The Price of Perception: The effect of ESG reputation risk on analysts' target price revisions

Abstract:

Firms that fail to meet environmental, social, and governance (ESG) expectations face reputation risk. We examine whether analyst target price revision magnitude is associated with abnormal reputation risk. This is important because when analysts signal risk through revisions, it can exacerbate market uncertainty. We find a positive association between revision size and abnormal reputation risk, particularly for downward revisions. Further tests evidence that this relationship is greater for firms in industries with greater ESG impact, particularly when that impact is more salient (i.e. for firms operating in environmentally impactful industries). We find that firms in environmentally impactful industries attempt to mitigate their exposure to reputation risk by signaling board environmental oversight, but these efforts do not reduce the effect of reputation risk on analyst target price revisions. Our results highlight the importance of industry context for reputation risk exposure on analysts' target price revisions.

Data Availability: Data are available from the public sources cited in the text.

Keywords: ESG, analysts' target price revisions, industry context, environmental oversight, reputation risk

1. Introduction

Investors increasingly demand information regarding environmental, social, and governance (ESG) risks. As ESG gains attention, firms that lag in mitigating these risks face reputational costs. This study examines the association between analysts' target price revisions and reputation risk, as well as the industry-specific and governance factors that may influence this relationship. Sell-side analysts' target prices help inform firm investment potential; thus, analysts are expected to appropriately incorporate the risks and opportunities that could affect a firm's financial position (Dechow and You 2020). Because a bad reputation can have financial repercussions, such as damaging access to capital, customers, or employees (Derrien, Krueger, Landier, and Yao 2022), reputation risk should factor into analysts' models.[1] Studying analysts' expectations of firm risk is important for informed decision making. However, we know very little about how analysts adjust for risk in their target price valuations (Lui, Markov, and Tamayo 2012). This area is understudied because of the insufficient data on analyst risk forecasts (Bochkay and Joos 2021). We use target price revision magnitude as a measure of analysts' forecast of firm risk. The advantage of using this measure of forward-looking firm risk is that it is not limited to observations of analysts who provide both upside and downside target price forecasts, which is only a small percentage of all analysts (Bochkay and Joos 2021).

'ESG' was devised to convey financially material risks and opportunities associated with a firm's environmental, social, and governance practices to investors (Dechow 2023). Given increased regulation, better information technology, and higher demand for ESG information, firm ESG media coverage can influence public perception of the firm. This creates the risk that a

[1] We recognize that a good reputation can serve as an asset to achieve favorable borrowing rates or generate loyalty (Cao, Myers, Myers, and Omer 2015). However, we believe that the negativity bias in both human behavior and social media algorithms make it less likely that reputational opportunities are value-relevant. We leave it to future research to explore the effect of a good reputation.

negative reputation will damage the company's financial position.[2] Reputation risk can affect both future cash flows and the discount rate[3], both of which are inputs to analysts' valuation models. Larger target price revisions in response to larger reputation risk suggest that analysts foresee reputational effects on valuation. However, analysts may ignore reputation risk if they do not anticipate that it will materially change firm value, or if they are uncertain about how it will change firm value. Analysts play a key role in price formation and information dissemination to investors; thus, revisions that signal risk can significantly exacerbate market uncertainty around firm value.

Importantly, we argue that reputation risk is sector-specific. Firm reputation may be determined both by what *is* happening amongst peers and by what *could* happen given the ESG risks and opportunities relevant to the industry. We argue that analysts are better able to contextualize sector-specific reputation risk, given that they are typically industry experts. We therefore raise the question: to what extent does a firm's industry contextualize reputation risk for analysts' target price revisions? Furthermore, firms are under high pressure to manage their ESG-related reputation (Asante-Appiah and Lambert 2023). Thus, we ask whether firms in industries with greater ESG impact attempt to manage reputation by signaling commitment to environmental oversight, and whether analysts alter their expectations in response to these signals.

Although there is evidence that the market reacts to ESG news, it cannot be inferred directly from the literature whether analysts' expectations include reputation risk. First, there is

[2] A preeminent ESG framework, The Taskforce on Climate-related Financial Disclosure (TCFD) argues that firms should disclose risks and opportunities that may be financially material to investors. Of these risks, they identify four transitions risks (policy/legal, market, technology, and reputation) and two physical risks (acute and chronic climate) (TCFD 2017).

[3] See Becchetti, Cucinelli, Ielasi, and Rossolini (2023).

no conclusive evidence on whether investors recognize reputation risk as a value-relevant subset of ESG risk; thus, its relevance for analysts' signals is also unknown. Second, analysts may not pay attention to reputation risk for a subset of firms if they deem it irrelevant to the firm's industry. For example, shareholder ESG resolutions and firm reactions to those resolutions tend to be concentrated in high-impact industries such as oil and gas (Frick 2024). Last, analysts' expectations of reputation risk may shift as the institutional logic that ESG activities reflect agency costs to benefit managers, rather than shareholders, diminishes over time (Ioannou and Serafeim 2015).

To address our questions, we begin by examining the relationship between reputation risk and the magnitude of analyst target price revisions. We construct *AbnormalRRI*, a measure of reputation risk, using the RepRisk Index (RRI) for the firm and its associated country-specific sector RRI average. RRI is a proprietary algorithm that uses media coverage of the company's ESG issues to quantify firm exposure to reputation risk. Importantly, RepRisk does not include firm-communicated goals and policies, which enables RRI to capture perception of the firm rather than a greenwashed or carefully crafted message. We relate this measure to 597,440 analyst target price revisions for US companies between 2007 and 2020, given the availability of RepRisk data.

We observe that analysts make larger target price revisions when reputation risk is high relative to the firm's sector average, (i.e. abnormal). We also separate our sample by the direction of the target price revision (upward vs downward). We find that the association between reputation risk and revision magnitude exists when analysts issue a downward revision, but the association is not significant for upward target price revisions. This suggests that analysts anticipate potential reputational damage having a negative impact on stock valuation. We additionally observe that the association between reputation risk and analysts' target price revision is significantly greater for firms in industries with a high potential for environmental impact and is weaker for firms in industries with high potential for social or governance impact. Consistent with the salience of environmental impact on reputation, we find that firms operating in environmentally impactful industries are more likely to signal commitment to environmental oversight by using relevant buzzwords in board committee names, including board members with relevant experience, or accruing connections to individuals that have relevant experience. Notably, we find no significant results suggesting that environmental oversight signaling alters analysts' incorporation of reputation risk into target price revisions.

Our research makes several contributions. First, we respond to Dechow (2023)'s call for research on whether analysts incorporate ESG risk and opportunity into their deliverables, given their significant role in the investment decision-making process (e.g., Asante-Appiah and Lambert 2023; Park, Yoon, and Zach 2023). This is important because analysts are valuable information intermediaries, and their expectations influence market perception of a firm's valuation. Additionally, the rise of ESG investing has increased the salience of reputation risk in the media, but we do not yet understand if informed market participants translate this risk into actual expectations of firm value. Second, we present the first analysis that measures reputation risk benchmarked against the sector average risk (*AbnormalRRI*), which is a key ESG performance consideration. Third, we make a unique contribution by creating composite measures of environmental, social, and governance risks and opportunities at the industry level to contextualize firm reputation. To the best of our knowledge, whether the effect of ESG risk exposure on analysts' target price revisions varies at the industry-level has yet to be explored in the literature. We provide important evidence about the value of industry context for ESG information. Last, we are among the first to propose measurements and test hypotheses regarding analyst behavior and the ESG oversight factors required to be disclosed by the SEC's rules on climate-related risks.[4]

2. Theory and Hypothesis Development

2.1 Reputation risk and firm value

Our first question examines the extent to which analyst target price revisions capture firm exposure to reputation risk. Changes to analyst target prices communicate information about changes in the elements of firm valuations, which includes the discount rate and expected future earnings or cash flows (Demirakos, Strong, and Walker 2004). Analysts may factor reputation risk into discount rate considerations. For example, if analysts anticipate that reputation risk will affect firm value, the required return on the stock should be higher for firms with higher reputation risk exposure. Moreover, reputation risk could drive away investors, resulting in higher cost of capital and lower firm value. For example, Chava (2014) shows that a firm's environmental considerations affect cost of equity and debt capital. Additionally, reputation risk can affect future cash flows if it results in loss of sales due to negative customer or employee reactions (Derrien et al. 2022). Relatedly, Yin, Peasnell, Lubberink, and Hunt (2014) show that analysts assign lower P/E multiples to valuations of high-risk firms measured using financial risk, earnings volatility, book-to-market ratio, and stock price volatility. Therefore, the size of the change in analysts' target prices demonstrates the analysts' expectations about risk in future earnings, cash flows, and valuation.

[4] On March 6, 2024, the SEC adopted a final rule requiring companies to disclose certain climate-related information in registration statement and annual reports. "The final rule will also require the identification, if applicable, of any board committee or subcommittee responsible for the oversight of climate-related risks and a description of the processes by which the board or such committee or subcommittee is informed about such risks" (SEC 2024).

Prior research offers reasons to favor target price revisions over earnings forecasts and recommendations. First, target prices contain information incremental to information in earnings forecasts and stock recommendations (Brav and Lehavy 2003). Gleason, Johnson, and Li (2013) show that analysts' target prices predict future returns and that this effect is incremental to the return predictability of buy–sell recommendations. Thus, evidence on the factors that affect target price decisions is valuable to researchers and investors. Moreover, most earnings forecasts are short-term and cover limited periods (e.g., a fiscal quarter), while stock recommendations are discrete (e.g., sell, hold, buy). In contrast, the continuous nature and direct valuation implications of target price forecasts make them a potentially useful investment signal regarding firm valuation.

There is an emerging stream of literature that utilizes reputation measures from RepRisk to examine analyst behavior, particularly the relationship between analyst accuracy and reputation risk. Prior researchers have found that forecast errors are higher when firms are exposed to more reputation risk but that ESG disclosure moderates this relationship (Schiemann and Tietmeyer 2022). Park et al. (2023) find evidence that analysts' target price forecasts and recommendations predict future ESG media incidents, but their research uses the number of firm-level incidents as the dependent variable. This suggests that analysts may convey information that predicts reputation-damaging events and highlights the importance of understanding whether they incorporate reputation risk into their forecasts of firm valuation.

While the relationship between reputation risk and target price revisions has yet to be investigated directly in the literature, we lean on research that utilizes forecast errors to inform our hypothesis (Schiemann and Tietmeyer 2022). We anticipate that analysts will expect greater price effects when reputation risk is higher. Given the information analysts glean from benchmarking against industry peers, we expect that analysts will contextualize reputation risk against sector peers. Thus, we predict:

> *H1: There is a positive association between analysts' target price revision magnitude and abnormal reputation risk.*

In addition to testing this hypothesis using our full sample, we also use the subsamples of downward and upward target price revisions to check the effect of valence on our predictions. As Benjamin Franklin once said, "It takes many good deeds to build a good reputation, and only one bad one to lose it." Because we consider reputation risk, i.e. the potential for reputational damage, we expect the relationship between reputation risk and analyst target price revisions to be stronger for downward revisions.

