

**WHITEPAPER**

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## Measuring Persistence in ESG Risk Management Culture

### Abstract

Are reports of Environmental, Social, and Governance (ESG)-related controversial events isolated or indicative of broader problems within a firm? Are controversial events more often observed in larger companies and certain sectors and regions? After controlling for these factors, we find that companies with a history of controversial ESG-related events are more likely to experience controversies in the future. This paper presents a methodology to measure a firm's likelihood for future ESG controversies relative to firms of comparable size, region, and sector. We also find that firms that improve their ESG culture (as indicated by improved Moody's ESG Assessment Scores) experience a reduction in the rate of future controversial ESG events.

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## 1. Introduction

Environmental, Social, and Governance (ESG) is a concept that grew out of socially responsible investing. Socially responsible investors have different views as to what constitutes socially responsible investments. One approach to responsible investment is to direct investment dollars away from firms that produce products or services that lead to controversial ESG events, which are events viewed as detrimental to the public good (henceforth “ESG events”).

ESG events — a radiation leak at a nuclear power plant (Environmental), a manufacturer outsourcing assembly to a firm that uses child labor (Societal), a firm paying a bribe for preferential access to a market (Governance) — are continually collected into a variety of databases. Large companies are more likely to incur ESG events, and certain types of companies are more susceptible due to the nature of their businesses. In this paper, we assess whether a company is more likely to experience ESG events, given its size and the nature of its business. Such an assessment can help investors and lenders gain further insight into the risk profiles of specific firms.

Currently, it is difficult to assess whether an ESG event is isolated or, rather, indicative of a broader cultural problem within a firm. In this paper, we present a methodology to address this question. We use the term “ESG risk management culture” much the way that the nuclear power industry uses the term “culture of safety.” The latter term was coined by the International Nuclear Safety Advisory Group to help reduce accidents in nuclear power plants, defining a culture of safety as: “The product of individual and group values attitudes, perceptions, competencies, and patterns of behavior that determine the commitment to, and the style and proficiency of an organization's health and safety management.”<sup>1</sup> We define an ESG risk management culture as the persistence with which firms introduce, maintain, and update risk mitigation measures (strategic, organizational, or managerial) to mitigate environmental, social, and governance events detrimental to the public good. In this paper, we focus on the following hypotheses:

- 1) Whether the risk of ESG event persists over time after controlling for sector size and region of the firm.
- 2) Whether adoption of ESG policies can lead to a reduction of future ESG events

We address the first hypothesis using two ESG event datasets, Moody's ESG controversy dataset and a dataset of ESG events provided by RepRisk, a Zurich-based ESG data science firm.<sup>2</sup> We demonstrate that firms with historically elevated ESG event rates relative to firms of comparable size and in the same sector are more likely to experience ESG events in the future.<sup>3</sup>

We address the second hypothesis by combining RepRisk data on ESG events with Moody's ESG Assessment Scores. We interpret marked improvement in a firm's overall ESG score as indicative of a firm strengthening its ESG Risk Management practices. Using a “Difference-in-Differences” methodology, we find that companies can reduce their future risk of ESG events.

Evidence of persistence in ESG event risk is consistent with two interpretations. The first is that the inherent characteristics of some firms lead them to have more ESG events than others. The second is that a weak ESG risk management culture leads some firms to have more ESG events than others. Evidence that firms that strengthen their ESG policies (as evidenced by better Moody's ESG Assessment Scores) reduce their rates of future ESG events is consistent with the second interpretation: At least a portion of the observed persistence in ESG events can be attributed to differences in ESG risk management culture.

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<sup>1</sup> NSAG's (1986) “Summary Report on the Post-Accident Review Meeting on the Chernobyl Accident.”

<sup>2</sup> RepRisk specializes in ESG and business conduct risk research and quantitative solutions. Founded in 1998 and headquartered in Switzerland, RepRisk leverages AI and machine learning technologies combined with human intelligence to analyze numerous public sources in 23 languages and to assess material ESG incidents. RepRisk's ESG risk database includes daily updates for more than 170,000 public and private companies and 40,000 infrastructure projects, sectors, and countries. To learn more, please visit [www.reprisk.com](http://www.reprisk.com).

<sup>3</sup> V.E, formerly Vigeo Eiris, has been a global leader in Environmental, Social, and Governance (ESG) research, data and assessments since the 1990s. In 2019, Moody's Corporation acquired a majority stake this company, which officially became part of Moody's ESG Solutions in 2020. Moody's ESG Solutions is a business unit of Moody's Corporation that serves the growing global demand for ESG and climate insights and its offering includes ESG scores and Controversy Risk Assessment data, among others. To learn more, please visit [www.moody.com/esg-solutions](http://www.moody.com/esg-solutions).

## 2. Academic Literature

Much has been written on ESG and responsible investing. Attention has focused on demonstrating that firms with “good” ESG ratings outperform firms with “poor” ESG ratings. Academics have also researched the differences in ESG ratings produced by different vendors.<sup>4</sup> However, attention to whether ESG ratings in fact measure exposure to ESG risks and the management of such risks has been more limited.

Gloßner (2018) investigates the persistence of ESG risks through a framework in which a big jump in the RepRisk Index (RRI) — a proprietary ESG metric that dynamically captures and quantifies an entity’s reputational risk exposure related to ESG issues — is indicative of “weak corporate social responsibility,” and “weak CSR” is persistent. Further, his interpretation of the results is that the market misprices “weak CSR,” which is why avoiding firms with recent jumps in RRI leads to equity outperformance.<sup>5</sup>

Eccles et al. (2014) identify a set of U.S. firms that adopted corporate policies related to environmental and social issues by 1993, before doing so became common. They match those firms to competitors with similar financial performance and characteristics, such as size, capital structure, and valuation, as of 1993. They find that firms that adopted sustainability policies outperformed their peers in the long run, doing better both in terms of the equity stock market and accounting metrics as of 2009.<sup>6</sup> The interpretation offered in the paper is that these firms — termed High Sustainability — differ in business conduct from their Low Sustainability counterparts. Changing the way a firm operates is an inherently time-consuming process. Therefore, time is an important factor in determining the success of any policy or effort intended to reduce ESG risk. In other words, we expect ESG risks to be persistent.

## 3. Data Description

For this study, we use three ESG datasets. We will describe each dataset in turn.

- 1) RepRisk’s Incident Data is used to establish persistence of ESG events.
- 2) Moody’s ESG Controversies are used to establish persistence as well as the responsiveness of a firm to ESG events.
- 3) Moody’s ESG Assessment Scores are combined with ESG events data to establish that improvements in ESG policies and risk management cultures can reduce the risk of future ESG events.

### 3.1 RepRisk’s Incident Data

One dataset used to study the first hypothesis contains ESG events identified by RepRisk. RepRisk defines an ESG event as “incidents such as criticism, adverse business conduct issues, and scandals” (henceforth “Incidents”). RepRisk’s definition of ESG Incidents includes 28 types of issues that can have a reputational, compliance, or financial impact on a company. There are 28 Issues based on international standards related to ESG issues and business conduct, such as: The World Bank Group Environmental, Health, and Safety Guidelines; The International Finance Corporation Performance Standard; the Equator Principles; The OECD Guidelines for Multinational Enterprises; and The International Labour Organization Conventions. In addition, RepRisk currently tracks 73 ESG Topic Tags that are specific and thematic, and that are linked together with at least one ESG Issue for more granular risk analysis.<sup>7</sup>

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<sup>4</sup> See for example, Christensen, Dane, George Serafeim, and Anywhere Sikochi, “Why is Corporate Virtue in the Eye of The Beholder? The Case of ESG Ratings.” (2019) Harvard Business School. See Also: Dorfleitner, Gregor, Gerhard, Halbritter, and Mai Nguyen “Measuring the level and risk of corporate responsibility – An empirical comparison of different ESG rating approaches”, *Journal of Asset Management*, Vol 16, 7 450-466, (2015); and Berg, Florian, Julian F. Koebel and Roberto Rigobon, “Aggregate Confusion: The Divergence of ESG Ratings”, MIT Sloan School of Management, August 2019; and Kotsantonis, Sakis, and George Serafeim, “Four Things No One Will Tell You About ESG Data.” *Journal of Applied Corporate Finance* 31, no. 2 (Spring 2019): 50–58.

<sup>5</sup> Simon Gloßner “The Price of Ignoring ESG Risks.” Catholic University Eichstätt-Ingolstadt, Germany, May 18, 2018 (Doctoral Dissertation Chapter).

