Managerial forward-looking and firm environmental risk: Evidence from a machine learning approach

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Abstract

We adopt a machine learning approach to create a forward-looking orientation (FLO) index for identifying corporate managers with better sustainable development strategies. We find that more forward-looking managers are associated with subsequent lower corporate environmental risk. The results are stronger when firms are confronted with higher exposure and risk to climate change, more attention from stakeholders, higher holdings from socially responsible investors, and fewer financial constraints. Firms with forward-looking managers reduce more Greenhouse Gas (GHG) emissions when mitigating environmental risk. Our results are robust to various specifications for index construction and remain after controlling for traditional proxies for managerial myopia.

JEL Classification: C45, G32, Q54

Keywords: Environmental risk, climate change, conference calls, machine learning, forward-looking orientation, greenhouse gas emissions

1. Introduction

Recent years have witnessed dramatic growth in sustainable investing.[1] A report by J.P. Morgan shows that the growth of ESG assets stateside is up over 200% in the past decade. The global socially responsible investing market is worth around $23 trillion in 2018.[2] Yet, it is practically challenging for investors to identify firms with sustainable development strategies as sustainability is not easily observable and verifiable. Although investors could rely on firms' disclosure regarding environmental issues, such a type of disclosure might be merely an act of greenwashing. For instance, managers who ostensibly emphasize climate issues in conference calls may only intend to get favorable ESG ratings and avoid difficult questions (Hail, Kim, and Zhang, 2021). Therefore, with trillions of dollars at stake, identifying managers or corporations that truly care about sustainable development becomes a critical issue.

Instead of focusing on what managers disclose about environmental issues, which they have incentives to cheap talk about, our paper takes a different approach to identify the managers' awareness of sustainable development by focusing on their forward-looking orientation. Based on a semi-supervised machine learning approach, we construct a managerial forward-looking index as a practical measure for capturing the extent of managerial orientation in the concept of sustainability. Specifically, we examine whether forward-looking managers are linked to lower subsequent corporate environmental risk.

Our hypothesis is rooted in a theory of intertemporal altruism and a psychological foundation regarding time perspective and individuals' sustainable behavior (e.g., Galperti and Strulovici, 2017; Milfont, Wilson, and Diniz, 2012). The environmental policy reflects direct altruism (forward-looking preference) toward the future (Galperti and Strulovici, 2017). Psychological and economic studies have shown that future-oriented individuals have a less

[1] e.g., Kruger (2015); McKinsey (2017); Riedle and Smeets (2017); JP Morgan (2018); Hartzmark and Sussman (2019); Azar, Duro, Kadach, and Ormazabal (2021); Barber, Morse, and Yasuda (2021); Bauer, Ruof, and Smeets (2021).

[2] See https://www.jpmorgan.com/insights/research/esg

present bias to overweight the present salient and tangible events, and tend to be mentally and behaviourally pro-environmental (Akerlof, 1991; Strathman et al., 1994; Milfont and Gouveia, 2006). In general, forward-looking managers are supposed to consider environmental issues more and take action to manage the related risks. Accordingly, we hypothesize that *firms with forward-looking managers have a lower corporate environmental risk*.

We identify forward-looking managers by the language characteristics managers use in Q&A sessions of Earnings Conference Calls and then create a forward-looking orientation (FLO) index at the firm-year level. Specifically, we first follow Li (2010) and select 18 seed words that measure managers' forward-looking orientation, such as *expect*, *forecast*, and *plan*. Then, we use a word embedding model (*word2vec* from Mikolov, Sutkever, Chen, Corrado, and Dean, 2013) to quantify text.[3] We select the top 150 words and phrases with the closest associations with the seed words to create an FLO dictionary. The method identifies words such as *target*, *envision*, *ambition*, and *commitment*, as well as phrases like *time frame*, *long-range plan*, and *ultimate goal* as part of our dictionary. Finally, we generate the FLO index using the term frequency-inverse document frequency (*tf.idf*) weighting.[4] Our FLO index directly operationalizes the concept of sustainability, which plausibly captures the innate managerial intention for sustainable development.

The measurement has several distinct advantages. First, the FLO index is a more systematic and explicit measure of managers' future orientation than the myopia proxies used in the prior literature. Proxies for managerial myopia such as compensation design and investment strategies only partially reflect managers' characteristics and are indirectly related to managerial forward-looking or sustainable orientation. Second, as argued by Li, Mai, Shen,

[3] Unlike the traditional machine learning methods such as naïve Bayesian which ignores the word order, our word2vec method learns the meaning of all words and phrases and finds words and phrases that are closely related to the seed words.
[4] For robustness, we choose the top 75, 300, and 450 words to create the FLO index. We also adjust the *tf.idf* weight with how similar each dictionary word is to the seed words. The results are qualitatively similar.

and Yan (2021), manually exhausting all the synonyms are almost impossible. Hence, based on the seed words, the machine learning approach is desirable for generating a more comprehensive dictionary than pure word listing or counting. Third, our measure differs from the prior studies that focus on the grammatic future tense of each language to represent future-oriented behavior (Chen, 2013; Na and Yan, 2020). Even though adopting language-based measures is relatively exogenous, it lacks variation among decision-makers speaking the same language, which limits its application empirically for studying the concerned topics.[5] Our FLO index instead relies on the word usage attributes of each individual and could vary across managers, firms, and time.

Before testing our hypothesis, we first validate the FLO index by comparing it with the conventional managerial myopia measures from five dimensions used in the prior literature, including institutional ownership (Edmans, 2009; Aghion, Van Reenen, and Zingales, 2013; Flammer and Bansal, 2017), short-termism based on investment change (Chen and Cheng, 2015; Kraft, Vashishtha, and Venkatachalam, 2018), earnings management (Jiang and Xin, 2022), managerial opportunism such as insider trading (Ali and Hirshleifer, 2017), and pay-for-performance sensitivity (Stein, 1988, 1989; Cheng and Walfield, 2005; Bergstresser and Philippon, 2006). We find significantly negative correlations between the FLO index and all the managerial myopia measures.[6]

We then use the data from MSCI (formerly KLD) to measure a firm's environmental risk. Following the existing studies, we construct the environmental score as the environmental strengths minus environmental concerns (e.g., Cronqvist and Yu, 2017). A higher environmental score represents a lower environmental risk. Based on a sample of 18,134 firm-

[5] For example, Chen (2013) finds that grammatically associating future and present tense makes people more future-oriented (e.g., the German) while separation makes the future feels more distant and makes saving harder (e.g., the English).

[6] The FLO index is also more correlated with managerial myopia measures than a simple counting measure using the 18 seed words with tf.idf weighting. Therefore, our word embedding method not only provides a valid measure of managerial forward-looking orientation but is more comprehensive than a traditional word-counting method.

year observations, we document a negative correlation between managerial forward-looking orientation and the firm environmental risk in the subsequent year. The result is in line with our hypothesis. In terms of economic magnitude, a one-standard-deviation increase in the FLO index is associated with a 95.4% increase in environmental score compared to the sample mean, which is quite substantial. Moreover, given that the environmental strengths measured from MSCI are prone to manipulation by firms' strategic disclosures and greenwashing behaviors, we separate the dependent variable into environmental strengths and concerns.[7] We find that the effect is mainly driven by the reduction of the concerns instead of the improvement in strengths.

Our results are robust to replacing the environmental risk measure with two other rating measures, including environmental ratings from Refinitiv ESG and the pure risk measures from RepRisk. Moreover, the FLO index remains significant and captures additional information regarding managerial forward-looking attributes after controlling for the conventional measures of managerial myopia. Our main findings are also robust to using different cut-offs of the FLO word dictionary or the decile ranking of the FLO index.

Next, we explore the cross-sectional variations to illustrate why and how forward-looking managers can reduce environmental risk. First, we find that forward-looking managers are more likely to reduce future environmental risks when they face higher threats from climate change. Regulatory and physical issues related to climate change have profoundly affected corporate operations (e.g, Bartram, Hou, and Kim, 2022; Sautner, Van Lent, Vilkov, and Zhang, 2022). When firms have higher climate risk exposure, forward-looking managers direct more attention and resources to address environmental issues. We adopt the proxies created by

[7] Chatterji et al., (2009) find little evidence between the prediction of environmental strength and environmental outcome. But the net environmental performance measure (summed strengths minus summed concerns) and pure concerns are related to real environmental consequences.

Sautner et al. (2022) to measure the threats from climate change and find that the main result is stronger when such threats are higher.

Second, investors who care more about sustainable investment pay more attention to the environmental performance of the firms (Kim et al., 2019; Cao, Titman, Zhan, and Zhang, 2021). Such investors tend to support corporate sustainability strategies and policies adopted by forward-looking managers, anticipating a long-term reward. In line with this argument, we find that the positive correlation between the FLO index and future environmental score is larger when socially responsible investors' ownership is higher. We measure the socially responsible investors' ownership by the holding from the SRI fund and public pension fund (e.g., Kim et al., 2019).

Third, the rising awareness of stakeholders' attention on environmental issues motivates forward-looking managers to allocate more resources to environmental risk planning. We anticipate a more prominent correlation between the FLO and environmental risk planning with more stakeholders' attention. We use two measures to proxy the attention from stakeholders: firms in the "brown" industry and the subsample of recent years. Managers in the "brown" industries are forced to reduce environmental concerns as they face stricter government regulations and public scrutiny. Meanwhile, the awareness of the climate and ESG issues is more prevalent in recent decades.[8] Consistent with these conjectures, we find that the correlation between the FLO index and environmental score is stronger among polluting industries and in recent years.

Last, even though it is the forward-looking managers who are more willing to take action on environmental issues, these actions are not without costs. To take care of the environmental issues by investing in green technology and utilizing renewable energy, companies are

[8] See e.g., Bernstein, Gustafson, and Lewis (2019); Addoum, Ng, and Ortiz-Bobea (2020); Engle, Giglio, Kelly, Lee, and Stroebel (2020), Krueger, Sautner, and Starks (2020), and Painter (2020); Ilhan, Sautner, and Vilkov (2022); Kim, Wang, and Wu (2022).

confronted with the risk of failure and externality costs (e.g., Dahlman, 1979; Owen, 2006; Alam, Atif, Chien-Chi, and Soytas, 2019). Even a forward-looking manager in a financially distressed firm has obstacles to investing in greenness, which has a distant reward. Hence, forward-looking managers might not succeed to reduce environmental concerns if their firms are financially constrained (Kim and Xu, 2022; Lin, Zhou, and Zou, 2022). We indeed find that the main results are weaker when firms are financially constrained, measured by the HP index, firm size, and accessibility to the bond market.

For a consequence test on Greenhouse Gas (GHG) emissions, we find that when firms improve their environmental concerns, those with forward-looking managers are more likely to achieve it by reducing firms' future GHG emissions.[9] In particular, our results show that firms with forward-looking managers curtail more GHG emissions in the future when their environmental risk is mitigated. Hence, the result suggests that managerial forward-looking orientation is associated with a long-lasting influence on firms' real environmental performance.

As a complementary result, we investigate the value relevance of the FLO index. Apart from long-term orientation for environmental issues, economic outcome is also an important pillar of sustainable development. Sustainability is defined as an ability to maintain and support a process over a long time, involving economic, social, and environmental aspects (e.g, Schoenmaker, 2018). In the spirit of Friedman doctrine, managers should always boost firm value to act on behalf of the shareholders. Burning investors' money to serve the public good (i.e., protecting the environment) is not a typical "sustainable" strategy (Friedman, 1970). We find that the FLO index is associated with higher firm value. The finding further complements

[9] In the ESG Special Report from The Economist 2022, "ESG" is mocked as "the three letters that won't save the planet." Instead, it is proposed that investors should simply focus on the environment or emissions alone so that the investment portfolio will have a real impact on environmental issues.

the argument that the FLO index can be regarded as a proxy for sustainability as it reflects both of the economic and environmental value embedded in sustainability.

To alleviate the endogeneity concern, we use the CEOs' countries of origin as the instrumental variables (IV) for the FLO index. The idea is that people from different countries with different culture varies in forward-looking orientation (House, Javidan, Hanges, and Dorfman, 2002; Preis, Moat, Stanley, and Bishop, 2012). These country-specific characteristics are exogenously correlated with managers' forward-looking orientation. However, there has yet to be a consensus on the ranking of a country or ethnic group's forward-looking orientation.[10] Therefore, we use country dummies instead of countries' forward-looking rankings as instrumental variables for the FLO index. This approach of using multiple dummy variables as instrumental variables to allow for first-stage heterogeneity has been proposed and adopted in the prior literature.[11] We first map the CEO's last name to its ancestral county using Forebears' genealogical records (e.g., Pacelli, 2019). We then conduct weak instrument and overidentification tests to validate our approach. The IV result is consistent with our main finding that the instrumented FLO index is negatively related to firm environmental concerns.