2.2 Reputation risk and industry impact

We acknowledge that firm reputation is dependent upon context (Bebbington, Larrinaga, and Moneva 2008). In fact, market prices only respond following ESG incidents for firms in industries that the Sustainability Accounting Standards Board (SASB) has designated as having material sustainability-related risks and opportunities (Serafeim and Yoon 2021). When testing how analysts may anticipate the effects of reputation, we consider that benchmarking not only reveals reputation risk above what *is* normal amongst peers, but also what *could* be normal given the industry impact. Specifically, we consider that the industry in which a firm operates determines what possible risks and opportunities can reasonably be assumed. For example, an energy company will have different risks related to ESG reputation than a financial services company. An energy company may also have more opportunities to have a positive environmental impact through the development of clean energy sources, which would be reputationally risky to ignore. Thus, when forecasting stock prices, analysts may differentially consider ESG risks and opportunities based on the industry context.

To explore how industry context may alter the relationship between reputation risk and analyst target price expectations, we classify firms according to whether they operate in industries with greater potential environmental, social, and/or governance risks and opportunities. We argue that analysts expect to see more reputation risk for firms in more impactful industries. We then consider two rival theories when forming our second hypothesis: confirmation bias and expectancy violation theory.

Confirmation bias is the tendency to seek evidence that is consistent with one's prior beliefs (Jonas, Schulz-Hardt, Frey, and Thelen 2001) and has been modeled for analyst forecasts (Pouget, Sauvagnat, and Villeneuve 2017). This can alter what information is consumed, how it is interpreted, or how it is recalled and applied. This can arise for analysts as a blend of an availability heuristic, whereby reputation risk is more salient, and an emotional response, whereby analysts feel discomfort with, and therefore ignore, surprising information. If analysts expect reputation risk for firms in impactful industries, confirmation bias could cause analysts to (1) underreact to reputation risk in industries where they do not anticipate risks or opportunities or (2) overreact to evidence in industries with more likely risks and opportunities, thus doubling down on prior assessments.

Expectancy violation theory suggests that human reactions depend heavily on prior expectations. Specifically, the theory proposes that individuals do not react to observed behaviors that align with expectations, since the observed behaviors confirm beliefs. However, when individuals hold an expectation and observe the opposite, their expectations are violated, which attracts additional attention and elicits stronger reactions (Burgoon and Burgoon 2001, Clor-Proell 2009). If analysts anticipate reputation risk, confirmation of this belief should not alter their perception. Rather, expectancy violation theory would suggest that analysts react strongly when a reputational risk arises unexpectedly. We would see evidence of the expectancy violation theory if reputation risk had a larger effect on analyst target price revisions for firms in less impactful industries.

Given that our rival theories are equally plausible, we state our hypothesis in terms of the null:

H2: The association between the analysts' target price revision magnitude and abnormal reputation risk is not affected by whether firms operate in high impact industries.

2.2 Managing reputational costs

The political hypothesis, originally introduced by Watts and Zimmerman (1986) suggests that increased attention compels firms to manage public perception to minimize political costs. Prior research has typically examined the political hypothesis in the context of earnings management. For instance, even predating the rise of environmental concern, oil and gas companies addressed perceptions of price gouging by managing earnings downward (Han and Wang 1998).

We note environmental impacts are most salient for ESG investors (Capital Group 2022, Pérez, Hunt, Samandrari, Nuttall, and Biniek 2022), which is reinforced by climate-related risk disclosure regulations (SEC 2024) and social media (Bebbington et al. 2008). Thus, we expect that firms in environmentally impactful industries face political costs related to the environment. If the political hypothesis holds true, we predict that firms operating in these industries will attempt to manage public perception by sending positive signals to the public. There are several signals that a firm could use; however, we model our tests based on the governance considerations outlined in the SEC rule for enhanced climate-related disclosure.

The SEC rule for enhanced climate-related disclosure requires firms to identify and disclose the committees responsible for oversight of climate-related matters and how they will be informed of these matters. Some firms may delegate responsibility for environmental matters to an existing committee, while others may establish a separate committee dedicated solely to environmental matters (SEC 2024). The requirement suggests that the presence of a specific committee can be valuable for evaluating a firm's ability to manage climate-related risk. We expect that firms in environmentally impactful industries will signal their commitment to environmental oversight by establishing separate environmental committees to reduce political costs or maximize political capital. Moreover, because committee naming conventions may not demonstrate focus as a low-cost signal (Burke, Hoitash, and Hoitash 2019a), we consider the expertise of board members and their connections as stronger signals of commitment to environmental oversight.[5] Experienced connections are a resource that can help position the board to stay informed of climate implications, risks, and opportunities. Formally stated:

H3a: Firms in environmentally impactful industries are more likely to signal commitment to environmental oversight.

Last, we examine whether firms' attempts to manage environmental reputation risk are successful. Dyck, Lins, Roth, Towner, and Wagner (2023) find evidence that adjusting governance mechanisms is necessary to achieve alignment of firm policies with investor environmental preferences. Board members who have environmental experience or have a network of experienced connections improve environmental performance (Homroy and Slechten 2019), but evidence also suggests that boards are more effective monitors when it comes to pursuing environmental opportunities rather than mitigating exposure to environmental risks

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[5] While this requirement is not included in the SEC's Climate-related disclosure rule (SEC 2024), it was featured in the proposed rule.

(Burke et al. 2019a). While there is evidence that analysts consider board characteristics as part of target price evaluations (Cheng, Su, Yan, and Zhao 2019), it is unclear at this point if analysts pay attention to ESG-related board characteristics and if so, whether this alters their incorporation of reputation risk into target price revisions. It is also unclear whether the costliness of the signal matters in this context. For example, signaling using a buzzword in the committee name can be viewed as 'cheap talk'. Given that the literature lacks sufficient theory to support a directional hypothesis, we state our hypothesis in terms of the null:

> *H3b: Signaling commitment to environmental oversight will not affect the association between the analysts' target price revision magnitude and abnormal reputation risk.*

3. Methodology

3.1 Data

To construct our sample, we obtain analyst target price forecasts from I/B/E/S Detail History file over the period January 2007 to December 2020. We retain target prices issued for US firms by identifiable analysts that have a 12-month forecast horizon. We require that the prior target price by the same analyst for the same company was issued within the previous 365 days. Table 1 presents the sample selection criteria. Our final sample consists of 597,440 target price forecasts for 2,670 US firms issued by 5,927 analysts at 489 brokerages.[6] Table 2 Panel A provides annual sample representation for firm, analyst, and brokerage in I/B/E/S from 2007 through 2020. Following prior literature (e.g., Bradshaw, Brown, and Huang 2013; Brav and Lehavy 2003), we calculate target price revision magnitude as the absolute value of the current

[6] The sample is comprised of 597,440 forecasts, but 26 singleton forecast observations drop from our model due to standard error clustering.

target price forecast less the last target price forecast, divided by the market price of the stock on the date of the current target price forecast.[7]

We leverage a unique dataset covering firm-month level data from RepRisk about negative coverage of ESG issues. On a daily basis, RepRisk screens more than 100,000 public sources and stakeholders across 23 languages. These include print media, online media, social media, government bodies, regulators, think tanks, newsletters, and other online sources. Sources are international, national, regional, and local. RepRisk defines 28 ESG issues listed in Appendix 2. The purpose of RepRisk's dataset is to systematically identify and assess material reputation risks. RepRisk analyzes information from public sources but intentionally excludes company self-disclosures. The RepRisk data set includes roughly 20,000 firms and covers the period 2007-2020. Included within the RepRisk package is the RepRisk Index (RRI), which is a dynamic risk score produced by a proprietary algorithm based on media and stakeholder coverage.

We use the RepRisk Index (RRI) to construct a new measure, *AbnormalRRI*, that captures a firm's reputation risk exposure to ESG issues beyond the sector average. Analysts' ability to rank firms within industries is considered one of the most important elements of their research (Boni and Womack 2006; Brown, Call, Clement, and Sharp 2015; Bradley, Gokkaya, and Liu 2017), and they are considered industry experts (Boni and Womack 2006; Kadan, Madureira, Wang, and Zach 2012). Given that analyst recommendations commonly benchmark firms against their industry peers (Kadan, Madureira, Wang, and Zach 2020), we anticipate that analysts will have a stronger reaction to reputation risk that is greater than average sector risk. This motivates us to construct our measure of abnormal reputation risk. *AbnormalRRI* is a composite measure of

[7] Our dependent variable is skewed to the right. To normalize the distribution of the dependent variable, we construct our dependent variable using the cube root of the target price revision magnitude. The cube root transformation can be used to normalize distributions when the data exhibits a positively skewed distribution. The skewed distribution of our dependent variable could not be normalized using the log transformation or square root.

RepRisk's *CurrentRRI* and *CountrySectorAverageRRI* measures, which reflects the current levels of media and stakeholder attention to ESG issues for the firm and its country-specific sector, respectively.[8] RRI takes values from zero (lowest risk exposure) to 100 (highest risk exposure). Table 2 Panel B provides sample representation and average current RRI by industry. Descriptive statistics for this and other variables used in our analysis are shown in Table 3.

A major distinction of RRI from other ESG ratings (e.g., MSCI, Sustainalytics, Bloomberg) is that it is based on media coverage and intentionally excludes company self-disclosures. This measure therefore distinguishes between ESG disclosure and ESG risk, where risk takes into consideration how the firm might be perceived. RepRisk's calculation of RRI takes into consideration the reach, frequency, severity, novelty, and timing of ESG incidents.[9] Yet using the number of incidents in a particular month, as done in prior studies, does not fully capture the current state of reputation risk.

We present a snapshot of RepRisk data for Wells Fargo in 2017 and 2010 in Appendices 3-A and 3-B, respectively. Wells Fargo has the largest number of incidents per year reported in 2017 (88 incidents), with the largest number of incidents per month reported in March 2017 (17 incidents). As shown in Appendix 3, changes in the number of incidents does not always proportionately correspond to changes in the RRI reputation risk measure. In fact, the 2017 period captures the greatest volume of incidents, whereas Wells Fargo experienced the greatest RRI volatility in the 2010 period. This confirms RepRisk's statement that companies with high

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[8] *CountrySectorAverageRRI* is composed of two equally-weighted components: the Headquarters ESG Risk Exposure and International ESG Risk exposure, which capture a firm's sector risk exposure in its headquarters' country and any other relevant countries, respectively.