<sup>6</sup> Eccles, Robert G., Ioannis Ioannou, and George Serafeim, “The impact of corporate sustainability on organizational processes and performance.” *Management Science*, 60, 2835–2857, 2014.

<sup>7</sup> RepRisk AG, “RepRisk Methodology Overview.” Privileged, April 2021, [reprise.com](https://reprise.com).

Along with the publication date of the source that flags the incident, RepRisk provides information on related countries, sectors, and related ESG Issues and assigns scores for three key parameters that characterize the incident: Severity, Reach, and Novelty. Severity refers to the harshness of the incident. Reach refers to influence, based on readership/circulation, as well as importance in the specific country of the information source, according to RepRisk's own rating. Novelty touches on the newness of the issues the entity faces.

Incidents comprise the primary data that RepRisk produces. To quantify a firm's overall reputational ESG risk, analysts use the ESG risk incidents to derive a RepRisk Index, an algorithm intended to measure a firm's ESG-related risk exposure.

The sample of companies for our analysis comprises the Moody's Investors Service rated universe. Of the 4,324 firms that have ever received a credit rating from Moody's Investors Service, RepRisk's database contains at least one ESG incident for 3,268 firms. Further, we require time-matched information on the size, location, and sector of each firm, leaving us with a final sample of 3,181 firms.

Figure 1A presents the coverage of incidents and the ratio of incidents per firm across years. The increase in incident counts from 2007 until 2015 reflects a number of data features. First, RepRisk expanded its coverage of media and stakeholder sources and broadened language coverage during this period. Second, recent, surging interest in ESG likely led to more vigorous media coverage of ESG incidents. Third, the expanding availability of social media, as well as RepRisk improving its search algorithm, likely also increased ESG incident coverage. On the other hand, we see a decrease in the incidents per firm ratio from 2017 onward. In general, declining incidents could indicate more companies trying to improve their ESG behavior. Last, the lower incident count from 2020 occurs because our dataset contains information only until July 2020.

Figure 1B presents the distribution by firm size measured in Total Assets (USD). The sample includes a suitable cross-section of both larger and smaller firms. There is a considerable spike in the incidents-per-firm ratio for large firms, which we expect, because larger firms have wider media coverage.

**Figure 1 RepRisk Incident Data Coverage.**

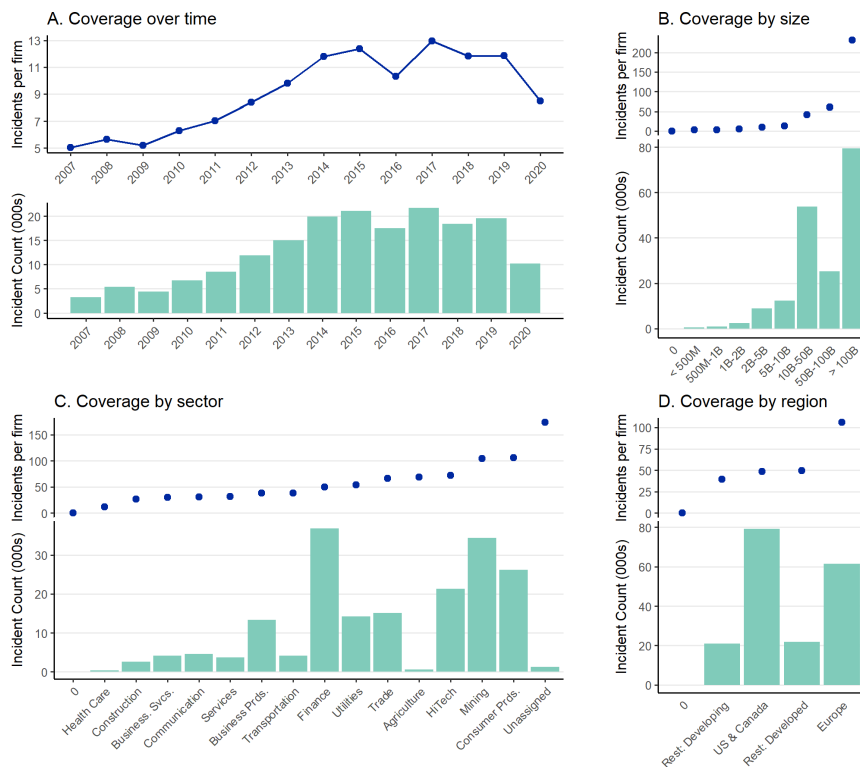


Figure 1D presents geographic incident distribution. We classify the 71 different countries in the dataset into four regions, where country refers to headquarter location. Since our focus is the rated universe, firms from the U.S. are heavily represented. The ratio of incidents per firm varies significantly across regions, with Europe showing the highest incident-per-firm ratio. This trait is due to countries such as Switzerland and Germany posting the highest ratio of incidents-per-firm, which may reflect more ESG awareness in that region.

### 3.2 Moody's ESG Solutions' Controversies and ESG Scores

The datasets used to demonstrate the robustness of the persistence effect and test the second hypothesis of this study come from Moody's ESG Solutions. Moody's ESG Solutions is a business unit of Moody's Corporation that serves the growing global demand for ESG and climate insights. Moody's ESG Solutions' data and insights include an ESG Controversy dataset and ESG Scores, that we leverage for this study. This section contains an overview of each of these resources.

#### Moody's ESG Controversy Data

Moody's ESG Solutions identifies companies' involvements in ESG events, referred to as "Controversies." Controversies form a part of Moody's ESG solution suite and are a direct input into Moody's ESG Assessment Scores and several other specialized assessments. Moody's screens a pre-defined population of companies daily, currently covering 10,000 + companies regarding their involvement in ESG controversies across 38 ESG issues. These 38 ESG issues are derived from international norms and standards related to ESG issues and business conduct, such as: *The Ten Principles of the Global Compact of the United Nations*, *The World Bank Group Environmental, Health, and Safety Guidelines*; *The International Finance Corporation Performance Standard*; *The Equator Principles*; *The OECD Guidelines for Multinational Enterprises*; and *The International Labour Organization Conventions* to name a few. This dataset currently contains over 20,000 entries across the broad range of ESG issues, with coverage going back to 2007.

Along with the date of the controversy, and the ESG issues involved, this dataset contains information on related countries, and sectors, and assigns scores for three key parameters that characterize the controversy: Severity, Responsiveness, and Mitigation. Severity concerns the harshness of the controversy. Responsiveness touches on the reaction and efforts of the firm towards managing the risks inherent to the controversy. Mitigation refers to the outcome of the firm's actions towards reducing the risks caused by the controversy. The three parameters and each event are reviewed by a team of ESG analysts according to Moody's ESG Solutions assessment.

Of the 4,324 firms that have ever received a credit rating from Moody's Investors Service, Moody's ESG Controversy Data contains at least one ESG controversy and time-matched information about the size, location, and sector for 2,260 firms.

Figure 2 Moody's ESG Controversy Data Coverage

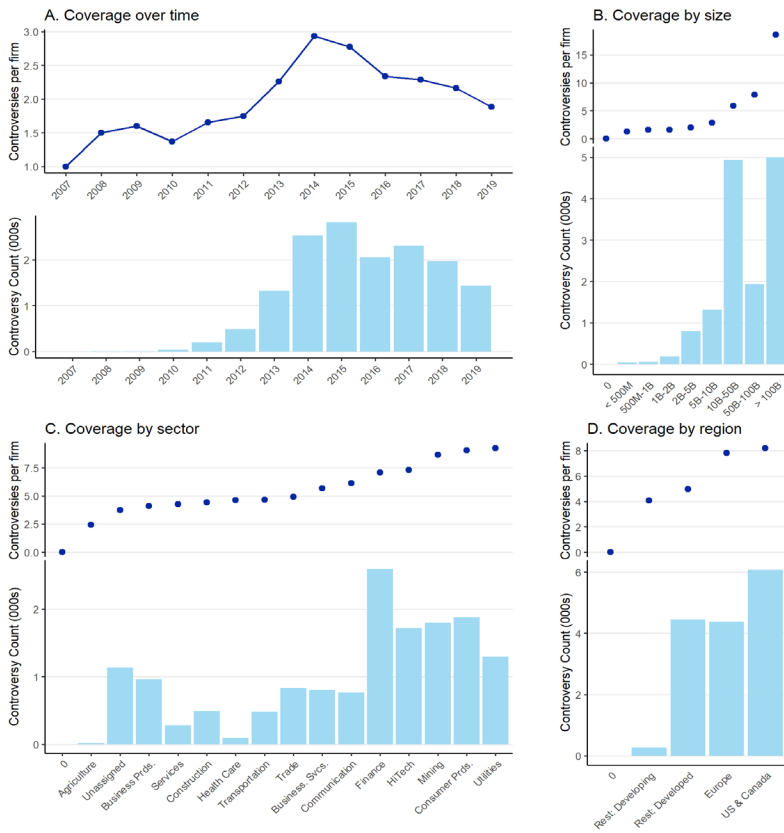


Figure 2A presents the coverage of controversies and the ratio of controversies-per-firm across years. There is an increase in controversy counts from 2007 until 2014 that we also find in the RepRisk incident dataset. Similarly, Moody's ESG Solutions improved a number of features of its process, and the surging interest in ESG likely led to more vigorous media coverage of ESG controversies. The decrease in the controversies-per-firm ratio from 2014 onward could be due to the increase in ESG awareness leading firms to try to improve their ESG behavior.

