricter environmental regulation leads to changes in investment decisions of firms operating manufacturing plants in the U.S. Also Kalmenovitz (2023) documents that regulatory intensity reshapes capital allocation, crowding out productive investment for financially constrained firms.

For each cluster $c \in \{1, \dots, C\}$, the representative factor $f_{c,t}$ is the geometric mean of the standardized returns on the portfolios assigned to that cluster. The low-minus-high quintile portfolio of environmental regulatory stringency is constructed based on the $RegStringency$ measure and resorted each July, when the regulatory text is published. Value-weighted returns are computed over the subsequent 12 months. The resulting long-short portfolio, $RegStringencyHL$, takes a long position in firms with low regulatory exposure and a short position in firms with high regulatory exposure, over the full sample from 1973 to 2022.

The returns of $RegStringencyHL$ are regressed onto the cluster factors $f_{c,t}$ using an expanding window, starting in 1983, hence the first regression contains 10 years worth of observations[3]:

$$RegStringencyHL_t = \gamma_t + \sum_{c=1}^{C} \beta_{c,t} f_{c,t} + \varepsilon_t, \tag{3}$$

[2]The taxonomy follows Table 9 of the JPK documentation. Data and documentation are available at `https://jkpfactors.com/`.

[3]*RegStringency* is a yearly measure and the regression contains the intercept and up to four variables, which are the geometric averages over the clusters. Starting with 10 observations ensures that we have at least twice as many observations as regressors in each regression.

where γ_t is the intercept, $\beta_{c,t}$ the parameter associated with cluster c, and ε_t an error term. The estimated coefficients $\hat{\beta}_{c,t}$ measure the exposure of *RegStringencyHL* to each thematic cluster. Clusters with a higher $\hat{\beta}_{c,t}$ receive a greater weight in the portfolio. Six estimation methods are considered: OLS, LASSO, and Ridge and Recursive Least Squares (RLS) with decay parameter $\lambda \in \{0.80, 0.95, 0.98\}$, which assigns weight $w_h = \lambda^{t-h}$ to the observation at time h. LASSO and Ridge use 5-fold cross-validation with model selection by minimum MSE. The latter assigns higher weights to more recent observations, which takes into account that recent years' observations may be more informative. We expand the set of factors in each regression iteratively by their contribution to the R^2 in the OLS regression. Debt Issuance (D) adds the most to R^2, followed by Profit Growth (P), Low Leverage (L), and Investment (I).

From the estimated $\hat{\beta}_{c,t}$, the portfolio at $t+1$ is formed by applying the coefficients estimated through t as fixed weights, that is,

$$r_{ERRP,t+1} = \sum_{c=1}^{C} \hat{\beta}_{c,t} f_{c,t+1}. \tag{4}$$

By construction, this portfolio hedges against risks arising from environmental regulation and provides a market-based estimate of regulatory risk exposure. Whereas the regulatory data are published only once a year, the r_{ERRP} portfolios allow measurement of market expectations at daily frequency, providing a real-time measure for risks arising from environmental regulation, when the actual regulatory text is unpublished or under discussion.

4.2 Environmental Regulatory Risk Portfolio validation

We validate the performance of all the specifications of the r_{ERRP} portfolios in Table 4. For this, we regress $RegStringencyHL_{t+1}$ onto the portfolio return $r_{ERRP,t+1}$, which is constructed using estimated weights $\hat{\beta}_{c,t}$ and applied to factors observed at $t+1$, or,

$$RegStringencyHL_{t+1} = \alpha\, r_{ERRP,t+1} + u_{t+1}. \tag{5}$$

A significant α indicates that the portfolio composition, fixed at t, remains suitable for tracking *RegStringencyHL* one period later. Table 4 reports the result of the estimation of Equations 3 and 5. We denote the portfolios by the factors they contain, namely Debt Issuance (D), Profit Growth (P), Low Leverage (L), and Investment (I). In the pre-2000 period, out-of-sample R^2 values vary substantially between clusters with more/less factors and estimation methods. The sign prediction accuracy, mspa, generally exceeds the 50% benchmark across estimators, with no estimation method dominating consistently across portfolios. These observations illustrate, that a definitive choice of portfolio size and estimation method, is challenging. In the post-2000 period, the RLS-based estimators outperform competing methodologies in terms of out-of-sample R^2. For the full DPLI factor set, the RLS estimators achieve an out-of-sample

R^2 of up to 5-times bigger than the competing methodologies. However, in terms of mspa, the picture is at times reversed. In this period DPL gives by far the best mspa.

These results show that some r_{ERRP} portfolios achieve good out-of-sample performance. However, as the 2-period split showed, the performance of the models varies and it is not possible to choose a best performing set or estimation method. Consequently, we propose a dynamic index construction methodology, selecting a representative set of portfolios, as the underlying basis for an Environmental Regulatory Risk Index, to be introduced in Section 4.4.

Table 4: We report the in-sample and out-of-sample performance of the ERRP portfolios constructed using different factor models and estimation methods, evaluated against the regulatory stringency low-high environmental regulatory stringency exposure portfolio. We report the summary statistics before and after 2000 to determine potential time dependent changes in performance. We find that the ERRP portfolios explain a substantial share of variation in environmental regulatory stringency in-sample, with performance varying across factor structures and estimators. Out-of-sample results show that RLS–based specifications perform particularly well in terms of R^2, whereas for mspa, the picture is at times reversed. The results show good out-of-sample performance of the portfolios, but no set of factors and estimation method outperforms over time.