[9] Novelty takes the values 2 or 1, for new and less new incidents, Reach and Severity take the values 3, 2, and 1, with 3 indicating the highest values of reach and severity of the incident. The Novelty, Reach and Severity of the incidents is embedded in the RRI calculation.

past exposure to risk incidents are less sensitive to new risk incidents than companies that have less past exposure.

While the RRI algorithm is proprietary, prior research has utilized the RRI measure to examine reputation risk (Schiemann and Tietmeyer 2022). Among prior research, Burke, Hoitash, and Hoitash (2019b) first introduced RRI into the literature and performed validation tests over the construct. Specifically, the authors demonstrate a negative correlation between RRI and popular reputation rankings such as Fortune's 'Most Admired Companies List' and Newsweek's 'Green Rankings List.' The authors also find increases in RRI and audit fees along the timeline of the Volkswagon emissions scandal. Given audit fees are comprised of both a cost and risk premium, auditors should incorporate additional risk into audit fees when reputation risk is high (Burke et al. 2019b). We rely on the extensive preexisting validation of the RRI measure to demonstrate the suitability of the measure for our purposes.

3.2 Research design

To test our first hypothesis, we investigate whether the size of analysts' target price revisions is sensitive to reputation risk. We estimate the following OLS regression model:

$$(1)\ TP\_Rev_{i,j,t} = \beta_0 + \beta_1\ AbnormalRRI_{j,t} + \beta_2\ RevisionInterval_{i,j,t} + \beta_3\ Following_{j,t} + \beta_4\ Companies_{i,t} + \beta_5\ BrokerSize_{i,t} + \beta_6\ FirmExperience_{i,j,t} + \beta_7\ Industries_{i,t} + \beta_8\ StockMomentum_{j,t} + \beta_9\ ExcessReturn_{j,t} + \beta_{10}\ EPSRevision_{i,j,t} + \beta_{11}\ ConsensusChange_{j,t} + \lambda_{year} + \lambda_{broker} + \lambda_{firm} + \varepsilon$$

where the dependent variable $TP\_Rev_{i,j,t}$ equals the absolute value of the current target price forecast less the last target price forecast divided by the market price of the stock on the date of the current target price forecast: $TP\_Rev_{i,j,t} = \left|\frac{(TP_{i,j,t} - TP_{i,j,t-1})}{Price_{j,t}}\right|$. We replicate this regression in cross-sectional analyses where we bifurcate the full sample $TP\_Rev_{j,t}$ according to the direction of the revision (upward vs downward). The subscripts represent analyst *i* in respect of firm *j* at time *t*. $AbnormalRRI_{j,t}$ is calculated as ($CurrentRRI_{j,t}$ – $CountrySectorAverageRRI_{j,t}$) / $CountrySectorAverageRRI_{j,t}$ (see Appendix 4 for variable definitions).

Given that target prices are likely to occur over different intervals, we control for the analyst's revision interval (*RevisionInterval*). Following prior research on analyst target prices (Ho, Strong, and Walker 2018), we control for firm-level analyst following (*Following*) and analyst-level variables: number of companies followed by the analyst (*Companies*), size of the broker (*BrokerSize*), firm experience (*FirmExperience)*, and number of industries followed by the analyst (*Industries*). We also control for market information based on prior evidence (Ho et al. 2018), including the relationship between target price revisions and stock momentum (*StockMomentum*), excess stock returns (*ExcessReturn*), and other analysts' target price revisions (*ConsensusChange*). We additionally control for the analysts' most recent earnings forecast revision (*EPSRevision*). All continuous variables are winsorized at the 1st and 99th percentile except variables sourced from RepRisk. Each regression includes year, broker, and firm fixed effects and clusters standard errors by year and analyst.

To test our second hypothesis, we acknowledge that while *AbnormalRRI* contextualizes firm reputation risk against the concurrent reputation risk of its sector peers, a firm's industry determines which ESG risks and opportunities it may possibly face. If a firm's potential ESG impact alters how analysts consume reputation risk information, we would expect the association of the magnitude of target price revisions and reputation risk to differ for firms in high-impact industries. By looking at the firm's industry capacity to make an impact, we attempt to avoid endogeneity issues associated with impactful firms, while also exploring the context in which the firms operate. We estimate the following OLS model:

$$(2)\ TP\_Rev_{i,j,t} = \beta_0 + \beta_1\ AbnormalRRI_{j,t} + \beta_2\ RelativeRRI_{j,t} \times IndImpact_j + \beta_3\ RevisionInterval_{i,j,t} + \beta_4\ Following_{j,t} + \beta_5\ Companies_{i,t} + \beta_6\ BrokerSize_{i,t} + \beta_7\ FirmExperience_{i,j,t} + B_8\ Industries_{i,t} + \beta_9\ StockMomentum_{j,t} + \beta_{10}\ ExcessReturn_{j,t} + \beta_{11}\ EPSRevision_{i,j,t} + \beta_{12}\ ConsenusChange_{j,t} + \lambda_{year} + \lambda_{broker} + \lambda_{firm} + \varepsilon$$

where $IndImpact_j$ is $EImpactInd_j$, $SImpactInd_j$, or $EGImpactInd_j$.

The *IndImpact* variables are indicators based on the specific risk and opportunities related to the firm's industry for each of the three ESG pillars, respectively. To create the indicator variables, we identify impactful industries utilizing the MSCI ESG Industry Materiality Map, which is designed to evaluate firms across unique industry-specific ESG risks and opportunities. MSCI weights industry impact across issues: 13 environmental risk and opportunity categories, 14 social risk and opportunity categories, and one governance category (see Appendix 1). We consider an industry to be environmentally impactful if the industry's composite score across all 13 environmental risk and opportunity category weightings is in the top quartile of all industries evaluated by MSCI. Firms that operate in an environmentally impactful industry are assigned an indicator variable of 1 for the variable *EImpactInd.* We repeat this process for *SImpactInd* and *GImpactInd.* In each case, the indicator is colinear with firm fixed effects when not interacted with *AbnormalRRI* and is therefore excluded from the regression model.

We use the *IndImpact* indicators to test our third hypothesis that reputation risk and political cost increase the likelihood that firms signal environmental oversight. Of the three pillars of ESG, key players in the industry recognize "E" as the dominant force driving ESG investment initiatives (Capital Group 2022, Pérez et al. 2022). Further, ESG regulation and frameworks reflect stakeholder demand; thus, the areas that standard setters prioritize capture stakeholder priorities. Given this attention, greater reputation risks are likely imposed on firms operating in environmentally impactful industries.

We expect firms that operate in environmentally impactful industries to address reputation risk by attempting to manage perception, minimize political costs, or build political capital. We test whether firms that operate in environmentally impactful industries are more likely to signal commitment to environmental oversight by explicitly naming an environmental board committee (e.g., "ESG Committee" or "Sustainability Committee"), including at least one member with environmental expertise, or maintaining connections with other individuals with environmental expertise.

We utilize a logit model to examine whether companies in environmentally impactful industries are more likely to signal commitment to environmental oversight on a yearly basis. We estimate the following logit regression:

$$\begin{aligned} EOversightSignal_{j,t} = {} & \beta_0 + \beta_1\, IndImpact_j + \beta_2\, Big3InstOwn_{j,t} + \beta_3\, Assets_{j,t} + \beta_4\, FirmAge_{j,t} + \\ & \beta_5\, Following_{j,t} + \beta_6\, BoardSize_{j,t} + \beta_7\, BoardIndependence_{j,t} + \\ & \beta_8\, BusinessSegments_{j,t} + \beta_9\, GeographicalSegments_{j,t} + \\ & \beta_{10}\, CEOTenure_{j,t} + \beta_{11}\, CEOAge_{j,t} + \beta_{12}\, CEOGender_{j,t} + \varepsilon \end{aligned}$$

where $EOversightSignal_{j,t}$ is $ECommitteeName_{j,t}$, $EExpertise_{j,t}$, or $EConnections_{j,t}$ and $IndImpact_j$ is $EImpactInd_j$, $SImpactInd_j$, or $EGImpactInd_j$.

ECommitteeName is an indicator variable equal to 1 if the firm has a board committee name with an environmental buzzword. Each unique committee name was coded with an indicator variable equal to one if it was environment-related and zero otherwise. Coding was performed independently without any firm-identifying information by two co-authors and any disagreements were resolved by the third co-author. *EExpertise* is an indicator equal to one if any member of the board has environmental expertise, and *EConnections* is an indicator equal to one if the number of unique board connections to individuals with environmental expertise is above the sample median by year. Given knowledge is gained through experience (Arrow 1962), we construct our measure of expertise based on the prior professional experience of board members. Consistent with the methodology employed by Homroy and Slechton (2019), environmental expertise is determined by whether title, role description, or company name includes "ESG," "Environment," "Sustain," "Climat," or "Ecolog" at any point before or during the observed year. These terms are intentionally abbreviated to ensure we capture as many variations of the word as possible by allowing room for varying suffixes (climate, climatologist, etc.). We count the number of connections to external directors with environmental expertise and eliminate any duplicative connections. We use ESG connections as a proxy for the resources available to directors in overseeing and navigating environmental-related risks, both external information and the environmental skill of the board (Homroy and Slechten 2019).

We control for factors that may influence the board's decision or ability to signal commitment to environmental oversight. The decision to signal environmental oversight may be determined by activist investor preferences and visibility. *Big3InstOwn* captures the percent of shares held by the largest, most ESG-activist investors: BlackRock, State Street, and Vanguard (Yang 2023).[10] *Following* demonstrates firm visibility. Capturing both the potential for accumulated experiences and a potential entrenchment, *BoardAge* is calculated as the average age of the members of the board of directors but is omitted from the model due to multicollinearity. Its inclusion does not alter the results.

[10] The results are unchanged by the inclusion of (1) an indicator equal to 1 if the firm operates in the European Union or United Kingdom, (2) the number of institutional owners, and (3) the percent of shares held by any institutional owner.

Further, we expect that larger and more mature firms, larger boards, and those with more outside directors will have more capacity to include environmental committees and expertise. *Assets* and *FirmAge* capture firm size and age and are logged. We control for *BoardSize* and *BoardIndependence* as the number of board members and the percentage of outside board members, respectively. On the other hand, firm complexity may create barriers to good environmental oversight or increase the strategic need: *BusinessSegments* and *GeographicalSegments* capture information that may contribute to operating or organizational boundaries ambiguity as left undefined in the SEC rule.[11] Finally, because environmental oversight is a joint effort between the board and management, and because information flows and allocations of environmental responsibility are a key focus of ESG frameworks, we include common CEO characteristics (Anderson, Mansi, and Reeb 2004).

