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Green new hiring

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Abstract
The mere marketing of firms as environmentally friendly does not mean that the firms are genuinely green. In this paper, we propose a new measure, *Green Score*, to capture firms' investment in green human capital based on the concentration of green skills required in firms' job postings. First, we find that firms that increase their *Green Score* have higher future profitability. Second, firms that increase their *Green Score* generate more green patents, and those green patents are of higher quality and receive more citations. Third, traditional ratings widely used to evaluate firms' environmental efforts do not consider firms' *Green Score*. Overall, our new action-based measure is simpler and less subjective and it offers a larger time-series variation than traditional disclosure-based environmental ratings.

Keywords Sustainability · Human capital · Green skills · Green patents · Greenwashing

JEL classifications Q56 · Q53 · J23 · J24 · G24 · M41

1 Introduction

Firms often market themselves as environmentally friendly and discuss the environmental efforts they have made. Ninety percent of the S&P 500 firms, for example,

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published sustainability reports in 2019.[1] The mere discussion of sustainability, however, does not necessarily mean that the firms have made genuine environmental efforts. Volkswagen, for example, had been touting its environmental efforts to reduce its carbon footprint for years before its 2015 emissions scandal.[2] Such greenwashing is common in practice because greenwashing firms can create the impression of being environmentally friendly while masking their actual environmental efforts (e.g., Delmas and Burbano 2011; Marquis et al. 2016).

There are potentially many ways to measure firms' environmental efforts, but many struggle with data availability. For example, one could measure a firm's environmental efforts by counting the number of new green jobs. Before its discontinuation in 2013 because of budget constraints, the Bureau of Labor Statistics (BLS) provided the only official statistics on green jobs based on its Green Goods and Services survey. The BLS's statistics, however, are not without criticism. First, the BLS Green Goods and Services survey is based on a very narrow definition of green jobs (Pollack 2012; Georgeson and Maslin 2019).[3] Second, the BLS's green job statistics are at the occupation level and do not vary across time and firms (Consoli et al. 2016). While one might measure firms' environmental efforts using the widely used KLD ratings,[4] KLD does not offer such data on labor. These obstacles limit our understanding of firms' environmental efforts and how they are related to firms' future performance.

In this paper, we use novel labor data to measure a firm's environmental efforts. Our idea builds on a simple premise: a firm that puts in environmental efforts needs people to execute them. Specifically, we exploit firms' demand for green skills in their job postings as a proxy for their investment in green human capital – a type of environmental effort. In our context, "green human capital" is the set of green skills in a firm's workforce, and "green skills" are environment-related skills (e.g., environmental science skills). We propose a new measure, *Green Score*, based on the concentration of green skills required in firms' job postings. If, for example, a new job needs five types of skills, one of which is green skills, the *Green Score* of the new job is 0.20. A firm that increases its *Green Score* invests more in green human capital and puts in more environmental efforts. Our primary motivation is not to shift the prior that firms' investment in green human capital impacts their future financial performance; nor do we argue that our measure is better than others used in the literature. Instead, we build on prior insights to operationalize a new measure from the novel data. This measure is consistent with the prior but has the potential for various practical applications.

It is not obvious that the concentration of green skills required in firms' job postings is associated with the firms' future financial performance. First, job postings could reflect firms' repeated attempts to fill open positions resulting from employee turnover. In this case, the concentration of green skills required in a job posting would remain the

[1] "90% of S&P 500 Index Companies Publish Sustainability Reports in 2019, G&A Announces in its Latest Annual 2020 Flash Report" (*Governance Accountability Institute* (July 16, 2020)).

[2] The Environmental Protection Agency found that Volkswagen violated the Clean Air Act by selling approximately 590,000 model-year 2009–2016 diesel motor vehicles equipped with "defeat devices" in the form of computer software designed to cheat on federal emissions tests. See https://www.epa.gov/vw/learn-about-volkswagen-violations.

[3] The BLS defines green jobs as "jobs in businesses that produce goods or provide services that benefit the environment or conserve natural resources."

[4] According to our search of Google Scholar in April 2021, 2,830 academic papers have mentioned the KLD dataset.

same. Intuitively, the hiring intensity of new jobs should be more critical for firms' future financial performance than the concentration of green skills required in firms' job postings. Second, firms could list more green skills in their job postings to attract job candidates with sustainability ideologies (e.g., Turban and Greening 1997; Burbano 2016). Listing green skills could be a form of green advertising to boost the firms' attractiveness to such candidates, even though the firms have no intention of stepping up their investment in green human capital. Last, green skills are specialized skills that could cost firms more. Prior literature shows that improving corporate social responsibility (CSR) performance can be a costly exercise that comes at the expense of shareholders (Di Giuli and Kostovetsky 2014; Lys et al. 2015; Manchiraju and Rajgopal 2017; Chen et al. 2018). The increase in staff costs due to new green hiring could ultimately reduce firms' future profitability.

On the other hand, anecdotal evidence suggests that the concentration of green skills required in firms' job postings could be associated with the firms' future financial performance. First, the concentration of green skills could be associated with firms' overall investment in sustainability. A firm, for example, may recruit new employees with specialized green skills to operate new eco-friendly manufacturing equipment. Firms that require a higher concentration of green skills in their jobs could also be developing new services or products built around environmental considerations. 3M, for example, pledged in 2019 to consider the environmental impact of its products in the product design process.[5] Hence, the concentration of green skills reflects firms' overall investment in sustainability and correlates with future financial performance. Second, the concentration of green skills in job postings could signal a firm's commitment to environmental efforts beyond just compliance. A recent study, for example, uses retail scanner sales data and finds that 51% of the growth in the consumer packaged goods market comes from sustainability-marketed products (Kronthal-Sacco et al. 2020). Hence, the increase in consumer demand eventually rewards the firms with more profitable business opportunities. Third, socially responsible firms can use the concentration of green skills required in firms' job postings as signals to attract prospective job candidates with lower pay (e.g., Turban and Greening 1997; Greening and Turban 2000; Burbano 2016).[6] The firms could eventually benefit financially because of lower employee costs.

Understanding to what extent firms' investment in green human capital is associated with future performance is crucial for several reasons. For executives, the existence of such an association is crucial in setting long-run value-maximizing strategies for stakeholders (Porter and van der Linde 1995). For regulators, evidence of such an association could have substantial policy implications for measuring and incentivizing firms' investment in green human capital. For researchers, examining such an association could provide a new tool that is less likely to be subject to firms' greenwashing. Last, in 2020 alone, the market sold more than $490 billion of sustainability-related

[5] See https://www.greenbiz.com/article/3m-embeds-sustainability-value-mandate-new-product-development.

[6] Anecdotal evidence suggests that millennials would be willing to take a $5,000 to $10,000 pay cut just to work for an environmentally responsible firm ("The Power of Purpose: The Business Case for Purpose (All the Data You Were Looking for Pt 2)," *Forbes* (March 7, 2020), and "Most Millennials Would Take a Pay Cut to Work at a [sic] Environmentally Responsible Company," *Fast Company* (February 14, 2019)).

investment products, and it shows no sign of slowing.[7] The sheer size of the global sustainability market underscores the pressing need for investors to understand the association.

To test our conjecture, we leverage the novel job-level data from Burning Glass Technologies (hereafter Burning Glass). Burning Glass is an employment data analytics firm specializing in extracting and standardizing the skills required for each job. First, we use the skills data from Burning Glass to identify jobs that require green skills. We compute *Green Score per Job*, the number of green skills divided by the number of skills in each job. After computing *Green Score per Job*, we calculate *Green Score*, the average *Green Score per Job* across all of a firm's jobs that require green skills in a given year. Appendix A Table 15 illustrates the steps to compute *Green Score per Job*. We estimate a series of regression specifications regressing firms' future profitability on this new measure, together with a comprehensive set of control variables associated with firms' future profitability. We also include *Firm Fixed Effects* in all our regression specifications to control for a host of time-invariant heterogeneities that could be associated with firms' future profitability. Our main prediction is that firms that increase their *Green Score* have higher future profitability.

Our main findings are as follows. First, we find that firms that increase their *Green Score* do have higher future profitability. The results are highly robust even after we control for a comprehensive set of control variables, *Firm Fixed Effects*, and *Year Fixed Effects*. In terms of economic magnitude, a one standard deviation increase in *Green Score* is associated with a 0.416% (= 0.040 × 0.104) increase in future *Return on Assets*. Relative to the median of *Return on Assets* at 3.797%, the estimate translates into an 11% increase in future *Return on Assets*. By conducting DuPont analyses, we find that increases in sales and net profit margin are the primary drivers of the improved profitability of firms that increase their *Green Score*.

Second, we find that firms that increase their *Green Score* generate more green patents, and those green patents are of higher quality and receive more citations. Such evidence shows a mechanism whereby *Green Score* is associated with better firm performance. Combined with our earlier results from the DuPont analyses, this evidence suggests that firms that increase their *Green Score* have more innovation activities and subsequently have better financial performance (i.e., profitability, sales, and net profit margin).[8]

Third, we show that the KLD ratings widely used to evaluate firms' environmental efforts do not consider firms' *Green Score*. Our *Green Score* is strongly associated with firms' future profitability, even after controlling for KLD ratings. Fourth, we find that firms do not proactively increase their *Green Score*. Instead, they sluggishly increase their *Green Score* over consecutive years in response to negative environmental shocks (e.g., negative publicity on environmental efforts, regulatory noncompliance).