		Eq. 3		Eq. 5				
	Estimation	Avg R^2	In sample mse	mse	mspa	R^2	coeff (α)	[t] α
Panel A: Pre-2000								
D	OLS	0.158	8.18e-04	2.14e-03	52.941	0.245	0.679	10.123
	Lasso	0.146	8.22e-04	2.12e-03	52.941	0.249	0.688	11.714
	Ridge	0.158	8.18e-04	2.14e-03	52.941	0.245	0.679	10.124
	$RLS_{0.80}$	0.220	9.52e-04	2.13e-03	52.941	0.248	0.511	10.551
	$RLS_{0.95}$	0.172	8.25e-04	2.12e-03	52.941	0.250	0.625	11.293
	$RLS_{0.98}$	0.163	8.19e-04	2.13e-03	52.941	0.248	0.656	10.635
DP	OLS	0.234	7.66e-04	2.40e-03	52.941	0.152	0.396	2.576
	Lasso	0.204	7.81e-04	2.33e-03	52.941	0.177	0.484	2.965
	Ridge	0.234	7.66e-04	2.40e-03	52.941	0.152	0.396	2.577
	$RLS_{0.80}$	0.325	1.01e-03	2.49e-03	58.824	0.121	0.287	1.950
	$RLS_{0.95}$	0.251	7.77e-04	2.40e-03	52.941	0.150	0.376	2.368
	$RLS_{0.98}$	0.240	7.67e-04	2.40e-03	52.941	0.152	0.388	2.500
DPL	OLS	0.275	7.26e-04	1.91e-03	64.706	0.326	0.735	4.396
	Lasso	0.225	7.50e-04	1.64e-03	70.588	0.419	0.901	24.546
	Ridge	0.275	7.26e-04	1.91e-03	64.706	0.326	0.736	4.409
	$RLS_{0.80}$	0.354	9.97e-04	2.57e-03	58.824	0.091	0.200	2.342
	$RLS_{0.95}$	0.286	7.36e-04	1.98e-03	64.706	0.302	0.689	2.739
	$RLS_{0.98}$	0.279	7.27e-04	1.92e-03	64.706	0.323	0.730	3.603
DPLI	OLS	0.304	7.02e-04	1.69e-03	70.588	0.404	0.829	9.391
	Lasso	0.186	7.88e-04	1.76e-03	64.706	0.377	0.992	8.996
	Ridge	0.304	7.02e-04	1.69e-03	70.588	0.404	0.830	9.408
	$RLS_{0.80}$	0.425	9.83e-04	2.42e-03	58.824	0.146	0.258	3.236
	$RLS_{0.95}$	0.323	7.13e-04	1.70e-03	70.588	0.399	0.807	4.430
	$RLS_{0.98}$	0.311	7.04e-04	1.67e-03	70.588	0.410	0.834	6.897
Panel B: Post-2000								
D	OLS	0.269	1.91e-03	8.17e-03	52.381	0.014	0.505	0.807
	Lasso	0.268	1.91e-03	8.16e-03	52.381	0.015	0.537	0.872
	Ridge	0.269	1.91e-03	8.17e-03	52.381	0.014	0.505	0.807
	$RLS_{0.80}$	0.282	2.57e-03	8.19e-03	52.381	0.011	0.388	0.689
	$RLS_{0.95}$	0.285	1.95e-03	8.20e-03	52.381	0.011	0.422	0.644
	$RLS_{0.98}$	0.277	1.92e-03	8.18e-03	52.381	0.012	0.470	0.737
DP	OLS	0.288	1.85e-03	7.47e-03	57.143	0.099	1.099	2.379
	Lasso	0.278	1.88e-03	7.59e-03	61.905	0.084	1.100	2.765
	Ridge	0.288	1.85e-03	7.47e-03	57.143	0.099	1.099	2.379
	$RLS_{0.80}$	0.327	2.43e-03	6.46e-03	71.429	0.220	1.447	3.012
	$RLS_{0.95}$	0.304	1.89e-03	7.15e-03	61.905	0.137	1.218	2.636
	$RLS_{0.98}$	0.295	1.86e-03	7.33e-03	57.143	0.115	1.156	2.467
DPL	OLS	0.377	1.64e-03	5.60e-03	71.429	0.324	3.146	4.177
	Lasso	0.349	1.73e-03	7.64e-03	52.381	0.078	1.874	4.543
	Ridge	0.377	1.64e-03	5.60e-03	71.429	0.324	3.146	4.177
	$RLS_{0.80}$	0.462	2.22e-03	4.70e-03	61.905	0.432	1.679	7.417
	$RLS_{0.95}$	0.405	1.68e-03	4.74e-03	57.143	0.427	2.938	6.550
	$RLS_{0.98}$	0.389	1.65e-03	5.15e-03	61.905	0.378	3.156	4.854
DPLI	OLS	0.379	1.63e-03	5.03e-03	76.190	0.393	2.961	4.747
	Lasso	0.351	1.72e-03	7.60e-03	57.143	0.083	1.949	4.313
	Ridge	0.379	1.63e-03	5.03e-03	76.190	0.393	2.962	4.746
	$RLS_{0.80}$	0.480	2.23e-03	4.30e-03	66.667	0.481	1.585	6.117
	$RLS_{0.95}$	0.410	1.68e-03	4.19e-03	66.667	0.494	2.654	7.040
	$RLS_{0.98}$	0.392	1.64e-03	4.58e-03	66.667	0.447	2.878	5.649