Figure 2B presents the distribution by firm size measured in Total Assets (USD). If we compare across size categories, firms in the largest size bucket have on average 15x more controversies than firms in the smallest size class. This can be explained by the fact that larger firms are more likely to have controversies that attract media attention and may require company disclosure. We see a similar pattern in the RepRisk database, where the largest firms have 200x more incidents, on average, than the smallest firms. This relative difference may reflect that

RepRisk's process relies more heavily on media-based information, therefore being more skewed toward the larger firms.

Figure 2C presents controversy distribution by sector and the number of controversies per firm in each sector. Finance, Consumer Products, High-Tech, and Mining are the most populous sectors in the controversy database. In this database, Utilities displays the highest controversies per firm ratio, showing more environmental-related controversies due to the nature of its businesses.

Figure 2D presents controversy distribution by geographic region. The classification into four regions is consistent with that in Figure 1D, where country refers to headquarter location. Firms from the U.S. are heavily represented in this sample too. The ratio of controversies per firm does not vary that significantly across regions, with U.S. and Europe showing a similarly high controversy-per-firm ratio.

### Moody's ESG Assessment Scores

The Moody's ESG Solutions' ESG Score (henceforth "Moody's ESG Assessment Scores"), formerly part of the V.E ESG assessment methodology<sup>8</sup>, is built around international standards and reference texts and provides the full picture of a company's ESG performance management at a given point in time. This dataset contains Moody's ESG Assessment Scores for more than 5,000 companies, normally updated every one or two years. A Moody's ESG Assessment Score is intended to measure the degree to which companies take into account and manage material ESG factors. A high Moody's ESG Assessment Score is intended to indicate that the company is effective at managing relationships with stakeholders and less likely to experience ESG-related business disruptions. In order to generate the scores, Moody's ESG Solutions analyses and scores up to 38 distinct ESG criteria that are framed within 40 industry-specific models.<sup>9</sup> Moody's ESG Assessment Scores range from 0–100, with a higher score attributed

<sup>8</sup> Please refer to Vigeo Eiris ESG Assessment Methodology Executive Summary (August 2020).

<sup>11</sup> Please refer to Vigeo Eiris ESG Assessment Methodology Executive Summary (August 2020).

to better performance. Improvements in Moody's ESG Assessment Scores often correspond to corporate initiatives to improve their ESG culture.

### Comparing ESG event Datasets

A key difference between the RepRisk and Moody's ESG Solutions' process is that RepRisk relies exclusively on information covered by the media, whereas Moody's ESG Solutions interprets information company disclosures. Moody's ESG Solutions has fewer recorded events per firm overall. One key factor driving this is that Moody's ESG Solutions more strongly aggregates reports referring to the same underlying case into single events.

## 4. Persistence of ESG Risk: Do Previous ESG events Predict More ESG events?

Two important factors drive ESG events: The nature of a firm's business operations and the general culture within its management that prevents ESG events from happening. Assuming that a firm's characteristics do not change quickly over time, we expect ESG risk to be persistent, meaning firms that have had ESG events in the past are more likely to experience ESG events in the future. If persistence exists, it implies that we can utilize historical ESG events to predict future ESG events.

One goal of this study is to create a metric that measures how much more likely a firm is to experience ESG events relative to itspeers. This section takes a preliminary step toward that goal by investigating whether persistence exists in ESG events. We find substantial evidence of persistence and show that this trait is robust after controlling for differences in size, sector, and region.

This section is structured as follows: First, we describe the construction of the measure for ESG events that we use to show that ESG risk is persistent. Second, we present the empirical approach for the analysis. Third, we present empirical results based on RepRisk incidents database and Moody's ESG controversy database.

### 4.1 ESG Event Rates: A Measure for ESG Risks

We use ESG event data that contains ESG events assigned to a firm and a date, as described in the previous section. Now, as we aim to quantify the relationship between past and future ESG performance, we must derive a measure of a firm's ESG events, an ESG event rate. This measure equals the number of events that a firm experiences during one year, adjusted for 1) the increase of the event-per-firm ratio over time, and 2) the fact that larger firms experience significantly more events.

Figures 1A and 2A show how the coverage of events increases over time, 2007–2014, and stabilizes afterward. To prevent this data characteristic from distorting results, we adjust the yearly number of incidents for years before 2014 as follows:

$$\text{Adjusted Number of events} = \text{Number of events} * (n_2/n_1)$$

Where  $n_1$  corresponds to the number of ESG events in the corresponding year (2007–2013) and  $n_2$  to the average annual number of ESG events over 2014–2019. For example, if the total number of events during 2011 was 8,000 and the average number of events during 2014–2019 was 18,000, the adjustment factor for a rate over 2011 equals 2.25.

Further, Figures 1B and 2B show how the coverage of ESG events increases with size. Larger firms have more ESG events, as they receive more media attention, but this does not necessarily mean they have a higher ESG risk. To enable comparability of ESG event rates across firms of different sizes, we apply a transformation that results in transformed, yearly event rates that are roughly independent of firm size. Specifically, we fit a loess curve through average incident rates for 50 size buckets, separately for corporate and financials. The fitted curve is then used as a size transformation, so that the transformed event rate is defined as: event rate divided by the value of the loess fit corresponding to the firm's size. Since we work with event rates in logarithmic space, this adjustment is equivalent to working with the residual event rate after subtracting the average incident rate by size category. For example, after the scaling, an event rate of 0.5 means 50% more events than would be expected given the firm's size.



We refer to the ESG event rates based on the RepRisk Incident Dataset as “incident rates” and as “controversy rates” to the ones based on Moody’s ESG Controversy Dataset, in turn.

Figures 3A and 3B present the relationship between firm size and ESG event rates using RepRisk’s incident rates, before and after being scaled by the size-implied incident rate. We see that the mean incident rate, after being scaled by size, is roughly constant across size buckets for both corporates and financials.

Figure 3 A. Incident Rates vs. Size, before scaling.

B. Incident Rates vs. Size, after scaling.

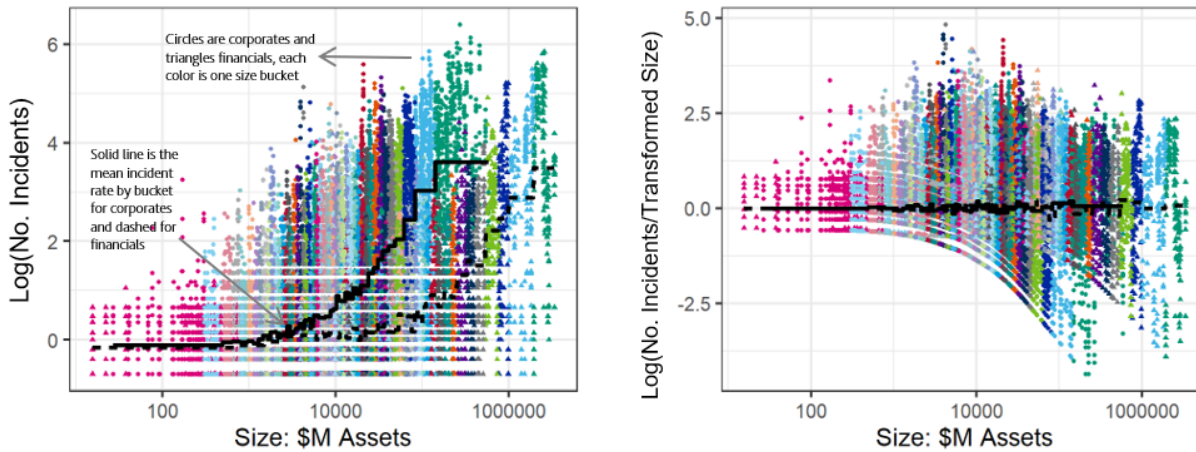


Figure 3: Based on RepRisk Incident Dataset

#### 4.2 Persistence Effect: Empirical Approach

We start the analysis using the datasets described previously. Further, to link past ESG event rates (henceforth “event rates”) with future event rates, we form five-year rolling windows at the firm level. The first two years of the window represent the past, and the last two years represent the future. The residual one year in the middle acts as a “gap” and controls for the possibility of some incidents originating from previous related additional incidents. We form five-year rolling windows for each firm and pool all the firm-cohort combinations.