Fifth, we find that hiring job candidates who have green skills costs firms more. We find that the salary premium is determined not only by the nature of the job, but also by the number of green skills required. This evidence also suggests that our results are

[7] "The Boom in ESG Shows No Signs of Slowing" (*Bloomberg* (February 10, 2021).

[8] These results are also consistent with prior studies' findings that innovative firms with more patents have higher profitability (e.g., Geroski et al. 1993; Roberts 1999) and higher sales growth (e.g., Balasubramanian and Sivadasan 2011; Farre-Mensa et al. 2020).

unlikely to be driven by assortative matching of sustainability ideology between firms and job candidates, because assortative matching should predict lower offered salaries.

To address endogeneity, we exploit the historical political voting preference of voters in the county of a firm's headquarters for instrumental variable (IV) estimation. We examine the presidential elections of 2000, 2004, and 2008. Such dated voting outcomes should be largely uncorrelated with future firm profitability because the elections took place before the start of our sample period (as long as ten years before). We construct an instrument, *% Voting for Democrat*, for the percentage of voters in a county voting for Democrats in a presidential election. We instrument *Green Score* with *% Voting for Democrat*. Across these IV estimations, we continue to find that the estimates of *Instrumented Green Score* are positive and statistically significant. The first-stage *F*-statistics are all well above the critical cutoff value of ten suggested by Stock and Yogo (2002). These statistics suggest that the instruments are not weak.

We also perform a battery of robustness checks to examine the sensitivity of our main results. First, we examine whether firms' overall hiring activities drive our results. We follow Gutiérrez et al. (2020) to construct firms' overall hiring intensity measure. Our main results remain robust after we control for these measures of firms' hiring intensity. We also show that our result is not driven by the concurrent increase in a firm's hiring of public relations officers. Second, we examine whether firms' investment in employee specialization drives our results. We construct five top skill specializations: information technology, sales, business, customer services, and supply chain. We find that none of the five specializations are associated with future firm profitability. This suggests that our results do not reflect a firm-wide strategy of hiring specialized employees across other domains.

Third, we alternatively measure *Return on Assets* and *Green Score*. We extend or shorten the measurement window of *Green Score*. We construct multiple alternative measures or alternatively cluster our standard errors to examine whether our main results are sensitive to the potentially repeated job postings. We also examine whether local economic conditions drive our results. Our results remain highly robust.

Last, we offer a simple application of our *Green Score* to detect greenwashing firms. Firms may strategically distort their environmental disclosure without increasing their investment in green human capital. Such greenwashing improves a firm's environmental rating without a corresponding increase in its investment in green human capital. We construct a *Greenwashing* measure that captures the difference between the concurrent increases in firms' KLD environmental ratings and *Green Score*. A firm that improves its environmental rating without a corresponding increase in its green human capital is likely to engage in greenwashing. We find that these greenwashing firms have lower future profitability.

We acknowledge several limitations of our measures. First, our measure of *Green Score* is based on Burning Glass's online job postings data, and job postings can remain unfilled. As a result, the number of job postings can be higher or lower than the number of actual hires.[9] Unfortunately, we do not have data on whether job postings are eventually filled, although recent studies have used employee resumes or H1B visa application data to validate that job postings data from Burning Glass are a reasonable

[9] If, for example, a firm is unable to find talent to fill a position, the number of job postings may be higher than the number of actual hires.

proxy for firms' actual hiring (Law and Shen 2021). Second, our measure of *Green Score* is based on the skills mentioned in firms' job postings. If firms do not discuss green skills in their job postings, our *Green Score* could misclassify jobs without green skills.[10] Firms may also strategically relabel non-green skills to green skills in their job postings for marketing purposes.[11] Third, firms can invest in areas other than hiring to improve their environmental footprints (e.g., investment in green machinery, donations to charities, employee training). While traditional rating agencies should have considered such efforts, our measure cannot capture them. If such unobserved firm characteristics explained our main results, however, the effect from these unobserved variables would have to be both sizable and largely uncorrelated with the set of observables we have included in the regressions (Altonji et al. 2005). Last but not least, we do not claim that our evidence is causal in nature, although we do provide some evidence to mitigate the endogeneity concern.

Our two main contributions are as follows. First, we propose a new action-based measure to quantify firms' investment in green human capital. Prior literature finds that traditional disclosure-based environmental ratings such as KLD ratings fail to capture firms' investment in green human capital because of firms' strategic disclosure (e.g., Chatterji et al. 2009; Delmas et al. 2013). Even studies that use KLD ratings vary in how they measure a firm's CSR performance.[12] The inconsistency in measuring sustainability or CSR in general makes it challenging to compare the findings of different studies. While one could use toxic emissions or environmental violations to measure firms' investment in green human capital, these data would limit the inference to the firms in a handful of polluting industries. The idea of building green human capital has been gaining political traction in recent years,[13] yet there is no measure of firms' investment in green human capital. Our new measure has several distinct features that complement the other measures in the prior literature. First, it is simple to measure. It is less subjective and offers a larger time-series variation than traditional environmental ratings, which typically rely on firm disclosure. It covers a much wider set of firms than traditional rating agencies, and it covers non-polluting industries. It also complements other industry-, output-, or occupation-based measures to quantify green human capital (e.g., Consoli et al. 2016). Our new measure also answers a recent call by Grewal and Serafeim (2020, abstract), who state that the "measurement [of sustainability] is the least developed … and represents promising opportunities for research." Our measure offers a practical tool to answer a broad set of questions.

[10] Our measure could underestimate a firm's environmental efforts if the firm outsources its environmental activities rather than hiring more employees with green skills. Such outsourcing activities, however, could be captured by third-party rating agencies (e.g., KLD).

[11] To the extent that these strategic behaviors correlate with a firm's advertising expenditure, we have controlled for a firm's *Advertising* in our regression specifications.

[12] Some studies, for example, include the ratings from KLD's corporate governance to measure a firm's CSR performance (e.g., Khan et al. 2016; Khan 2019), whereas other studies do not (e.g., Albuquerque et al. 2019). In addition, some studies count the raw number of strengths or concerns unilaterally to measure a firm's CSR performance (e.g., Hoi et al. 2013), and some studies take a net difference between scaled strengths and scaled concerns (e.g., Deng et al. 2013; Albuquerque et al. 2019).

[13] For example, Representative Alexandria Ocasio-Cortez proposed the Green New Deal in 2019. The Organization for Economic Co-operation (OECD) also published a whitepaper on skills developments in a green economy in 2014.

Second, our findings contribute to the CSR literature. Prior studies find mixed evidence on the association between KLD rating and future firm performance.[14] We find that firms' investment in green human capital, proxied by the concentration of green skills required in firms' job postings, is associated with future profitability after we control for KLD ratings. Our results on green patents also illuminate a mechanism whereby *Green Score* is associated with better firm performance. Finally, recent studies use novel data (e.g., Twitter in Crowley et al. (2019), RepRisk in Li and Wu (2020), and Violation Tracker in Raghunandan and Rajgopal (2020)) to measure firms' environmental efforts and detect greenwashing. By using firms' job postings data to measure firms' investment in green human capital, our paper complements their findings.

Our findings also have practical implications. First, they will be of interest to the executives of firms who want to improve their firms' environmental efforts. Our results will be informative to firm executives – especially those with the worst environmental track records – by suggesting that firms could step up their investment in green human capital more proactively and thereby increase their future profitability.

Second, our findings draw a useful distinction between increasing investment in green human capital and increasing the number of green jobs. As every job requires a different level of skills, not all green jobs are created equal. Hence, creating green jobs does not necessarily mean that a firm is increasing its investment in green human capital.

Third, our results may be useful to external stakeholders. Environmental, social, and governance (ESG) rating agencies will be interested in our finding that traditional ESG ratings do not capture the investment in green human capital reflected in our new measure. Beyond evaluating firms' disclosures to determine their environmental efforts, ESG rating agencies and activists could consider the new information embedded in our *Green Score* measure to guide their actions. Regulators may also be interested in our evidence that regulatory penalties seem to be a driver of improved investment in green human capital.

2 Testable hypothesis, data, and research design

2.1 Testable hypothesis

As mentioned in the introduction, our work builds on the prior literature that shows it pays to be socially responsible. Prior studies generally document a positive association between firms' CSR performance and operating performance (e.g., Margolis et al.

[14] Prior studies generally find a positive association between firms' CSR performance and firm profitability (e.g., Margolis et al. 2007; Edmans 2011, 2012; Deng et al. 2013; Flammer 2013; Servaes and Tamayo 2013; Eccles et al. 2014; Dimson et al. 2015; Ferrell et al. 2016; Khan et al. 2016; Lins et al. 2017; Albuquerque et al. 2019; Dai et al. 2021). Some studies, however, document a negative or no association between CSR performance and firm profitability (Di Giuli and Kostovetsky 2014; Zhao and Murrell 2016; Manchiraju and Rajgopal 2017; Chen et al. 2018).

2007; Edmans 2011, 2012; Deng et al. 2013; Flammer 2013; Servaes and Tamayo 2013; Eccles et al. 2014; Dimson et al. 2015; Ferrell et al. 2016; Khan et al. 2016; Lins et al. 2017; Albuquerque et al. 2019; Dai et al. 2021).