Hypothesis 3b asks whether firms' efforts to signal commitment to environmental oversight are effective in moderating how analysts incorporate reputation risk. To test this hypothesis, we interact *AbnormalRRI* with the *EOversightSignal* indicator and re-estimate our original model. We estimate the following OLS regression:

$$\text{(3)}\quad TP\_Rev_{i,j,t} = \beta_0 + \beta_1\,AbnormalRRI_{j,t} + \beta_2\,EOversightSignal_{j,t} + \beta_3\,AbnormalRRI_{j,t} \times EOversightSignal_{j,t} + \beta_4\,RevisionInterval_{i,j,t} + B_5\,Following_{j,t} + \beta_6\,Companies_{i,t} + \beta_7\,BrokerSize_{i,t} + \beta_8\,FirmExperience_{i,j,t} + B_9\,Industries_{i,t} + \beta_{10}\,StockMomentum_{j,t} + \beta_{11}\,ExcessReturn_{j,t} + \beta_{12}\,EPSRevision_{i,j,t} + \beta_{13}\,ConsenusChange_{j,t} + \lambda_{year} + \lambda_{broker} + \lambda_{firm} + \varepsilon$$

where $EOversightSignal_{j,t}$ is $ECommitteeName_{j,t}$, $EExpertise_{j,t}$, or $EConnections_{j,t}$.

[11] Our results are robust to the inclusion of year and firm fixed effects though not econometrically sound in a logistic regression.

4. Results

4.1 Hypothesis Tests

1. Is there a positive association between the magnitude of analysts' target price revisions and abnormal reputation risk?

Table 4 reports the results of regressing *TP_Rev* on *AbnormalRRI* using equation (1). If analysts believe that reputation risk is value-relevant, greater reputation risk will cause them to make a larger target price revision. If this is the case, we expect a significant coefficient on *AbnormalRRI*. In Column (1) of Table 4, the variable of interest is *AbnormalRRI*, which is both positive and significant ($\beta = 4.30$, p-value < 0.01).[12] Consistent with benchmarking on sector reputation risk, the magnitude of analysts' target price revisions is positively associated with reputation risk that is higher than sector average. *AbnormalRRI* that is 1 standard deviation higher is associated with *TP_Rev* that is larger by 0.25%. This represents an increase of 8.96% since the mean revision size is 0.1644. The result reinforces the hypothesis that analysts consider the risk associated with reputation to have a statistically and economically significant effect on valuation, as reflected by larger target price revisions. As in prior research, we find that target price revision magnitudes are significantly associated with analysts' consensus target price revisions, stock momentum and excess stock return. We find target price revision magnitudes are positively associated with the analysts' firm-specific experience and industry coverage.

We further predict that the association between analysts' target price revision magnitudes and reputation risk is more pronounced in the case of negative revisions. In columns (2) and (3) of Table 4, we separate our sample by the direction of the revision, upward and downward,

[12] Our results are also robust to excluding firms that do not have an associated GIC industry code, and to scaling the dependent variable by lagged target price or market price on the date of the target price forecast.

respectively. The results of Table 4 column (3) show that for the subsample of downward target price revisions (negative signal from analysts), *TP_Rev* is greater when *AbnormalRRI* ($\beta = 4.87$, p-value < 0.01) is higher. This is the same result we find in column (1) of Table 4 for the full sample of target price revisions. For the subsample of upward target price revisions (positive signal from analysts), the association between *AbnormalRRI* and *TP_Rev* is not significant. This is consistent with our hypothesis that analyst revisions will be disproportionately large for downward revisions as opposed to upward revisions. Our study is the first to document the difference in how reputation risk affects analysts' positive vs. negative target price forecast revisions. This result also confirms our prediction that the association between analysts' target price revisions and reputation risk is more pronounced in the case of negative analysts' revisions.

2. Is the association between analysts' target price revision magnitude and abnormal reputation risk affected by whether firms operate in high impact industries?

Table 5 presents the estimation results of equation (2). The results suggest that analysts incorporate reputation risk into target price revisions for firms in impactful industries.[13] The positive and significant coefficient on the interaction between *AbnormalRRI* and the *EImpactInd* indicator ($\beta = 9.12$, p-value < 0.05) shows the positive association between target price revisions and reputation risk for firms in environmentally impactful industries. While *AbnormalRRI* on its own is insignificant, the coefficient on the interaction term alone shows that the effect is economically significant. For firms in environmentally impactful industries, *AbnormalRRI* that is one standard deviation higher is associated with *TP_Rev* that is larger by 0.18%. This represents an increase of 3.69%. Of our competing theories supporting H2, these results are consistent with

[13] Our results are robust to using sector-level impact instead of industry-level impact.

Confirmation Bias, whereby analysts seek reputation risk when it is most salient, i.e. when there is more ESG impact.

We see that while the interaction of *AbnormalRRI* and *EImpactInd* is positively associated with revision magnitude, this effect is reversed for firms in industries with more social or governance impact. Columns (3) and (4) show a statistically significant positive relationship between *AbnormalRRI* and *TP_Rev* ($\beta = 6.42$, p-value < 0.01; $\beta = 4.82$, p-value < 0.01), but is negative for the interaction of *AbnormalRRI* and *SImpactInd* ($\beta = -7.46$, p-value < 0.01), and *AbnormalRRI* and *GImpactInd* ($\beta = -7.69$, p-value < 0.01).[14] This finding implies analysts do not expect reputation risk to be value-relevant for firms in industries with high social and governance impact. We acknowledge that it could be argued that social factors such as labor practices, employee relations, and diversity and inclusion could receive attention and visibility because they directly impact stakeholders and communities. Yet, the empirical results are consistent with environmental impact being more important relative to the other pillars (Capital Group 2022; Pérez et al. 2022). These results further support the Confirmation Bias theory, such that analysts do not incorporate existing reputation risk for firms in industries where it is less salient.

3. Are firms in environmentally impactful industries more likely to signal commitment to environmental oversight? Does signaling environmental oversight affect the association between the analysts' target price revision magnitude and abnormal reputation risk?

We estimate equation (3) and present the results in Table 6.[15] We follow the investor attention to environmental issues (Capital Group 2022; Pérez et al. 2022) and focus on environmentally impactful industries. To measure signals of environment oversight, we rely on

[14] Our results are also robust to dividing industries around the median of MSCI's composite weighting and to replacing our *EImpactInd* indicator with an indicator for whether the industry has an above-median number of environmentally material factors per SASB Materiality Map.
[15] Our analysis in Table 6 is at the firm-year level while all other tables are at the analyst forecast level.

the SEC rule for climate-related disclosure guidance on environmental governance.[16] The results in Panel A show that firms in environmentally impactful industries are more likely to signal commitment to environmental oversight using environmental board committees ($\beta = 1.61$, p-value < 0.01). This is economically significant; the odds of signaling are 5 times higher for firms in environmentally impactful industries. Those firms in industries with social or governance impact are less likely to signal environmental oversight using board committee names, as evidenced by the negative association ($\beta = -1.33$, p-value < 0.01; $\beta = -0.56$, p-value < 0.01). This is likewise economically meaningful, such that the odds of signaling decrease by 73.55% and 42.88% for industries with high social and governance impact, respectively. In untabulated analysis, we find that our inferences hold when we replace the dependent variable with a variable that captures whether the board has an environmental or social committee, given many earlier environmental efforts were originally captured by broad 'corporate responsibility efforts.'

Because board committee naming conventions may be "cheap talk," we replace the governance measure with an indicator for whether firms have at least one member with environmental expertise on the board. Table 6 – Panel B presents results showing that firms in environmentally impactful industries are more likely to have board members with environmental expertise ($\beta = 0.90$, p-value < 0.01). The odds of signaling are 2.46 times higher for firms in environmentally impactful industries. Consistent with the results in Panel A of Table 6, firms in socially impactful industries are less likely to have board members with environmental expertise ($\beta = -0.64$, p-value < 0.01), with the odds of signaling being 47.27% lower.

[16] These results are robust to using an indicator for an above-median number of connections with environmental expertise, the number of board members with expertise, the number of connections with expertise, and an indicator for whether the number of board members or connections with expertise increased from the previous year.

Because members of a board may rely on the expertise of their connections if they lack the requisite expertise themselves, we replace the expertise measure with an indicator for whether the board has an above-median number of connections with environmental expertise. These results are presented in Table 6 - Panel C. Firms in environmental impactful industries are more likely to have a large cohort of connections with environmental expertise ($\beta = 0.30$, p-value < 0.01) and the odds of signaling are 1.35 times higher for firms in environmentally impactful industries. Consistent with the evidence in Table 6 Panels A and B, firms in socially impactful industries are less likely to have an above-median number of connections with environmental expertise ($\beta = -0.24$, p-value < 0.05). The odds of signaling are 21.34% lower for firms in socially impactful industries. While we see a positive association with *GImpactInd*, this is likely due to boards with strong governance practices being likely to have more-connected directors in general.

Untabulated results of estimating equation (4) show no significant relationship between *TP_Rev* and the interaction term of *AbnormalRRI* measure with any of the *EOversightSignal* indicators. This suggests that despite firm efforts to send positive signals through environmental committees or expertise, this does not appear to influence analysts' expectations of the value-relevance of reputation risk. Because analysts may ignore environmental oversight signals that remain unchanged over time, we test whether they respond to increases or decreases in the number of members or connections with expertise, but the interaction term remains insignificant. We also considered that the signal might by associated with larger positive revisions, while reputation risk may be associated with larger negative revisions, thereby muting any effects on revision magnitude. Our results remain insignificant when using the directed, rather than absolute, revision. Thus, we find no evidence to suggest that analysts are receptive to firms' attempts to manage reputation risk through governance. This result is particularly interesting, as firms seem to consider the costs and benefits of environmental oversight signals without any discernible benefits. We encourage future research to explore firms' motives and challenges behind engaging in signaling activities.

4.2 Supplemental Analysis – Firms in "Brown" vs. "Green" Industries

Given investor, regulatory, and social media focus, environmental impact is the most reputationally salient of the three ESG pillars (Capital Group 2022; Pérez et al. 2022); thus, we perform additional analysis on industries with high environmental impact. We anticipate that the expected effect of reputation is likely determined by whether risks or opportunities are more relevant for the industry. For firms in industries with greater environmental impact, we parse the impact according to environmental risks and opportunities by examining firms in "brown" and "green" industries respectively.

In supplemental analysis, we replace the indicator for environmentally impactful industries (*EImpactInd)* with indicators for industries with high environmental risks (*BrownInd)* and opportunities (*GreenInd)*. We consider an industry to be "brown" if MSCI's weighting of 9 environmental risks is in the top quartile of all industries evaluated by MSCI.[17] Similarly, we consider an industry to be "green" if the MSCI's weighting of 3 environmental opportunities is in the top quartile of all industries evaluated. Notably, a firm in a "green" industry may suffer reputation risk if it fails to capitalize on available opportunities.