Our paper contributes to two streams of literature. First, we contribute to the burgeoning literature on sustainable finance (e.g., Riedle and Smeets, 2017; Kruger, 2015; Hartzmark and Sussman, 2019; Barber et al., 2021; Bauer et al., 2021). To the best of our knowledge, we are the first to adopt a machine learning method to identify the managerial forward-looking

[10] For instance, Pries et al. (2012) use Google Search for future-oriented words to rank the countries, and China ranks 41st as the one among myopia countries. US News ranks the forward-looking countries in 2021 based on a global perception-based survey including bureaucratic, dynamic, entrepreneurial, innovation, and technological expertise. According to US News, China ranks 6th. (https://www.usnews.com/news/best-countries/most-forward-thinking-countries). While CEOWORD Magazine ranks China 26th after comparing 152 countries across 10 key categories: availability of government online services, mobile accessibility, bureaucratic, cashless payments, availability of high-speed internet at home, entrepreneurial, innovative, technological expertise, open access to the internet, and digitally forward-thinking lifestyles. (https://ceoworld.biz/2021/01/31/ranked-worlds-most-forward-thinking-countries-2021/).

[11] See Angrist and Keueger (1991), Hansen, Hausman, and Newey (2012), Hansen and Kozbur (2014), Jackson, Johnson, and Persico (2016). Hansen et al. (2012) point out that using many valid instruments such as dummies could improve efficiency, though it also makes the usual inference procedures inaccurate.

orientation and apply this measure to the field of sustainable finance. Given that sustainability is not easily observed or verifiable, there is a valid concern that managerial discussions or disclosures of environmental issues could be just greenwashing. Our paper offers a novel and practical method to identify managers with a general forward-looking orientation. We argue that these managers could pay more attention to corporate sustainability by addressing future environmental risks based on the theoretical foundation of intertemporal ultruism. Our study offers an alternative methodology for investors to identify corporate managers with better sustainable development strategies, circumventing the challenges such as discrepancies among different ESG ratings and corporate greenwashing behaviors.

Second, our paper also contributes to a growing literature on forward-looking disclosure. Prior studies have shown that forward-looking disclosure is related to overall risk factors or specific litigation risk in the financial report (Huang, Shen, and Zang, 2021; Cazier, Merkley, and Treu, 2019; Li, 2010). We expand the literature on forward-looking disclosure by constructing the managerial forward-looking index derived from Q&A sessions of the conference calls and then assessing its potential influence on environmental risk based on a theory of intergeneration altruism. Since pro-environmental behavior has a strong link with the forward-looking preference (direct intergeneration altruism) from a temporal perspective (e.g, Galperti and Strulovici, 2017; Milfont, Wilson, and Diniz, 2012), we provide coherent evidence that environmental risk is a principal and relevant outcome associated with forward-looking managers.

2. Related Literature and Hypothesis Development

2.1 Environmental Risk

Sustainability or sustainable finance has raised great attention among investors, regulators, scholars, and all the other stakeholders (e.g., McKinsey, 2017; JP Morgan, 2018; Barber et al., 2021; Bauer et al., 2021; Kim and Yoon, 2022). Google Trends shows that the searches (interests) for "ESG" increases dramatically in recent years in the U.S.[12] Prior studies have documented that investors react to the ESG news and use the ESG risk factors to shape the expected return and fund flow (Sharfman and Fernando, 2008; Kim et al., 2019). Consulting firms also suggest that ESG investments are plausibly value-adding (McKinsey, 2019; Welch and Yoon, 2021). Among the three components, the "E" factor has attracted the greatest attention from stakeholders with the rising threat of global warming. The Economist (July 23rd, 2022) critiques the ESG measurement and proposes to use a simple measure, Emission, instead.[13]

For general stakeholders, a recent survey of U.S. adults shows that approximately 60% of Americans believe that global climate change is a major threat to the country, compared to a percentage of 44% in the year 2009.[14] Besides, other stakeholders apart from investors can exert real impacts on the business outcomes (e.g., Klassen & Mclaughlin, 1996). Green supply chain management is critical for operational efficiency and profitability (Srivastava, 2007; Kumar, Teichman, and Timpernagel, 2011). Green-oriented consumers can affect sales volume through their preference for green products (Roe, Teisl, Levy, and Russell, 2001). Moreover, environmentalism has gradually intervened the business operations to a larger extent than ever. A recent example is that Shell is sued by an environmental group in the Netherlands due to CO_2 emissions. The court rules that by 2030, Shell must cut its emissions by 45% compared to the level in 2019. Such a lawsuit simply due to carbon emission has brought tremendous costs for Shell both economically and reputationally.

Regulators also show intense interest in the establishment and enforcement of environmental regulations. Governments from all over the world have endeavored to propose

[12] https://trends.google.com/trends/explore?date=today%205-y&geo=US&q=ESG On average, the interest index provided by Google Trend is 50 in the year 2022, representing the term is half as popular. The index has experienced a huge expansion from the year 2019.
[13] https://www.economist.com/weeklyedition/2022-07-23
[14] https://www.pewresearch.org/fact-tank/2020/04/21/how-americans-see-climate-change-and-the-environment-in-7-charts/

and inspect numerous climate policies to tackle global warming issues (e.g., Bernstein, Gustafson, and Lewis, 2019; Addoum, Ng, and Ortiz-Bobea, 2020). In the early 1970s, the U.S. Clean Air Act has been blamed for its side effects on economic impact (Becker and Henderson, 2000; Greenstone, 2002; Ryan, 2012; Walker, 2011; 2013). During the next decades, the governments sought a win-win situation to protect the environment as well as maintain or boost the economy. Accordingly, the appearance of market-based approaches such as carbon trading, carbon tax, and green procurement has become more popular on a global scale (Clarkson, Li, Pinnuck, and Richardson, 2015).

Under such an atmosphere of the prevalence of environmental protection, investors have gradually incorporated climate and environmental risk (both the physical risk and regulation risk) into their portfolios (Krueger, Sautner, and Starks, 2020; Bolton and Kacperczyk, 2021). Hartzmark and Sussman (2019) use an experiment to demonstrate that mutual funds in the U.S. collectively put a positive value on sustainability. Lars Rebein, the CEO of Novo Nordisk claims that "in the long term, social and environmental issues become financial issues" (Harvard Business Review, 2015).

Combining the discussion above, in this paper, we propose a new perspective to identify firms with sustainable development strategies to deal with environmental risk by focusing on a managerial forward-looking orientation (FLO). Given that sustainable quality is not directly observable or verifiable while firms have been blamed for green-washing (Bebchuk and Tallarita, 2020; Chatterji, Levine, and Toffel, 2009), our FLO index assists investors to date back to managerial language attributes to identify the corporate's sustainability.

2.2 Forward-Looking Disclosure

Current literature has documented that forward-looking disclosure is associated with more risk factors, such as litigation risk, earnings volatility, and analyst dispersion, etc., (e.g., Li, 2010; Bozanic, Roulstone, and Buskirk, 2018; Cazier et al., 2019; Huang et al., 2021). The origin of the forward-looking statement is derived from The Private Securities Litigation Reform Act of 1995, which provides a "safe harbor" for forward-looking statements and encourages companies to provide prospective information for shareholders. Cazier et al. (2019) find that litigation risk varies between qualitative forward and non-forward-looking statements in financial reports. Huang et al. (2021) show that, after the SEC's mandate of risk disclosure in 2005, firms that did not disclose risk factors before adopt more qualitative forward-looking statements after the mandate. Bozanic et al. (2018) propose that earnings-related forward-looking statements are more sensitive to uncertainty. Incorporating the forward-looking information into the empirical measures generate a more comprehensive proxy for firms' voluntary disclosures.

Our paper differs from the current forward-looking literature in two aspects. First, we focus on environmental risk instead of any other uncertainties in that environmental risk has drawn great attention from the whole society as discussed in Section 2.1. Environmental risk planning, as part of the strategy embedded in sustainable development, can be a principal and relevant outcome connected with the forward-looking managers who consider sustainability solemnly. Second, prior studies generally focus on well-structured documents such as financial reports and earnings announcements containing forward-looking statements. While forward-looking information beyond the financial report (e.g., in conference calls) is also important and more instantaneous.[15] As far as we know, there is very limited literature focusing on forward-looking information based on the material of conference calls. One related study is by Brochet, Loumioti, and Serafeim (2015) who examine the correlation between the disclosure horizon of

[15] In 2013 and 2014, CFA Institution encourages companies to disclose more forward-looking information apart from the ones in the financial report. (https://www.cfainstitute.org/-/media/documents/article/position-paper/forward-looking-information-a-necessary-consideration-in-sec-review.ashx)

voluntary disclosure within the conference calls with accruals and real activity earnings management.[16]

In particular, we rely on the language characteristics of managers used in the Q&A sessions of conference calls to develop a managerial forward-looking index. Compared to the well-structured documents in the financial reports such as MD&A discussions and earnings announcements, the contents of the immediate responses from the managers during the Q&A session together with the machine learning approach plausibly better capture the comprehensiveness of managerial forward-looking orientation.

2.3 Hypothesis Development

Our hypothesis is based on a theory of intertemporal altruism and time perspective for environmental externality. Regarding the social dilemma (i.e., environmental externality), the prior psychological literature provides social concern perspectives such as valuing the well-being of others instead of free-ride (Olson, 1965; Joireman, 2005). While another important perspective is the temporal concern or time perspective, which is closely related to individual sustainable behavior (e.g., Milfont et al., 2012). For instance, compared to individuals with present or past preferences, those with forward-looking or future preferences would more likely to hold a pro-social attitude and engage in water conservation practice (Milfont and Gouveia, 2006; Corral-Verdugo et al., 2006). Therefore, when managers are more forward-looking, they are supposed to care more about environmental risk planning.

Besides, from the practical perspective, forward-looking managers have both the willingness and feasibility to affect the corporate environmental outcome. As for willingness, environmental risk has been the focus of the public in recent years. Managers are exposed to a highly greenness-demanding atmosphere as there are numerous regulations regarding climate

[16] Parts of our validation tests of the FLO index in our paper share a similar tenet as the one in Brochet et al. (2015) as we also use earnings management as a proxy for managerial myopia to validate our FLO index. However, we differentiate our work by focusing on a more comprehensive machine learning approach and its association with environmental risks.

issues, appeals from the stakeholders for green products and clean energy, and preferences from green investors such as public pension funds and socially responsible institutional investors (Welch and Yoon, 2021; Flammer and Bansal, 2017). Thereby, forward-looking managers would be willing to minimize the negative impact of corporate environmental risk in the expectation of sustainable development of the firm.

As for feasibility, senior managers, as key corporate decision makers, their habits and preferences would largely influence corporate decision outcomes including corporate risk takings (O'Sullivan, Zolotoy, and Fan, 2021; Benmelech and Frydman, 2015; Li and Tang, 2010). For instance, Benmelech and Frydman (2015) find that the military experience of CEOs encourages firms to adopt more conservative corporate policies. Na and Yan (2020) show that managers' language characteristics regarding future tense usage are associated with more tax avoidance in the current phase. By analogy, to some extent, apart from the regulations or the requirements of stakeholders, managerial appetites for sustainability can influence the corporates' environmental outcomes. Combining both theoretical foundation and practical reasoning, we propose that forward-looking managers care about long-term planning and shall reduce corporate environmental risks accordingly.

H1: Managerial forward-looking is associated with less environmental risk

Nevertheless, whether forward-looking managers should care about environmental risk planning may remain uncertain *ex-ante*. First, forward-looking managers might only focus on future financial performance but not on environmental issues. Based on the Friedman doctrine, the ultimate social responsibility is to create profit.[17] To act on behave of the shareholders, forward-looking managers shall not use shareholders' money to serve the public good, such as protecting the environment under the free market. Considering the substantial and consistent

[17] https://www.nytimes.com/1970/09/13/archives/a-friedman-doctrine-the-social-responsibility-of-business-is-to.html?smid=url-share

abatement cost, even forward-looking managers shall be hindered from taking actions to reduce environmental risk if the market does not reward greenness.[18] In the long run, they might intentionally ignore environmental risk or rationally scarify environmental performance in exchange for future financial performance. Second, similar to the "green-washing" behavior, it is possible that managers can involve in "future-washing" by over-emphasizing the future-related articulations to drive away the intention of investors on the current performance.[19] It thus remains an empirical question whether our FLO index is negatively related to firms' environmental risk.

3. Data and Methodology

3.1 Data and Sample

Our sample starts with all the public firms having conference calls from 2004 to 2018. We first follow the prior literature to parse the Q&A and presentation sessions of the manuscripts of conference calls (e.g., Jung, Wong, and Zhang, 2017; Li et al., 2021). To guarantee the consistency of the contents and language comprehension of Q&A sessions, we only select all the earnings conference calls. Since the conference call is held by quarter, we obtain an original 127,136 manuscripts based on firm-quarter (4,381 unique firms) after merging with Compustat and I/E/B/S dataset based on tickers and company names.

Next, we use natural language processing (NLP) algorithms to parse the Q&A sessions and identify the answers by different executives or senior managers.[20] We categorize the managers into three types: CEO, CFO, and others. For the main analysis, we combine all the

[18] Since it is still debatable whether environmental risk management is value-enhancing. Some literature documents that ESG investment is conducive to competitiveness and enhances shareholder value (e.g., Klassen and McLaughlin, 1996; Flammer, 2015). While the opponent voice states that "stakeholderism" might be just for show and has marginal or even negative consequences on firms (Bebchuk and Tallarita, 2020). Similarly, Khan, Serafeim, and Yoon (2016) claim that only material sustainability investment matters for shareholder value. Environmental policies requiring firms to go green can even hurt the local economy (e.g, Greenstone, 2002; Greenstone et al., 2012).

[19] While the possibility of "future-washing" will prevent us from finding any results in the validation test or other analysis.