Unlike prior studies, however, we focus on firms' investment in green human capital. To the best of our knowledge, no study so far has shown a clear association between firms' investment in green human capital and future performance. We conjecture that the concentration of green skills required in firms' job postings is a proxy for firms' investment in green human capital. As every job requires a different level of skills, not all jobs requiring green skills are created equal. A high concentration of green skills might be necessary to adopt the most advanced environmental technology. For example, in 2011 the average concentration of green skills required in General Electric's job postings was twice as high as the industry average. Some of these job postings with a high concentration of green skills were looking for talent in industrial hygiene. Industrial hygienists are trained to detect and reduce hazardous waste in the workplace that can affect the health and well-being of workers. Subsequently, in 2014, General Electric filed a green patent for the development of a new sensor system to detect hazardous gas (i.e., Patent No. US9366192B2). Hence, we conjecture that the concentration of green skills, not green jobs, is a meaningful proxy for firms' investment in green human capital. Such investment in green human capital could be positively associated with firms' future operating performance for several reasons.

First, as mentioned in the introduction, the concentration of green skills could be associated with firms' overall investment in sustainability. Firms that post jobs with a higher concentration of green skills could also be developing new services or products built around environmental considerations. To do so, those firms may recruit new employees with specialized green skills for operations. Hence, the concentration of green skills could reflect firms' overall investment in sustainability and correlate with future financial performance.

Second, the concentration of green skills required in job postings could reflect firms' commitment to environmental issues beyond just compliance. Consumers' preference for green products could allow firms to adopt a premium pricing strategy (Brown and Dacin 1997; Downar et al. 2021). Hence, such efforts could help attract additional customer bases and increase customer loyalty, increasing firms' sales revenue. Investment in green human capital could also help firms minimize unnecessary production activities (e.g., reducing unnecessary packaging for environmental reasons), leading to better future operating performance.

Last, listing green skills could be a form of green advertising that signals firms' commitment to environmental protection. These firms may match with job candidates who share the same ideology even though the jobs pay less. The firms could eventually benefit financially because of better employee engagement and lower employee costs (Turban and Greening 1997; Greening and Turban 2000; Edmans 2011; Burbano 2016).

In view of the above, we state our main testable hypothesis as follows:

> *H1*: Firms with job postings that require a higher concentration of green skills have higher future profitability.

2.2 Data

Our data on green hiring come from Burning Glass. Burning Glass is an employment data analytics firm that provides real-time data on online job postings and skills in demand. It crawls nearly 40,000 online job boards and company websites. After removing duplicate job postings, Burning Glass extracts and standardizes job-level characteristics such as employer name, job title, location of the position, education requirements, and skill requirements. Specifically, Burning Glass de-duplicates job postings based on job titles and job descriptions, and it removes repeated postings that may concurrently appear on several job platforms.[15]

Burning Glass data have two unique features that suit this study. First, Burning Glass has extensive coverage of online job postings. It covers about 60%–70% of online job postings with a particular tilt toward high-skill professions (Carnevale et al. 2014). Second, Burning Glass standardizes information at the job-posting level through its machine-learning algorithm. Standardized job-level characteristics allow researchers to examine various dimensions of labor demand across firms and occupations. Hence, researchers can observe both the quantity (i.e., number) and quality (types) of skills in the job postings at the firm level.[16]

Burning Glass data do, however, have two limitations. First, Burning Glass scrapes and parses only online job postings. The use of online job postings might undercount the actual labor demand, but recent studies in labor economics suggest that Burning Glass has better coverage than national survey-based data such as the Job Openings and Labor Turnover Survey by the United States Bureau of Labor Statistics (Hershbein and Kahn 2018). Second, Burning Glass data capture employers' demands but do not reveal whether such job postings are eventually filled, which is a common critique of such job postings data.

In addition to using job data from Burning Glass, we leverage several other datasets. First, we obtain firms' financial information from Compustat. We use the crosswalk file provided by Burning Glass to merge the data from Burning Glass with the data from Compustat. We exclude firms in the regulated utilities and finance industries. Next, we require firms to have at least $10 million in total assets. Our sample period runs from 2010 to 2019Q3 (the last year of our Burning Glass data).

Second, we use the MSCI KLD (hereafter KLD) for CSR ratings.[17] KLD is the oldest and most extensively used rating in scholarly research (Eccles et al. 2020). Since 1991, KLD has monitored and evaluated firms' environmental efforts, capturing firms' environmental concerns (e.g., toxic emission, chemical waste) in seven indicators and their environmental strengths (e.g., opportunities for renewable energy) in 14

[15] Our investigations confirm Burning Glass's de-duplication of repeated job postings with the same job title. First, we find that for two consecutive job postings of a given firm in the same city, only 3.3% of the job postings have the same job titles. Second, we find that the median (mean) number of days it takes to observe two job postings of a given firm in the same city with identical job titles is 128 (221) days. Hence, it is unlikely for job postings to be duplicate job postings with the same job titles. Moreover, including *Firm Fixed Effects* should remove and wash away the variation in *Green Score* due to potentially repeated job postings with identical descriptions across years. We also conduct several robustness tests in Section 4.8 to examine whether repeated job postings could drive our main results. Our main results remain robust.

[16] Burning Glass does not use the job title of a job posting to classify the skill requirements of the job posting.

[17] MSCI KLD, formerly known as Kinder, Lydenberg, & Domini, was acquired by RiskMetrics in 2009. MSCI currently manages the ratings.

indicators. KLD collects data from multiple sources (e.g., annual reports, sustainability reports, and news media) to evaluate each indicator and assigns a binary score depending on whether a firm meets the assessment criteria for that particular indicator.

Third, we use data from Violation Tracker. Since 2000, Violation Tracker has tracked the number of environmental violations compiled from over 50 federal agencies as part of the Corporate Research Project of the nonprofit organization Good Jobs First. We classify a violation as an environmental violation if it falls into one of the following offense categories: (1) energy conservation violation, (2) environmental violation, (3) fuel economy violation, or (4) offshore drilling violation.[18]

Fourth, we use data from RepRisk. For every day since 2007, RepRisk has tracked firms' environmental incidents as reported in over 90,000 news sources (e.g., social media, newspapers). RepRisk also classifies each environmental incident according to its severity (e.g., based on the harshness of an incident and the extent of its impact). As a firm's CSR incident could be broadcasted over multiple news platforms, RepRisk avoids duplication by retaining only the initial environmental incident. Thus, each environmental incident is unique. For each firm-year, we focus on environmental incidents with high severity.

Last, we use patent data from Wharton Research Data Services (WRDS) and patent classification codes from the United States Patent and Trademark Office (USPTO) to identify firms' green patents. Green patents are patents that contain environmental technologies. Examples of environmental technologies are technologies involving environmental management, water-related adaptation, greenhouse gases, and climate change mitigation. We follow Haščič and Migotto (2015), Cohen et al. (2020), and Sautner et al. (2021) to classify a green patent based on its international and cooperative patent classifications.

Table 1, panel A reports our sample selection process. Our main sample includes 14,583 firm-year observations by 2,443 firms between 2011 and 2019 (i.e., the last year of Burning Glass data). Panel B tabulates the distribution of observations by year in our main sample. Burning Glass's coverage of Compustat firms increases slightly from 2011 to 2014 and then remains steady.

2.3 Research design

Our main regression specification is as follows:

$$Return\ on\ Assets_{i,t+1} = \alpha + \beta_1 Green\ Score_{i,t-1} + \beta_2 X_{i,t} + \lambda_i + \mu_t + \varepsilon_{i,t} \quad (1)$$

Return on Assets$_{i,t+1}$ is the one-year-ahead return on assets (*NI*) divided by total assets (*AT*) of firm i. The outcome variable is measured in year $t + 1$, as there may be a time lag between firms' investment in green human capital and the realization of return on assets. We construct our main measure, *Green Score*, as follows. First, we identify all of a firm's jobs that require green skills in a given year. In Burning Glass's taxonomy,

[18] We thank Aneesh Raghunandan for generously providing the corrected crosswalk file for Violation Tracker used in Raghunandan (2021). We improvise Aneesh's crosswalk file by conducting additional manual checks to correct possible inconsistencies and matching errors. In turn, we have shared the improvised crosswalk with Aneesh.

Table 1 Sample selection

Panel A: Sample selection

Descriptions	# Firms	# Firm-Years
Compustat universe covered by Burning Glass	5,165	30,019
Excluding utilities and finance firms	(1,119)	(7,084)
At least $10 million firm size	(211)	(935)
Missing Compustat financial data	(1,003)	(7,028)
Dropped due to *Firm Fixed Effects*	(389)	(389)
Main sample	**2,443**	**14,583**

Panel B: Sample distribution by year

Year	# Observations
2011	1,372
2012	1,472
2013	1,598
2014	1,694
2015	1,722
2016	1,683
2017	1,673
2018	1,715
2019	1,654
Total	**14,583**

Panel A reports the sample selection process for our main sample. Panel B tabulates the distribution of observations by year in our main sample

green skills are those skills under the Environment skill cluster family. Examples include skills relating to water treatment, hazardous materials, environmental regulations, and environmental compliance. Then, we compute *Green Score per Job*, the number of green skills divided by the number of skills in each job. *Green Score per Job* is measured at the job level. For example, if a job requires five sets of skills and one set is green skills, the *Green Score per Job* is 0.20. (See Appendix A Table 15 for an example.) After computing *Green Score per Job*, we compute *Green Score*, which is the average *Green Score per Job* across all of a firm's jobs that require green skills in a given year. *Green Score* is measured at the firm-year level. Firms with a higher *Green Score* have jobs that require a higher concentration of green skills than firms with a lower *Green Score*. Because jobs are sometimes posted in the months after firms' fiscal year-end, we use *Green Score* at calendar year *t*-1 to avoid potential look-ahead bias.[19] Our main variable of interest is β_1. A positive (negative) β_1 indicates that the extent of green skills required in a firm's jobs that require green skills is associated with improved (deteriorated) future firm performance. Our main prediction is that firms with a higher *Green Score* have higher future profitability (i.e., positive β_1).