We present the results of analysis in Table 7. Panel A shows the effect of reputation risk on analyst valuation expectations for firms in "brown" and "green" industries. Consistent with

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[17] We use items 1 to 9 from Appendix 1 because they are 'inside out' negative environmental externalities that are likely to make the industry suffer reputational risk. We exclude item 10 because it is an 'outside in' source of risk against which firms should try to protect themselves. Although it is a source of operational risk, it is not a direct source of reputational risk.

the confirmation bias theory, which suggests that salience will affect analysts' inclusion of reputation risk in environmentally impactful industries, our results hold for firms in "brown" industries (*BrownInd*) ($\beta = 14.17$, p-value < 0.01) where environmental risks might most directly correspond to reputation risk. While there is a positive and statistically significant association between reputation risk and target price revision broadly, there is no statistically significant effect for firms in "green" industries. Thus, while reputation risk is associated with target price revision magnitude, it does not differ for firms that have environmental opportunities. This finding is intuitive, given it is much harder to track forgone opportunities, than it is to track threats that come to fruition.

Panel B shows the impact of reputation risk on likelihood to signal based on whether the firm operates in a "brown" or "green" industry. The results in Panel B of Table 7 are consistent with the political hypothesis. Firms in "brown" industries are more likely to signal environmental oversight by committee name, expertise, and connections ($\beta = 1.86$, p-value < 0.01, $\beta = 0.82$, p-value < 0.01, $\beta = 0.19$, p-value < 0.05), but firms in "green" industries are neither more nor less likely to signal. The odds of a "brown" firm signaling through committee name, expertise, or connections are 6.42, 2.27, and 1.21 times higher, respectively.

4.3 Limitations

We recognize limitations to our available sample and construct. First, our sample ends in 2020, which precedes substantial developments in the ESG space. We acknowledge that ESG factors garner even more attention in the period after our sample, but we expect this to bias against our results, which are robust to beginning our sample period with the founding of SASB in 2011. Second, our board-related tests require us to manually identify environmental board committees. We attempted to minimize the possibility of human error by utilizing multiple, independent coders; however, we recognize that our manual coding process could result in the inclusion or exclusion of misinterpreted committee names. Furthermore, because governance decisions are within the firms' control, the governance signaling tests may be subject to endogeneity concerns.

4.4 Robustness Analysis

Causality

To address questions of causality, we examine the effect of *AbnormalRRI* on analysts' target price revisions in the presence of two exogenous shocks: the Paris Agreement and Larry Fink's 2015 ESG shareholder letter. We exploit these two events, which altered attention to ESG broadly and brought reputation risk to the foreground as an ESG issue. We argue that a difference-in-difference design around an exogenous increase in attention to ESG provides a setting to address potential endogeneity concerns. Specifically, we address the concern that analysts' revisions may contribute to the computation of abnormal RRI or firms' reputation environment, which may lead to reverse causality. In Table 8, we present the results of a specification that attempts to offer causal evidence.

We first rely on Larry Fink's 2015 shareholder letter, published on April 10, 2016, in which he first uses the term "ESG" and describes Blackrock's sustainable investing platform. He identifies this as a defining moment that brought ESG investing into common practice, thereby changing the relevance of reputation risk to firm valuation. We define a balanced sample period around this date with our pre-treatment period starting in 2011. We define our treatment group, *Fink*, using an indicator equal to 1 in the period after the shareholder letter for firms in which Blackrock held at least 4.5% of shares. *AbnormalRRI* alone is not statistically significant, yet the interaction between *AbnormalRRI* and *Fink* is positive and significant ($\beta = 4.57$, p-value < 0.01).

Reputation risk is positively associated with analyst target price revision magnitude in the sample period after the first Larry Fink ESG shareholder letter for relevant firms.

We repeat the analysis using the Paris Climate Agreement from December 15, 2015, as our treatment. The Paris Climate Agreement is a global compact targeting climate change and emission reductions specifically, and its wide media coverage in 2015 brought climate impacts into the realm of firm reputation. While the scope of the Paris Agreement is narrower than that of Larry Fink's shareholder letter, its audience was broader. While the United States joined the Paris Climate Agreement, the relevant frameworks and regulations originated in Europe. Thus, we define our treatment group, *Paris*, using an indicator equal to 1 in the period after the Paris Climate Agreement for firms with operations in Europe. While *AbnormalRRI* alone is not statistically significant, we find the interaction term between *AbnormalRRI* and *Paris* is positive and significant ($\beta = 39.31$, p-value < 0.01). This suggests that the effect of reputation risk on analyst target price revisions is significantly larger in the post-Paris agreement period for firms that were most directly relevant.

Change in Abnormal RRI

We conduct an additional analysis to mitigate the concern that a large change in reputation risk might be affecting analyst target price revisions. In Table 8, we control for the absolute value of the percent change in *AbnormalRRI, ChangeRRI,* between the analysts' current and last target price for the firm. While *ChangeRRI* captures how reputation risk has changed since the analyst's original target price forecast, it does not capture the severity of the reputation risk. Moreover, because abnormal reputation risk is composed of both firm-specific and sector-average reputation risk, a change may be the result of either factor or both. We therefore argue that including both *ChangeRRI* and *AbnormalRRI* is necessary to understand the effect of changing reputation risk on analysts' target price revisions.

Our results on the relationship between abnormal reputation risk and target price revision hold when we add this control. Additionally, we find that *ChangeRRI* is not significant (Column (1) of Table 8). Additionally, we partition our sample by whether abnormal reputation is improving (i.e. *AbnormalRRI* is decreasing), deteriorating (i.e. *AbnormalRRI* is increasing), or constant. We repeat our analysis on these three subsamples while controlling for *ChangeRRI*. In Column (2) of Table 8, we find that in the subsample where reputation is getting worse, our main results hold for *AbnormalRRI* ($\beta = 5.20$, p-value <0.05), and the coefficient on *ChangeRRI* is positive and significant ($\beta = 1.31$, p-value <0.05). Together, these coefficients suggest that when abnormal reputation is deteriorating, a worse reputation and a larger deterioration both add to analyst revision size. Column (3) shows the association between reputation risk and revision magnitude when reputation risk is constant, i.e. when *ChangeRRI* is equal to zero, and shows that an unchanged abnormal reputation risk has no effect on target price revision magnitude, consistent with a causality argument. For the subsample where reputation is improving, in Column (4), *ChangeRRI* remains positive and significant ($\beta = 1.51$, p-value < 0.05), while the level of *AbnormalRRI* is no longer significant.

Current RRI

Our main analysis uses *AbnormalRRI*, which is our novel measure of the firms' reputation risk relative to the sector average. We expect the relative reputation risk results to be amplified given the importance of the sector context. We additionally test that our results hold when we replace *AbnormalRRI* with *CurrentRRI*, RepRisk's firm-specific reputation risk index score, in our models. We find that our results, untabulated, remain robust when we use individual firm reputation risk exposure in the regression, i.e. not abnormal reputation risk, whether we control for sector average reputation risk or not. Additionally, in untabulated analysis, we restrict our sample to firms that experience no change in firm-specific reputation risk (i.e. independent of sector average) between the analyst's current forecasting date and their prior target price forecast. We find that there is no significant relationship between *TP_Rev* and *AbnormalRRI* if *CurrentRRI* does not change.

Environmental Impact

Since environmental issues currently receive more attention (Capital Group 2022; Pérez et al. 2022) and reputation risk is associated with larger target price revisions in environmentally impactful industries, we repeat our analysis using the sub-sample of companies for which environmental reputation risk is most prominent. According to RepRisk, the RRI measure does not have components and cannot be disaggregated according to "E," "S," and "G" pillars. To isolate firms with more environmental reputation risk, we therefore identify those for which more RepRisk risk incidents have been classified as "E" than classified as either "S" or "G," allowing for incidents to be classified as related to more than one pillar. We do this with important caveats: (1) reputation is an issue of perception that may not have a directly associated "reality," i.e. incident (Eccles, Newquist, and Schatz 2007) and (2) the three pillars of ESG are inherently interconnected, and many incidents are recorded as relating to more than one pillar.

We find that the relationship between reputation risk and target price revisions is stronger if we condition on environmentally prominent reputation risk. In this untabulated analysis, we interact *AbnormalRRI* with *BrownInd* using the environmental reputation risk sample and find a positive and significant coefficient. We also interact *AbnormalRRI* with the *IndImpact* indicators to find results consistent with the main analysis.

5. Conclusion

Given increased regulation and demand for ESG information, ESG media coverage increasingly influences public perception of the firm. This exacerbates the risk that a negative reputation will affect the company's future cash flows and the discount rate, and potentially damage its financial position. We argue that reputation risk is relevant for analysts' valuations. We further argue that analyst attention to reputation risk should be context-dependent: considering both the concurrent reputation of sector peers and the ESG impact inherent to the firm's industry.

We provide evidence that analysts' target price revision magnitudes are associated with abnormal reputation risk, particularly downward target price revisions. We find a positive association between reputation risk and the magnitude of target price revisions only for firms in environmentally impactful industries, where reputation risk is most salient, and especially in "brown" industries. We build on the political hypothesis and find that firms operating in these industries are more likely to attempt to manage reputation risk by signaling environmental oversight. Specifically, these firms are more likely to establish environmental board committees, include members with environmental expertise, or foster connections with environmental expertise. For these firms, we find that their efforts are unsuccessful in mitigating analyst reactions to reputation risk, and the price of perception remains high.

Our study makes several important contributions. We contribute to the growing literature on how market participants process reputation risk, providing evidence that analysts view reputation risk to be value-relevant and extend our contribution by looking at abnormal reputation risk. We contribute to the literature by emphasizing the importance of industry context when analyzing reputation risk. To our knowledge, the analyst literature has yet to consider the factors determining how analysts incorporate ESG information. We use industry impact, captured using a novel measure constructed from the MSCI ESG Industry Materiality Map, to demonstrate that analysts incorporate reputation risk only when it is salient to the firm's industry. Last, our signaling test is among the first to propose measurements and test hypotheses related to the SEC climate-related disclosures specific to board oversight.