[20] We use the Stanford CoreNLP package version 3.9.1 (released on 2018-02-27) to parse the text.

contests of answers from different executives to generate the FLO index as we examine the forward-looking orientation at a corporate level. In the Internet Appendix IA 7, we only include the contents of the CEO, the most powerful decision maker regarding business operations, to create the FLO index, the results are similar. For each firm, we further take an average of the FLO index within the year.

Finally, we merge the FLO index with the environmental score in the next year (*t+1*) from Morgan Stanley Capital International (MSCI), formerly Kinder, Lydenberg, and Domini Research & Analytics, Inc. or RiskMetrics-KLD. We only focus on the environmental themes regarding the strengthens and concerns. For the environmental theme, the measure of the strengths covers pollution prevention, recycling, clean energy, etc., based on firms' public disclosure or commitments; the measure of the concerns covers hazardous waste, regulatory problems, substantial emissions, other toxic chemicals, etc.[21] Hence, the environmental score is used by investors to assess firms' environmental risks. We drop the observations if the firm is not covered by MSCI, which reduces the sample size to 22,952 firm-year observations. In the regression analysis, we only include the sample firms with non-missing control variables, leading to 18,134 observations at the firm-year level, with 1,728 unique firms.

Our control variables are derived from Compustat and CRSP. Board characteristics are from BoardEx. Data related to institutional investors are from the Thomson Reuters database of 13F filings. For additional tests, our alternative environmental risk measures are from Refinitiv ESG (formerly Asset4) and RepRisk. Refinitiv ESG measures firms' ESG performance across 10 main themes based on publicly available and auditable data.[22] The value ranges from 0 to 100, and a higher value represents better environmental performance. RepRisk focuses on the risk or downside of the firm's operations and supply chains regarding negative

[21] https://wrds-www.wharton.upenn.edu/documents/1454/MSCI_ESG_KLD_STATS_2018_Data_Set_Methodology_Final.pdf
[22] Refinitive ESG Methodology. https://www.refinitiv.com/en/sustainable-finance/esg-scores

ESG incidents from the popular press on a daily basis.[23] A higher value represents higher risk. All the variables are aggregated to an annual level.

3.2 Machine Learning Method to Construct the FLO index

To construct the FLO index, we use a machine learning method to process the Q&A session of the Earnings Conference Calls in a way similar to Li et al. (2021).[24] We first clean the sentences in the Answers from managers. We follow a pipeline of sentence segmentation and tokenization, lemmatization, and Named Entity Recognition (NER) to clean the raw texts. Next, we remove punctuation marks, stop words, and single-letter words. After the initial data cleaning process, we use the *phrases* module from the Gensim library in Python to find two- and three-word phrases that are specific to our corpus. Then, we adopt the *Word2Vec* module from the Gensim library in Python to train our model.

Word2Vec is a recent breakthrough in NLP technology. Specifically, *Word2Vec* is a word embedding method that estimates a word's meaning based on its occurrences in the test through a neural network with one hidden layer. Two main architectures frequently used for *Word2Vec* are Continuous Bag of Words (CBOW) and Continuous Skip-Gram. CBOW tries to predict a target word from a list of context words, while Continuous Skip-Gram does the opposite and predicts the neighboring words of a given word. We use the Continuous Skip-Gram model with a negative-sampling method. The negative-sampling method is presented by Mikolov et al. (2013) as an alternative to the hierarchical softmax method and is shown to be efficient in model estimation. It uses the simple concept that a good model should differentiate fake signals from real ones. Moreover, it improves computation efficiency by only updating K weights each time (K is a small number such as five). In other methods, all the weights are updated each

[23] RepRisk Methodology. https://www.reprisk.com/news-research/resources/methodology
[24] Details of the method can be found in Internet Appendix IA 3.

time, taking thousands of observations into consideration. The objective function of the Skip-Gram and negative sampling is as follows:

$$J_t(\theta) = log\sigma(u_O^T v_c) + \sum_{j\sim P(w)} [-log\sigma(-u_j^T v_c)]$$

Where the sigmoid function is $\sigma(x) = 1/(1 + e^x)$. T is the time step, and θ is the various variables at that time step. The first term maximizes the probability of occurrence for all the actual words in the context window. The second term iterates over some random words j, which are not in the context window and minimizes the probability of co-occurrence. The random words are sampled based on their occurrence frequency $P(w)$. $P(w) = \frac{f(w)^{3/4}}{\sum_{j=0}^{n}(f(w_j)^{3/4})}$, where $f(w)$ is the frequency of the word in the corpus. The 3/4 power makes less frequent words sampled more often.

After the *Word2Vec* process, we obtain a 300-dimensional vector for each of the 113,992 words and phrases in the corpus. Each vector represents the meaning of the corresponding word or phrase, and the cosine similarity between two vectors quantifies the association between two words. A higher cosine similarity between two words indicates that these two words often appear in the same context with similar neighboring words.

Afterward, we generate a dictionary to measure the forward-looking orientation based on the seed words from Li (2010). First, we compute the average of the vectors of the seed words $\bar{V}^{FLO} = \frac{1}{18}\sum_{i=1}^{18}[x_1^i, x_2^i, \dots, x_{300}^i]$, where *i* is each word in the seed word list. Then, we compute the cosine similarity between this average vector and each unique word in the corpus. Specifically, the cosine similarity between the average vector and word j is $\frac{\bar{V}^{FLO} \cdot V^j}{\|\bar{V}^{FLO}\| \cdot \|V^j\|}$. We select the top 75, 150, 300, and 450 words with the closest associations with the seed words as the expanded dictionary for the forward-looking orientation measure. The seed words and dictionary are listed in IA 2.

For each transcript, we use the term frequency-inverse document frequency (*tf.idf*) weighting to compute the FLO index. The *tf.idf* is calculated as $tf(t,d) \cdot idf(t,D)$. The term frequency $tf(t,d)$ is the relative frequency of term *t* within document *d*, which is the number of times a term occurs in a given document. $idf(t,D) = log\frac{1+n}{1+df(t)} + 1$, where *n* is the total number of documents in the document set *D*, and $df(t)$ is the number of documents in the document set *D* that contain the term *t*. We aggregate the *tf.idf* weightings for all the words in the FLO dictionary to get the FLO index for each Earnings Conference Call document. Then, we aggregate the FLO index into the firm-year level and obtain 36,572 firm-year observations.

The autocorrelation of the FLO index is 0.737 (non-tabulated), suggesting a relatively sticky pattern of the managerial forward-looking orientation. Figure 1 illustrates the FLO index distribution across years. The y-axis shows the yearly median value of the FLO index, which ranges from 0.95 to 1. The x-axis is the sample year from 2004 to 2018.

3.3 Research Design

We use the equation below to conduct a panel regression analysis to test the relationship between the FLO index and future environmental risk.

$$ENV\_SCORE_{i,t+1} = \beta_0 + \beta_1 FLO_{i,t} + \gamma X_{i,t} + Firm\,\&Year\ FE + \varepsilon_{i,t} \qquad (1)$$

The dependent variable is the environmental score in year *t+1* (*ENV_SCORE*), which is the strengths (*ENV_STR*) minus the concerns (*ENV_CON*) regarding environments in the MSCI dataset. A higher environmental score represents a lower environmental risk. We also decompose the *ENV_SCORE* and use *ENV_STR* and *ENV_CON* as separate dependent variables. The variable of interest is *FLO_INDEX*, the managerial forward-looking orientation index based on a machine learning approach. Our main *FLO_INDEX* is based on a cut-off of 150 vocabularies. For the robustness test, we also adopt different cut-offs or decile rankings.

Control variables include firm fundamental characteristics that might affect the environmental risk in the future such as the firm size (*SIZE*), firm value (*Tobin's Q*), leverage ratio (*LEV*), operating cash flow (*OCF*), profitability (*ROA*), R&D investment (*RND/SALE*) and stock return (*RETURN*) following O'Sullivan et al. (2021) and Cronqvist and Yu (2017). We also include firm and year fixed effects to alleviate the concern regarding time-invariant or macroeconomic variables that are omitted in the regression.

To further show that our FLO index captures the essence of forward-looking, we include the conventional managerial myopia measures as additional controls for the horse-racing tests. The measures include (i) institutional ownership (*INS_OWN*) (Edmans, 2009; Aghion et al., 2013; Flammer and Bansal, 2017), (ii) short-termism based on investment change such as change of property, plant, and equipment (*CH_PPE*), capital expenditure (*CAPX*), and cut in R&D (*RND_CUT*) (Chen and Cheng, 2015; Kraft et al. 2018), (iii) earnings management based on abnormal accruals of Modified Jones Model and Dichow and Dichev's Model (*MJ_ABACCR* and *DD_ABACCR*) (Jiang and Xin, 2022), (iv) insider trading such as opportunistic net sales (*OPP_NSALE*) (Ali and Hirshleifer 2017), and (v) pay-for-performance sensitivity (*PSPF*) (Stein 1988, 1989; Cheng and Walfield, 2005; Bergstresser and Philippon, 2006).

We also add the determinants specified in IA 6 for the FLO index as additional controls, which include the board's characteristics and insiders' ownership. Board surveillance and insiders' ownership structure may also plausibly affect the forward-looking behaviors of the managers (e.g., Gugler, Mueller, and Yurtoglu, 2008; Delis, Gaganis, Hasan, and Pasiouras, 2017). Characteristics of the board of directors include directors' number (*DIR_NUM*), directors' male percentage (*DIR_PCT_MALE*), directors' network (*DIR_NETWORK*), percentage of independent directors (*DIR_PCT_IND*), the standard deviation of directors' age (*DIR_AGE_SD*), and insider ownership (*INSIDE_OWN*).

4. Results

4.1 Validation Test of FLO Index

Table 2 shows the validation test of our FLO measure. We compare the FLO index with the relevant managerial myopia measures documented in the prior literature. We look at the five dimensions of the measurements mentioned in Section 3.3. Specifically, higher institutional ownership, more long-term investment, and less opportunistic behavior such as earnings management, insider sales, and lower pay-for-performance sensitivity all represent less managerial myopia.

We find that the FLO index is positively associated with higher institutional ownership (*IOR*), higher long-term investment activities such as capital expenditure (*CAPX*), change of the net value of property, plant, and equipment (*CH_PPE*), and change of R&D expenditure (*CH_RND/SALE*). It is also negatively associated with less R&D cut-off (*RND_CUT*), fewer earnings management (*MJ_ABACCR* and *DD_ABACCR*), less opportunistic insider sales (*OPP_SALE* and *OPP_NSALE*), and lower pay-for-performance sensitivity (*PSPF*). While the highest magnitude of the Pearson Correlation is the one between our FLO index and institutional ownership (0.321), all the other magnitudes of the correlations are below 0.3. The results suggest that even though the FLO index based on the machine learning approach is correlated with managerial myopia measures, it carries different information from the traditional myopia proxies.[25]

4.2 Managerial Forward-Looking and Corporate Environmental Risk

We test our main hypothesis based on equation (1), and the results are shown in Table 3. In Column 1, the correlation between the FLO index (*FLO*) in year *t* is positively associated with the environmental score (*ENV_SCORE*) at the 1% level after adding firm and year fixed effects. The magnitude of the coefficient is 0.182, suggesting that a one-standard-deviation

[25] Although the correlation between our FLO index based on the machine learning method and pure word counting method (FLO_18) is 0.818, on average, the FLO index has a stronger correlation with managerial myopia measures than FLO_18. It is plausible that our word embedding method not only provides a valid measure of managerial forward-looking orientation but is more comprehensive than a traditional word-counting method.

increase in the FLO index is associated with a 95.4% (0.182 × 0.236 /0.045) increase in the *ENV_SCORE*, compared to the sample mean. The magnitude is significant and larger than other factors documented in the prior literature (e.g, Cronqvist and Yu, 2017; Desjardine, Grewal, and Viswanathan, 2022).[26]

In Columns 2 and 3, we separate the environmental concern and strength separately and find that the coefficient on *FLO* is only significant in Column 2. The results indicate that forward-looking managers tend to reduce corporate environmental concerns instead of flaunting their positive image on environmental strengths. Besides, the prior literature studies show that compared to *EVN_STR*, *ENV_SCORE* and *ENV_CON* are more reliable measures for future verified environmental performance instead of a cheap talk (e.g., Chatterji et al., 2009). The results in Columns 2 and 3 collectively show that firms with higher FLO indexes would consider corporate environmental risks in the future instead of catering to rating agencies.

Our findings are robust to using the alternative measures of environmental risk such as RepRisk and Refinitive ESG.[27] The results are also robust when using the decile rankings of the index in case of outliers or skewness of the measure. The results are not sensitive to different cut-offs and weighting methods for the index, suggesting the index created by the machine learning methods is not ad hoc (see Section 4.4 for more details). In addition, the results are qualitatively similar when we replace the overall managerial forward-looking with the CEOs' FLO index (*CEO_FLO*) (See IA 6).

4.3 Mechanism Tests

[26] For example, Cronqvist and Yu (2017) show that when a CEO has a daughter, the corporate CSR rating is 9.1% higher compared to the sample median. We manually calculate the impact of having a daughter on the corporate environmental rating as 0.051 compared to the sample mean, using the coefficient on the CEO daughter (0.26) divided by the sample mean of the normalized environmental score (5.1). While our magnitude of a one-standard-deviation increase of the FLO index is roughly 18 times (0.954/0.051) the effect of a CEO having a daughter.