[19] For example, if a firm has a June year-end and we use the job posting data in the same calendar year to construct *Green Score*, the six months used to construct *Green Score* will mechanically overlap with the first six months of firm profitability.

X represents a vector of firm-specific characteristics identified in the prior literature as determinants of a firm's future profitability (e.g., Fama and French 1995, 2000). First, to control for persistence and mean reversion in earnings, we include *Return on Assets* and *Loss*. *Loss* is an indicator variable equal to one if a firm's *Return on Assets* in year *t*-1 is negative. Second, we include *Firm Size* because small firms may exhibit more heterogeneity in growth and operating performance than large firms. Third, we include *Book-to-Market* and *Dividend* to control for variation in expected profitability (e.g., Fama and French 1995). Next, we include *Property, Plant, and Equipment* and *R&D* to capture the capital intensity of firms and *Leverage* to capture the liabilities arising from the financing activities of firms (e.g., Nissim and Penman 2003). We also include *Institutional Ownership*, which is the percentage of institutional ownership in a firm. Prior literature shows that institutional ownership is strongly associated with firms' future profitability (e.g., Ferreira and Matos 2008; Dimson et al. 2015). Last, we include *CapEx* and *Advertising* to control for firms' investments in tangible assets and advertising intensity (Albuquerque et al. 2019).

We regress firm *i*'s *Return on Assets* on *Green Score*, a *k*-vector of firm-level control variables (*X*), *Firm Fixed Effects* (λ), and *Year Fixed Effects* (μ). *Firm Fixed Effects* are included to control for unobserved heterogeneity in firm profitability across firms because they remove the time-invariant firm characteristics (e.g., firm culture) that could be associated with future firm profitability.[20] *Year Fixed Effects* absorb time-series variation in firm profitability. We cluster standard errors at the firm level because the residuals are likely correlated within a firm.[21] Appendix B Table 16 explains the construction of all variables in detail.

3 Main results

3.1 Overview of *Green Score*

In this section, we first present an overview of *Green Score* in our sample. Figure 1 plots the time trends of *Green Score* during our sample period. *Green Score* exhibits a slight increase in the earlier sample period and decreases around 2016 when President Donald Trump is elected. This pattern is consistent with anecdotal evidence that the industry demand for green skills decreased after the Trump administration reversed many environmental regulations.[22]

Table 2, panel A tabulates the distribution of *Green Score* by state and by county. The states with the highest (lowest) *Green Score* are Montana, Maine, West Virginia,

[20] *Green Score* is a flow measure, and *Firm Fixed Effects* help capture the changes in future firm profitability in response to *Green Score*. Such change in *Green Score* reflects firms' investment in green human capital, which could also represent the potential change in firms' culture towards environmental issues.

[21] Our main results are robust to alternative clustering of standard errors (e.g., by industry or by firm and year). We report the results in Section 4.8.

[22] "The Trump Administration Rolled Back More Than 100 Environmental Rules. Here's the Full List," the *New York Times* (January 20, 2021).

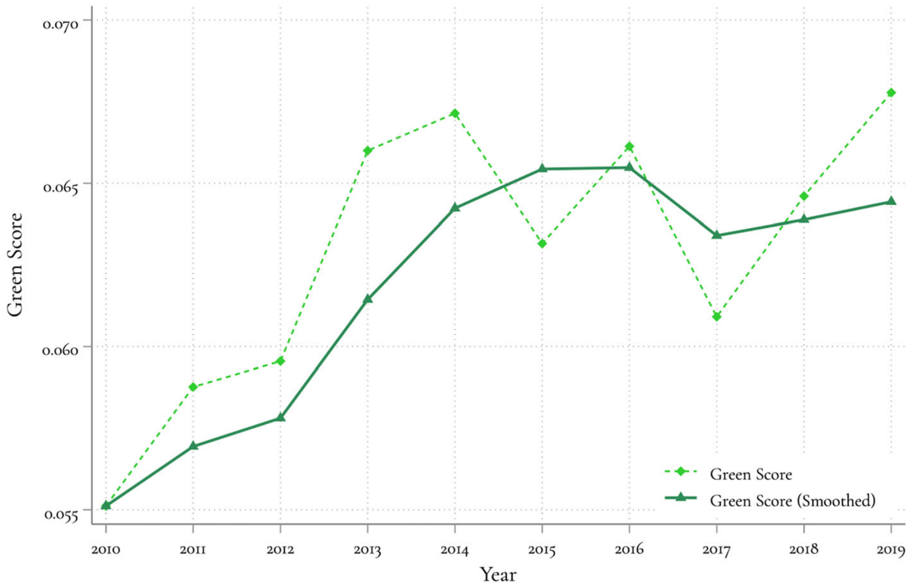

Fig. 1 Time trends of *Green Score*. This figure plots the time trends of *Green Score*. *Green Score* is the average *Green Score per Job* across a firm's jobs that require green skills in a given year. *Green Score per Job* is the number of green skills divided by the number of skills in each job. Dotted lines represent the cross-sectional average of *Green Score* for all firms in a given year. Solid lines represent the three-year moving average of *Green Score*

Rhode Island, and Mississippi (District of Columbia, Massachusetts, Delaware, California, and Washington).[23] Fig. 2A plots the distribution of *Green Score* by county. The overall pattern suggests that *Green Score* varies significantly across counties even within the same state. Take Texas as an example. Figure 2B shows significant variation within Texas. Figure 2C shows another example: Louisiana's "Cancer Alley," the dark green tract in the bottom right corner. The tract is known to house many industrial plants that release cancer-causing chemicals.[24] While *Green Score* is darker in the bottom right corner, there is still some variation within Louisiana.

Table 2, panel B tabulates the average *Green Score* by industry. "Oil, Gas, and Coal Extraction and Products" and "Chemicals and Allied Products" are the two industries with the highest *Green Score* relative to other industries, which is consistent with the core business models of these two industries. In contrast, firms in "Healthcare" and "Business Equipment" have lower *Green Score*s than other industries.

Table 2, panel C tabulates the top ten green skills and green job titles with the highest *Green Score*. The most frequent green skills relate to water treatment, which involves treating contaminated water to protect the environment. The other top green skills relate to handling hazardous materials and waste, environmental compliance, and

[23] In Table 2, the county with the highest *Green Score* is Green, WI. We manually read through the job postings in this county requiring green skills. These job postings have a high *Green Score* because they require workers to have skills to handle hazardous waste or materials. There is no evidence that Burning Glass misclassifies the jobs as jobs requiring green skills simply because these jobs are in Green County.

[24] "Welcome to 'Cancer Alley,' Where Toxic Air is About to Get Worse," *ProPublica* (October 30, 2019).

Table 2 Overview of *Green Score*

Panel A: By State (County)			
Top 5 States	***Green Score***	**Top 5 Counties**	***Green Score***
MT	0.233	Green, WI	0.751
ME	0.225	Garfield, UT	0.722
WV	0.214	Valley, MT	0.667
RI	0.206	Union, NM	0.667
MS	0.203	Mora, NM	0.667
Bottom 5 States	***Green Score***	**Bottom 5 Counties**	***Green Score***
DC	0.113	Moore, TN	0.052
MA	0.141	Martin, KY	0.053
DE	0.149	Lawrence, TN	0.057
CA	0.149	Cimarron, OK	0.059
WA	0.155	Tucker, WV	0.061

Panel B: By industry

Industry	***Green Score***	***Average # Skills Per Job***
Oil, Gas, and Coal Extraction and Products	0.133	12.41
Chemicals and Allied Products	0.125	13.28
Manufacturing	0.091	12.41
Others	0.090	11.09
Consumer Durables	0.078	12.06
Wholesale and Retail	0.070	9.75
Consumer Nondurables	0.067	11.84
Healthcare	0.042	15.16
Business Equipment	0.041	14.23
Average	**0.069**	**12.71**

Panel C: Top 10 green skills and green job titles

Top 10 Green Skills	**Top 10 Green Job Titles**
Water Treatment	Associate Environmental Engineer
Hazardous Materials	Waste Water Technician
Hazardous Waste	Staff Environmental Engineer
Environmental Laws and Regulations	Environmental Protection Specialist
Environmental Regulations	Environmental Geologist
Environmental Compliance	Junior Environmental Engineer
Hazardous Material Handling	Environmental Engineer
Environmental Science	Environmental Scientist
Hazard Analysis	Principal Environmental Engineer
Environmental Management	Environmental Planner

Panel A reports the distribution by state and by county. Each county must have at least ten green jobs during the sample period. Panel B reports the distribution by industry. In panel C, *Top 10 Green Skills* reports the top ten green skills for green jobs with at least five skills. *Top 10 Green Job Titles* reports the top ten job titles with the highest *Green Score* for green jobs with least five skills and twenty observations