4.3 Climate attention and regulation

A natural question is whether the r_{ERRP} portfolios merely proxy for attention society is presently paying to climate and environmental topics. Several indices have been proposed in the literature to measure the attention of the public to climate issues and the policy uncertainty around it. In this section we assess how the ERRP portfolio differs from the proposed measures in the literature. To assess this, we regress the ERRP portfolios onto the indices controlling for the market returns. The results reported in Table 5 are from r_{ERRP} estimated with OLS as input to the regression $r_{ERRP,t} = \eta + \xi IDX_t + \delta MKT_t + v_t$, where η is the intercept, ξ the parameter associated with the index under investigation, IDX, δ the parameter associated with the market return and v_t an error term. In Table 9, we report the average R^2 and standard deviation across the ERRP portfolios for each factor composition and estimation method. We observe that the R^2 of the regressions is stable across specifications, showing the robustness of the assessed results.

Panel A of Table 5 covers the Sentometrics US media climate index (Ardia et al., 2023) (ABBI) at monthly and daily frequency and the WSJ-based level-difference and AR(1) innovation indices of Engle et al. (2020) (EGLKS). Panel B covers the Climate Policy Uncertainty index of Gavriilidis (2021) (CPU) and its narrow and broad variants (Gavriilidis et al., 2026). The CPU is calculated from news articles in The New York Times, The Wall Street Journal, and The Washington Post, mentioning keywords representing environmental, policy, and uncertainty terms. The narrow and broad versions have each a different underlying keyword dictionary for the three topics. By their construction, these indices measure news attention and coverage to environmental uncertainty. Note that the reported metrics for the Fraser EFW index (Gwartney et al., 2023) are not coefficients but correlations between r_{ERRP} and IDX, since the index is only available at yearly frequency.

It is only natural to expect some relationship between climate attention and environmental regulatory risk, as they are naturally intertwined. However, for ABBI, none of the coefficients are significant and the R^2 is rather small. Turning to the EGLKS index, we observe a R^2 of around 0.1 for both specifications and significant parameters for the AR(1) innovation specification. The EGLKS index is built from Wall Street Journal coverage, selected because the WSJ is the predominant media source consumed by market participants.

Turning to the three climate policy uncertainty indices reported in Panel B, we find coefficients are statistically insignificant for all specifications at the 5% level. The R^2 rises modestly from 0.034 to 0.043 as the dictionary coverage broadens from CPU to CPU narrow to CPU broad. However, the R^2 remains on a low magnitude, showing that the ERRP portfolios, which track stringency of regulation, do not overlap with uncertainty about environmental policy, and therefore offer a complementary view.

The index closest in definition to what ERRP measures, is the OECD Environmental Policy Stringency (EPS) index. The index is available with yearly frequency, but for the reported

U.S. version, a sizable portion of its values are constant over the years. Therefore we compare their performance, observing that the OECD EPS increases over the years, indicating stricter regulation in the U.S. Recall that we observed the same for the *RegStringency* measure used in this study. This shows that the two measures have comparable performance, as one would expect for indices measuring relatable quantities.

While conceptually not as similar to ERRP as the EPS index, the Fraser EFW index (Gwartney et al., 2023), which measures the presence/absence of regulation in credit, labor, and all kind of aspects of business in the U.S., shows more fluctuations. A higher value of the index reflects a lower regulatory burden. The Fraser EFW correlation ranges from 0.17 in magnitude in the D specification to values between 0.09 and 0.11 in magnitude in the remaining specifications. Given the Fraser index covers all kinds of regulation, not only environmental one, a high correlation is not expected. We regard its size of correlations reasonable given this limitation. Table 9 confirms the observed quantitative patterns across OLS, Lasso, Ridge, and RLS estimators, with small standard deviations of R^2 within each index-specification.

Table 5: We determine whether the ERRP portfolios are proxied for by climate attention and whether they correlate with established regulatory indices. We regress the respective index innovations onto the ERRP estimated with OLS, while controlling for the market return. We report the estimated coefficient with the corresponding T-statistic in parentheses below. For the index with only annual observations available, we report correlation coefficients. Denote n is the number of observations in the regression sample (DPLI specification). Best R^2 is the maximum across all specifications. The results show that ERRP is not proxied for by climate attention. They also show reasonable correlation coefficients with Fraser EFW, taking into account that the measures represent different aspects of regulation. $^{\dagger}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Freq.	Index	D	DP	DPL	DPLI	n	Best R^2
Panel A: Climate attention indexes							
Mon.	Sentometrics (ABBI)	0.0466 (0.48)	0.0721 (0.86)	0.0978 (1.11)	0.0951 (1.09)	228	0.014
Daily	Sentometrics (ABBI)	0.0202 (1.33)	0.0145 (0.97)	0.0062 (0.40)	0.0057 (0.37)	4784	0.013
Mon.	EGLKS	-0.0363 (-1.01)	-0.0517 (-1.40)	-0.0673† (-1.73)	-0.0678† (-1.75)	402	0.092
Mon.	EGLKS AR(1) innovation	-0.0716† (-1.71)	-0.1034* (-2.50)	-0.1095* (-2.53)	-0.1086* (-2.45)	402	0.099
Panel B: Regulation and policy stringency indexes							
Mon.	CPU	-0.0408 (-0.63)	-0.0559 (-1.03)	-0.0382 (-0.74)	-0.0407 (-0.79)	444	0.034
Mon.	CPU narrow	-0.0309 (-0.49)	-0.0711 (-1.29)	-0.0606 (-1.21)	-0.0626 (-1.27)	444	0.036
Mon.	CPU broad	-0.0868 (-1.05)	-0.1265† (-1.92)	-0.1023† (-1.71)	-0.1046† (-1.76)	444	0.043
Ann.	Fraser EFW	-0.1656	0.0856	0.1129	0.0924	27	