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Table 1
Sample Selection

All I/B/E/S target prices for US firms issued between January 1, 2007 and December 31, 2020	820,063
Less: Target prices without 12-month forecast horizon	16,468
Less: Observations without target price within previous 365 days	86,649
Less: Observations without RepRisk RRI data	32,393
Less: Observations without control variables	87,113
Final Sample	597,440

Table 2
Sample Distribution

Panel A: By year

Year	Number of Firms	Number of Industries	Number of Analysts	Number of Brokers
2007	1,390	164	1,727	189
2008	1,482	167	1,974	202
2009	1,465	167	2,018	223
2010	1,528	170	2,247	231
2011	1,563	172	2,347	220
2012	1,576	175	2,295	204
2013	1,615	172	2,245	203
2014	1,654	171	2,268	198
2015	1,700	172	2,216	192
2016	1,670	167	2,165	190
2017	1,649	165	2,131	200
2018	1,652	165	2,081	200
2019	1,641	162	2,095	192
2020	1,621	162	2,049	194
All years	2,670	181	5,927	490

Table 2
Sample Distribution

Panel B: By Sector						
	Firm-Year Level			Forecast Level		
Sector	Frequency	% of Sample	*CurrentRRI*	Frequency	% of Sample	*CurrentRRI*
Energy	1,743	8%	10.71	70,249	12%	14.99
Materials	1,429	7%	10.21	30,668	5%	14.41
Industrials	3,386	16%	7.52	74,778	13%	11.93
Consumer Discretionary	3,550	17%	9.40	98,348	17%	14.57
Consumer Staples	1,181	5%	15.74	30,602	5%	22.56
Health Care	2,706	12%	6.46	64,556	11%	10.28
Financials	3,030	14%	8.41	91,853	16%	13.67
Information Technology	2,416	11%	6.28	70,373	12%	10.35
Communication Services	651	3%	11.11	20,538	4%	18.42
Utilities	789	4%	15.06	19,432	3%	19.89
Real Estate	595	3%	4.63	9,016	2%	5.92
All industries	21,476	100%	8.88	580,411	100%	13.74

Notes: Panel A provides the number of firms, industries, analysts and brokerage houses in the sample by year. The data is sourced from I/B/E/S for the sample period January 2007 through December 2020. Panel B provides the number of firm-years and forecasts by sector and their corresponding average firm reputation risk. Panel B does not include the 730 (17,029) firm-years (forecasts) that do not have a recorded GIC code. At the firm-year level, *CurrentRRI* is averaged within each firm-year. The average *CurrentRRI* over the sample period is then averaged at the 2-digit GIC level.

Table 3
Descriptive Statistics

Variable	Num	Min	Mean	Median	Max	Std Dev
TP_Rev	597,440	0.00	0.46	0.44	1.05	0.17
Upward TP_Rev	356,453	0.02	0.44	0.43	1.05	0.13
Downward TP_Rev	234,035	0.02	0.51	0.48	0.11	0.19
AbnormalRRI	597,440	-1	-0.44	-0.47	2.95	0.57
CurrentRRI	597,440	0	13.70	13	78	14.63
CountrySectorAverage	597,440	3	23.77	22	71	5.68
EImpactInd	569,077	0	0.28	0	1	0.45
SImpactInd	571,100	0	0.39	0	1	0.49
GImpactInd	580,411	0	0.17	0	1	0.37
ECommitteeName	8,402	0	0.08	0	1	0.28
EExperience	19,593	0	0.10	0	1	0.29
EConnections	17,249	0	0.52	1	1	0.50
BrownInd	575,125	0	0.27	0	1	0.45
GreenInd	580,411	0	0.19	0	1	0.40
Fink	477,909	0	0.44	0	1	0.50
Paris	477.909	0	0.10	0	1	0.30
ChangeRRI	580,220	0	0.61	0.08	61.90	1.42
RevisionInterval	597,440	0	73	84.93	364	68.92
Following	597,440	3	20.15	19	48	10.14
Companies	597,440	2	19.74	19	49	8.38
BrokerSize	597,440	2	76.48	61	268	64.6
FirmExperience	597,440	0	4.81	3	22	4.62
Industries	597,440	1	6.06	5	18	3.95
StockMomentum	597,440	-14.58	0.48	0.09	22.42	3.95
ExcessReturn	597,440	-0.13	-0.001	-0.001	0.12	0.03
EPSRevision	597,440	-2.2	0.01	0.01	2.05	0.42
ConsensusChange	597,440	-1.08	-0.02	0.01	0.36	0.19
CEOTenure	19,593	0	4.64	3	60	4.98
Big 3 Inst Ownership	19,593	0	7.40	9.63	19.26	3.73
Assets	19,593	2.62	7.96	7.90	12.46	1.80
Firm Age	19,593	-3.95	2.72	2.91	4.55	1.11
Num Analysts	19,593	1	12.92	11	66	9.07
Board Size	19,593	1	10.43	10	37	2.96
Board Independence	19,593	0	79.59	83.33	95.83	12.39
Business Segments	19,593	0	6.86	5	33	5.45
Geographical Segments	19,593	0	7.36	6	152	7.81
CEO Age	19,593	42	48.62	49	55	3.97
CEO Gender	19,593	0	0.05	0	1	0.22

Notes: The table depicts the distributions of the variables used in our analyses. All continuous variables are winsorized at the 1st and 99th percentile except variables sourced from RepRisk. Appendix 4 provides variable definitions.

Table 4
Association between Reputation Risk and Price Target Revision Magnitude

	TP_Rev	*Upward TP_Rev*	*Downward TP_Rev*
AbnormalRRI	4.30***	1.56	4.87***
	(1.09)	(0.96)	(1.46)
RevisionInterval	0.22***	0.23***	0.23***
	(0.04)	(0.01)	(0.02)
Following	-0.26	-0.80*	-0.34
	(0.37)	(0.37)	(0.48)
Companies	-0.13	-0.10	-0.01
	(0.13)	(0.10)	(0.17)
BrokerSize	-0.06**	-0.02	-0.02
	(0.03)	(0.02)	(0.03)
FirmExperience	0.16	0.26***	0.33**
	(0.11)	(0.09)	(0.13)
Industries	0.81***	0.70**	0.80**
	(0.25)	(0.24)	(0.30)
StockMomentum	-0.83	6.06***	-11.48***
	(0.84)	(0.20)	(1.40)
ExcessReturn	197.51***	-231.19***	327.45***
	(41.46)	(17.07)	(45.45)
EPSRevision	-10.95***	1.43	-20.00***
	(2.98)	(1.10)	(4.64)
ConsensusChange	-178.84***	13.40	-215.14***
	(13.31)	(18.95)	(4.27)
Observations	597,374	356,302	233,956
R-squared	0.33	0.36	0.47

Notes: This table reflects the results of OLS regressions of target price forecast revision magnitudes on abnormal reputation risk, such that a higher RRI is associated with more risk. Revision magnitudes (TP_Rev) are calculated as the cube root of the absolute value of the change in analyst target price scaled by the market price on the date of the current target price. In columns (2) and (3) we bifurcate our sample into upward and downward revisions respectively. The variable of interest, *AbnormalRRI,* is calculated as the difference between the firm reputation risk index (RRI) score and the country-sector benchmark, scaled by the benchmark (both sourced from RepRisk). All regressions include year, broker, and firm fixed effects and cluster standard errors by year and analysts. Year, broker and firm-specific intercepts are not tabulated for brevity. *, **, *** signify statistical significance at p-values less than 0.1-, 0.05-, and 0.01-levels, respectively. Appendix 4 provides variable definitions.

Table 5
Association between Reputation Risk, Industry Context, and Price Target Revision Magnitude

	TP_Rev		
AbnormalRRI	1.16	6.42***	4.82***
	(1.56)	(1.70)	(1.24)
AbnormalRRI x EImpactInd	9.12**		
	(3.69)		
AbnormalRRI x SImpactInd		-7.46**	
		(2.91)	
AbnormalRRI x GImpactInd			-7.69**
			(3.15)
RevisionInterval	0.22***	0.22***	0.22***
	(0.04)	(0.04)	(0.04)
Following	-0.15	-0.15	-0.15
	(0.37)	(0.36)	(0.36)
Companies	-0.11	-0.12	-0.12
	(0.13)	(0.13)	(0.12)
BrokerSize	-0.07**	-0.07**	-0.07**
	(0.03)	(0.03)	(0.03)
FirmExperience	0.16	0.16	0.16
	(0.11)	(0.11)	(0.11)
Industries	0.80***	0.81***	0.81***
	(0.25)	(0.25)	(0.24)
StockMomentum	-0.75	-0.76	-0.78
	(0.83)	(0.84)	(0.84)
ExcessReturn	195.54***	195.65***	195.68***
	(42.78)	(42.52)	(42.31)
EPSRevision	-11.41***	-11.40***	-11.27***
	(3.20)	(3.18)	(3.12)
ConsensusChange	-179.26***	-179.39***	-177.71***
	(13.75)	(13.75)	(13.85)
Observations	569,017	571,040	580,346
R-squared	0.33	0.33	0.33

Notes: This table reflects the results of OLS regressions of target price forecast revision magnitudes on abnormal reputation interacted with indicators for high industry impact, such that a higher RRI is associated with more risk. Revision magnitudes (TP_rev) are calculated as the cube root of the absolute value of the change in analyst target price scaled by the market price on the date of the current target price. *AbnormalRRI* is calculated as the difference between the firm reputation risk index (RRI) score and the country-sector benchmark, scaled by the benchmark (both sourced from RepRisk). "E," "S," and "G" industry impact indicators equal 1 if the industry falls within the top-quartile of risks and opportunities associated with the given ESG pillar according to the weightings provided by the MSCI Materiality Map. All regressions include year, broker, and firm fixed effects and cluster standard errors by year and analysts. Year, broker and firm-specific intercepts are not tabulated for brevity. *, **, *** signify statistical significance at p-values less than 0.1-, 0.05-, and 0.01-levels, respectively. Appendix 4 provides variable definitions.