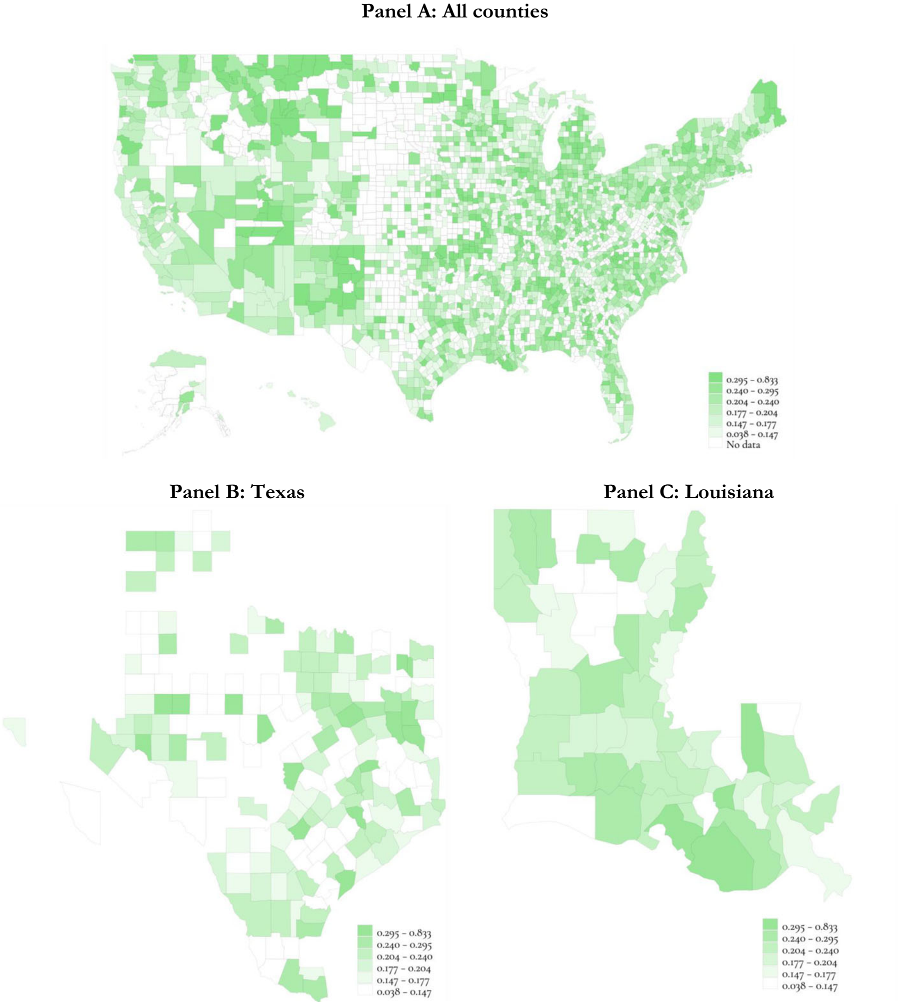

Fig. 2 Geographical distribution. Panel A plots the distribution of *Green Score* by county from 2010 to 2019. Panel B plots the distribution for Texas and Louisiana. *Green Score* is the average *Green Score per Job* across a firm's jobs that require green skills in a given year. *Green Score per Job* is the number of green skills divided by the number of skills in each green job. We first compute the cross-sectional average *Green Score* across all firms in a county in a given year. Then, we compute the time-series average of *Green Score* for each county. We require each county to have at least ten green jobs

hazard analysis. The distribution of green skills suggests that not all green skills are compliance-driven.

The job title with the highest *Green Score* is "associate environmental engineer." As mentioned earlier, Appendix A Table 15 provides an example of the job. The job title with the second-highest *Green Score* is "waste water technician," which involves processing wastewater and producing clean, safe drinking water. Several other job titles with a high *Green Score* are also related to environmental engineering.

Table 3 summarizes the statistics of the main variables used in this study. The average *Green Score* is 0.069. Given that the average number of skills required per job

Table 3 Summary statistics

Variables	Mean (1)	Stdev (2)	25th (3)	50th (4)	75th (5)	#Obs. (6)
Table 4						
Green Score	0.069	0.104	0.000	0.024	0.111	14,583
Return on Assets %	−0.076	15.933	−1.738	3.797	7.679	14,583
Firm Size	9,082	34,775	306	1,234	4,703	14,583
Property, Plant, & Equipment	0.231	0.219	0.069	0.151	0.324	14,583
Leverage	0.218	0.186	0.037	0.200	0.344	14,583
Book-to-Market	0.728	18.018	0.239	0.419	0.705	14,583
R&D %	0.004	0.040	0.000	0.000	0.000	14,583
Loss	0.284	0.451	0	0	1	14,583
Dividend	0.452	0.498	0	0	1	14,583
Institutional Ownership	0.591	0.361	0.256	0.732	0.894	14,583
CapEx	0.043	0.045	0.016	0.029	0.054	14,583
Advertising	0.011	0.027	0.000	0.000	0.007	14,583
Table 5						
Green Score	0.070	0.104	0.000	0.032	0.111	14,408
Net Profit Margin %	−0.022	0.262	−0.016	0.039	0.090	14,408
Asset Turnover	1.001	0.696	0.524	0.832	1.319	14,583
Gross Profit Margin	0.166	0.117	0.082	0.139	0.218	12,207
Sale in million $	6,956	25,017	274	1,090	3,867	14,460
Cost of Goods Sold	0.662	0.594	0.244	0.497	0.885	14,583
SGA Expenses	0.261	0.204	0.106	0.204	0.370	13,368
Table 6						
Green Score	0.068	0.104	0	0	0.110	15,282
# Patent	69.411	422.268	0	0	13	15,282
# Green Patents	4.198	58.726	0	0	0	15,282
Env. Management Technologies	1.143	25.013	0	0	0	15,282
Water-Related Adapt. Technologies	0.309	8.979	0	0	0	15,282
Greenhouse Gases Technologies	0.022	0.387	0	0	0	15,282
Climate Change Mitig. Technologies	2.805	43.100	0	0	0	15,282
# Citations	45.715	554.515	0	0	1	15,282
# Green Citations	1.358	22.073	0	0	0	15,282
Table 7						
CSR 1	0.028	0.113	−0.053	0.000	0.073	9,979
CSR 2	0.023	0.062	−0.023	0.000	0.051	9,979
CSR 3	0.079	0.677	−0.333	0.000	0.417	9,979
ENV 1	0.065	0.172	0.000	0.000	0.083	9,979
ENV 2	0.043	0.101	0.000	0.000	0.100	9,979
Table 8						
CSR 1	0.025	0.090	0.000	0.000	0.045	12,802
CSR 2	0.018	0.051	0.000	0.000	0.027	12,802

Table 3 (continued)

Variables	Mean (1)	Stdev (2)	25th (3)	50th (4)	75th (5)	#Obs. (6)
CSR 3	0.085	0.537	0.000	0.000	0.143	12,802
ENV 1	0.044	0.142	0.000	0.000	0.000	12,802
ENV 2	0.029	0.086	0.000	0.000	0.000	12,802
Table 9						
Panel A						
Green Score (t+1)	0.091	0.108	0.000	0.077	0.132	6,511
# Bad Green News	1.137	3.988	0	0	0	6,511
# Bad Green News (Ln)	0.312	0.704	0	0	0	6,511
# Environmental Violations	0.219	1.335	0	0	0	9,185
# Environmental Violations (Ln)	0.091	0.334	0	0	0	9,185
$ Environmental Violations in $100,000	1.275	57.955	0	0	0	9,185
$ Environmental Violations (Ln)	1.006	3.324	0	0	0	9,185
Green Score (t+3)	0.227	0.236	0.050	0.179	0.334	5,311
# Bad Green News	1.221	4.108	0	0	0	5,311
# Bad Green News (Ln)	0.335	0.724	0	0	0	5,311
# Environmental Violations	0.207	1.260	0	0	0	7,709
# Environmental Violations (Ln)	0.089	0.326	0	0	0	7,709
$ Environmental Violations in $100,000	1.440	63.154	0	0	0	7,709
$ Environmental Violations (Ln)	0.998	3.314	0	0	0	7,709
Panel B						
# Green Jobs (t+1)	28.377	245.95	0	0	7	6,511
# Green Jobs (t+3)	83.341	629.64	0	2	19	5,302
Table 10						
Salary	66,809	46,618	33,280	55,000	86,500	394,470
Green Score per Job	0.017	0.095	0	0	0	394,470
# Green Skills	0.069	0.367	0	0	0	394,470
Years of Experience	3.376	2.857	1	2	5	394,470
Years of Education	11.191	5.915	12	12	16	394,470
Table 11						
% Voting for Democrat						
2000: Bush vs. Gore	0.526	0.126	0.429	0.526	0.615	12,627
2004: Bush vs. Kerry	0.542	0.135	0.446	0.540	0.641	12,628
2008: McCain vs. Obama	0.596	0.129	0.515	0.595	0.692	12,628
Table 12						
IT Score	0.210	0.143	0.127	0.181	0.272	14,583
Sales Score	0.176	0.140	0.083	0.161	0.243	14,583
Business Score	0.142	0.086	0.110	0.140	0.168	14,583
Customer Services Score	0.104	0.091	0.063	0.093	0.129	14,583
Supply Chain Score	0.139	0.117	0.070	0.130	0.186	14,583

Table 3 (continued)

Variables	Mean (1)	Stdev (2)	25th (3)	50th (4)	75th (5)	#Obs. (6)
Table 13						
Alternative *Return on Assets*	0.077	0.164	0.056	0.108	0.155	14,595
Long-Run *Green Score*	0.189	0.244	0.000	0.107	0.305	13,120
Green Score (Fiscal)	0.066	0.096	0.000	0.000	0.109	14,583
Green Score (First Instance: Year)	0.068	0.103	0.000	0.000	0.110	14,583
Green Score (First Instance: Firm)	0.066	0.103	0.000	0.000	0.109	14,583
Green Score (Inversely Weighted)	0.046	0.079	0.000	0.000	0.071	14,583
Green Score (All Jobs)	0.006	0.023	0.000	0.000	0.003	14,583
Table 14						
Greenwashing (1/0)						
All ESG Pillars	0.060	0.237	0	0	0	14,583
Environmental Pillar	0.042	0.200	0	0	0	14,583
Non-Environmental Pillars	0.056	0.229	0	0	0	14,583

This table reports the summary statistics for the variables in this study. % indicates that the numbers reported are in percentage points. Detailed definitions of all variables are in Appendix B Table 16

in our sample is about 12, the average *Green Score* translates into about one set of green skills. We also tabulate the correlation matrix (Pearson's correlation and Spearman's rank correlations) of our main variables in Online Appendix Table 1. *Green Score* is not highly correlated with any other main variables. And we conduct simple univariate analyses of our main variables and tabulate them in Online Appendix Table 2. Firms with higher *Green Score* tend to be larger firms with higher profitability.