4.4 Environmental Regulatory Risk Index

In this section we construct from the different specifications of the ERRP portfolios an index for risks arising from environmental regulation and evaluate its performance relative to market risk over the past 40 years. We showed that the ERRP portfolios behave as suitable measures for risks arising from environmental regulation. However, factor structures and estimation methods showed differing behavior across metrics and time, see Table 4. Even though RLS-based estimators excelled in the two periods, in shorter time periods they might still underperform. As such, we refrain from choosing a specification and estimation method, instead we construct an equally weighted index, termed ERRI, from the portfolios. By construction, this will ensure, that each portfolio contributes to the measurement of risks arising from environmental regulation at high frequencies. However, we also do not want portfolios, which at a given point in time do not represent risks arising from environmental regulation well, to enter the index. The index construction methodology by Trimborn and Härdle (2018) chooses dynamically the number of portfolios encompassing the index by conducting model selection via the AIC criterion.

The candidate constituents are the r_{ERRP} portfolios of Table 4, namely the four factor-cluster specifications (D, DP, DPL, DPLI) combined with the six estimation methods (OLS, Lasso, Ridge, $\text{RLS}_{0.80}$, $\text{RLS}_{0.95}$, $\text{RLS}_{0.98}$), hence 24 candidate portfolios in total. At every monthly reallocation date, the AIC criterion picks which of these 24 portfolios enters the equally weighted index and how many by regularising the number of portfolios. We term the resulting equally weighted index ERRI and denote its log return $r_{ERRI,t}$. Because both the set and the number of constituents are re-selected by AIC every month, a portfolio whose tracking performance deteriorates can be dropped at the next reallocation, and the number of constituents adjusts accordingly. This may raise stability concerns. Across the observed sample, the index never selects more than $K_{\max} = 5$ constituents at any reallocation date. We show with Model Confidence Sets (MCS) (Hansen et al., 2011), that the indices with 1 - 5 fixed constituents are statistically indistinguishable in the MCS. Hence, ERRI's methodology allows it to flexibly react to recent developments, while having a stable long-run performance.

The AIC never selects more than $K_{\max}$ constituents, hence the unconstrained ERRI, with return $r_{ERRI,t}$, coincides at every reallocation date with one of the indices with fixed number of constituents. The relevant question is therefore whether the unconstrained index has inherent instability due to its design. We construct $K_{\max}$ *constrained* alternatives: for each $k \in \{1,\ldots,K_{\max}\}$, the number of constituents is fixed at exactly k at every reallocation date, while the methodology still chooses by likelihood contribution which k of the 24 candidate ERRP portfolios fills these slots. This yields the constrained index return series $r^{(k)}_{ERRI,t}$. The tracking-error loss differential of the constrained index relative to the unconstrained ERRI is

$$d^{(k)}_t = r^{(k)}_{ERRI,t} - r_{ERRI,t}, \qquad k = 1,\ldots,K_{\max}. \tag{6}$$

The MCS procedure is applied to $d^{(k)}_t$ with $B = 10{,}000$ bootstrap replications, see Table

6. All five constrained specifications are retained in the superior set, with MCS p-values far away from common significance levels. Hence, reverting to a fixed number of constituents does not produce a statistically significant deterioration in tracking performance relative to the unconstrained index.

Table 6: Model Confidence Set results for the fixed-k ERRI specifications, $k = 1, \dots, 5$. The results show that the differences in the non-dynamic variants of ERRI are statistically insignificant. Therefore, ERRI's methodology allows to flexibly react to recent development, while having a comparable long-run performance compared to its non-dynamic counterparts.

k	MCS p-value	Loss
1	1.0000	1.02e-06
2	0.4687	9.74e-06
3	0.7707	6.88e-06
4	0.8413	6.17e-06
5	0.7261	7.43e-06

4.5 Validation

We determine the market expected compensation for exposure to risks arising from environmental regulation from the ERRI index and analyse it relative to the market index. For this, we subtract the innovations in the market index, represented by the S&P500 index, from the innovations in the ERRI index, see Figure 3.

The compensation for risks arising from environmental regulation is a return compensation linked to a specific risk and we compare it therefore against all other risks the market perceives. By this we determine if the market considers risks arising from environmental regulation to be relatively high or low at a given time point. We expect the excess return to be in the negative domain most of the time given we evaluate it against all other risks in the market. Indeed we observe the excess return to be in the negative domain for most of the time. What first catches the eye, is a strong spike in the excess return for risks arising from environmental regulation in November 1987. This spike predates the signing of the Global Climate Protection Act by the U.S. in December. This law directed the U.S. government to begin developing strategies to address climate change, including monitoring and reporting on greenhouse gas emissions and coordinating climate research and policy efforts through federal agencies. Naturally, this law changed the regulatory landscape drastically and we would expect market participants to react strongly to it. Indeed, the market considered this a huge risk to firms' business models, as apparent from the high excess return.