Table 6
Likelihood of Signaling Environmental Oversight

Panel A: Board "E" Committee			
		ECommitteeName	
EImpactInd	1.61***		
	(0.15)		
SImpactInd		-1.33***	
		(0.20)	
GImpactInd			-0.56***
			(0.20)
Big3Own	0.02	0.02	0.02
	(0.03)	(0.02)	(0.02)
Assets	0.28***	0.32***	0.23***
	(0.08)	(0.08)	(0.07)
FirmAge	0.14	0.15	0.26**
	(0.09)	(0.10)	(0.11)
Following	0.00	-0.00	-0.00
	(0.01)	(0.01)	(0.01)
BoardSize	0.01	0.00	-0.00
	(0.02)	(0.02)	(0.03)
Independence	0.02***	0.02**	0.02**
	(0.01)	(0.01)	(0.01)
BusinessSegments	0.00	0.00	0.01
	(0.01)	(0.01)	(0.01)
GeographicalSegments	0.03***	0.02**	0.03***
	(0.01)	(0.01)	(0.01)
CEOTenure	-0.04*	-0.05*	-0.06**
	(0.03)	(0.03)	(0.03)
CEOAge	0.26***	0.24***	0.24***
	(0.04)	(0.04)	(0.04)
CEOGender	0.18	0.26	0.26
	(0.27)	(0.26)	(0.27)
Observations	8,266	8,340	8,402
Pseudo R-squared	0.17	0.13	0.10

Table 6
Likelihood of Signaling Environmental Oversight

Panel B: Board "E" Expertise

	EExpertise		
EImpactInd	0.90***		
	(0.14)		
SImpactInd		-0.64***	
		(0.16)	
GImpactInd			-0.01
			(0.16)
Big3Own	-0.01	-0.01	-0.01
	(0.02)	(0.02)	(0.02)
Assets	0.11**	0.13**	0.11**
	(0.05)	(0.05)	(0.05)
FirmAge	-0.06	-0.04	0.01
	(0.07)	(0.07)	(0.07)
Following	0.00	-0.00	-0.00
	(0.01)	(0.01)	(0.01)
BoardSize	0.10***	0.10***	0.09***
	(0.02)	(0.02)	(0.02)
Independence	0.01**	0.01**	0.01**
	(0.01)	(0.01)	(0.01)
BusinessSegments	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)
GeographicalSegments	0.02**	0.01*	0.02***
	(0.01)	(0.01)	(0.01)
CEOTenure	0.00	-0.00	-0.01
	(0.01)	(0.01)	(0.01)
CEOAge	0.07***	0.07***	0.07***
	(0.01)	(0.01)	(0.01)
CEOGender	0.09	0.17	0.12
	(0.24)	(0.23)	(0.23)
Observations	19,082	19,205	19,593
Pseudo R-squared	0.07	0.06	0.05

Table 6

Likelihood of Signaling Environmental Oversight

Panel C: Board “E” Connections			
		EConnections	
EImpactInd	0.30***		
	(0.09)		
SImpactInd		-0.24**	
		(0.10)	
GImpactInd			0.24**
			(0.09)
Big3Own	-0.02	-0.02	-0.03
	(0.02)	(0.02)	(0.02)
Assets	0.27***	0.28***	0.28***
	(0.04)	(0.04)	(0.04)
FirmAge	-0.05	-0.05	-0.03
	(0.04)	(0.04)	(0.04)
Following	0.03***	0.03***	0.03***
	(0.01)	(0.01)	(0.01)
BoardSize	0.20***	0.20***	0.19***
	(0.02)	(0.02)	(0.02)
Independence	0.03***	0.03***	0.03***
	(0.00)	(0.00)	(0.00)
BusinessSegments	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)
GeographicalSegments	0.03***	0.03***	0.03***
	(0.01)	(0.01)	(0.01)
CEOTenure	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)
CEOAge	-0.02**	-0.02**	-0.02**
	(0.01)	(0.01)	(0.01)
CEOGender	-0.07**	-0.07**	-0.07**
	(0.03)	(0.03)	(0.03)
Observations	16,815	16,931	17,249
Pseudo R-squared	0.21	0.20	0.20

Notes: This table presents the results of logistic regressions that estimate the likelihood of signaling commitment to environmental oversight based on high industry impact indicators. The signal of commitment to environmental oversight is captured by whether the board has (1) a committee with an environmental buzzword in Panel A, (2) any members with environmental expertise in Panel B, and (3) an above yearly median number of connections to individuals with environmental expertise in Panel C. “E,” “S,” and “G” industry impact indicators equal 1 if the industry falls within the top-quartile of risks and opportunities associated with the given ESG pillar according to the weightings provided by the MSCI Materiality Map. We cluster standard errors by year and analysts in all regressions. *, **, *** signify statistical significance at p-values less than 0.1-, 0.05-, and 0.01-levels, respectively. Appendix 4 provides variable definitions.

Table 7
Environmental Risks and Opportunities

Panel A: Association between Reputation Risk, Industry Context, and Price Target Revision Magnitude		
	TP_Rev	
AbnormalRRI	-0.22	4.13***
	(1.49)	(1.32)
AbnormalRRI x BrownInd	14.17***	
	(3.58)	
AbnormalRRI x GreenInd		-3.74
		(3.04)
RevisionInterval	0.22***	0.22***
	(0.04)	(0.04)
Following	-0.17	-0.14
	(0.37)	(0.36)
Companies	-0.12	-0.12
	(0.13)	(0.12)
BrokerSize	-0.07**	-0.07**
	(0.03)	(0.03)
FirmExperience	0.16	0.16
	(0.11)	(0.11)
Industries	0.79***	0.80***
	(0.24)	(0.24)
StockMomentum	-0.76	-0.78
	(0.83)	(0.83)
ExcessReturn	195.40***	195.93***
	(42.28)	(42.33)
EPSRevision	-11.21***	-11.24***
	(3.14)	(3.13)
ConsensusChange	-177.80***	-177.80***
	(13.71)	(13.79)
Observations	575,062	580,348
R-squared	0.33	0.33

Table 7
Environmental Risks and Opportunities

Panel B: Likelihood of Signaling Environmental Oversight						
	ECommitteeName		*EExperience*		*EConnections*	
BrownInd	1.86***		0.82***		0.19**	
	(0.16)		(0.14)		(0.09)	
GreenInd		-0.28		0.23		0.19*

		(0.20)		(0.17)		(0.10)
Big3Own	-0.05*	-0.06**	-0.00	-0.01	-0.02**	-0.02**
	(0.03)	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)
Assets	0.27***	0.24***	0.07***	0.07***	-0.07**	-0.07**
	(0.04)	(0.04)	(0.01)	(0.01)	(0.03)	(0.03)
FirmAge	0.17	0.28	0.07	0.12	0.63***	0.62***
	(0.27)	(0.27)	(0.24)	(0.23)	(0.17)	(0.17)
Following	-0.00	-0.00	0.10***	0.09***	0.19***	0.19***
	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
BoardSize	0.02***	0.02**	0.01**	0.01**	0.03***	0.03***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)
Independence	0.29***	0.25***	0.10**	0.11**	0.27***	0.28***
	(0.08)	(0.08)	(0.05)	(0.05)	(0.04)	(0.04)
BusinessSegments	0.11	0.26**	-0.03	0.00	-0.03	-0.03
	(0.09)	(0.11)	(0.07)	(0.07)	(0.04)	(0.04)
GeographicalSegments	-0.00	-0.00	0.00	-0.00	0.03***	0.03***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
CEOTenure	0.01	0.01	0.01	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
CEOAge	0.03***	0.03***	0.02***	0.02**	0.03***	0.03***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
CEOGender	0.03	0.02	-0.01	-0.01	-0.03	-0.03
	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
Observations	8,326	8,402	19,422	19,593	17,094	17,249
Pseudo R-squared	0.19	0.10	0.07	0.05	0.20	0.20

Notes: Panel A reflects the results of OLS regressions of target price forecast revision magnitudes on abnormal reputation risk interacted with indicators for “brown” and “green” industries, such that a higher RRI is associated with more risk. Revision magnitudes are calculated as the cube root of the absolute value of the change in analyst target price scaled by the market price on the date of the current target price. *AbnormalRRI* is calculated as the difference between the firm reputation risk index (RRI) score and the country-sector benchmark, scaled by the benchmark (both sourced from RepRisk). *BrownInd* (*GreenInd*) equals 1 if the industry receives top-quartile weighting in MSCI Materiality Map for environmental risks (opportunities). Panel B reflects the results of logistic regressions of whether the board signals environmental oversight. The signal of commitment to environmental oversight is captured by whether the board has a committee with an environmental buzzword in column (1), any members with environmental expertise in column (2), and an above yearly median number of connections to individuals with environmental expertise in column (3). All regressions in Panel A include year, broker, and firm fixed effects and cluster standard errors by year and analysts. All regression in Panel B cluster standard errors by year and analysts. Year, broker and firm-specific intercepts in Panel A are not tabulated for brevity. *, **, *** signify statistical significance at p-values less than 0.1-, 0.05-, and 0.01-levels, respectively. Appendix 4 provides variable definitions.

Table 8
Associations between Reputation Risk and Target Price Revision Magnitude Given Exogenous Shocks to ESG Salience

	TP_Rev	
	(1)	(2)
AbnormalRRI	0.98	1.69
	(1.86)	(1.76)
Fink	-42.66***	
	(2.39)	
AbnormalRRI x Fink	4.57***	
	(1.30)	
Paris		39.31***
		(3.29)
AbnormalRRI x Paris		2.87**
		(1.46)
RevisionInterval	0.20***	0.20***
	(0.04)	(0.04)
Following	-0.58	-0.57
	(0.54)	(0.54)
Companies	-0.13	-0.13
	(0.14)	(0.14)
BrokerSize	-0.07*	-0.06*
	(0.03)	(0.03)
FirmExperience	0.24**	0.26**
	(0.10)	(0.10)
Industries	0.70**	0.70**
	(0.27)	(0.27)
StockMomentum	-0.46	-0.55
	(0.97)	(0.95)
ExcessReturn	182.43***	183.75***
	(40.10)	(40.58)
EPSRevision	-10.68**	-10.62**
	(3.77)	(3.77)
ConsensusChange	-164.78***	-167.59***
	(7.94)	(7.75)
Observations	477,845	477,845
R-squared	0.32	0.32

Notes: This table reflects the results of Difference-in-Difference regressions of target price forecast revision magnitudes on abnormal reputation risk where the treatment is shocks to the salience of ESG. Revision magnitudes are calculated as the cube root of the absolute value of the change in analyst target price scaled by the market price on the date of the current target price. *AbnormalRRI* is calculated as the difference between the firm reputation risk index (RRI) score and the country-sector benchmark, scaled by the benchmark (both from RepRisk). In Column (1), the treatment is Larry Fink's 2016 shareholder letter, and the control group is the population of firms with no more than 4.5% of shares held by Blackrock. In Column (2), the treatment is the 2015 Paris Climate Agreement, and the treatment is the population of firms without European business segments. All regressions include year, broker, and firm fixed effects and cluster standard errors by year and analysts. Year, broker and firm-specific intercepts are not tabulated for brevity *, **, *** signify statistical significance at p-values less than 0.1-, 0.05-, and 0.01-levels, respectively. Appendix 4 provides variable definitions.