We expect ESG culture to be more complex for the larger firms and, hence, more difficult to change over time. We also observe that firms in certain industries and countries are more likely to have ESG incidents in the two datasets. In this regard, we look at the persistence effect, conditional on size, sector, and region, to test the finding’s robustness.

Formally, we can characterize each observation in our analysis with future event rates as the dependent variable and past event rates as the independent variable. We quantify the relationship between past and future event rates conditional on a third variable, which takes the form of size, sector, and region, respectively. We construct the analysis as follows:

1. Order the dataset by *size* (or *sector*, or *region*) and split it into five classes accordingly.
2. For each class, split the dataset into buckets by past event rates.
3. For each bucket, compute the mean of past and future event rates.
4. For each class, draw a scatterplot of each pair of means.

Further, we look at persistence over longer horizons by repeating the analysis with gaps of 2, 3, 4, and 5 years instead of 1. We expect persistence to decrease somewhat over time, as firms’ characteristics change, and ESG culture also may change.

#### 4.3 Persistence Effect of ESG Event Rates

Across both ESG event datasets tested we find a strong, positive correlation between past and future ESG event rates when controlling for firm features. Figure 4 shows the test outcome based on RepRisk Incident Dataset and Figure 5 shows the test

outcome using Moody's ESG Controversy Dataset. Specifically, panel A shows the test outcome for the specific case using size as the control variable, measured in total assets. Panels B and C show the test outcome by sector and region, respectively. Figure 4 A shows that the persistence effect varies by size in a way that is stronger for larger firms. This finding remains consistent with our intuition, as larger firms have more complex structures, which makes ESG risks more persistent, as the improvements or changes they may need are harder to establish.

**Figure 4 Persistence effect across size quintiles, sectors, and regions.**

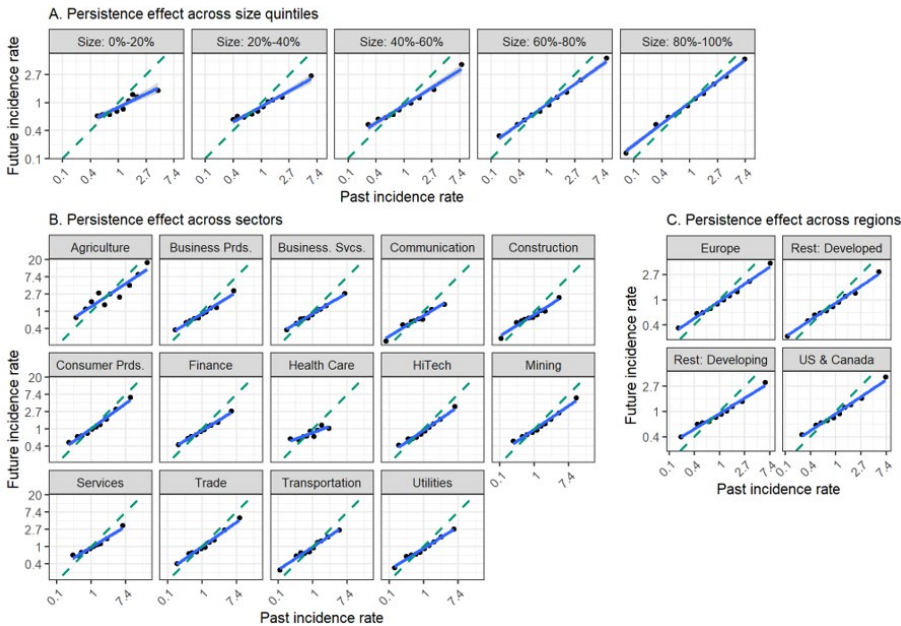
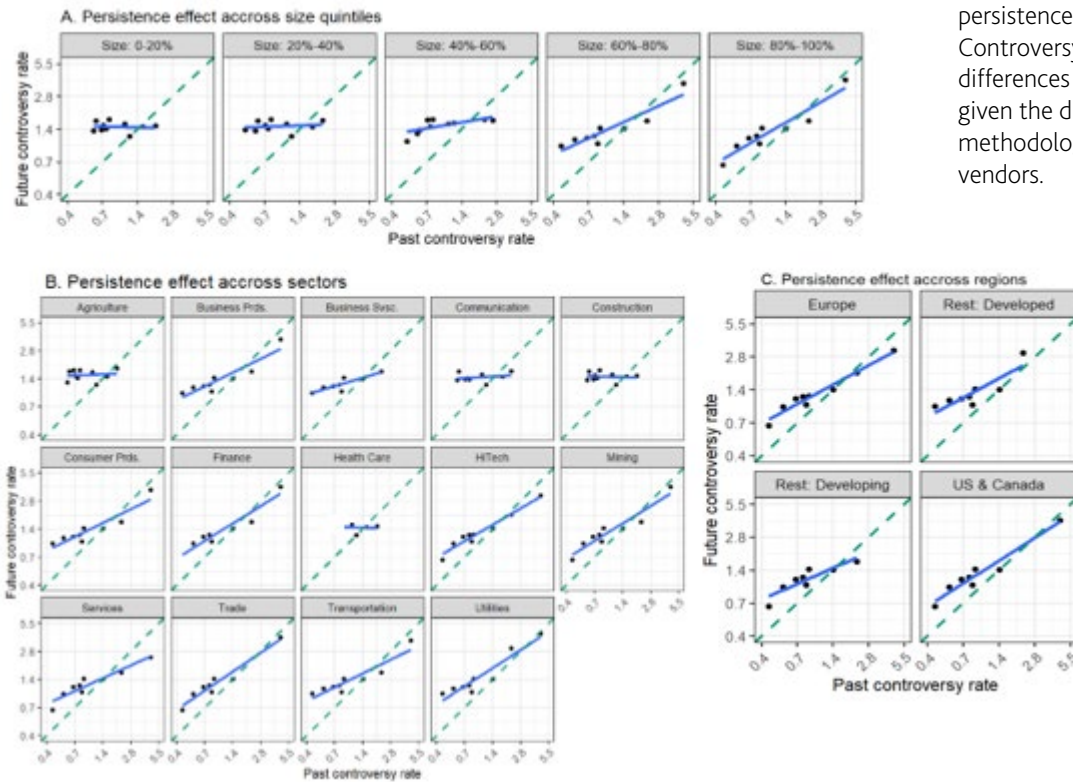


Figure 4B shows that the effect is similarly strong for all sectors, except for Health Care, for which the effect is weaker. This difference can be explained by the fact that the Health Care sector experiences very few incidents, which makes the ESG risk for these firms more difficult to quantify.

According to Figure 4C, the effect is similarly strong across all four regions. When performing the test using country as the control variable, we find that the effect is stronger for developed economies. This finding can be explained by the fact that these countries have a higher coverage of incidents, which may reflect more ESG awareness (see Figure 11 in the Appendix).

Figure 5 Persistence effect, based on Moody's ESG Controversy Dataset.

Figure 5 shows similar patterns of persistence based on Moody's ESG Controversy Dataset. There are some differences by sector, which we expect given the differences in the methodologies of the two data vendors.



As the gap grows larger, past information turns out to be less useful in predicting the future. Figure 6 shows how the slope line that depicts the relationship between past and future incident rates decrease as the gap increases. Figure 7 shows how the slope line that depicts the relationship between past and future controversy rates also decrease as the gap increases.

Figure 6 Persistence effects observed over long horizons, based on RepRisk's Incident Dataset.