In the aftermath of the Global Climate Protection Act, volatility in the excess return gradually decreased until 1996, after which it strongly increased again. In the same year, the Food Quality Protection Act was signed as well as an Amendment to the Safe Drinking Water Act. They changed how the EPA regulates pesticides in food, created a single health-based standard, and added extra protections for infants and children. We observe that the market saw this again as a notable risk to firms' business models compared to all other risks.

Risks arising from environmental regulation dropped notably in the summer of 1997. This decline coincide with the Byrd-Hagel Resolution, which was unanimously passed in the U.S. senate, and which required the U.S. to not pass new regulations to lower emissions if it would cause economic harm to the U.S. economy. This effectively prevented the U.S. from ratifying the Kyoto Protocol. While it was still signed by the U.S., it was never ratified as a result of this Resolution, and the market apparently saw this as a huge relief for firms' business models, as the ERRI index excess return shows. The symbolic signing of the Protocol resulted therefore only in a modest positive jump in the excess return which instantly moved back into the negative domain. Given the merely symbolic nature of the signing, we would expect the ERRI index to react precisely in this manner.

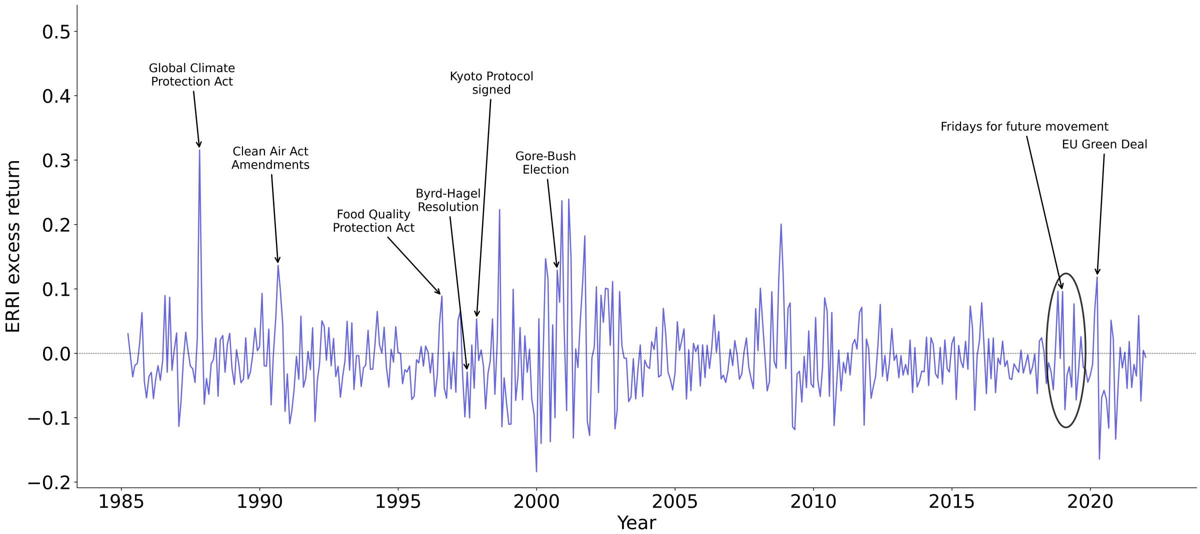
We observe a sharp decline of the excess return for risks arising from environmental regulation at the end of 1999. Recall that the excess return is obtained relative to all other risks in the market, so this drop comes at a time when it was clear that the U.S. government would not implement the Kyoto Protocol, while the markets were more concerned about the Y2K risk and risks from the large dot-com investments, which ultimately were a bubble.

In the last few months of 2000, we observe that the excess return for risks arising from environmental regulation spiked strongly. During this time it was not clear for weeks whether Al Gore or George W. Bush won the presidential election. Al Gore was known as an environmental advocate, hence his election would have signaled stricter environmental regulation. Investors would naturally consider this as a high risk to firms' business models, which is precisely what the excess return for risks arising from environmental regulation, derived from the ERRI index, indicates.

Following a period of modest volatility in the ERRI excess return, we observe a spike of heightened risks arising from environmental regulation in late 2018. This coincides with the start of Greta Thunbergs climate protest which was joined by people globally as early as 2019. However, the market continued to evaluate the risks arising from environmental regulation as lower compared to other risks. As this time period coincided with Donald Trumps first term in office, naturally the risk for stricter environmental regulation was low as he and his team supported laxer environmental regulation. However, we do see larger volatility in the excess return which shows that the market did take the protests as a serious risk to firms' business models, potentially as stricter regulation might be introduced after Trumps term.