3.2 Firm profitability

In this section, we examine whether firms that increase their *Green Score* have higher future profitability. We estimate the regression specification in eq. (1).

Table 4 summarizes the main results. In column 1, we find that the estimate of *Green Score* is positively and statistically significant when we control for *Firm Fixed Effects* and *Year Fixed Effects*. In column 2, we continue to find that the estimate of *Green Score* is positively and statistically significant, controlling for a comprehensive set of control variables and *Firm Fixed Effects* and *Year Fixed Effects*. In other words, firms that increase their *Green Score* have higher future performance. Controlling for *Firm Fixed Effects* and *Year Fixed Effects* ensures that our results reflect an average within-firm change in profitability when a firm increases its *Green Score*, after we account for macroeconomic conditions and time trends in *Green Score*. Relative to the median of *Return on Assets*, a one standard deviation increase in *Green Score* is associated with an 11.0% (= 0.040× 0.104 ÷ 3.797) increase in future *Return on Assets*.

Overall, we find strong evidence that the concentration of green skills in a firm's new job postings exhibits a significantly positive association with firms' future profitability.[25]

3.3 What drives improvement in firm profitability?

In this section, we investigate the main drivers of the improvement in firm profitability. We first conduct a DuPont analysis to decompose *Return on Assets* into two components: *Net Profit Margin* and *Asset Turnover*. *Net Profit Margin* is net income divided by sales. *Asset Turnover* is sales divided by total assets. We replace *Return on Assets* with either *Net Profit Margin* or *Asset Turnover* and re-estimate the same regression specification as in column 2 of Table 4. To account for persistence in each dependent variable, we also control for the lagged values of the dependent variables.

Table 5, columns 1–2 summarize the results. In column 1, we use *Net Profit Margin* as the dependent variable. We find that the estimate of *Green Score* is positive and statistically significant. A one standard deviation increase in *Green Score* is associated with a 3.6% (= 0.345 × 0.104) increase in future *Net Profit Margin*. In column 2, we use *Asset Turnover* as the dependent variable. We find that the estimate of *Green Score* is not statistically significant. The results from the DuPont decomposition suggest that a better net profit margin rather than higher asset utilization is the main driver of improved return on assets.

In columns 3–6, we delve more deeply into the individual components of firms' *Return on Assets*. Column 3 uses *Gross Profit Margin* as the dependent variable. *Gross Profit Margin* is sales minus cost of goods sold, divided by sales. We do not observe any significant increase in *Gross Profit Margin*. Column 4 uses *Sales (Ln)* as the dependent variable. *Sales (Ln)* is the natural logarithm of sales. As *Sales (Ln)* and *Firm Size (Ln)* are highly correlated (i.e., Pearson correlation ~0.9), we do not control for *Sales (Ln)* in this column. We find that *Green Score* has a positive and statistically significant association with future sales. Because we have included *Firm Fixed Effects*, the results suggest that firms that increase their *Green Score* have higher future sales growth. A one standard deviation increase in *Green Score* is associated with a 0.84% (= 0.081 × 0.104) increase in sales. Given that the median (mean) sales are $1,090 million ($6,956 million), the estimate translates into a $9.2 million ($58.43 million) increase per firm-year. The patterns in sales and net profit margin are consistent with prior studies showing that firms' CSR activities increase product differentiation, resulting in less price-elastic demand and higher profit margin (Albuquerque et al. 2019).

In columns 5–6, we use *Cost of Goods Sold* and *SGA Expenses* as the dependent variables. *Cost of Goods Sold* is the cost of goods sold divided by sales. *SGA Expenses*

[25] Albuquerque et al. (2019) document a positive association between Tobin's Q and firms' overall CSR rating. There are two main differences between their paper and ours. First, their composite CSR measures are based on six categories in KLD (i.e., employee relations, environment, human rights, product quality, community, and diversity). In contrast, our study does not use the composite CSR measure but focuses on a firm's investment in green human capital. Second, while Tobin's Q and ROA are positively correlated, Tobin's Q reflects future investor or market expectation, whereas ROA reflects firms' past earnings performance.

Table 4 Firm profitability

	Dependent Variable: *Return on Assets* ($t+1$)	
Independent Variables	(1)	(2)
Green Score	0.039***	0.040***
	(2.82)	(3.36)
Return on Assets		0.186***
		(7.95)
Firm Size (Ln)		0.001
		(0.15)
Property, Plant, & Equip.		0.072*
		(1.92)
Leverage		−0.064***
		(−3.43)
Book-to-Market (Ln)		−0.054***
		(−15.04)
R&D		−0.048
		(−0.68)
Loss		0.005
		(1.31)
Dividend		−0.002
		(−0.36)
Institutional Ownership		0.007
		(0.92)
CapEx		−0.031
		(−0.55)
Advertising		−0.149
		(−0.72)
Firm Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
# Observations	14,583	14,583
Adjusted-R^2	0.648	0.682

This table reports the coefficient estimates of ordinary least squares regressions. Each observation is at the firm-year level. *Return on Assets* is the net income or loss divided by total assets. *Green Score* is the average *Green Score per Job* of a firm in a given year. Details of other variables are in Appendix B Table 16. Standard errors are clustered at the firm level, and *t*-statistics are in parentheses. Intercepts are included for estimation but not tabulated. ***, **, and * indicate two-tailed *t*-statistics with statistical significance at the 1%, 5%, and 10% level, respectively

is selling, general, and administrative expense divided by total assets. We observe a marginally significant negative association in the estimates of *Green Score* in column 6. The results suggest that *Green Score* helps reduce *SGA Expenses*. A one standard deviation increase in *Green Score* is associated with a 0.14% (= 0.013 × 0.104) decrease in selling, general, and administrative expenses. Given that the median firm

Table 5 What drives improvement in firm profitability?

	Dependent Variables:					
	Net Profit Margin $(t+1)$	*Asset Turnover* $(t+1)$	*Gross Profit Margin* $(t+1)$	*Sales (Ln)* $(t+1)$	*Cost of Goods Sold* $(t+1)$	*SGA Expenses* $(t+1)$
Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)
Green Score	0.345***	0.007	0.026	0.081***	−0.019	−0.013*
	(2.93)	(0.30)	(0.90)	(2.64)	(−0.85)	(−1.86)
Net Profit Margin	0.536					
	(0.74)					
Asset Turnover		0.519***				
		(27.35)				
Gross Profit Margin			−0.083			
			(−0.16)			
Sales (Ln)						
Cost of Goods Sold					0.520***	
					(23.68)	
SGA Expenses						0.489***
						(13.95)
Control variables	Identical to those in Table 4, column 2 (except that column 4 does not include *Sales (Ln)* due to multicollinearity)					
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
# Observations	14,408	14,583	12,207	14,460	14,583	13,368
Adjusted-R^2	0.588	0.930	0.472	0.973	0.926	0.881

This table reports the coefficient estimates of ordinary least squares regressions. Each observation is at the firm-year level. *Net Profit Margin* is net income divided by sales. *Asset Turnover* is sales divided by total assets. *Gross Profit Margin* is sales minus cost of goods sold, divided by sales. *Sales (Ln)* is the natural logarithm of sales. *Cost of Goods Sold* is the cost of goods sold (COGS) divided by sales. *SGA Expenses* is selling, general, and administrative expenses divided by total assets. Details of other variables are in Appendix B Table 16. Standard errors are clustered at the firm level, and t-statistics are in parentheses. Intercepts are included for estimation but not tabulated. ***, **, and * indicate two-tailed t-statistics with statistical significance at the 1%, 5%, and 10% level, respectively

size in our main sample is $1,234 million, the estimate translates into savings of about $1.7 million (= 0.14% × $1,234) per firm-year.

Overall, the analyses above suggest that an increase in sales and net profit margin are the primary drivers of the improved profitability for firms that increase *Green Score*.

3.4 Green patents

Our earlier results document a positive association between *Green Score* and firms' profitability. To provide more insights into a potential mechanism through which

Green Score is associated with better firm performance, we examine firms' innovation activities. Prior studies find that investment in human capital generates more innovations and increases future profitability (e.g., Israelsen and Yonker 2017; Custódio et al. 2019; Chen et al. 2021). Thus, we use a firm's patents as a proxy for its innovation activities. We construct a set of patent-based variables. # *Patents* is the number of patents applied for and eventually granted from year $t + 1$ to year $t + 3$. # *Green Patents* is the number of green patents applied for and eventually granted from year $t + 1$ to year $t + 3$. Since investment in human capital could take a longer period to generate innovation outputs, we follow prior literature to measure the patent-based variables over a three-year window (e.g., He and Tian 2013; Glaeser et al. 2021). We also follow prior studies to adjust the numbers of patents for truncation (Hall et al. 2001; Fang et al. 2014). We use these new variables as the dependent variables, and we re-estimate our baseline specifications using the same set of control variables and fixed effects.