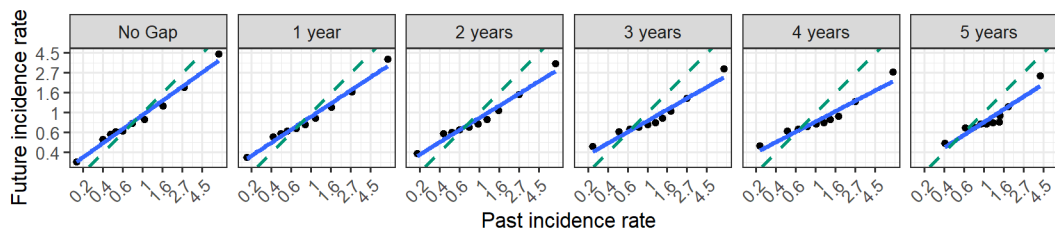
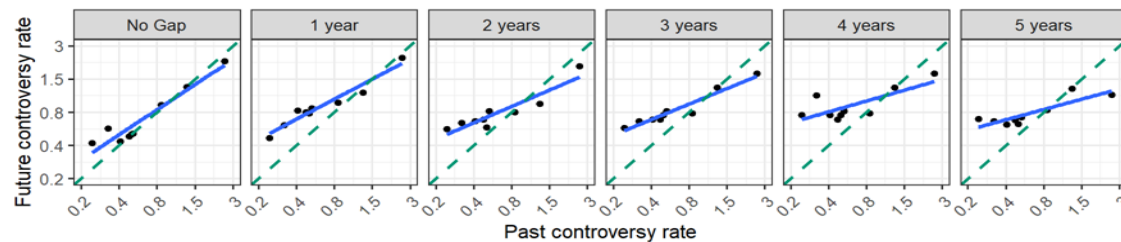


Figure 7 Persistence effects observed over long horizons, based on Moody's ESG Controversy Dataset.



## 5. Scoring Firms on ESG Risk by Predicting ESG events

The main component of our approach to scoring firms on their future likelihood of experiencing ESG events relative to peers is predicting ESG event rates. Once we estimate predictions at the firm level, we normalize these so that they reflect firm-specific performance compared with peers. The first step requires building a model that predicts future ESG event rates. We construct the model components using findings discussed in the previous section: the firm-specific ESG performance, as measured by the size-neutral number of events per year, is persistent, but decays over time. This section builds upon these stylized facts and outlines the process for scoring firms on ESG risk by predicting future incident rates. We illustrate our methodology using RepRisk's incident rates.

### 5.1 Model Framework

We start by defining the components of the incident rate: 1) the asymptotic incident rate and, 2) the firm-specific factor. We refer to incident rate with  $y$  and to the aforementioned components with  $c$  and  $ry$ , respectively. The incident rates over the horizon, decomposed into the two components follow:

$$y_{it} = c_i + ry_{it}$$

Where, recall from Section 3.4, that the Incident rate for firm  $i$  on year  $t$  is defined as the size-neutral number of annual incidents.:

$$y_{it} = \log(\text{Number of Incident per Year}_{it}) - E(\log(\text{Number of Incident}_{it})|\{\text{Size}_i, \text{Broad Sector}_i\})$$

Where  $\text{Broad Sector}_i \in \{\text{Corporate}, \text{Financial}\}$  and  $c_i$  is the expected value of the log of the incident rate in the distant future:  $\lim_{t \rightarrow \infty} E(y_{it}) = c_i$ . This component, which we also refer to as central incident tendency, expresses the baseline risk that firms face, given the sector and region they operate in. The second term,  $ry_{it}$ , is the firm-specific component of the incident rate. The "r" stands for relative, as it can be interpreted as the percentage difference between the incident rate and the expected incident rate given  $c_i$ , since we are working on the log-scale.

Prediction of future  $y_{it}$  can be expressed as:

$$E[y_{i,t+x}|I_t] = E[c_i|I_t] + E[ry_{i,t+x}|I_t]$$

Where  $I_t$  represents information up to time  $t$ . On the one hand, the expectation of the asymptotic factor is based on firm-specific components that do not vary over time. On the other hand, we leverage the autoregressive structure of the firm-specific component to compute a closed-form expression for variance and expectation at time  $t+x$ , described in detail in later sections.

The last step, after modeling the predicted incident rates,  $\hat{y}$ , is to turn the predictions into an Event Propensity Score that measures the risk of future ESG incidents for the firm relative to the firm's peers. Our proposed score measures this risk in terms of how many standard deviations the firm is away from the mean, i.e., we convert the prediction into a z-score at the peer group level:

$$\text{Event Propensity Score}_{i,t+x} = \frac{\hat{y}_{i,t+x} - \text{mean}(\hat{y}_{t+x})}{\sqrt{\text{var}(\hat{y}_{t+x})}}$$

#### Central Incident Tendency

We measure the baseline risk of firms in a given sector and region as the average, observed annual, size-adjusted incident rate across firms and over time. Intuitively, we expect a higher central incident tendency for the Mining, Energy, and Natural Resources sector than for the Health Care sector, for example. Further, the baseline risk for the Mining, Energy, and Natural Resources sector is higher in Europe than in North America. One possible reason for this difference — we see more ESG awareness in Europe than in North America, which leads to more attention on ESG issues in the media. Similarly, the baseline risk for this industry is also higher in developing countries than in North America. A possible explanation is that developing countries institute fewer ESG policies, which implies a poor ESG culture that leads to more ESG-related issues. Figure 8 depicts the central incident tendency by sector and region.

Figure 8 Central Incident tendency.

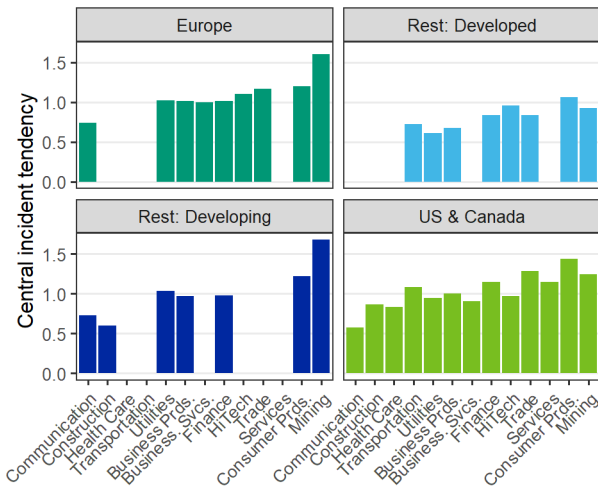


Figure 9 Decay of the persistence coefficient.

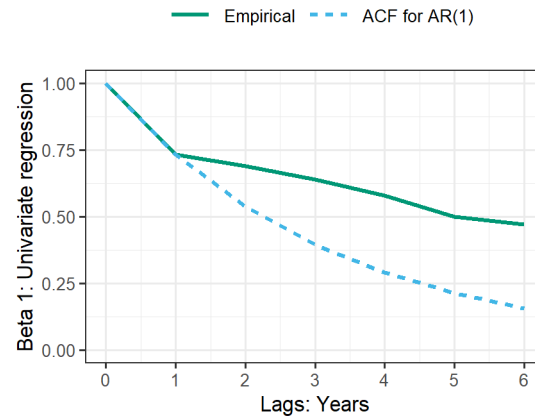


Figure 8 and 9: Based on RepRisk Incident Dataset

### Firm-Specific Factor

The firm-specific factor, or the idiosyncratic factor, captures the firm's incident rate when compared to the firm-specific sector and region average incident rates. We model the firm-specific factor utilizing the framework below, which uses a combination of an AR(1) process and a transitory component that fits the data better than either alone. An AR(1) process implies that the correlation between  $ry_{i,t}$  and  $ry_{i,t+x}$  will decline in proportion to  $x$ . A standalone white noise process implies that  $ry_{i,t+x}$  is independent over time, which is counterfactual. Figure 9 shows how, empirically, the persistence declines rapidly but becomes more stable than would be implied by an AR(1) process. The dotted blue line measures the amount of persistence implied by the correlation between the current year and the prior year. The dotted blue line declines much more rapidly with time than the solid green line, which is what is empirically observed.

$$\begin{aligned}
 ry_{i,t} &= y_{i,t} - c_i \\
 ry_{i,t} &= \psi_{i,t} + \delta_{i,t} \\
 \psi_{i,t} &= \phi \cdot \psi_{i,t-1} + \epsilon_{i,t}
 \end{aligned}$$

We estimate  $\phi$ ,  $Var(\delta_{i,t})$  and  $Var(\epsilon_{i,t})$  using method of moments. It consists of expressing the population moments (i.e., the expected values of powers of  $ry_{i,t}$ ) as functions of the parameters of interest. As empirically there are many moments and only three free parameters, the system is over-identified. We use optimization to solve for the parameters that minimize the SSE<sup>10</sup> between the analytical and empirical variance-covariance. The theoretical variance-covariance is defined by the following set of equations:

$$\begin{aligned}
 Var(ry_{i,t}) &= \frac{Var(\epsilon_{i,t})}{1-\phi^2} + Var(\delta_{i,t}) \\
 Cov(ry_{i,t}, ry_{i,t-x}) &= \frac{\phi^x Var(\epsilon_{i,t})}{1-\phi^2}
 \end{aligned}$$

Specifically, from the data, we observe the sample moments  $Var(ry_{i,t})$  and  $Cov(ry_{i,t}, ry_{i,t-x})$  for  $x \in \{1, 2, \dots, 10\}$ , which are the variance and auto covariances of  $ry_{i,t}$ . For a given set of parameters  $\{\phi, Var(\delta_{i,t}) \text{ and } Var(\epsilon_{i,t})\}$ , the framework implies that the

<sup>10</sup> SSE: Sum of squared errors is the sum of the squared of the residuals (deviations between predicted and actual empirical values of the data).