Despite the deregulation in the U.S., we still observe a strong positive spike in risks arising from environmental regulation in January and February 2020. In January 2020, the European Union passed the European New Green Deal. Given the EU is an important market for U.S. firms, it is only natural that the market saw this as a notable risk to U.S. firms' business models. Also, around this time the U.S. New Green Deal was plenty discussed by U.S. presidential candidates, such as Elisabeth Warren and Bernie Sanders. Indeed the Biden administration

Figure 3: This Figure displays the excess return of the ERRI index relative to the market. We observe pronounced spikes around major environmental policy and political events, indicating periods in which markets perceived risks arising from environmental regulation to be particularly salient. For most of the sample, the excess return is negative, suggesting that risks arising from environmental regulation is generally small relative to other market risks, but rises sharply during episodes of heightened environmental regulatory uncertainty. We also observe that events strongly decreasing risks arising from environmental regulation, such as the Byrd-Hagel Resolution, are accompanied by a negative spike in the ERRI excess return. This particular event even dampened the risk from the signing of the Kyoto Protocol as it was clear it would not be ratified by the U.S. senate.



implemented stricter regulation when they assumed office.

However, once the U.S. decided on various policies to curb the Covid-19 pandemic, including a national emergency, risks arising from environmental regulation moved out of markets focus and other risks such as store closures dominated the risk environment for firms' business models. This explains the predominantly negative excess return for risks arising from environmental regulation relative to all other risks in 2020 and 2021.

5 Policy implications

Our findings provide several insights relevant for policymakers when designing and evaluating environmental regulation. While our analysis focuses on financial market reactions, these reactions reflect investors' expectations about firms' ability to adjust to stricter regulatory environments. As such, they offer information that can aid policy impact assessments.

First, our results show that markets differentiate between firms based on their environmental profiles when regulatory stringency increases. High-emission firms experience lower returns when facing higher regulatory stringency, whereas firms with lower emissions see comparatively better outcomes. This shows that markets expect emission-intensive firms to incur higher adjustment costs. Policymakers should therefore anticipate heterogeneous effects across industries and may consider accompanying measures for firms or sectors that face disproportionately high regulatory burdens. Such measures could include targeted support for innovation, transition funding, or phased implementation schedules.

Second, we find that firms with high cash holdings are viewed by investors as better positioned to respond to stricter regulation. Investors expect a positive and statistically significant return compensation for these firms when regulatory stringency increases. However, for firms with lower cash reserves the effect is considerably more volatile. Naturally, regulation can distort a business model so much, that it requires substantial investments. These are tougher to shoulder for firms which have to increase their debt burden for this, which would result in uncertainty for investors about the firms future. On the other hand, our results indicate that financially flexible firms are expected by investors to adjust better to stricter regulatory requirements. From a policy perspective, this shows that limited finances can result in a lot of uncertainty about a firm's future when faced with stricter environmental regulation. Policies that ease financing frictions, such as credit support for environmental investments, may ease the burden on low cash firms.

Finally, our Environmental Regulatory Risk Index (ERRI) provides a way to track market expectations of risks arising from environmental regulation at higher frequencies than the regulatory text itself would allow for. Evaluation of the impact of regulation often occurs via event studies, which do not allow for continuous tracking of its expected impact, ERRI offers a tool for observing how investors perceive ongoing developments related to environmental policy.

6 Conclusions

The aim of this paper is to determine from market expectations how firms are affected by risks arising from environmental regulation. We use a text-based measure of environmental regulatory stringency derived from the legal documents published by the U.S. Environmental Protection Agency. By combining this measure with industry-level relevance scores, we obtain a time-varying regulatory risk exposure that allows us to study how firms' stock returns are affected by regulatory stringency. By relying on financial market reactions, we obtain information about how investors perceive firms' ability to adjust to changes in environmental regulation. This allows us to study which firms are expected to be more exposed to stricter regulatory environments and which characteristics shape this exposure.

We find that financial flexibility plays an important role in how firms are perceived under stricter environmental regulation. Firms with high cash holdings experience positive and statistically significant return compensation when regulatory stringency increases, whereas the effect is highly volatile for low cash firms. This indicates that investors view financially flexible firms as better positioned to adjust to a changing regulatory environment. For firms with lower cash reserves, the high volatility of the expected return compensation shows that there is a lot more uncertainty about the firms' future when presented with stricter environmental regulation.

We further show that firms' environmental profiles are an important determinant of how they are affected by changes in regulatory stringency. Firms with higher emissions experience lower returns when regulatory stringency rises, whereas firms with lower emissions are comparatively less affected. This indicates that investors expect risks arising from environmental regulation to be more relevant for firms with a poor environmental profile.

A second objective of our study is to derive a high-frequency measure that captures market-based expectations of risks arising from environmental regulation. The regulatory text is released infrequently and therefore does not allow for continuous tracking of changes in regulatory expectations. To address this, we construct low-high environmental regulatory stringency exposure portfolios to track markets perceived risks arising from environmental regulation. From the portfolios, we design the Environmental Regulatory Risk Index (ERRI), which provides a high-frequency market-expectations based measure of risks arising from environmental regulation. We analyse the index reactions to regulations such as the 'Global Climate Protection Act', the 'Kyoto Protocol', and the 'European Green Deal', among others, thereby validating and showing how investors perceive the risks arising from environmental regulation from these events. We furthermore analyse ERRI's reactions during developments which may result into stricter or weaker environmental regulation, such as the presidential candidacy of Al Gore and the climate protests led by Greta Thunberg, thereby proving a measure to evaluate markets perceived risks arising from environmental regulation from these developments.