[27] Even though the ESG rating has been blamed for its low correlation (Brandon, Krueger, and Schmidt, 2021), our FLO index has a consistent prediction using different sources of datasets.

In this section, we examine why and how forward-looking managers reduce environmental risks. The mechanisms we examine include the firms' exposure/risk to climate change, stakeholders' attention, sustainable investors, and financial constraints.

4.3.1 Threats from the Climate Change

We conjecture that forward-looking managers are more likely to reduce future environmental risk when they are confronted with higher threats from climate change. As both regulatory and physical issues related to climate change may profoundly affect corporate operations (e.g, Bartram et al., 2022; Sautner et al., 2022), it is more urgent for managers to reduce environmental risk when firms are exposed to higher climate change issues or risks.

We use the index created by Sautner et al. (2022) to measure firms' exposure or risk to climate change. *CC_EXPO* captures the firms' overall exposure to climate change, including both physical and regulatory exposure. *CC_RISK* measures firms' overall risk regarding climate change. The details of the measure can be found in Sautner et al. (2022).[28] We partition the firms into high and low groups based on their yearly median values of *CC_EXPO* and *CC_RISK*. *HIGH_ CC_EXPO* (*HIGH_CC_RISK*) equals one if *CC_EXPO* (*CC_RISK*) is above the yearly median; zero otherwise.

In Panel A of Table 4, we find that the coefficients on the interaction terms *FLO* × *HIGH_CC_EXPO* and *FLO* × *HIGH_CC_RISK* are both positive and significant at the 5% level, suggesting that the positive relationship between the forward-looking index (*FLO*) and environmental score (*EVN_SCORE*) is more substantial when firms are confronted with higher climate change exposure or risk. The results provide a plausible explanation for why forward-looking managers care about future environmental risk given that there are also other risk factors they might need to consider.

[28] The authors provide the index on this website: https://osf.io/fd6jq/. The index is based on a machine learning approach using conference call transcripts.

4.3.2 Sustainable Investors

Since sustainable investors are shown to care more about the environmental performance of the firms (Kim et al., 2019; Krueger et al. 2020; Cao et al., 2021; Bolton and Kacperczyk, 2021), we propose that such investors are more interested in firms with forward-looking managers and assist the implementation of the policies to reduce the future environmental risks. As found by Flammer and Bansal (2017), shareholders voting on long-term managerial compensation leads to better long-term strategies such as stakeholder relationships.

In Panel B of Table 4, we use two proxies for sustainable investors following the prior literature (e.g, Kim et al., 2019). Public pension funds and socially responsible investors shall pay more attention to the environmental issues regarding the portfolio firms. To create investors' ownership based on the public pension fund (*IOR_PPF*), we rely on the investor classification from Bushee's website. To create the investors' ownership based on socially responsible investors (*IOR_SRI*), we follow the methods in Cao et al. (2021) and use the value-weighted ESG scores (from the MSCI KLD database) of their portfolio holdings. Then, we partition the firms into two subsamples based on the yearly median values of the two variables. *HIGH_IOR_PPF* (*HIGH_IOR_SRI*) equals one if *IOR_PPF* (*IOR_SRI*) is above the yearly median; zero otherwise.

We find that the coefficients on the interaction terms of *FLO* × *HIGH_IOR_PPF* and *FLO* × *HIGH_IOR_SRI* are all positive and significant at the 1% and 10% levels, respectively. The positive relation between the FLO index and future environmental score is stronger when ESG-oriented investors' ownership is higher. The findings support our argument that ESG-oriented investors could identify firms with sustainable strategies and thus exert a stronger positive impact on firms' future environmental risk planning.

4.3.3 Stakeholders' Attention across Years and Industries

We posit that stakeholders' attention is also one of the reasons why forward-looking managers would consider the environmental issue. Compared to the early years, the overall attention across society has increased dramatically. Thus, we propose that compared to earlier years, the forward-looking managers in recent years shall be more responsive to environmental issues.

In addition, regulations are heavily imposed on highly polluting industries, and environmentalists also have a higher vigilance toward these firms. Thus, managers in such "brown" industries are forced to pay attention to environmental risks. Accordingly, we propose that our main results should also be stronger among polluting industries. We classify an industry as a polluting industry if it is Agriculture, Transportation, Electric Power, and Oil industry since these industries emit the most greenhouse gas.[29] We adopt two proxies to measure stakeholders' attention across the year and industry. In Panel C of Table 4, *LATE_YEAR* is a dummy variable that equals one if the year is larger than the year 2010; zero otherwise.[30] *POLLUT_IND* is a dummy variable that equals one if the firm belongs to a highly polluting industry; zero otherwise.

Consistently, we find that the coefficients on the *FLO* × *LATE_YEAR* and *FLO* × *POLLUT_IND* are both positive and significant at the 1% level. The coefficients on *LATE_YEAR* and *POLLUT_IND* are absorbed by year fixed effect and firm fixed effect, respectively. The results echo our argument that when the stakeholders' attention is more salient (i.e., in recent years and for polluting industries), the forward-looking managers are more likely to attach importance to corporate environmental risk.

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[29] As shown by EPA, the first three industries constitute more than 63% of GHG emissions. https://www.epa.gov/ghgemissions/inventory-us-greenhouse-gas-emissions-and-sinks#:~:text=In%202020%2C%20U.S.%20greenhouse%20gas,sequestration%20from%20the%20land%20sector). We also include oil industry to be the polluting industry as people conventionally regard the industry as "brown" (e.g, BP Mexico Gulf Oil Spill; Shell: Netherlands court orders oil giant to cut emissions). Our results are robust by not including the oil industry (untabled).

[30] The results are robust by changing dummy variables into continuous measures for the year (untabled). We choose 2010 as the cut-off because it is the middle of our sample year, which is from 2004 to 2018.

4.3.4 Feasibility to Reduce Environmental Risk: Financial Constraints

Next, we examine the feasibility of managers reducing environmental risks based on firms' financial constraints. Managers are trading off the abatement cost and potential regulation liabilities and investors' punishment (Lin et al., 2022; Bartram et al., 2022; Kim and Xu, 2022). For financially constrained firms that do not have enough funding to invest in green technology, even forward-looking managers would forego the environmental investment to guarantee routine operation activities. Therefore, we expect that financial constraints will weaken the positive relationship between the forward-looking index (*FLO*) and environmental score (*EVN_SCORE*).

In Panel D of Table 4, we use three proxies for financial constraints: HP index (*HP_INDEX*), firm size (*SMALL*), and firms' access to the bond market (*UNRATED*) (e.g, Bartram et al., 2022). *HP_INDEX* is proposed by Hadlock and Pierce (2010), with higher values of the HP index representing firms being more financially constrained. Then we partition the sample based on yearly median values of *HP_INDEX*. *SMALL* is a dummy variable equal to one if the firm size is lower than the yearly median value; zero otherwise. *UNRATED* is a dummy variable equal to one if the firm is not covered by an S&P rating for a long-term bond; zero otherwise. *SMALL* and *UNRATED* also represent that firms are more financially constrained.

We find that the coefficients on the interaction terms of *FLO* × *HIGH_HP_INDEX*, *FLO* × *SMALL*, and *FLO* × *UNRATED* are all negative and significant at the 1% or 5% levels. The results suggest that financial constraints mitigate the positive correlation between *FLO* and future *ENV_SCORE*. Even forward-looking managers are willing to reduce future environmental risk, they are less likely to take real actions when their hands are tight.

In summary, forward-looking managers tend to reduce future environmental risk when firms are confronted with higher exposure/risk to climate change, have higher stakeholders' attention, and have higher holdings from sustainable investors. Besides, only when firms are less financially constrained, forward-looking managers are able to reduce environmental risk.

4.4 Additional Tests

In this section, we conduct several additional tests to establish the robustness of our main finding. In Panel A of Table 5, we replace the dependent variable of environmental risk with the risk measures in RepRisk (*RepRisk_RR`I*) and the environmental score in Refinitiv ESG (*Refinitiv_EVNSCORE*). The higher value of *RepRisk_RRI* and the lower value of *Refinitiv_EVNSCORE* both represent higher environmental risks. Thus, we find that our FLO index is negatively correlated with *RepRisk_RRI* and positively correlated with *Refinitiv_EVNSCORE*. Both the coefficients of Columns 1 and 2 of Panel A are significant at the 5% level.[31] Our FLO index has a consistent prediction of firms' environmental risk using different sources of environmental ratings, even though these rating agencies have been blamed for the low correlation among their scores (Chatterji, Durand, Levine, and Touboul, 2016; Brandon, Krueger, and Schmidt, 2021). The results suggest that the FLO index captures the essence of the environmental risking planning of the firms.

In Panel B, we add additional control variables such as the myopia proxies used in the validation test (Table 2) and the variables used in the determinants test for the FLO index (see Internet Appendix IA 5). Adding the additional control variables such as pay-for-performance sensitivity significantly reduces the sample size to 4,013, which is the reason we do not include these variables in our main regression. As shown in Panel B, our results still hold after controlling for these additional variables. The results are similar to the ones in Table 3. The coefficients on the *FLO* are still positive in Column 1 and negative in Column 2. It suggests

[31] Given the low correlation among different ESG ratings, our FLO index can still show consistent prediction across different ratings. In addition, by combining the results of real consequence on the future GHG emissions in Table 6, we are more confident to conclude that managers in the sustainable firms identified by our FLO index can "walk through the talk" by reducing future carbon emissions after they take actions to reduce environmental risks.

that our main finding is not driven by the conventional managerial myopia or the monitoring of the board of directors. For myopia measures, only the coefficient on opportunistic net sales (*OPP_NSALE*) is significantly negative, suggesting that managers with more opportunistic insider sales are more irresponsible for the corporate environmental risk.

From Panels C to E, we conduct focus on various specifications of our FLO index. In Panel C, we replace the FLO index with a decile ranking of the index (*DECILE_FLO*) to count for the skewness or outliers of the original measurement. The results are qualitatively similar. In Panel D, we use different cut-offs for the dictionary. We find that the coefficients on *FLO_75*, *FLO_300*, and *FLO_450* are all positive and significant at the 1% level. In Panel E, we replace the FLO index with the other four machine learning measures based on a weighted index with different cut-offs of the dictionary. The weight is assigned by the distance between the machine-learned words and the original seed words based on the Cosine function (See Internet Appendix IA 3 for an in-depth explanation). When the words are closer in meaning to the original seed words, they will be given a higher weight. Again, all the coefficients for the four Columns are positive and significant. The results suggest that our FLO index created by the semi-supervised machine learning method is fairly robust despite the discretions on the choice of dictionary cut-offs and weighting methodology.

4.5 Consequences of Future GHG Emissions

Although we have shown that forward-looking managers implement risk planning regarding environmental issues, exhibited in their environmental rating performance, it is perhaps more relevant to examine whether such risk planning also leads to real environmental outcomes. In this regard, we examine the real consequence of future GHG emissions. Firms' annual GHG emissions are from the EPA dataset.[32] We look at the GHG emissions in years

[32] The availability of the data on GHG emissions further restrict our sample period from 2010 to 2018 as the earliest report year for GHG emissions from EPA is 2010. Since the number of firms covered by the GHG emissions report is also limited, this also reduces our sample size. Nevertheless, one advantage to use GHG emissions instead of toxic emissions is that the first one is applicable to all industries and closely related to the

t+1 and *t+2* for the forward-looking managers who take action and reduce the environmental risk in year *t*.

As shown in Table 6, the coefficient on *FLO × ENV_SCORE (t+1)* are all negatively significant and slightly increases in the next two years when the dependent variable is future GHG emissions with natural log transformation (*LnEMISSION*). The results are similar using *FLO (t+1) × ENV_SCORE (t+1)*. The results indicate that firms with a higher FLO index significantly curtail GHG emissions in the future via the mitigation of future environmental risk. Thus, managerial forward-looking orientation has a real and long-lasting impact on firms' environmental performance, instead of green-washing.

4.6 Value Relevance

Other than environmental risk, another important pillar of sustainability is the economic consequence. We thus also examine the correlation between the FLO index and firm value measured by the natural logarithm of Tobin's Q following Dou, Masulis, and Zein (2019). Table 7 shows that our FLO index is positively correlated with firm value in the same year after controlling for firm and year fixed effects. The result complements the validity test that the FLO index serves as a proxy for sustainability apart from its importance regarding environmental risk. This result is robust to not restricting the sample with non-missing values for environmental score (*ENV_SCORE*) (untabled).

4.7 Endogeneity

To alleviate any potential endogeneity concerns, we use the CEOs' countries of origin as the instrumental variable (IV) for the FLO index. We map a CEO's last name to its ancestral county using Forebears' genealogical records (e.g., Pacelli, 2019). Such ancestral country origin is relatively exogenous in terms of the forward-looking attributes of the managers.

climate issue. While the latter only matters for industries producing toxic chemicals such as petrochemical and paper industries. As our FLO index captures a broader notion of sustainability, we chose to use GHG emissions for the consequence test.