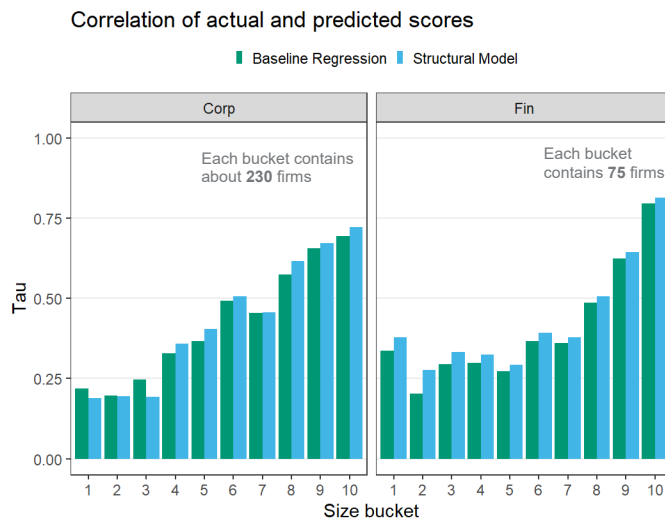
sample moments will converge in distribution to values given by the righthand sides of these equations. We choose the parameters to minimize the sum of the squared error between the sample moments and the implied moments.

## 5.2 Validating Our Proposed Event Propensity Scores

### Benchmarking Against the Linear Regression Approach

We assess score power by looking at the out-of-sample performance of the scores at ranking firms on their ESG risks within their peer group. We benchmark the outcome against that of a score implied by incident rates predicted using a linear regression model with three lags, size interaction, and sector- and region-specific intercepts (the Appendix presents a summary table). Figure 10 shows the correlation of actual and predicted scores within a size group for corporates and financials, separately. We find that the ranking power of the scores implied by incident rates predicted through the structural model we propose outperforms the linear regression approach.

**Figure 10** Kendall's tau of actual and predicted Proposed Event Propensity Scores one year ahead.



We construct the analysis as follows:

1. Estimate the model using the pooled panel from 2014–2018 and predict incidence rates for 2019.
2. Compute ESG Event Propensity Scores with the predicted and the actual rates.
3. Rank firms according to our proposed scores.
4. Use the correlation (Kendall's tau) of the actual and predicted ESG scores — implied "rankings" as a measure of goodness of fit.

Kendall's tau<sup>11</sup> indicates to what extent the predicted and actual scores are monotonically related, that is, to what extent the rankings implied by the actual and predicted scores coincide. If Kendall's tau equals 1, there is a 100% match between the two rankings; if it is -1, the rankings are exactly the opposite.

We also see that both models are better at predicting future incident rates for larger firms. As the incident per firm ratio is significantly higher for larger firms, there is more information available for modeling firm performance, which reduces the signal-to-noise ratio for this part of the population. This finding is also reflected in the persistence effect, shown to be stronger for larger firms, making the model's predictive power higher for these firms.

### Case Study: Evidence from the Mining, Energy, and Natural Resources Sector

This case study examines the ESG performance, measured by our proposed score, of a selected firm within the Mining, Energy, and Natural Resources sector. Specifically, the firm is a leading gold producer headquartered in North America. Our choice was motivated by a written complaint by a firm regarding their ESG ratings, claiming that incidents in the distant past were given too much weight, and that they were assigned responsibility for incidents outside their control, among other reasons.

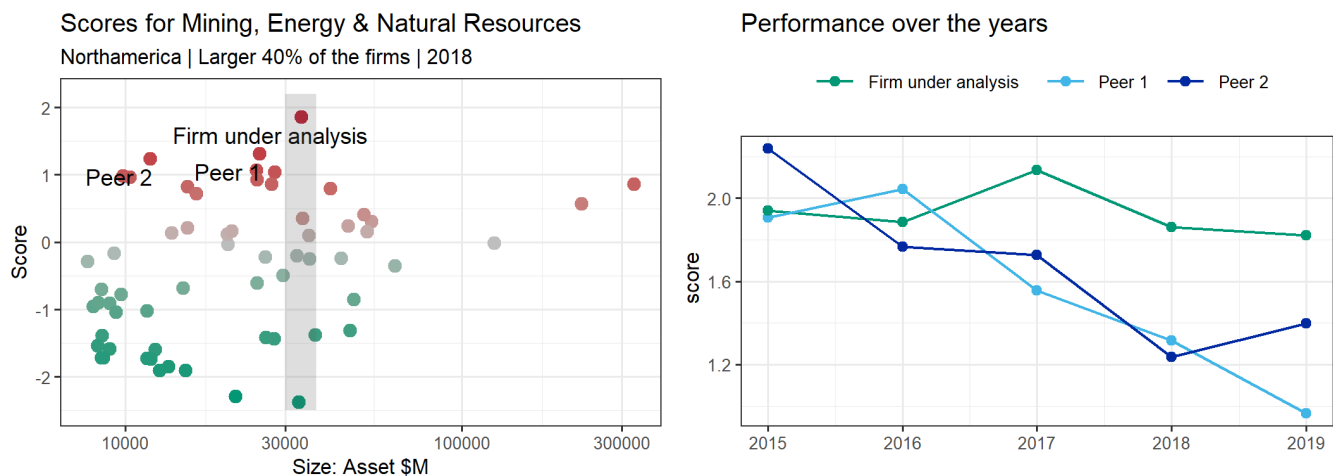
In our view, these complaints summarize the challenges of creating an ESG metric, which must take into account firm-specific past performance (as existing policies do not change quickly over time), as well as idiosyncratic risks firms face, given sector and region

<sup>11</sup> Kendall's tau is sometimes referred to as "Kendall rank correlation coefficient."

operations. For instance, the mining sector as a whole is viewed as very high-risk for soil/water pollution and land use restrictions, as well as for water shortages and natural and man-made hazards. In fact, this company experienced multiple accidents, in which human error was a contributing factor reported in the year prior to a pipeline rupture. Only after such a major issue, the firm put in place a policy to enable the business continuation of the troubled site.

Figure 11 shows the Event Propensity Score for this firm relative to its peers in 2018. The peer group includes 40% of larger firms that operate in the North American Mining, Energy, and Natural Resources sector. We see, according to our score, that this firm performed the worst among its peers in 2018. The right panel shows how the score worsened in 2017 and recovered thereafter. Further, we compare its performance across years, with the two firms whose scores were the second and third highest that year, "Peer 1" and "Peer 2." These two firms show improved scores over the years, more than the firm under analysis. The difference in their 2019 scores and our firm's 2019 score is larger than during earlier years.

**Figure 11** Event Propensity Score for Firm under analysis and its peers.



It is an open question whether ESG policies lead to a reduction in ESG incident rates, and if so, by how much. There is no easy way to tell whether the frequency with which we observe ESG incident rate changes, due to a time trend (e.g., increasing media attention) or a specific company's engagement in ESG policies. We address this question by using a Difference-in-Differences methodology, which we use to check whether ESG policies introduced by a company reduce the number of events it will be subject to in the future.

## 6. Does the Adoption of ESG Policies Lead to a Reduction of Future ESG events?

We have shown that some firms experience persistently elevated ESG event rates relative to firms in comparable sectors and regions and of comparable size. It remains to be demonstrated that elevated numbers of ESG-related events are a symptom of weak ESG risk management cultures versus persistent firm characteristics outside the control of the firm's stakeholders. This section demonstrates that investments in ESG policies can lead to lower ESG event rates, supporting the hypothesis of an improving ESG risk management culture.