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A Appendix

A.1 Relevance Score calculation

The relevance score $Relevance_{j,p,t}$ is obtained from the RegData database Al-Ubaydli and McLaughlin (2017). We briefly highlight the procedure used to obtain the relevance score. As mentioned the score is obtained via a classification model composed by two algorithms: Logistic regression (Logit) with Lasso penalty and Random Forests. The training sample consists of proposed and final rules published in the CFR from 2000 to 2016 with exact matches of the full NAICS industry name, the name of a parent industry, or the name of a child industry as indicators of direct relevance to an industry. They then used the estimated models to classify each CFR part and the tuning parameters are set using five fold cross validation. The relevance score ranges between 0 and 1, whereas a higher score indicates a higher likelihood that a given text targets an industry. Further details about the procedure can be found in McLaughlin and Nelson (2021).

A.2 Estimator

The estimator proposed by Hjalmarsson (2010) is briefly outlined below, with further details available in their paper. To simplify the notation, we discuss the model here in a simplified version. The predictive regression framework presented in Hjalmarsson (2010) is defined for time point t and asset i:

$$\begin{aligned} y_{i,t} &= \alpha_i + \beta_i' x_{i,t-1} + u_{i,t}, \\ x_{i,t} &= A_i x_{i,t-1} + v_{i,t}. \end{aligned}$$

The first equation is the predictive regression, the second equation shows that $x_{i,t}$ follows a first-order vector autoregressive process with the autoregressive coefficient matrix parameterized as local to unity: $A_i = I + C_i/T$. The estimator takes the form

$$\hat{\beta}^{+}_{RD} = \left(\sum_{i=1}^{n} \hat{\mathbf{X}}'_{i,-1} \hat{\mathbf{X}}^{dd}_{i,-1} \right)^{-1} \left(\sum_{i=1}^{n} \hat{\mathbf{X}}'_{i,-1} \hat{\mathbf{Y}}^{dd}_{i} \right),$$

where $\hat{\mathbf{X}}_{i,-1} = \mathbf{M_H} \mathbf{X}_{i,-1}$ and $\hat{\mathbf{Y}}_i = \mathbf{M_H} \mathbf{Y}_i$. Here $\mathbf{M}_{\bar{\mathbf{H}}} = \mathbf{I} - \bar{\mathbf{H}} \left(\bar{\mathbf{H}}' \bar{\mathbf{H}} \right)^{-1} \bar{\mathbf{H}}'$, a $T \times T$ matrix. The matrix is obtained from $\bar{\mathbf{H}}$, which is the $T \times m$ matrix of observations on $\bar{H}_t = \frac{1}{n} \sum_{i=1}^{n} x_{i,t-1} = \bar{x}_{\cdot,t-1}$. T denotes the number of time-series observations, while m is the dimension of the regressor vector. The estimator is based on a forward demeaning procedure applied to both variables, i.e., $\widehat{\mathbf{X}}^{dd}_{i,-1}$ and $\widehat{\mathbf{Y}}^{dd}_{i}$ contain the observations on:

$$y^{dd}_{i,t} = y_{i,t} - \frac{1}{T-t+1} \sum_{s=t}^{T} y_{i,s}, \qquad x^{dd}_{i,t} = x_{i,t} - \frac{1}{T-t+1} \sum_{s=t}^{T} x_{i,s}.$$

The asymptotic distribution of the resulting estimator is as follows: as $n \to \infty$ and $T \to \infty$,

$$\sqrt{n}T\left(\hat{\beta}^{+}_{RD} - \beta\right) \xrightarrow{d} N\left(0, \left(\underline{\Omega}^{RD}_{xx}\right)^{-1}\left(\underline{\Phi}^{RD}_{wx}\right)\left(\underline{\Omega}^{RD}_{xx}\right)^{-1}\right).$$

Estimates of the matrices entering the asymptotic variance-covariance matrix expression are adapted from the expressions provided in Hjalmarsson (2010), Section D (see the "baseline" recursive demeaning estimator):

$$\begin{aligned}
\hat{u}^{dd}_{i,t} &= \widehat{\mathbf{Y}}^{dd}_{i} - \hat{\beta}^{+}_{RD}\widehat{\mathbf{X}}^{dd}_{i,-1}, \\
\underline{\hat{\Phi}}^{RD}_{ux} &= \frac{1}{n}\sum_{i=1}^{n}\frac{1}{T^2}\sum_{t=1}^{T}\sum_{s=1}^{T}\left(\hat{u}^{dd}_{i,t}\hat{\mathbf{X}}_{i,t-1}\right)\left(\hat{u}^{dd}_{i,s}\hat{\mathbf{X}}_{i,s-1}\right)', \\
\underline{\hat{\Omega}}^{RD}_{xx} &= \frac{1}{n}\sum_{i=1}^{n}\frac{1}{T^2}\sum_{t=1}^{T}\left(\hat{\mathbf{X}}_{i,t-1}\hat{\mathbf{X}}'_{i,t-1}\right).
\end{aligned}$$

Corresponding t-statistics and asymptotic p-values are obtained from the estimated variance-covariance matrix in the asymptotic distribution above. Note the frequency mismatch between annual regressors and monthly returns in our specifications, that is Equations 1 and 2. We repeat the same annual value across twelve consecutive months, which artificially introduces additional persistence in the regressor. The effect of this additional persistence on our statistical inference is at least partially alleviated by the forward-demeaning performed in the Hjalmarsson (2010) estimator, which was explicitly designed to remove estimation bias and provide consistent standard errors in the presence of persistent regressors.