Empirically, there is no such consensus on the forward-looking orientation for a specific ethnic group.[33] We thus use country dummies instead of countries' forward-looking rankings or scores as instrumental variables for the FLO index. Our method is based on the prior studies that adopt multiple dummy variables as instrumental variables to allow for the first-stage heterogeneity (e.g, Angrist and Krueger, 1991; Hansen et al., 2012; Hansen and Kozbur, 2014; Jackson et al., 2016). As shown in Table 8, when using country dummies as IVs for our FLO index, the coefficient on the fitted value of the FLO index ($\widehat{FLO}$) shows a positive (negative) and significant relationship with *ENV_SCORE* (*ENV_CON*). The result is consistent with our main finding.[34]

5. Conclusion

Recent years have witnessed a boom in attention to environmental issues. Nevertheless, there are empirical challenges for investors to identify truly sustainable firms, as sustainability is not easily observable and verifiable. Moreover, green-washing behaviors exist among managers, which makes identifying truly sustainable firms quite challenging for stakeholders.

In this paper, to identify sustainable firms concerning environmental risk, we adopt a machine learning approach to create a firm-level forward-looking orientation (FLO) index. We validate our FLO index by comparing it with heterogenous managerial myopia measures. Our FLO index is negatively associated with the myopia measures, providing validity to our

[33] For instance, Pries et al. (2012) use Google search for future-oriented words to rank the countries, and China ranks 41st as the one among myopia countries. US News ranks the forward-looking countries in 2021 based on a global perception-based survey including bureaucratic, dynamic, entrepreneurial, innovation, and technological expertise. According to US News, China ranks 6th. (https://www.usnews.com/news/best-countries/most-forward-thinking-countries). While CEOWORD Magazine ranks China 26th after comparing 152 countries across 10 key categories: availability of government online services, mobile accessibility, bureaucratic, cashless payments, availability of high-speed internet at home, entrepreneurial, innovative, technological expertise, open access to the internet, and digitally forward-thinking lifestyles. (https://ceoworld.biz/2021/01/31/ranked-worlds-most-forward-thinking-countries-2021/).

[34] Specifically, in the first stage, we regress the FLO index on the country dummies of the CEOs with control variables, firm fixed effects, and year fixed effects (see IA 4). We use a group of African countries as a benchmark. Managers from European countries such as the Netherlands and Luxembourg are more forward-looking. Managers from India are likely to be less forward-looking. Interestingly, we find that managers from U.S. or China are either more or less forward-looking with insignificantly negative coefficients. We conduct a Hansen J-test for overidentification. The instruments pass the tests as the p-value of the J statistic is 0.66. The instruments are not weak as the Kleibergen-Paap RK Wald F statistic is 247.62.

measure. We then show that forward-looking managers are associated with lower corporate environmental risk.

We further find that forward-looking managers would take the environmental issue more seriously when firms are confronted with higher pressure from stakeholders, green investors, and climate risks. However, our result also shows that forward-looking managers are unable to reduce environmental risk when their firms are financially constrained. In addition, we illustrate that firms with forward-looking managers can have a *real impact* on firms' future GHG emissions after they take actions to reduce environmental risk. Therefore, our FLO measurement is unlikely to capture just managerial green-washing behavior.

To sum up, our paper provides a new perspective to identify sustainable firms. To the best of our knowledge, we are the first to adopt a machine learning method to identify the managerial forward-looking orientation and apply this method to the field of sustainable finance. Moreover, our paper also extends the knowledge of forward-looking disclosure by focusing on environmental risk instead of litigation risk associated with the forward-looking statement.

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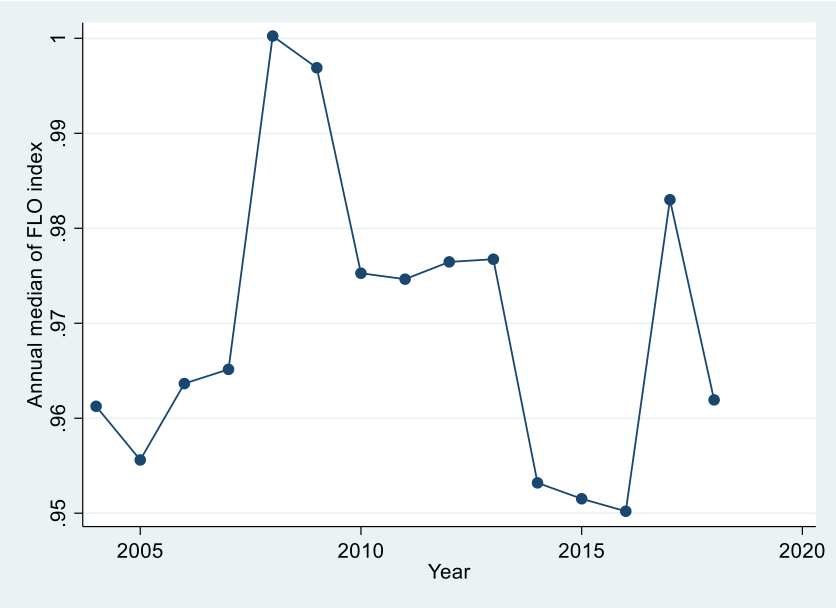
Figure 1. FLO index distribution across years



This figure shows the median value of the FLO index across the years. The data is from 2004 to 2018. The FLO index is the managerial forward-looking index based on the machine learning method with the word cut-offs at 150. Then we plot the median value of the FLO index within each year. The distribution of the mean of the index is qualitatively similar to using the median.

Table 1. Summary statistics

	Mean	St.Dev	p25	Median	p75
FLO	0.958	0.236	0.803	0.958	1.116
ENV_SCORE	0.045	0.630	0.000	0.000	0.000
ENV_CON	0.201	0.602	0.000	0.000	0.000
ENV_STR	0.163	0.535	0.000	0.000	0.000
RepRisk_RRI	9.972	12.405	0.000	0.000	20.000
Refinitiv_ENVSCORE	29.917	28.264	0.950	23.280	54.070
LnEMISSION	13.261	2.170	11.509	13.163	14.749
SIZE	7.406	1.705	6.149	7.293	8.505
Tobin's Q	2.149	1.430	1.261	1.676	2.468
LEV	0.528	0.245	0.355	0.523	0.676
OCF	0.080	0.128	0.053	0.093	0.138
ROA	0.018	0.152	0.009	0.045	0.082
RND/SALE	0.225	1.451	0.000	0.004	0.069
RETURN	0.139	0.476	−0.142	0.089	0.335
CC_EXPO (×1000)	0.970	2.396	0.116	0.297	0.734
CC_RISK (×1000)	0.033	0.162	0.000	0.000	0.000
IOR_PPF	0.019	0.011	0.010	0.018	0.026
IOR_SRI	0.097	0.067	0.045	0.085	0.135
HP_INDEX	−3.854	0.562	−4.430	−3.828	−3.398
UNRATED	0.562	0.496	0.000	1.000	1.000
IOR	0.773	0.201	0.665	0.810	0.915
PSPF	0.221	0.416	0.034	0.086	0.221
OPP_SALE	0.109	0.261	0.005	0.028	0.093
OPP_NSALE	0.098	0.271	0.004	0.027	0.090
CAPX	0.054	0.058	0.019	0.035	0.066
CH_PPEN	0.023	0.070	−0.004	0.006	0.030
CH_RND/SALE	−0.022	0.499	−0.003	0.000	0.002
RND_CUT	0.424	0.494	0.000	0.000	1.000
MJ_ABACCR	0.032	0.038	0.009	0.020	0.041
DD_ABACCR	0.044	0.038	0.020	0.033	0.053
INSDE_OWN	0.057	0.097	0.007	0.019	0.053
DIR_NUM	8.959	2.146	7.000	9.000	10.000
DIR_PCT_MALE	0.875	0.106	0.800	0.875	1.000
DIR_NETWORK	1.660	0.910	0.996	1.476	2.150
DIR_PCT_IND	0.924	0.113	0.875	1.000	1.000
DIR_AGE_SD	7.464	2.247	5.900	7.200	8.900

This table shows the summary statistics of key variables used in the main regression, cross-sectional tests, and additional tests. *FLO* is the managerial forward-looking index based on the machine learning method with the word cut-offs at 150. *ENV_SCORE* is the number of environmental strengths minus environmental concerns based on the MSCI database. All the continuous variables are winsorized at the 99% level. The variable definitions can be found in the Internet Appendix IA 1.

Table 2. Validation test of the FLO index

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) FLO	1.000											
(2) FLO_18	0.818***	1.000										
(3) IOR	0.312***	0.180***	1.000									
(4) CAPX	0.082***	0.030***	−0.034***	1.000								
(5) CH_PPE	0.068***	0.054***	−0.004	0.650***	1.000							
(6) RND/SALE	0.031***	0.005	0.014	0.014	−0.002	1.000						
(7) RND_CUT	−0.026***	0.014*	−0.072***	−0.084***	−0.025***	−0.213***	1.000					
(8) MJ_ABACCR	−0.150***	−0.084***	−0.073***	−0.014*	0.019**	−0.059***	0.033***	1.000				
(9) DD_ABACCR	−0.100***	−0.026***	−0.057***	−0.059***	0.023***	−0.044***	0.037***	0.359***	1.000			
(10) OPP_SALE	−0.072***	−0.068***	0.032***	0.028***	0.050***	0.006	0.008	0.072***	0.038***	1.000		
(11) OPP_NSALE	−0.037***	−0.048***	0.049***	0.026**	0.049***	0.016	0.002	0.052***	0.023**	0.974***	1.000	
(12) PFPS	−0.031***	−0.054***	−0.078***	0.059***	0.065***	0.006	−0.012	−0.064***	−0.075***	−0.005	0.009	1.000

This table shows the validity tests of the *FLO* and its correlation with traditional managerial myopia measures. We choose five dimensions to validate the measure: institutional ownership, managerial myopia/ short-termism (capital expenditure, change in property, plant, and equipment, change in R&D or R&D cut), earnings management, insider trading, and CEO pay for performance sensitivity. We also compare the machined learned approach of the FLO index and simple word count based on the seed words approach of the FLO index (*FLO_18*). The variable definitions can be found in the Internet Appendix IA 1. Statistical significance at the 1%, 5%, and 10% levels are represented by ***, **, and *, respectively.

Table 3. Managerial forward-looking and corporate environmental risk

	(1)	(2)	(3)
Dependent Variable =	*ENV_SCORE*	*ENV_CON*	*ENV_STR*
FLO	0.182***	−0.179***	0.019
	(5.058)	(−5.727)	(0.611)
SIZE	−0.025	0.159***	0.126***
	(−1.296)	(8.545)	(8.028)
Tobin's Q	−0.015**	0.021***	0.006
	(−2.175)	(4.690)	(1.026)
LEV	−0.193***	0.160***	−0.038
	(−4.528)	(4.490)	(−0.977)
OCF	0.013	−0.002	0.025
	(0.243)	(−0.049)	(0.517)
ROA	−0.125***	0.063*	−0.068*
	(−2.857)	(1.849)	(−1.883)
RND/SALE	0.001	−0.001	−0.000
	(0.420)	(−0.747)	(−0.092)
RETURN	0.004	−0.015**	−0.014*
	(0.417)	(−2.399)	(−1.739)
Constant	0.188	−0.971***	−0.743***
	(1.294)	(−6.752)	(−6.180)
Firm & Year FE	Yes	Yes	Yes
Obs.	18,134	18,134	18,134
R-squared	0.411	0.585	0.498

This table shows the main regression result of the correlation between the FLO index and future environmental risk. The independent variable is the FLO index based on 150 words cut-off. The dependent variable in Column 1 is the environmental score (*ENV_SCORE*) in year *t+1* calculated as the number of environmental strengths (*ENV_STR*) minus the number of concerns (*ENV_CON*). The dependent variable in Column 2 is the number of environmental concerns in year t+1. The dependent variable in Column 3 is the number of environmental strengths in year *t+1*. We add firm and year fixed effects for three columns. All the variables are defined in the Internet Appendix IA 1. *, **, *** indicate two-sided statistical significance at the $p < 0.1$, $p<0.05$, and $p<0.01$ levels, respectively based on robust standard errors of the coefficient estimates clustered at the firm level.