To establish a causal relationship between ESG policies and ESG events, we use a "Difference-in-Differences" (DiD) approach. DiD establishes causation through a "natural experiment." We can easily demonstrate the intuition behind the approach using a medical example. It is reasonable to assume that people treated for a disease are likely to be sick, and sick people often recover without treatment. We can show treatment causes an improvement in health by showing that the health of the treatment group improves relative to the untreated group (i.e., the control group). The improvement in the treatment group versus the control group is the so-called DiD approach (c.f., Angrist and Pischke, 2008). It is called a "natural experiment," because the assignment to the control group versus the treatment group is done by nature rather than by the scientist, as in the case of a "controlled experiment."

Likewise, companies that introduce many ESG policies may be those that suffer the negative consequences of multiple past events. Our objective is not to show that companies that have an "ESG treatment" have either low rates of ESG events or

declining rates of ESG events, but rather experience a decline in rates of ESG events relative to firms that do not implement an “ESG Treatment.” We use substantial improvements in the Moody’s ESG Solutions’ ESG score as an indicator that a firm has made a substantial investment in strengthening its ESG risk management culture.

Table 1 shows companies that experienced significant ESG score improvements introduced multiple ESG improvement policies. For example, ALD Automotive, a subsidiary of SocGen, received the highest-ever ESG score change in Moody’s ESG Assessment Scores dataset (18 to 67 in 2020), and, accordingly, this change occurred after presenting its new, five-year strategic plan “MOVE 2025” and issuing €500 million green bonds, used to finance and refinance clean transportation projects and to promote transition to a low-carbon future.

**Table 1 Companies with Moody’s ESG Assessment Score changes and relevant policies.**

COMPANY NAMES	JUMP	CHANGES	YEAR	INDUSTRY	COUNTRY	NOTES
ALD (SocGen)	49	18->67	2020	Business Support Service	France	ALD has presented its new 5-year strategic plan “MOVE 2025” in 2020
Poste Italiane	47	23->66	2019	Transport and Logistics	Italy	Poste Italiane has launched “Deliver 2022” ESG strategic plan in 2019
Incitec Pivot	31	15->46	2009	Chemicals	Australia	Incitec Pivot has launched a 5-year healthy, safety, and environment strategy in 2008
Kawasaki Kisen Kaisha	31	17->48	2010	Transport and Logistics	Japan	Kawasaki Kisen Kaisha has begun to issue Social and Environmental Report since 2009

Source: V.E and company websites

### 6.1. Difference-in-Differences Model

The DiD model is a statistical technique used in econometrics that attempts to mimic an experimental research design using observational study data by evaluating the differential effect of a treatment on a “treatment group” versus a “control group” in a natural experiment (Angrist and Pischke (2009)).

DiD has become one of the most popular research designs used to evaluate causal effects of policy interventions. In its canonical format, there are two time periods and two groups: In the first period, no one is treated, and in the second period, the units in the first group are treated (the treated group), and the units in the second group are not (the control group).

Consider the DiD model setting as:

$$y'_{it} = \sum_{i=2}^N \alpha_i D_i + \sum_{t=1}^T \beta_t Y_t + c I_{it} + \epsilon_{it},$$

in which,

1.  $y'_{it}$  is the transformed number of events for company  $i$  at time  $t$ ;
2.  $I_{it}$  is the post-treatment dummy, and  $I_{it} = 1$  if and only if the firm  $i$  has received the treatment at time  $t$ ;
3.  $Y_t$  is the time dummy;
4.  $D_i$  is the treatment dummy;
5.  $\epsilon_{it}$  is the error term.

As was the case in the 2-sample, 2-period DiD model above, we are interested in  $c$  here, because it tells that, on average, there will be  $c \times \text{scaling factor}$  fewer ESG events after the treatment.

In our case, we define the treatment group, which consists of the firms that experienced large improvements in their ESG scores, and the control group, which consists of the firms that did not. We further define the treatment group into two subgroups. One includes the companies which have taken the moderate ESG policies and experienced their maximum ESG score changes larger than 10. The other includes the companies that have implemented substantial ESG policies and have experienced maximum ESG score changes larger than 15.



In a word, if we define  $change_{it}$  as the company  $i$ 's ESG score change at year  $t$ , we have:

1. Moderate treatment:  $\max(change_{it}) \geq 10$ ;
2. Substantial treatment:  $\max(change_{it}) \geq 15$ ;
3. No treatment (control group):  $\max(change_{it}) \leq 5$ .

Bertrand, Duflo, and Mullainathan (2004) argue that DiD estimation is prone to over-rejecting the null hypothesis in the presence of autocorrelation. The logic follows that, if there are multiple observations over time, the pre- and post-treatment instances are implicitly assumed to be independent by the model. If the observations are, in fact, correlated, this assumption leaves us with a false impression of strong evidence against the null from multiple observations, which we (incorrectly) treat as unrelated. The authors evaluate several methods for addressing the problem. The solution that we adopt is equivalent to using heteroskedasticity and autocorrelation consistent standard errors, as proposed in the seminal paper by Newey and West (1987). Bertrand et al. (2004) have shown it to efficiently resolve the false rejection problem on a randomly generated, autocorrelated dataset. The method has the additional advantage of being widely used and understood.

## 6.2 Difference-in-Differences Results

Table 2 DiD Regression Results using RepRisk Incidents.

DEPENDENT VARIABLE	MODERATE TREATMENT			SUBSTANTIAL TREATMENT		
	POST_TREATMENT COEFFICIENT	STD ERROR	T-VALUE	POST_TREATMENT COEFFICIENT	STD ERROR	T-VALUE
Transformed	-0.14***	0.04	-3.62	-0.27***	0.07	-3.98
Corrected Transformed	-0.14**	0.05	-2.66	-0.27***	0.08	-3.31
<b>Size</b>	<b>19,909</b>			<b>14,367</b>		

Note: Significance cutoff: 0 '\*\*\*\*' 0.001 '\*\*\*' 0.01 '\*\*' 0.05 '\*' 0.1 '.' 1

Table 3 Model Results by Size.

	\$1 BILLION	\$10 BILLION	\$100 BILLION	\$1 TRILLION
No Treatment	1.9	8.4	20.0	82
After Moderate Treatment	1.8(2.6%)	8.1(3.4%)	18.2(9.1%)	73.4(17.6%)
After Substantial Treatment	1.8(5.7%)	7.8(6.7%)	16.4(17.9%)	54(34.1%)

Note: Table shows the number of RepRisk incidents and the percentage reduction from the No Treatment group (in the parentheses)

Table 2 implies that, on average, there will be  $0.14 \times \text{scaling factor}$  fewer RepRisk incidents if a company made moderate improvements in ESG policies, and  $0.27 \times \text{scaling factor}$  fewer RepRisk incidents if a company made substantial improvements in ESG policies, in which a scaling factor is a size-specific factor, and the larger the size of the company, the larger the scaling factor is. In both cases, the large T stats allow us to reject the null hypothesis that the treatment did not lead to a reduction in future incidents with a high degree of confidence.

Table 3 implies that introducing what we called moderate ESG policies will reduce the number of RepRisk incidents a \$100-billion company is subject to by 9%. Substantial ESG policies will reduce the incidents and controversy numbers by 18%. The estimated reduction is greater for large companies. As with the finding that larger companies have more persistence in ESG incidents, this finding may reflect a better "signal to noise ratio" when inferring a latent variable (the ESG risk management culture) from ESG incidents of a large firm relative to a small firm.

This section introduces a new finding. Future work will determine the extent to which the finding is robust to alternative specifications, as well as different ESG incident datasets. We will also test whether or not the impact changes if we focus on Environmental incidents and policies, Societal incidents and policies, and Governance incidents and policies. Finally, we will evaluate the extent to which the rejection of the null hypothesis is robust to alternative methods for calculating the P value.

## 7. Summary

We find that ESG event risk persists, show how to measure this phenomenon, and present a method for scoring firms based on their ESG risks with respect to their peers. This persistence finding is consistent with two explanations: differences in ESG events rates (after controlling for size, region, and sector) can be explained by either differences in inherent firm characteristics outside the control of the firm's stakeholders or, alternatively, differences in ESG risk management cultures. Additionally, we find that firms that have improved their ESG policies, as indicated by an improved Moody's ESG Solution's ESG Score, lower their future rate of ESG events, as measured by both RepRisk Events and Moody's ESG Controversies using a DiD approach. The DiD finding is consistent with the second explanation: that there is an ESG Risk Management culture that persists over time but can be improved through improvements in ESG policies.