A.3 Residual Diagnostics

In this section we report the residual diagnostic tests for all regression specifications. For each specification we test for heteroskedasticity with the Breusch-Pagan (BP) Lagrange Multiplier test (Breusch and Pagan, 1979), for first-order serial correlation using the Durbin-Watson (DW) statistic, and for higher-order serial correlation using the Ljung-Box (LB) test at lags 1, 5, and 10, averaged across firms. The results are reported in Table 7. Heteroskedasticity is strongly present across all specifications, with BP p-values of zero up to three digits in every case. Serial correlation, however, is absent at all horizons across all specifications: DW statistics are close to 2, and Ljung-Box mean p-values are well above conventional significance levels. The absence of serial correlation is expected given that the forward-demeaning step in the Hjalmarsson (2010) estimator removes within-firm time dependence.

Table 7: Residual diagnostic tests for all regression specifications. The Breusch-Pagan (BP) test examines the null of homoskedasticity. The Durbin-Watson (DW) statistic tests for the absence of AR(1) serial correlation (values near 2 indicating no correlation). Ljung-Box (LB) mean p-values are averaged across firms at lags 1, 5, and 10. Eq. 1 : baseline predictive regression (full sample and cash-split sub-samples); Eq. 2 columns report results for each emissions specification.

	Eq. 1			Eq.2 — Environmental Profile					
	Full	High Cash	Low Cash	SC1 Int.	SC1 Abs.	SC1+2 Int.	SC1+2 Abs.	SC1+2+3 Int.	SC1+2+3 Abs.
BP LM statistic	4612.0	443.8	2079.9	4340.8	5124.0	4194.5	5518.5	4536.5	5793.1
BP p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
DW statistic	2.110	2.022	2.144	2.125	2.142	2.122	2.141	2.127	2.142
LB lag 1 (mean p)	0.432	0.488	0.436	0.423	0.411	0.423	0.409	0.420	0.405
LB lag 5 (mean p)	0.341	0.354	0.336	0.319	0.313	0.326	0.313	0.323	0.315
LB lag 10 (mean p)	0.336	0.331	0.360	0.321	0.321	0.328	0.319	0.327	0.321

A.4 Robustness to Industry Growth Controls

We test whether omitted-variable bias from industry-level growth dynamics, rather than regulatory stringency, drives the results in Table 2. We extend Equation 1 with the Federal Reserve's Industrial Production index (IP) as a control variable, matched to the firms in our sample via 3-digit NAICS codes. The control variable is available for 45% of the firms in our sample. We include two specifications of the control in the regression: the AR(1) innovation of the 12-month IP growth rate and its first difference (Δ IP).

In Table 8 we report the change in *RegStringency* and model fit following inclusion of the additional control variable. We report the results from Table 2 as baseline. Since the control variable is only available for a part of the sample, we recompute the baseline, Equation 1, on this smaller sample. The coefficient falls to 0.2846, but remains significant. Turning to the equations including the control variables, we observe the coefficient of *RegStringency* to remain significant with minor changes in its magnitude. This indicates robustness of the results.

Table 8: Decomposition of $\hat{\beta}_1$ on *RegStringency* into sample composition and omitted-variable effects. We report the results from Table 2 as baseline. Matching firms with the FRED IP coverage, decreased the sample, on which we recomputed Equation 1. We extend the equation then with the AR(1) innovation and first difference of the Fed's industrial production index. The coefficient of *RegStringency* remains significant with minor changes in its magnitude. This indicates robustness of the results. Standard errors are reported in parentheses below the coefficient. Significance: $^{\dagger}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

	Baseline	Baseline (restricted)	+ AR(1) Innov IP	+ Δ IP
RegStringency	0.4254***	0.2846**	0.2842**	0.2829**
	(0.0894)	(0.0922)	(0.0904)	(0.0914)
Number of firms	217	99	99	99
Observations	52080	23760	23760	23760
R^2	0.0498	0.0176	0.0177	0.0176

A.5 Climate Attention and Regulation Indices

Table 9: R^2 of regressing the mimicking portfolio (ERRP) on each climate/regulation index, by factor specification. We report the mean and standard deviation of R^2 across the estimation methods (OLS, Lasso, Ridge, RLS_λ with $\lambda \in \{0.80, 0.95, 0.98\}$). The results show little variation in R^2 with respect to the estimation method, which shows the robustness of the results reported in Table 5.

Freq.	Index	D		DP		DPL		DPLI	
		mean R^2	±std	mean R^2	±std	mean R^2	±std	mean R^2	±std
Mon.	Sentometrics (ABBI) – Mon.	0.007	±0.001	0.041	±0.011	0.020	±0.008	0.021	±0.008
Daily	Sentometrics (ABBI) – Daily	**0.081**	±0.011	**0.043**	±0.010	0.015	±0.005	0.015	±0.006
Mon.	EGLKS	0.003	±0.000	0.006	±0.002	0.085	±0.019	0.099	±0.016
Mon.	EGLKS AR(1) innovation	0.007	±0.001	0.014	±0.003	0.091	±0.021	0.104	±0.018
Mon.	CPU	0.002	±0.001	0.007	±0.007	0.032	±0.019	0.037	±0.015
Mon.	CPU narrow	0.002	±0.000	0.009	±0.007	0.034	±0.019	0.039	±0.014
Mon.	CPU broad	0.008	±0.001	0.020	±0.009	0.039	±0.018	0.043	±0.014