Table 4. Cross-sectional tests

Panel A: Threats from climate change

Dependent Variable =	*ENV_SCORE*	
	(1)	(2)
FLO × HIGH_CC_EXPO	0.113**	
	(2.496)	
FLO × HIGH_CC_RISK		0.156**
		(2.223)
FLO	0.127***	0.164***
	(3.268)	(4.531)
HIGH_CC_EXPO	−0.104**	
	(−2.577)	
HIGH_CC_RISK		−0.125*
		(−1.814)
Constant	0.239	
	(1.622)	
Controls	Yes	Yes
Firm & Year FE	Yes	Yes
Obs.	17,901	17,901
R-squared	0.412	0.412

Panel B. Sustainable investors

Dependent Variable =	*ENV_SCORE*	
	(1)	(2)
FLO × HIGH_IOR_PPF	0.211***	
	(3.686)	
FLO × HIGH_IOR_SRI		0.088*
		(1.770)
FLO	0.080**	0.151***
	(2.139)	(3.966)
HIGH_IOR_PPF	−0.181***	
	(−3.413)	
HIGH_IOR_SRI		−0.059
		(−1.286)
Constant	0.229	0.207
	(1.569)	(1.353)
Controls	Yes	Yes
Firm & Year FE	Yes	Yes
Obs.	17,398	16,366
R-squared	0.408	0.406

Panel C. Stakeholders' attention across years and industries

Dependent Variable =	*ENV_SCORE*	
	(1)	(2)
FLO × LATE_YEAR	0.398***	
	(5.767)	
FLO × POLLUT_IND		0.293***
		(2.780)
FLO	−0.024	0.124***
	(−0.500)	(3.405)
Constant	0.101	0.195
	(0.710)	(1.337)
Controls	Yes	Yes
Firm & Year FE	Yes	Yes
Obs.	18,134	18,134
R-squared	0.416	0.412

Panel D. Financial constraints

Dependent Variable =	*ENV_SCORE*		
	(1)	(2)	(3)
FLO × HIGH_HP_INDEX	−0.150**		
	(−2.355)		
FLO × SMALL		−0.263***	
		(−3.674)	
FLO × UNRATED			−0.245***
			(−2.806)
FLO	0.248***	0.322***	0.296***
	(4.627)	(4.907)	(3.872)
HIGH_HP_INDEX	0.209***		
	(3.213)		
SMALL		0.290***	
		(4.114)	
UNRATED			0.246***
			(2.796)
Constant	0.050	−0.050	0.052
	(0.321)	(−0.284)	(0.307)
Controls	Yes	Yes	Yes
Firm & Year FE	Yes	Yes	Yes
Obs.	18,134	18,134	15,551
R-squared	0.412	0.413	0.456

This table shows the cross-sectional tests focusing on the firms' exposure/risk to climate change, stakeholders' attention, sustainable investors, and financial constraints. In Panel A, the climate change exposure/risk (*CC_EXPO / CC_RISK*) is based on the index created by Sautner et al. (2022). The High-low partition is based on the yearly sample median. In Panel B, we use public pension fund holding (*IOR_PPE*) and SRI investor holding (*IOR_SRI*) as proxies for sustainable investors. In Panel C, *LATE_YEAR* is a dummy variable that equals one if the year is larger than the year 2010; zero otherwise. *POLLUT_IND* is a dummy variable that equals one if the firm belongs to a highly polluted industry; zero otherwise. The coefficients on *LATE_YEAR* and *POLLUT_IND* are absorbed by year FE and firm FE respectively. In Panel D, we use three proxies, the HP index, Firm size, and S&P bond rating for financial constraints. Continuous variables are partitioned based on the yearly sample median. Control variables in Table 3 are included. All the variables are defined in the Internet Appendix IA 1. *, **, *** indicate two-sided statistical significance at the p< 0.1, p<0.05, and p<0.01 levels, respectively based on robust standard errors of the coefficient estimates clustered at the firm level.

Table 5. Additional tests

Panel A. Other environmental risk measures

	(1)	(2)
Dependent Variable =	*RepRisk _RRI*	*Refinitiv_EVNSCORE*
FLO	−1.071**	3.097**
	(−2.090)	(2.300)
SIZE	2.187***	4.422***
	(8.355)	(4.433)
Tobin's Q	0.325***	0.191
	(2.882)	(0.648)
LEV	−0.098	−2.420
	(−0.128)	(−0.963)
OCF	2.101*	1.679
	(1.911)	(0.582)
ROA	−2.722***	−2.463
	(−3.075)	(−1.191)
RND/SALE	0.037	0.060
	(0.570)	(0.881)
RETURN	0.032	−0.606*
	(0.189)	(−1.732)
Constant	−7.506***	−9.630
	(−3.581)	(−1.119)
Firm & Year FE	Yes	Yes
Obs.	13,709	8,491
R-squared	0.601	0.866

Panel B. Additional controls

Dependent Variable =	(1) *ENV_SCORE*	(2) *ENV_CON*	(3) *ENV_STR*
FLO	0.337***	−0.252***	0.106
	(3.228)	(−3.820)	(1.016)
SIZE	0.130	0.251***	0.396***
	(1.617)	(4.854)	(4.890)
Tobin's Q	−0.013	0.029***	0.017
	(−0.538)	(2.986)	(0.690)
LEV	−0.170	0.196**	0.049
	(−0.916)	(2.054)	(0.255)
OCF	−0.055	0.271	0.260
	(−0.184)	(1.430)	(0.867)
ROA	−0.202	0.064	−0.123
	(−0.960)	(0.454)	(−0.520)
RND/SALE	0.007	0.065	0.081
	(0.098)	(1.415)	(1.006)
RETURN	−0.093***	−0.022	−0.105***
	(−2.676)	(−1.199)	(−3.249)
IOR	0.365	0.183	0.557*
	(1.256)	(1.240)	(1.948)
PSPF	0.166	−0.008	0.153
	(1.231)	(−0.113)	(1.148)
OPP_NSALE	−0.130*	−0.027	−0.154**
	(−1.886)	(−0.916)	(−2.072)
RND_CUT	−0.005	0.023*	0.016
	(−0.148)	(1.743)	(0.537)
CAPX	0.098	0.365	0.546
	(0.136)	(0.693)	(0.907)
CH_PPE	−0.671**	0.061	−0.618**
	(−2.162)	(0.243)	(−2.456)
DD_ABACCR	0.046	0.221	−0.133
	(0.053)	(0.400)	(−0.168)
MJ_ABACCR	−0.424	0.059	−0.375
	(−1.265)	(0.331)	(−1.093)
INSIDE_OWN	−0.211	−0.448**	−0.632
	(−0.395)	(−2.251)	(−1.221)
DIR_NUM	−0.010	0.011	0.004
	(−0.550)	(0.995)	(0.214)
DIR_PCT_MALE	−0.047	0.001	0.019
	(−0.153)	(0.005)	(0.064)
DIR_NETWORK	0.125**	−0.021	0.092*
	(2.333)	(−0.608)	(1.828)
DIR_PCT_IND	0.097	0.179	0.290
	(0.267)	(0.877)	(0.837)
DIR_AGE_SD	−0.013	0.004	−0.009
	(−0.972)	(0.547)	(−0.652)
Constant	−1.460	−2.350***	−4.054***
	(−1.593)	(−3.615)	(−4.512)
Firm & Year FE	Yes	Yes	Yes
Obs.	4,031	4,031	4,031
R-squared	0.490	0.497	0.582

Panel C. Decile ranking of the FLO index

Dependent Variable =	(1) *ENV_SCORE*	(2) *ENV_CON*	(3) *ENV_STR*
DECILE_FLO	0.015***	−0.013***	0.004
	(5.288)	(−5.572)	(1.470)
Constant	0.282*	−1.066***	−0.737***
	(1.938)	(−7.388)	(−6.171)
Controls	Yes	Yes	Yes
Firm & Year FE	Yes	Yes	Yes
Obs.	18,134	18,134	18,134
R-squared	0.412	0.585	0.498

Panel D. Other cut-offs of the dictionary

Dependent Variable =	*ENV_SCORE*		
	(1)	(2)	(3)
FLO_75	0.195***		
	(3.982)		
FLO_300		0.167***	
		(5.791)	
FLO_450			0.125***
			(5.294)
Constant	0.215	0.171	0.181
	(1.469)	(1.179)	(1.254)
Controls	Yes	Yes	Yes
Firm & Year FE	Yes	Yes	Yes
Obs.	18,134	18,134	18,134
R-squared	0.411	0.412	0.412

Panel E. Other weighted methods

Dependent Variable =	*ENV_SCORE*			
	(1)	(2)	(3)	(4)
FLO_75WEI	0.380***			
	(3.149)			
FLO_150WEI		0.418***		
		(4.040)		
FLO_300WEI			0.433***	
			(4.695)	
FLO_450WEI				0.374***
				(4.509)
Constant	0.236	0.213	0.196	0.199
	(1.607)	(1.454)	(1.345)	(1.368)
Controls	Yes	Yes	Yes	Yes
Firm & Year FE	Yes	Yes	Yes	Yes
Obs.	18,134	18,134	18,134	18,134
R−squared	0.411	0.411	0.411	0.411

This table shows the additional tests on the negative correlation between the FLO index and future environmental risk. Panel A adopts two additional databases of environmental risk: RepRisk current risk index and Refinitiv ESG environmental score in year *t+1*. Panel B adds additional controls. Panel C replaces the independent variable as the decile ranking of the FLO index. Panel D adopts different cut-offs of the words-embedding model. Panel E adopts the weighted method of forward-looking words to create an FLO index with different cut-offs. Control variables in Table 3 are included. All the variables are defined in the Internet Appendix IA 1. *, **, *** indicate two-sided statistical significance at the $p< 0.1$, $p<0.05$, and $p<0.01$ levels, respectively based on robust standard errors of the coefficient estimates clustered at the firm level.

Table 6. Consequences on future GHG emissions

Dependent Variable =	*LnEMISSION (t+2)*		*LnEMISSION (t+3)*	
	(1)	(2)	(3)	(4)
FLO (t) × ENV_SCORE (t+1)	−0.232**		−0.272***	
	(−2.424)		(−2.611)	
FLO (t+1) × ENV_SCORE (t+1)		−0.265**		−0.295***
		(−2.511)		(−2.736)
FLO (t)	−0.290*		−0.175	
	(−1.769)		(−0.873)	
FLO (t+1)		−0.069		−0.332*
		(−0.433)		(−1.836)
ENV_SCORE (t+1)	0.277***	0.320***	0.295***	0.326***
	(2.635)	(2.681)	(2.612)	(2.704)
SIZE	0.219	0.231	0.151	0.158
	(1.359)	(1.408)	(0.971)	(1.011)
Tobin's Q	−0.052	−0.038	−0.012	−0.007
	(−0.681)	(−0.500)	(−0.170)	(−0.102)
LEV	0.481	0.536*	0.425	0.452
	(1.609)	(1.709)	(1.418)	(1.427)
OCF	1.247**	1.201**	0.485	0.427
	(2.560)	(2.294)	(1.237)	(1.015)
ROA	0.221	0.172	−0.220	−0.253
	(0.631)	(0.415)	(−0.884)	(−0.862)
RND/SALE	3.422	3.896	0.480	0.652
	(1.165)	(1.312)	(0.334)	(0.457)
RETURN	0.031	0.031	0.085	0.081
	(0.650)	(0.622)	(1.581)	(1.454)
Constant	11.205***	10.797***	11.831***	11.917***
	(7.297)	(6.943)	(8.111)	(7.971)
Firm & Year FE	Yes	Yes	Yes	Yes
Obs.	1,645	1,623	1,584	1,562
R-squared	0.914	0.914	0.913	0.914

This table shows the two consequence tests focusing on the future GHG emission. The dependent variable is the firm level GHG emission in years *t+2*, and *t+3*. Annual emission data is available from the year 2009 to the year 2019. Reporting year is from 2010 to 2020. We regress the future emission on the interaction term of the FLO index in year t or *t+1* multiplied by the environmental score (*ENV_SCORE*) in year *t+1*. The coefficients on the interaction term further show the future emission when forward-looking managers reduce environmental risk in the next year. Control variables in Table 3 are included. All the variables are defined in the Internet Appendix IA 1. *, **, *** indicate two-sided statistical significance at the p< 0.1, p<0.05, and p<0.01 levels, respectively based on robust standard errors of the coefficient estimates clustered at the firm level.

Table 7. Value relevance of the FLO index

	(1)
Dependent Variable =	*LnTobin's Q*
FLO	0.027**
	(2.017)
SIZE	−0.133***
	(−15.155)
LEV	0.087***
	(2.887)
OCF	0.285***
	(5.938)
ROA	0.256***
	(7.806)
RND/SALE	0.006
	(1.222)
RETURN	0.166***
	(30.731)
Constant	1.937***
	(29.428)
Firm & Year FE	Yes
Obs.	18,134
R-squared	0.821

This table shows the value relevance of the FLO index. The dependent variable is the natural logarithm of Tobin's Q in year t. The results are qualitatively similar when replacing the logarithm with the value of Tobin's Q. All the variables are defined in the Internet Appendix IA 1. *, **, *** indicate two-sided statistical significance at the p< 0.1, p<0.05, and p<0.01 levels, respectively based on robust standard errors of the coefficient estimates clustered at the firm level.

Table 8. Endogeneity - CEOs' countries of origin as an instrumental variable

	Second Stage		
	(1)	(2)	(3)
Dependent Variable =	*ENV_SCORE*	*ENV_CON*	*ENV_STR*
$\widehat{FLO}$	1.076*	−0.950**	0.154
	(1.816)	(−2.460)	(0.306)
SIZE	−0.052*	0.181***	0.119***
	(−1.654)	(7.097)	(4.395)
Tobin's Q	−0.018**	0.022***	0.004
	(−2.433)	(4.325)	(0.562)
LEV	−0.167***	0.125***	−0.048
	(−3.494)	(3.290)	(−1.120)
OCF	−0.029	0.017	0.006
	(−0.467)	(0.364)	(0.125)
ROA	−0.089*	0.008	−0.086**
	(−1.648)	(0.204)	(−2.005)
RND/SALE	0.004	−0.004	−0.000
	(1.265)	(−1.625)	(−0.119)
RETURN	0.019	−0.027***	−0.011
	(1.319)	(−2.643)	(−0.875)
Firm & Year FE	Yes	Yes	Yes
Obs.	16,037	16,037	16,037
Centered R-squared	0.374	0.535	0.493

This table represents the second-stage regression results based on 2SLS. In the first state, we regress the FLO index on the origin country dummy of the CEO with control variables, firm, and year fixed effects (first-stage regression result is reported in IA Table). Then we regress the environmental risk (*ENV_SCORE*, *ENV_CON*, *ENV_STR*) on the instrumented FLO index ($\widehat{FLO}$). All the variables are defined in the Internet Appendix IA 1. *, **, *** indicate two-sided statistical significance at the p< 0.1, p<0.05, and p<0.01 levels, respectively based on robust standard errors of the coefficient estimates clustered at the firm level.