Table 9
Association between Reputation Risk and Price Target Revision Magnitude Given Changes in Reputation Risk

	TP_Rev			
	(1)	(2)	(3)	(4)
AbnormalRRI	2.65**	5.20**	-1.77	1.59
	(1.16)	(2.12)	(6.57)	(2.27)
ChangeRRI	1.44***	1.31**		1.51**
	(0.44)	(0.51)		(0.52)
RevisionInterval	0.21***	0.22***	0.23***	0.21***
	(0.04)	(0.05)	(0.03)	(0.04)
Following	-0.25	0.13	-0.80**	-0.39
	(0.37)	(0.47)	(0.28)	(0.44)
Companies	-0.12	-0.16	-0.09	-0.10
	(0.13)	(0.17)	(0.10)	(0.16)
BrokerSize	-0.07**	-0.05	-0.05	-0.09**
	(0.03)	(0.05)	(0.03)	(0.03)
FirmExperience	0.16	0.17	0.13	0.19*
	(0.11)	(0.14)	(0.17)	(0.10)
Industries	0.80***	0.68**	0.73**	0.67*
	(0.25)	(0.28)	(0.28)	(0.35)
StockMomentum	-0.81	-0.51	-4.93*	-0.70
	(0.83)	(0.58)	(2.48)	(0.90)
ExcessReturn	199.36***	180.57***	198.36***	175.61***
	(41.52)	(50.26)	(39.34)	(46.44)
EPSRevision	-10.73***	-13.69***	-8.46***	-10.88**
	(2.86)	(3.64)	(2.01)	(3.88)
ConsensusChange	-178.84***	-183.88***	-164.56***	-179.39***
	(13.53)	(12.34)	(16.10)	(10.47)
Observations	580,155	122,115	226,899	230,836
R-squared	0.33	0.35	0.35	0.34

Notes: This table reflects the results of OLS regressions of target price forecast revision magnitudes on abnormal reputation risk. Revision magnitudes (TP_Rev) are calculated as the cube root of the absolute value of the change in analyst target price scaled by the market price on the date of the current target price. *AbnormalRRI* is calculated as the difference between the firm reputation risk index (RRI) score and the country-sector benchmark, scaled by the benchmark (both from RepRisk). *ChangeRRI* is calculated as the absolute percent change in *AbnormalRRI* between the analyst's current and previous target price forecast for the firm. Column (1) shows results for the entire sample and Columns (2)-(4) show the subsamples in which reputation risk has worsened, not changed, and improved, respectively. All regressions include year, broker, and firm fixed effects and cluster standard errors by year and analysts. Year, broker and firm-specific intercepts in Panel A are not tabulated for brevity *, **, *** signify statistical significance at p-values less than 0.1-, 0.05-, and 0.01-levels, respectively. Appendix 4 provides variable definitions.

Appendix 1
MSCI Materiality Map Issues

ESG component	MSCI Issues
Environmental	(1) Carbon Emissions, (2) Biodiversity & Land, (3) Toxic Emissions & Waste, (4) Water Stress, (5) Packaging Material & Waste, (6) Raw Material Sourcing, (7) Electronic Waste, (8) Product Carbon Footprint, and (9) Financing Environmental Impact, (10) Climate Change Vulnerability, (11) Opportunities in Clean Tech, (12) Opportunities in Clean Building, and (13) Opportunities in Renewable Energy.
Social	(1) Labor Management, (2) Health & Safety, (3) Human Capital Development, (4) Supply Chain Labor Standards, (5) Product Safety & Quality, (6) Chemical Safety, (7) Consumer Financial Protection, (8) Privacy & Data Security, (9) Responsible Investment, (10) Community Relations, (11) Controversial Sourcing, (12) Access to Finance, (13) Access to Health Care, and (14) Opportunities in Nutrition and Health
Governance	Composite of: Governance, Ownership and Control, Board Pay, Accounting, Business Ethics, and Tax Transparency

Appendix 2
RepRisk ESG Issues in RRI

Environment	Social		Governance
Environmental footprint: • climate change, GHG emissions, and global pollution • local pollution • impacts on landscapes, ecosystems, and biodiversity • overuse and wasting of resources • waste issues	Community relations • human rights abuses and corporate complicity • impacts on communities • local participation issues • social discrimination	Employee relations • forced labor • child labor • freedom of association and collective bargaining • discrimination in employment • occupational health and safety issues • poor employment conditions	Corporate Governance • corruption, bribery, extortion, money laundering • executive compensation issues • misleading communication • fraud • tax evasion • tax optimization • anti-competitive practices

<table>
<tr><td>• animal mistreatment</td><td></td><td></td><td></td></tr>
<tr><td colspan="4">Cross-cutting issues
• controversial products and services
• products (health and environmental issues)
• supply chain issues
• violations of national legislation
• violations of international standards</td></tr>
</table>

Appendix 3 - A

Wells Fargo 2017 RRI

Wells Fargo has the highest number of yearly incidents in 2017. In March, Wells Fargo had 17 incidents, and the RRI increased by 4 points. For comparison, Wells Fargo had 4 incidents in February with no RRI change and 5 incidents of greater severity and reach in April when RRI improved by 1 point. Incidents do not directly translate into reputation risk (captured by RRI).

Data Date	Firm Reputation Risk	Trend	Abnormal Reputation Risk
Feb 28, 2017	59	-2	90.32%
March 31, 2017	63	4	117.24%
April 30, 2017	62	-1	113.79%

	Incident Salience (1-3)			ESG Impact Indicator		
Incident Date	Severity	Reach	Novelty	Environment	Social	Governance
Feb 07, 2017	1	1	1	1	1	
Feb 15, 2017	1	2	1	1	1	
Feb 16, 2017	1	1	1	1	1	
Feb 24, 2017	1	2	1	1	1	
Mar 01, 2017	1	1	1		1	
Mar 03, 2017	1	1	2			
Mar 03, 2017	1	1	2	1	1	1
Mar 09, 2017	2	3	1			1
Mar 09, 2017	2	1	1			1
Mar 11, 2017	1	1	1		1	1
Mar 12, 2017	1	3	1			1
Mar 13, 2017	2	3	1		1	1
Mar 14, 2017	1	2	1			1
Mar 15, 2017	1	2	1			1
Mar 15, 2017	2	1	1			1
Mar 16, 2017	2	3	1			1
Mar 24, 2017	1	2	1		1	1
Mar 27, 2017	1	2	2	1	1	1
Mar 27, 2017	2	2	2			1
Mar 28, 2017	2	3	1			1
Mar 28, 2017	2	2	1		1	1
Apr 03, 2017	2	3	1		1	1
Apr 11, 2017	2	3	1			1
Apr 12, 2017	2	2	1			1
Apr 16, 2017	1	1	1	1	1	
Apr 21, 2017	1	2	1			1

In 2010, Wells Fargo had its highest RRI scores, increasing from 35 to 55 from April to May. Notably there are only 4 incidents in May, further supporting that risk and incidents do not directly correspond one-to-one.

Appendix 3 – B
Wells Fargo

Data Date	Firm Reputation Risk	Trend	Abnormal Reputation Risk
April 30, 2010	35	12	66.67%
May 31, 2010	55	20	161.90

	Incident Salience (1-3)			ESG Impact Indicator		
Incident Date	Severity	Reach	Novelty	Environment	Social	Governance
May 11, 2010	2	3	1			1
May 12, 2010	1	2	2	1	1	
May 19, 2010	1	2	1		1	
May 21, 2010	1	2	2			1

Appendix 4
Variable Definitions

Dependent Variables	
TP_Rev	Cube root of the absolute difference between current and most recent target price forecast made by the analyst about the firm, scaled by the market price on the day of the most recent forecast
ECommitteeName	Indicator variable equal to 1 if the firm has a board committee name with an environmental buzzword.
EExpertise	Indicator equal to one if any member of the board has environmental expertise.
EConnections	Indicator equal to one if the number of unique board connections to individuals with environmental expertise is above the sample median by year.
Independent Variables	
AbnormalRRI	(*CurrentRRI – CountrySectorAverageRRI*) / *CountrySectorAverageRRI*
CurrentRRI	"The current level of media and stakeholder coverage of a company related to ESG issues," sourced from RepRisk.
CountrySectorAverageRRI	The average level of media and stakeholder coverage for a particular country-sector combination, sourced from RepRisk
EImpactInd	Indicator variable equal to one if the firm operates in an industry with an MSCI environmental risk and opportunity weight in the top quartile of all industries.
SImpactInd	Indicator variable equal to one if the firm operates in an industry with an MSCI social risk and opportunity weight in the top quartile of all industries.
GImpactInd	Indicator variable equal to one if the firm operates in an industry with an MSCI governance attention weight in the top quartile of all industries.

BrownInd	Indicator variable equal to one if the firm operates in an industry with an MSCI environmental risk weight in the top quartile of all industries.
GreenInd	Indicator variable equal to one if the firm operates in an industry with an MSCI environmental opportunity weight in the top quartile of all industries.
Fink	Indicator equal to 1 if the firm-year is in the period after the Larry Fink shareholder letter was issued in 2016 and Blackrock held at least 4.5% of shares of the firm.
Paris	Indicator equal to 1 if the firm-year is in the period after the Paris Climate Agreement and has operations in Europe.
ChangeRRI	The absolute value of the percentage change in AbnormalRRI calculated over the RevisionInterval.
Control Variables	
RevisionInterval	Number of days since the analyst’s last target price forecast for the firm
Following	Number of analysts following the firm in the calendar year (from EPS forecast)
Companies	Number of companies followed by the analyst in the calendar year (from EPS forecasts)
BrokerSize	Number of analysts working at the broker in the calendar year (from EPS forecasts)
FirmExperience	Number of years between analyst's earliest EPS forecast for the firm and the current forecast
Industries	Number of distinct industries followed by the analyst (from EPS forecast)
StockMomentum	Market cap on the day before the analyst's current announcement minus the market cap on the trading day associated with the analyst's most recent target price forecast before the current announcement
ExcessReturn	Value-weighted return on the day before the analyst's current announcement minus the return on the day before the analyst's current announcement
EPSRevision	Difference between the EPS forecast for the most imminent forecast period end date that occurs after the target price forecast announcement date and the most recent EPS forecast fitting the same specifications
ConsensusChange	Difference in the target price consensus for the latest statistical period associated with the target price forecast announcement date and the target price consensus during the statistical period associated with the analyst's most recent target price forecast for the firm (scaled by the current market price)
Big3InstOwn	Percent of shares held by BlackRock, State Street, and Vanguard, sourced from Refinitiv
Assets	Log of the firm’s annual total assets, sourced from Compustat
FirmAge	Log of the number of years between IPO date and current, sourced from CRSP
BoardSize	Number of board members, sourced from BoardEx
BoardIndependence	Number of outside board members / board size, sourced from BoardEx
BoardAge	The average age of the members of the board of directors
BusinessSegments	Number of business segments, sourced from Compustat
GeographicalSegments	Number of geographical segments, sourced from Compustat

CEOTenure	Number of years between start date and current, sourced from BoardEx
CEOAge	Number of years between date of birth and current, sourced from BoardEx
CEOGender	Indicator variable equal to 1 if Female and 0 otherwise, sourced from BoardEx