Table 6 summarizes the results.[26] The results in column 1 show that firms that increase their *Green Score* generate more patents. A one standard deviation increase in *Green Score* is associated with about a 2.35% (= 0.226 × 0.104) increase in the number of overall patents and a 0.92% (= 0.088 × 0.104) increase in the number of green patents. To put this number into perspective, Li et al. (2021) find that the adoption of addback statutes is associated with a 4.77% decrease in the number of patents. In our paper, firms that increase their *Green Score* from zero to one generate 22.6% more patents and 8.8% more green patents.

We further classify green patents into different categories based on the underlying environmental technologies. # *Green Patents (Environmental Management Technologies)* is the number of green patents on environmental management technologies applied for and eventually granted from year $t + 1$ to year $t + 3$. # *Green Patents (Water-Related Adaptation Technologies)* is the number of green patents on water-related adaptation technologies applied for and eventually granted from year $t + 1$ to year $t + 3$. # *Green Patents (Greenhouse Gases Technologies)* is the number of green patents on greenhouse gases technologies applied for and eventually granted from year $t + 1$ to year $t + 3$. # *Green Patents (Climate Change Mitigation Technologies)* is the number of green patents on climate change mitigation technologies applied for and eventually granted from year $t + 1$ to year $t + 3$. Columns 3–6 show that the effect comes mainly from green patents related to environmental management technologies and climate change mitigation technologies.

Last, we examine the quality of firms' patents. We follow prior literature to use the number of citations as a proxy for patent quality (e.g., Fang et al. 2014; Sunder et al. 2017; Glaeser et al. 2021; Li et al. 2021). # *Citations* is the number of citations of applied-for and granted patents from year $t + 1$ to $t + 3$. # *Green Citations* is the number of citations of applied-for and granted green patents from year $t + 1$ to $t + 3$. As we did with the earlier patent variables, we adjust the number of all citations for truncation. We also exclude patents' self-citations to minimize their influence. Table 6, columns 7–8 suggest that firms that increase their *Green Score* receive more citations on their patents and green patents. In column 7, a one standard deviation increase in

[26] The sample size in Table 6 is slightly larger than that in Table 4 because some firms have missing ROA in year $t + 1$.

Table 6 Green patents

Independent Variables	# *Patents (Ln)* (1)	# *Green Patents (Ln)* (2)	# *Green Patents (Environmental Management Technologies) (Ln)* (3)	# *Green Patents (Water-Related Adaptation Technologies) (Ln)* (4)	# *Green Patents (Greenhouse Gases Technologies) (Ln)* (5)	# *Green Patents (Climate Change Mitigation Technologies) (Ln)* (6)	# *Citations (Ln)* (7)	# *Green Citations (Ln)* (8)
Green Score	0.226**	0.088*	0.051*	0.010	0.004	0.090*	0.276**	0.108**
	(2.15)	(1.74)	(1.82)	(0.81)	(0.43)	(1.91)	(2.37)	(2.50)
Control Variables	Identical to those in Table 4, column 2							
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# Observations	15,282	15,282	15,282	15,282	15,282	15,282	15,282	15,282
Adjusted-R^2	0.733	0.670	0.598	0.552	0.531	0.654	0.630	0.433

This table reports the coefficient estimates of ordinary least squares regressions. Each observation is at the firm-year level. # *Patents* is the number of patents applied for and eventually granted from year $t + 1$ to year $t + 3$. # *Green Patents* is the number of green patents applied for and eventually granted from year $t + 1$ to year $t + 3$. # *Green Patents (Environmental Management Technologies)* is the number of green patents on environmental management technologies applied for and eventually granted from year $t + 1$ to year $t + 3$. # *Green Patents (Water-Related Adaptation Technologies)* is the number of green patents on water-related adaptation technologies applied for and eventually granted from year $t + 1$ to year $t + 3$. # *Green Patents (Greenhouse Gases Technologies)* is the number of green patents on greenhouse gases technologies applied for and eventually granted from year $t + 1$ to year $t + 3$. # *Green Patents (Climate Change Mitigation Technologies)* is the number of green patents on climate change mitigation technologies applied for and eventually granted from year $t + 1$ to year $t + 3$. The number of all patents above is truncation-adjusted. # *Citations* is the number of citations of applied-for and granted patents from year $t + 1$ to $t + 3$. # *Green Citations* is the number of citations of applied-for and granted green patents from year $t + 1$ to $t + 3$. The number of all citations is truncation-adjusted and excludes self-citations. *Green Score* is the average *Green Score per Job* of a firm in a given year. Details of other variables are in Appendix B Table 16. Standard errors are clustered at the firm level, and *t*-statistics are in parentheses. Intercepts are included for estimation but not tabulated. ***, **, and * indicate two-tailed *t*-statistics with statistical significance at the 1%, 5%, and 10% level, respectively

Green Score is associated with about a 2.9% (= 0.276 × 0.104) increase in # *Citations*. In column 8, the estimate of *Green Score* is positive and statistically significant. A one standard deviation increase in *Green Score* is associated with about a 1.12% (= 0.108 × 0.104) increase in # *Green Citations*.

Overall, our results on green patents show one channel through which *Green Score* is associated with better firm performance. Prior studies find that innovative firms that generate more patents have higher profitability (e.g., Geroski et al. 1993; Roberts 1999) and higher sales growth (e.g., Balasubramanian and Sivadasan 2011; Farre-Mensa et al. 2020). These findings are consistent with our results from the DuPont analyses and our results on green patents. Firms that increase their *Green Score* have more innovation activities and subsequently have better financial performance (i.e., profitability, sales, and net profit margin).

4 Determinants and robustness of *Green Score*

4.1 Is *Green Score* new?

Given the clear association between *Green Score* and future firm profitability, the obvious question is to what extent traditional CSR rating agencies consider *Green Score* when evaluating firms' investment in green human capital. We use the KLD ratings to examine this question because they are the most extensively used CSR ratings in scholarly research (e.g., Eccles et al. 2020). We estimate the following regression specification:

$$Rating_{i,t} = \alpha + \beta_1 Green\ Score_{i,t} + \beta_2 X_{i,t} + \lambda_i + \mu_t + \varepsilon_{i,t} \quad (2)$$

Ratings is KLD ratings, and we follow prior studies to construct five different measures of *Ratings* (Deng et al. 2013; Albuquerque et al. 2019). *CSR 1* is the difference between *STR1* and *CON1*. *STR 1* is the sum of strengths across all six CSR categories (i.e., community, diversity, employee relations, environment, product, and human rights), divided by the sum of the maximum possible strengths across the six CSR categories. *CON 1* is the sum of concerns across the six CSR categories, divided by the sum of the maximum possible concerns across the six CSR categories for each firm-year. *CSR 2* is the difference between *STR 2* and *CON 2*, divided by the sum of the maximum possible strengths and the maximum possible concerns across the six CSR categories for each firm-year. *STR 2* is the sum of strengths across the six CSR categories. *CON 2* is the sum of concerns across the six CSR categories. *CSR 3* is the difference between *STR 3* and *CON 3*. *STR 3* is the sum of strengths of each of the six CSR categories, divided by the maximum possible strengths of each CSR category for each firm-year. *CON 3* is the sum of concerns of each of the six CSR categories, divided by the maximum possible concerns of each CSR category for each firm-year. *ENV 1* is the difference between *ENV STR* and *ENV CON*. *ENV STR* is the sum of environmental strengths, divided by the maximum possible strengths in the environment category. *ENV CON* is the sum of environmental concerns, divided by the maximum possible concerns in the environment category for each firm-year. *ENV 2* is the difference between the sum of environmental strengths and the sum of environmental concerns, divided by the sum of the maximum possible strengths and concerns in the environment category for each firm-year.

We regress each of these five KLD measures on *Green Score* and the same control variables and fixed effects. Our main variable of interest is β_1. A statistically significant β_1 estimate would indicate that KLD considers *Green Score* when evaluating firms' investment in green human capital.

Table 7 summarizes the results. Before elaborating on the results, we caution readers that the number of observations significantly decreased from 14,583 in Table 4 to 9,979 in Table 7. The decrease is expected because KLD does not cover every firm in Compustat and because 2018 is the last year of KLD data. In columns 1–3, we find that the estimates of *Green Score* are not statistically significant at the conventional level. Focusing on the KLD ratings on the environmental pillar, we see that the estimates of *Green Score* in columns 4–5 are also not statistically significant at the conventional level. This evidence suggests that KLD ratings do not consider firms' *Green Score* when evaluating firms' environmental efforts. The evidence also suggests that firm signaling is unlikely to explain our results because even disclosure-based KLD ratings do not well capture *Green Score*.

4.2 *Green Score* and KLD

As we show in the previous section that KLD ratings do not consider *Green Score*, we now examine *Green Score* and KLD ratings in explaining firms' future performance. Specifically, we re-estimate our main specification in Table 4, column 2 by including both *Green Score* and one of the five KLD measures (i.e., *CSR 1*, *CSR 2*, *CSR 3*, *ENV 1*, and *ENV 2*, which are defined in the previous section). The sample period for this test is from 2011 to 2018 because 2018 is the last year of KLD data.