Internet Appendix

"Managerial forward-looking and firm environmental risk: Evidence from the machine learning approach"

The purpose of this internet appendix is to provide additional tests for our findings. These additional tests are labeled with the extension "IA" for "Internet Appendix" (e.g., Table IA), while the tables reported in the main text are labeled with the original table name. We discuss the supplementary tables below.

IA 1 is the variable definitions containing all variables used in the main tables and the analysis in the internet appendix.

IA2 lists the words of the dictionary for our FLO index after machine learning and manual checking. As we have different cut-offs, we have several dictionaries with different quantities of the word after the word-embedding model. Some vocabularies are ambiguous or unreadable abbreviations such as "rp", "sg" etc. Thus, we manually drop such words before creating the FLO index.

IA3 illustrates the technical introduction of the word-embedding model and TFIDF weighting method.

IA4 is the first stage regression results of the FLO index on the CEO's origin country dummy. We use a group of African countries as a benchmark, and the coefficients on each country dummy manifest the relatively forward-looking orientation of managers compared to the managers with the last name of African origin.

IA5 shows the determinants for the FLO index. We find that firms' fundamentals are highly correlated with the index. In Column 1, Big firms and firms with higher leverages are more likely to have managers with forward-looking orientation. While higher firm value and intensive R&D investment are negatively associated with the FLO index. When adding characteristics of the board of directors in Column 2, it suggests that those characteristics are plausibly irrelevant to the FLO. The results indicate that our FLO index is not merely a reflection of internal corporate governance after controlling for firm and year fixed effects. While in Column 3, we add managerial incentives and find that the pay-for-performance sensitivity of the compensation is negatively related to the FLO index, which is consistent with our validation test in Table 2.

IA 6 is a robustness test by replacing the FLO index with the CEOs' FLO index, where we only use the CEOs' answers to conduct machine learning and create the CEO_FLO index. The purpose of the test is that CEOs are key senior managers who determine the business strategy of corporations. Compared to CFOs or other types of senior managers. It is more likely that CEOs would focus on sustainable development strategy as a whole instead of only focusing on earnings or revenues.

Internet Appendix

IA 1. Variable definition

Variable	Definition
FLO	Managerial forward−looking measure based on machine learning method with the cut off of 150 vocabularies. *FLO_150WEI* is weight-adjusted based on the closeness of the words to the seed words.
DECILE_FLO	The decile ranking of FL_150 among our sample. *DECILE_FL_150* equals one if *FL_150* belongs to the lowest 10 percentile; it equals one0 if FL_150 belongs to the highest 10 percentile.
FLO_18	Weighted−frequency count of 18 seed words that measure managerial forward−looking orientation in the QA section of earnings conference calls.
FLO_75	Managerial forward−looking measure based on machine learning method with the cut off of 75 vocabularies. *FLO_75WEI* is weight-adjusted based on the closeness of the words to the seed words.
FLO_300	Managerial forward−looking measure based on machine learning method with the cut off of 300 vocabularies. *FLO_300WEI* is weight-adjusted based on the closeness of the words to the seed words.
FLO_450	Managerial forward−looking measure based on machine learning method with the cut off of 450 vocabularies. *FLO_450WEI* is weight-adjusted based on the closeness of the words to the seed words.
ENV_SCORE	The environmental score is calculated as the number of environmental strengths minus the number of environmental concerns from the MSCI dataset. Higher *ENV_SCORE* represents a lower environmental risk
ENV_CON	The number of environmental concerns from the MSCI dataset.
ENV_STR	The number of environmental strengths from the MSCI dataset.
RepRisk_RRI	Current risk index from RepRisk, ranging from 0 to 100. The higher value of *RepRisk_RRI* represents a higher risk.
Refinitiv_EVNSCORE	Environmental score from Refinitiv ESG dataset (Original Asset4). The higher value of *Refinitiv_EVNSCORE* represents a lower environmental risk.
SIZE	The natural logarithm of the total assets.
Tobin's Q	*Tobin's Q* is calculated as the market value of equity (*PRCC_F* * *CSHO*) plus the book value of total assets (*AT*) minus the book value of equity (*CEQ*), then scaled by the book value of total assets (*AT*). *LnTobin's Q* is the natural logarithm of *Tobin's Q*.
LEV	Long-term debt scaled by the total asset.
OCF	Operating cash flow scaled by total asset
ROA	Income before extraordinary items scaled by total asset
RND/SALE	Research and development (*R&D*) expenditure scaled by sales. *RND* is replaced with 0 if missing.
RETRUN	Buy-hold annual return.
IOR	Institutional ownership ratio calculated as the sum of shares held by each institution divided by the total shares outstanding
CAPX	Capital expenditure scaled by total asset
CH_PPE	The change of *PPENT* (net value of total Property, Plant, and Equipment) scaled by total asset
CH_RND/SALE	Change of *R&D* expenditure scaled by sales.
RND_CUT	An indicator variable equals one if the change of *R&D* expenditure is smaller than 0; zero otherwise
MJ_ABACCR	Modified Jones Model (Dechow et al., 1995) for non-singed abnormal accrual, measured as the absolute value of the residual. It is the cross-sectional abnormal accrual based on industry-year-quarter regression.

	$$TA_{i,t} = \beta_0 + \beta_1 1/AT_{i,t-1} + \beta_2(\Delta REV_{i,t} - \Delta AR_{i,t}) + \beta_3 PPE_{i,t} + \epsilon$$ where *TA* is total accrual, the sum of changes in accounts receivables, inventories, accounts payable, taxes payable, other accounts that affect accruals, and depreciation, multiplied by −1 and deflated by lagged total assets. ΔREV is the change in sales; ΔAR is the change in accounts receivable; *PPE* is gross property, plant, and equipment.
DD_ABACCR	Modified Dechow-Dichev discretionary accruals, measured as the 5-year rolling window standard deviation of residuals from the Dechow and Dichev [2002] model modified by McNichols [2002]. It's the cross-sectional abnormal accrual based on industry-year-quarter regression. $$\Delta WC_{i,t} = \beta_0 + \beta_1 CFO_{i,t-1} + \beta_2 CFO_{i,t} + \beta_3 CFO_{i,t+1} + \beta_4 PPE_{i,t} + \beta_4 \Delta SALE_{i,t} + \epsilon$$ We scale the variable by total assets in the beginning quarter. ΔWC is the same calculation as total accrual.
OPP_SALE	Shares that are opportunistically sold by insiders (officers or directors) as a percentage of the firm's shares outstanding, aggregated for each firm-year. Opportunistic trades are defined as by Cohen et al. (2012). An insider is considered to be an officer or a director if his/her highest role (ROLECODE1) belongs to 'CB', 'D', 'DO', 'H', 'OD', 'VC', 'AV', 'CEO', 'CFO', 'CI', 'CO', 'CT', 'EVP', 'O', 'OB', 'OP', 'OS', 'OT', 'OX', 'P', 'S', 'SVP', 'VP' in Thomson Reuters database.
OPP_NSALE	Net opportunistic sales as the opportunistic sales minus opportunistic purchases. *OPP_NSALE* is the net value of opportunistically sold by insiders as the percentage of shares outstanding, aggregated for each firm-year.
PFPS	Pay for performance sensitivity following Bergstresser and Philippon (2006) to calculate *ONEPCT* as the total change in value of executives' stock and stock options portfolio in response to a one percent change in stock price. Next, we calculate *PFPS* as *ONEPCT/ (ONEPCT + Salary + Bonus).*
INSIDE_ONW	The total number of shares held in aggregate by all officers and directors divided by the number of shares outstanding.
LATER_YEAR	A dummy variable equals one if year is larger than the year 2010; zero otherwise.
POLLUT_IND	A dummy variable equals one if the firm belongs to a highly polluted industry; zero otherwise. The highly polluting industry contains agriculture, transportation, electric power, plus the oil industry.
IOR_PPF	The public pension fund's ownership ratio follows Kim, Wan, Wang, and Yang (2019). The classification of public pension funds is from Professor Bushee's website.
IOR_SRI	Socially responsible investor ownership ratio, following Cao, Titman, Zhan, and Zhang (2019)
SMALL	Dummy variable equals one if the *SIZE* is lower than the yearly median value.
HP_INDEX	HP index used in (Hadlock and Pierce 2010). *HP_INDEX* = $-0.737 \times SIZE + 0.043 \times SIZE^2 - 0.04 \times AGE$, where *SIZE* is capped at the log of ($4.5 billion) and *AGE* is capped as 37 years.
UNRATED	Dummy variable equals one if the firm is not covered by the S&P rating for long-term bond; zero otherwise.
DIR_NUM	Number of directors.
DIR_PCT_MALE	Percentage of the male directors
DIR_NETWORK	Directors network size divided by 1000.
DIR_PCT_IND	Percentage of the independent directors
DIR_AGE_SD	Standard deviation of the directors' ages.
LnEMISSION	Natural logarithm of the firm's greenhouse gas emission each year.

IA 2. Dictionary of forward-looking after machine learning and manual checking

Cut-offs	Words included
Seed Words (1−18)	{"estimate","expect","anticipate","believe","plan","hope","intend","intent","intention","seek","project","forecast","objective","goal","future","expectation","hopefully","assume"}
CUT_OFF (19−75)	{"projection","hopeful","target","guidance","likely","presumably","anticipated","aspiration","thereafter","expected","envision","assumption","commit","contemplate","feel_comfortable","time_frame","anticipation","estimation","able","feasibility_study","achieve","outlook","strive","timeframe","contingency","commitment","ambition","rate","profitability","fiscal","top_line","long_range_plan","path","earnings","nda_filing","ultimate_goal","guide","go","least","likelihood","milestone","pace","remainder","think","remain_committed","revenue","payout","budget","adjusted_ebitda","midpoint","result","timetable"}
CUT_OFF (76−150)	{"belief","date","threshold","ebitda","cash_flow","continue","period","course","net_income","timeline","progressively","baseline","topline","highly_confident","probability","full_year_guidance","planned","schedule","return","thereby","confident","minimum","balance","aim","trajectory","ordinal_half","therefore","level","foreseeable","range","capital_expenditure","operating_income","expenditure","near_term","operating_profit","hurdle_rate","confidence","pivotal_trial","margin","allow","roe","order","profit","milestone_payment","prepare","reserve","backlog","pro_forma","achieve_objective","mid−year","full−year","probably","shareholder_value","clinical_study","midpoint_guidance","certainly","gradually","chapada","phase_iii","waiver","lrp","midyear","originally","thus","dividend","originally_anticipate","indication","position","scop_study","revenue_stream","achievable","accelerated"}
CUT_OFF (151−300)	{"revise_guidance","means","midterm","capital","suggest","attempt","scenario","ebit","desire","midpoint_range","accrual","scrubber","priority","production","dropdown","allowance","funding","towards","ppa","modestly","enrollment","phase","even","payout_ratio","guideline","fund","program","funding_mechanism","debt_repayment","proceeds","wassa","sustainable","taxable_income","contract","outlay","model","envisage","substantially","oibda_margin","basis","cash","gualcamayo","necessary","volume","number","annualize","foresee","breakeven","dividend_policy","growth","near_term","share","mid_teens","obviously","revise","adjust_ebitda","sometime","calendar","possibly","share_repurchase","annualize_basis","megawatt","entitlement","pivotal_study","noi","medium_term","authorization","curve","ounce","eps","ensure","exceed","incentive_compensation","suspect","capex","potentially","organic_growth","budgeting","possible","go_forward_basis","presume","track","mayfield_dealer","sustained","forward","yet","line_sight","obligation","view","accrue","onward","expense","sbic","framework","necessitate","mine_life","toward","proceed","attain","accordance","indeed","throughout_remainder","unitholder","march","subsequent","ultimately","ind","incrementally","appropriation","gross_margin","primary_endpoint","sustain","registration_trial","earn_out","predict","possibility","opex","potential","try","after_tax_return","strategy","earning","federal_funding","year_end","refund","bottom_line","steady_state","double_digit","provision","guarantee","increment","manner","predicate","esp","unlikely","pivotal_phase","fort_hill","upon","per_annum","operating_expense","profitable","accordingly","beyond","aspirational_goal"}

CUT_OFF (301−450)	{"feasibility","resolution","smelter","pretax","tonne","regular_dividend","tax_credit","revpar","incentive","cod","aspire","sustainably","registration_study","borrowing","output","subsequent_quarter","organically","meaningfully","buyback","capitalization","achievement","nius","bogey","shareholder","top_line","membership","ep_accretion","long_term","need","investment","otherwise","free_cash","mandate","share_buyback","albeit","dod_budget","indicate","determination","execute","solid_foundation","begin","capacity","ounce_gold","bogoso/prestea","probability_success","pay_debt","irr","dividend_payout","base","ideally","per_ounce","time","submission","submission_fda","thinking","repayment","interim_analysis","pathway","ebit_margin","contractual_obligation","charter","tonnage","prefeasibility_study","incremental","vest","pilar","see","yield","contingency_plan","authorize","clinical_trial","comfortably","completion","eventual","ability","subsequently","roa","approximate","stage","pit","term","contractual_commitment","nominally","could","estimated","incentive_fee","opportunity","commercialization","book","fuel_clause","afe","promise","cost","tuition","balance_sheet","cash_outlay","end","accelerate","working_capital","ce_mark","eligible","rio_nance","price","break_even","irp","comfortable","planning","ind.","dose","hurdle","latter_part","same_store_noi","presumption","suruca","bonus_depreciation","filer","forecasting","approximately","cost_savings","intended","entitle","gross_profit","criterion","modeling","original","maintain","eventually","mid_term","renewable","tce","cohort","slightly","mission","eac","prospectus","significantly","tonne_per","restricted_stock","fully","upper_end","modest","regulatory_approval","unit_holder","regulatory_filings","way"}

This table lists the words included in the FLO index. Starting with the seed words, we adopt the word-embedding model to seek related words of the seed words. We use different cut-offs to calculate the FLO index. For instance, FLO_75 is the index based on the seed words and cut-off lists from 0 to 75. We manually drop a few unclear or ambiguous words such as “rp”, “fy15”, “sg” etc. Including these words does not change the results. Our seed words follow Li (2010), while the words such as “will”, “could”, “can” etc. are recognized as stop words from the sample during the text-cleaning stage. Besides such words could be regarded as modal particles instead of future orientation.