Our research includes three related, forthcoming whitepapers. The first investigates the business impact of ESG events. Preliminary findings show significant effects of ESG-related news on firms' abnormal stock returns, with the magnitude of the effect dependent on event characteristics and a firm's history of events. The second paper investigates whether ESG performance retains impact upon business outcomes, if we control for firm size or EDF measure. Preliminary findings indicate that a minority of firms with severe ESG issues exhibit inferior asset and equity returns. However, we find no evidence that minor ESG events (which occasionally befall most firms) have a similar effect. The third paper aims to extend the second result in this paper: that policy interventions intended to promote a stronger ESG risk management culture reduce the likelihood of future ESG events. Specifically, we examine the extent to which the result remains consistent with alternative specifications, event datasets, and statistical methods.

We suggest three areas for future research related to the measurement of persistence in ESG events. As mentioned, ESG events with a higher severity degree are expected to be more expensive for firms. Since, throughout this paper, we focus on the likelihood for overall ESG events, the first area for development is to measure the likelihood for ESG events with different severity degrees. Further, the intrinsic characteristics of firms make them susceptible to specific types of ESG risk; for example, a mining firm is exposed to more E-type risk than a financial firm. In this regard, the second area for future work aims to measure Environmental, Social, and Governance event risk separately. The third forthcoming whitepaper suggests that the introduction of policies advocating for a stronger ESG risk management culture reduces the persistence of ESG risk. In that regard, predicting changes in event rates is a powerful complement for a forward-looking measure of ESG risk and constitutes the third area for future research.

## Appendix

### Robustness of the Persistence Effect using RepRisk's Incident Dataset

One major concern — many corporate ESG incidents play out over an extended period, leading to the incidents being recorded over a long span and in multiple media sources. RepRisk takes incidents only once and from the most influential source, and only adds the incident again if the risk profile of the incident changes. Specifically, multiple entries about the same ESG incident can occur if 1) if a new development is related to the same incident, 2) the incident appears in a more influential source, and/or 3) the incident appears again for the same company in the same country after six weeks. In order to ensure that duplicated incidents do not drive the outcome of the analysis, we test the robustness of the persistence effect after making the following exclusions with different stringencies at the firm-level:

Type 1: Exactly the same countries, issues and severity, reach, and novelty.

Type 2: Exactly the same countries and issues.

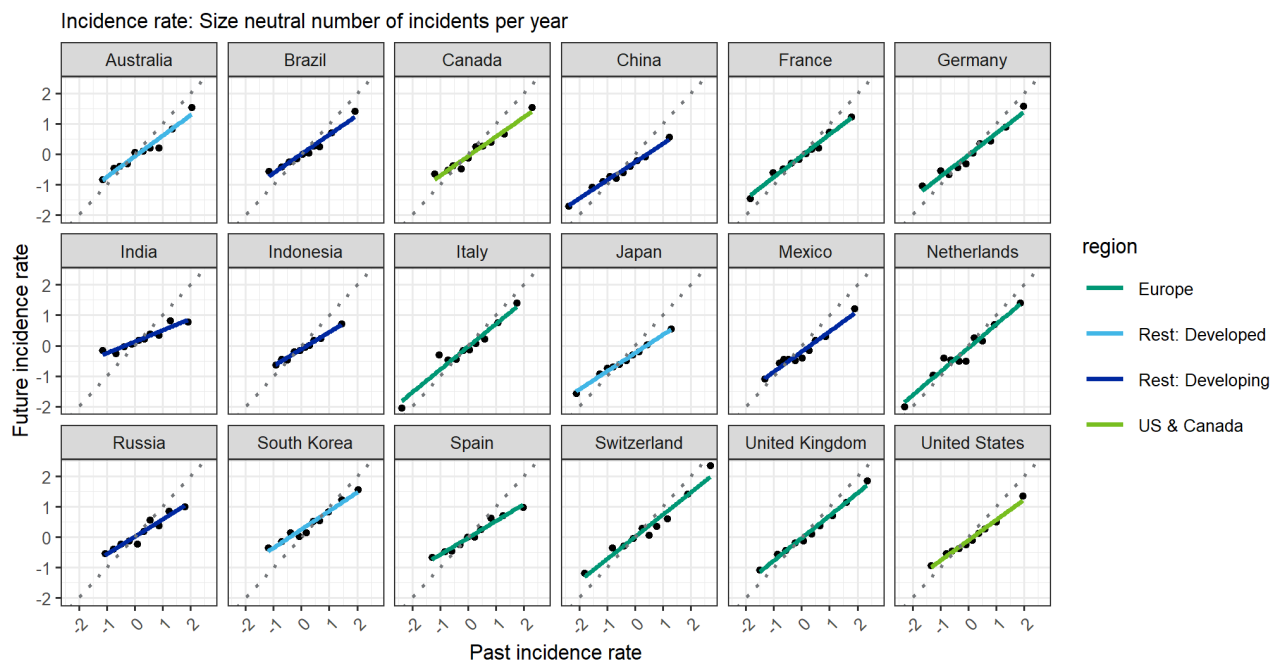
Type 3: Exactly the same issues and at least one country that coincides or exactly the same countries and at least one issue that coincides.

Results are robust for different sample constructions. Identification remains conservative, as a firm can have two separate incidents with the same issue, in the same country, which we exclude. This process constitutes an important robustness check, which rules out the possibility of too many incidents and duplicated incidents driving the analysis outcome, and it confirms our view that incidents recorded subsequent to a major ESG incident weights ESG incidents by their importance, a quality characteristic of RepRisk's data, but our method does not drive the outcome.

### Persistence Effect for Selected Countries

Figure 12 shows the persistence effect with country as the control variable, for countries with more than 27 firms top-18 countries by number of firms. Overall, the persistence effect is stronger for most of the developed economies, for which we also find a higher coverage of incidents.

Figure 12 Persistence effect across selected countries/regions.



## Baseline Regression

Table 4 reports summaries of the four models used to analyze incident rates in the panel. Model (1) models the incident rate as an AR 1 process; Model (2) as an AR 3 process; Model (3) uses size, sector, and region-specific dummies; and Model (4) combines the AR 3 with size, sector, and region-specific intercepts and size interaction with the first lag. We observe that the beta coefficients of the explanatory variables are below 1 across models. If the coefficients equal 1, that would mean that future incident rates are not expected to change with respect to past incident rates. The coefficients in Table 2 indicate that firms are expected to decrease (improve) their ESG incident rates in the future.

**Table 4** Linear autoregressive models for the incident rate.

Model (4): Baseline Regression				
INDEPENDENT VARIABLE	INCIDENT RATE			
	(1)	(2)	(3)	(4)
Incident rate: Lag 1	0.73***	0.49***		0.35***
Incident rate: Lag 2		0.23***		0.22***
Incident rate: Lag 3		0.12***		0.12***
Lag 1: Size: 20%-40%				0.08***
Lag 1: Size: 40%-60%				0.12***
Lag 1: Size: 60%-80%				0.15***
Lag 1: Size: 80%-100%				0.20***
Size: 40%-60%			0.12***	0.09***
Size: 60%-80%			0.18***	0.15***
Size: 80%-100%			0.23***	0.22***
Sector: Mining			0.33***	0.09***
Sector: Utilities			-0.04*	0.03*
Sector: Trade			0.25***	0.16***
Sector: HiTech			0.06**	0.07***
Sector: Business. Svcs.			-0.06*	0.06**
Sector: Construction			-0.31***	-0.01
Sector: Transportation			0.03	0.11***
Sector: Services			0.19***	0.15***
Sector: Health Care			-0.19***	0.03
Sector: Communication			-0.39***	-0.02
Region: Europe			0.01	-0.0002
Region: Rest, Developed			-0.30***	-0.06***
Region: Rest, Developing			-0.02	0.02*
Constant	-0.07***	-0.10***	-0.17***	-0.25***
<b>Observations</b>	<b>26,847</b>	<b>26,847</b>	<b>20,889</b>	<b>20,889</b>
<b>R<sup>2</sup></b>	<b>0.51</b>	<b>0.54</b>	<b>0.04</b>	<b>0.55</b>
Note:	* p < 0.05 ** p < 0.01 *** p < 0.001			

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