IA 3. Technical introduction of the word-embedding model

We use a method similar to Li et al. (2021) in constructing the forward‒looking orientation measurement. We use the QA section of earnings conference calls and remove the questions asked by analysts and the speech by operators. The name of the speakers and their titles are also removed from our analysis. In this way, we are able to focus on speeches made by CEOs, CFOs, and other company executives.

Then, we use the Stanford CoreNLP package version 3.9.1 (released on 2018-02-27) to parse the text. We follow a pipeline of sentence segmentation and tokenization, lemmatization, and Named Entity Recognition (NER). Sentence segmentation splits the text into a list of individual sentences, and tokenization splits each sentence into individual words. Then lemmatization transforms the words into their base forms. For example, "was" is transformed into "be", and "made" is transformed into "make". Lastly, we replace named entities with tags using NER. For example, "As of August 2022, Microsoft has a market cap of $ 2.049 Trillion." is transformed into "As of [NER: DATE] [NER: ORGANIZATION] has a market cap of [NER: MONEY]." [35]

Next, we remove punctuation marks, stop words, and single‒letter words. We use a stop words list from the NLTK corpus. Words such as "we", "an", "be", "will", "should", "by", and "how" are removed.[36]

After the initial data-cleaning process, we follow Li et al. (2021) and use the *phraser* module from the *genism* library to find two- and three-word phrases that are specific to our corpus. We set the parameters as follows:

- min_count = 5: ignore all words and bigrams with a total collected count lower than 5;
- threshold = 10: a phrase of words "a" followed by "b" is accepted if the score of the phrase is greater than 10;
- scoring = 'default': bigram scoring function based on the original Mikolov, et al. (2013)

If the score for any two words is greater than 10, we concatenate them using an underscore and treat them as a single word. Then, we run the algorithm again to learn three-word phrases.

We use the *Word2Vec* module from the *genism* library in Python to train our model, with parameters set as below:

- vector_size = 300: we use a vector of size 300 to represent a word;
- window = 5: the maximum distance between the current and predicted word within a sentence is 5;
- min_count = 5: ignores all words that appeared less than 5 times in the corpus;
- negative = 5: uses negative sampling, and 5 "noise words" are drawn.

After training, we have a 300-dimensional vector for each of the 113,992 words in the corpus. Each vector represents the meaning of the corresponding word, and the cosine similarity between two vectors quantifies the association between two words. Therefore, we are able to use the 18 seed words from Li (2010) to generate a dictionary to measure the forward-looking orientation. We first compute the average of the vectors of the seed words and then compute the cosine similarity between this average vector and each unique word in the corpus. We select the top 75, 150, 300, and 450 words with the

[35] An in-depth description of each steps can be found in https://stanfordnlp.github.io/CoreNLP/.
[36] The stop words corpus can be downloaded at https://www.nltk.org/nltk_data/.

closest associations with the seed words as the expanded dictionary for the forward−looking orientation measure. The expanded dictionary is in IA Table 2.

After generating the forward-looking orientation dictionary, we measure the FLO index at the firm-year level. If there are multiple conference calls in the same year, we take the average for the FLO indexes. For each transcript, we use the term frequency-inverse document frequency (TFIDF) weighting to compute the FLO score. TFIDF puts higher weights on terms that appear more frequently within the transcript and lower weights on terms that appear more frequently across all documents. For robustness tests, we adjust the TFIDF weight with how similar each dictionary word is to the seed words. Specifically, the dictionary words are ranked by similarity, and the similarity weights are 1/log(1+rank). For example, "estimate" is the first dictionary word for forward-looking orientation, and its weight is the TFIDF weight times 1/log (1+1).

IA 4. First-stage regression results of the FLO index on the CEO's original country

	First Stage			
Dependent Variable = FLO	Coef.	s.e	t−value	p−value
Argentina	0.038	0.040	0.940	0.349
Australia	0.005	0.030	0.170	0.866
Austria	0.011	0.065	0.160	0.871
Bangladesh	−0.034	0.042	−0.820	0.412
Belgium	−0.001	0.047	−0.010	0.989
Bolivia	0.181***	0.022	8.410	0.000
Brazil	−0.023	0.030	−0.760	0.449
Cambodia	0.021	0.027	0.780	0.436
Canada	0.002	0.031	0.060	0.951
Chile	0.050*	0.030	1.670	0.095
China (Mainland)	−0.055	0.039	−1.420	0.155
Croatia	−0.064	0.083	−0.760	0.445
Cyprus	−0.041	0.045	−0.900	0.369
Denmark	0.047	0.039	1.210	0.226
England	−0.004	0.026	−0.140	0.890
France	−0.003	0.027	−0.130	0.897
Germany	−0.018	0.022	−0.830	0.405
Greece	−0.103	0.150	−0.690	0.493
Hong Kong	−0.015	0.023	−0.630	0.532
Hungary	0.047	0.085	0.550	0.584
India	−0.065**	0.030	−2.120	0.034
Indonesia	−0.043	0.037	−1.180	0.236
Iran	−0.046	0.078	−0.590	0.558
Iraq	−0.308	0.288	−1.070	0.284
Ireland	−0.016	0.052	−0.310	0.758
Italy	−0.022	0.023	−0.930	0.351
Japan	−0.070	0.056	−1.250	0.210
Jordan	−0.153***	0.024	−6.290	0.000
Korea South	0.138	0.114	1.210	0.227
Lebanon	0.006	0.062	0.090	0.925
Luxembourg	0.195**	0.083	2.350	0.019
Malta	0.042	0.041	1.010	0.313
Mauritania	0.282***	0.020	14.080	0.000
Mexico	−0.007	0.033	−0.220	0.824
Myanmar	−0.021	0.045	−0.470	0.636
Netherlands	0.071**	0.032	2.230	0.026
North Korea	0.140***	0.021	6.710	0.000
Northern Cyprus	0.188***	0.020	9.530	0.000
Norway	0.032	0.075	0.420	0.673
Pakistan	−0.029	0.059	−0.490	0.624
Panama	−0.068***	0.020	−3.370	0.001
Philippines	−0.072*	0.041	−1.750	0.080
Poland	−0.022	0.042	−0.530	0.595
Romania	−0.060**	0.030	−2.030	0.043
Russia	−0.020	0.053	−0.390	0.700
Saudi Arabia	−0.145	0.152	−0.950	0.342
Scotland	−0.044	0.078	−0.570	0.567
Spain	−0.038	0.123	−0.310	0.758
Sri Lanka	−0.022	0.058	−0.380	0.701
Sweden	−0.015	0.027	−0.530	0.596
Switzerland	0.040	0.028	1.400	0.161
Thailand	0.283***	0.029	9.810	0.000
Turkey	0.008	0.066	0.120	0.904
U.S.A.	−0.017	0.020	−0.860	0.390
Ukraine	−0.073*	0.043	−1.690	0.092
Vietnam	0.071*	0.041	1.750	0.081

Yemen	0.046**	0.021	2.130	0.034
Constant	0.684***	0.050	13.760	0.000
Controls		Yes		
Firm & Year FE		Yes		
R-squared		0.667		
Obs.		16,037		
Kleibergen-Paap rk Wald F		247.62		

This table shows the first stage regression result by regressing the FLO index on the CEO's original country dummy variables. CEO's origin country is mapped with the CEO's last name based on the dictionary in Forebears. The benchmark group is Africa. We originally map 122 countries based on the CEOs' last names in our sample and group African countries as one category (The IV results of separating the African country dummies remain qualitatively similar). We use the current period financial data to construct control variables in the tests. Standard errors are clustered at the firm level. We include firm and year fixed effects in the first stage regression.

IA 5. Determinant model of managerial forward-looking

Dependent Variable =	*FLO*			
	(1)	(2)	(3)	(4)
Fundamentals				
SIZE	0.034***	0.040***	0.039***	0.018
	(10.125)	(6.720)	(6.437)	(1.313)
Tobin's Q	−0.026***	0.004*	0.004*	−0.001
	(−10.868)	(1.690)	(1.724)	(−0.156)
LEV	0.068***	−0.008	−0.006	−0.041
	(4.784)	(−0.564)	(−0.398)	(−0.996)
OCF	0.000	0.030	0.035	0.070
	(0.010)	(1.292)	(1.476)	(1.142)
ROA	0.108***	−0.027	−0.032*	−0.001
	(4.666)	(−1.536)	(−1.843)	(−0.023)
RND/SALE	−0.008***	−0.002	−0.002*	−0.008
	(−5.138)	(−1.622)	(−1.709)	(−0.450)
RETURN	0.000	−0.019***	−0.020***	−0.035***
	(0.062)	(−5.994)	(−6.103)	(−5.197)
Board of Directors				
DIR_NUM			−0.002	−0.001
			(−1.461)	(−0.218)
DIR_PCT_MALE			−0.052	−0.072
			(−1.642)	(−1.253)
DIR_NETWORK			−0.002	0.002
			(−0.448)	(0.203)
DIR_PCT_IND			0.014	−0.033
			(0.545)	(−0.547)
DIR_AGE_SD			−0.001	0.005**
			(−0.925)	(2.024)
Managers				
INSIDE_OWN				0.047
				(0.524)
INSIDE_OPPSAL				0.017
				(1.086)
PSPF				−0.045*
				(−1.949)
Constant	0.726***	0.661***	0.730***	0.929***
	(30.417)	(14.318)	(12.230)	(6.301)
Firm & Year FE	No	Yes	Yes	Yes
Obs.	18,134	18,134	17,265	4,272
R-squared	0.156	0.669	0.666	0.770

This table shows the determinants model of the FLO index. The dependent variable is the FLO index in year *t*. The independent variable has been categorized into 3 aspects including firm fundamentals, characteristics of the board of directors, and managerial incentives. All the variables are defined in the Internet Appendix IA 1. *, **, *** indicate two-sided statistical significance at the p< 0.1, p<0.05, and p<0.01 levels, respectively based on robust standard errors of the coefficient estimates clustered at the firm level.

IA 6. CEO forward-looking and environmental risk

	(1)	(2)	(3)
Dependent Variable =	*ENV_SCORE*	*ENV_CON*	*ENV_STR*
CEO_FLO	0.094***	−0.110***	−0.004
	(2.602)	(−3.120)	(−0.132)
SIZE	−0.011	0.150***	0.133***
	(−0.547)	(7.678)	(7.667)
Tobin's Q	−0.004	0.020***	0.017***
	(−0.620)	(4.423)	(2.707)
LEV	−0.202***	0.159***	−0.052
	(−4.440)	(4.272)	(−1.234)
OCF	−0.053	0.013	−0.034
	(−0.915)	(0.293)	(−0.719)
ROA	−0.082	0.091**	−0.000
	(−1.624)	(2.185)	(−0.002)
RND/SALE	0.007	−0.004	0.003
	(1.268)	(−0.992)	(0.525)
RETURN	−0.017*	0.022***	0.003
	(−1.732)	(3.063)	(0.324)
Constant	0.189	−0.991***	−0.774***
	(1.215)	(−6.531)	(−5.846)
Firm & Year FE	Yes	Yes	Yes
Obs.	16,760	16,760	16,760
R-squared	0.409	0.573	0.501

This table shows the regression result based on CEO's language only. The independent variable is the FLO index based on 150 words cut-off with the CEO speech in a conference call Q&A session. The dependent variable in Column 1 is the environmental score (*ENV_SCORE*) in year *t+1*. The dependent variable in Column 2 is the number of environmental concerns in year *t+1*. The dependent variable in Column 3 is the number of environmental strengths in year *t+1*. We add firm and year fixed effects for three columns. All the variables are defined in the Internet Appendix IA 1. *, **, *** indicate two-sided statistical significance at the $p< 0.1$, $p<0.05$, and $p<0.01$ levels, respectively based on robust standard errors of the coefficient estimates clustered at the firm level.