Table 8 summarizes the results. Columns 1–5 consistently show that the estimates of *Green Score* remain positive and their magnitudes change little across columns. In contrast, none of the five KLD measures are associated with *Return on Assets*. Even if we exclude *Green Score* from the regression specifications, the results in Online Appendix Table 3 show that none of these five KLD measures significantly explain firms' future profitability. In Online Appendix Table 4, we show that only a small fraction of the effect of KLD ratings on *Return on Assets* is mediated by *Green Score*. In Online Appendix Table 5, we also show that there is no evidence that *Green Score* moderates the effect of KLD ratings on future performance. Overall, our evidence in this section suggests that there is different information in *Green Score* than what has previously been detected using KLD measures.

4.3 What drives *Green Score*?

Given the positive association between *Green Score* and firm performance, why doesn't every firm simply increase the number of green skills (relative to the total number of skills) required per green job? We conjecture that firms do not proactively

Table 7 Is the *Green Score* new?

	Dependent Variables:				
	CSR 1	*CSR 2*	*CSR 3*	*ENV 1*	*ENV 2*
Independent Variables	(1)	(2)	(3)	(4)	(5)
Green Score	0.009	0.006	0.065	0.004	0.001
	(0.88)	(1.09)	(0.87)	(0.26)	(0.10)
Return on Assets	0.006	0.001	0.049	0.031*	0.018**
	(0.50)	(0.19)	(0.61)	(1.89)	(2.09)
Firm Size (Ln)	0.002	0.002	0.009	−0.029***	−0.020***
	(0.45)	(1.01)	(0.31)	(−4.28)	(−5.37)
Property, Plant, & Equip.	0.060**	0.030**	0.441**	0.105**	0.046*
	(2.09)	(2.09)	(2.28)	(2.33)	(1.93)
Leverage	0.011	0.007	0.058	0.058***	0.039***
	(0.92)	(1.08)	(0.72)	(3.23)	(3.80)
Book-to-Market (Ln)	0.008***	0.004***	0.041***	0.007*	0.004
	(3.16)	(3.17)	(2.78)	(1.65)	(1.42)
R&D	−0.015	−0.008	−0.207	−0.002	−0.002
	(−0.79)	(−0.83)	(−1.13)	(−0.20)	(−0.34)
Loss	0.002	0.001	0.014	0.007	0.003
	(0.73)	(0.64)	(0.78)	(1.63)	(1.39)
Dividend	0.003	0.002	−0.002	−0.005	−0.002
	(0.50)	(0.65)	(−0.08)	(−0.58)	(−0.50)
Institutional Ownership	0.020**	0.007	0.143**	0.019	0.003
	(2.19)	(1.54)	(2.25)	(1.25)	(0.42)
CapEx	−0.029	−0.015	−0.579*	−0.086	−0.035
	(−0.67)	(−0.70)	(−1.79)	(−1.07)	(−0.84)
Advertising	0.089	0.029	0.843	0.072	−0.003
	(0.98)	(0.63)	(1.26)	(0.84)	(−0.06)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
# Observations	9,979	9,979	9,979	9,979	9,979
Adjusted-R^2	0.642	0.675	0.507	0.595	0.634

This table reports the coefficient estimates of ordinary least squares regressions. Each observation is at the firm-year level. The sample period is from 2011 to 2018 (the last year of KLD data). *CSR 1* is the difference between *STR1* and *CON1*. *STR 1* is the sum of strengths across all six CSR categories (i.e., community, diversity, employee relations, environment, product, and human rights), divided by the sum of the maximum possible strengths across the six CSR categories. *CON 1* is the sum of concerns across the six CSR categories, divided by the sum of the maximum possible concerns across the six CSR categories for each firm-year. *CSR 2* is the difference between *STR 2* and *CON 2*, divided by the sum of the maximum possible strengths and the maximum possible concerns across the six CSR categories for each firm-year. *STR 2* is the sum of strengths across the six CSR categories. *CON 2* is the sum of concerns across the six CSR categories. *CSR 3* is the difference between *STR 3* and *CON 3*. *STR 3* is the sum of strengths of each of the six CSR categories, divided by the maximum possible strengths of each CSR category for each firm-year. *CON 3* is the sum of concerns of each of the six CSR categories, divided by the maximum possible concerns of each CSR category for each firm-year. *ENV 1* is the difference between *ENV STR* and *ENV CON*. *ENV STR* is the sum of environmental strengths, divided by the maximum possible strengths in the environment category. *ENV CON* is the sum of environmental concerns, divided by the maximum possible strengths in the environment category for each firm-year. *ENV 2* is the difference between the sum of environmental strengths and the sum of environmental concerns, divided by the sum of the maximum possible strengths and concerns in the environment category for each firm-year. Details of other variables are in Appendix B Table 16. Standard errors are clustered at the firm level, and *t*-statistics are in parentheses. Intercepts are included for estimation but not tabulated. ***, **, and * indicate two-tailed *t*-statistics with statistical significance at the 1%, 5%, and 10% level, respectively

increase their investment in green human capital but rather do so reactively in response to negative environmental shocks such as activist campaigns or environmental disasters or incidents (e.g., Blacconiere and Patten 1994; Baron 2001). Prior literature shows that firms' investment in sustainability offers insurance-like protection to counter the effects of negative environmental shocks (e.g., Godfrey 2005; Godfrey et al. 2009; Flammer 2013). To test this conjecture, we estimate the following regression specification:

Table 8 *Green Score* and KLD

	Dependent Variable: *Return on Assets* (t+1)				
Independent Variables	(1)	(2)	(3)	(4)	(5)
Green Score	0.043***	0.043***	0.043***	0.043***	0.043***
	(3.52)	(3.52)	(3.53)	(3.52)	(3.52)
CSR 1	0.015				
	(1.06)				
CSR 2		0.024			
		(1.00)			
CSR 3			0.003		
			(1.38)		
ENV 1				−0.002	
				(−0.25)	
ENV 2					−0.004
					(−0.31)
Control Variables	Identical to those in Table 4, column 2				
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
# Observations	12,802	12,802	12,802	12,802	12,802
Adjusted-R^2	0.700	0.700	0.700	0.700	0.700

This table reports the coefficient estimates of ordinary least squares regressions. The sample period is from 2011 to 2018 (the last year of KLD data). Each observation is at the firm-year level. *Return on Assets* is the net income or loss divided by total assets. *Green Score* is the average *Green Score per Job* of a firm in a given year. *CSR 1*, *CSR 2*, *CSR 3*, *ENV 1*, and *ENV 2* are all net differences between KLD strengths and concerns. Details of these variables are in Appendix B Table 16. Standard errors are clustered at the firm level, and *t*-statistics are in parentheses. Intercepts are included for estimation but not tabulated. ***, **, and * indicate two-tailed *t*-statistics with statistical significance at the 1%, 5%, and 10% level, respectively

Table 9 What drives *Green Score*?

Panel A: Green Score

	Dependent Variables:					
	Green Score (*t*+1)			*Green Score* (*t*+3)		
Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)
# Bad Green News (Ln)	0.005*			0.010**		
	(1.85)			(2.04)		
# Environmental Violations (Ln)		0.006			0.025***	
		(1.40)			(3.01)	
$ Environmental Violations (Ln)			0.001*			0.002**
			(1.94)			(2.52)
Return on Assets	0.000	0.012	0.012	−0.079**	−0.069**	−0.069**
	(0.01)	(0.96)	(0.98)	(−2.31)	(−2.54)	(−2.54)
Firm Size (Ln)	0.012***	0.010***	0.010***	0.030***	0.040***	0.040***
	(2.91)	(2.65)	(2.64)	(2.75)	(4.25)	(4.30)
Property, Plant, & Equip.	0.004	−0.017	−0.016	0.081	0.004	0.003
	(0.12)	(−0.52)	(−0.50)	(0.99)	(0.05)	(0.04)
Leverage	−0.009	−0.008	−0.007	0.003	−0.007	−0.007
	(−0.61)	(−0.54)	(−0.53)	(0.08)	(−0.20)	(−0.22)
Book-to-Market (Ln)	−0.005*	−0.002	−0.002	−0.004	−0.003	−0.003
	(−1.80)	(−0.98)	(−0.97)	(−0.63)	(−0.58)	(−0.58)
R&D	0.033	0.041	0.041	−0.068	−0.076	−0.076
	(0.64)	(1.08)	(1.08)	(−0.69)	(−1.61)	(−1.61)
Loss	0.006	0.010***	0.010***	0.006	0.002	0.002
	(1.44)	(2.70)	(2.71)	(0.80)	(0.37)	(0.35)
Dividend	0.004	−0.001	−0.001	0.012	−0.011	−0.011
	(0.70)	(−0.13)	(−0.12)	(1.06)	(−1.00)	(−1.00)
Institutional Ownership	0.017**	0.002	0.002	0.079***	0.011	0.012
	(2.16)	(0.32)	(0.30)	(4.32)	(0.68)	(0.72)
CapEx	0.013	0.050	0.050	0.006	0.091	0.093
	(0.22)	(0.91)	(0.92)	(0.06)	(0.74)	(0.76)
Advertising	0.049	0.281*	0.280*	−0.162	0.191	0.189
	(0.28)	(1.88)	(1.87)	(−0.42)	(0.58)	(0.57)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
# Observations	6,511	9,185	9,185	5,311	7,709	7,709
Adjusted-R^2	0.438	0.439	0.440	0.738	0.726	0.726

Table 9 (continued)

Panel B: Green jobs						
Independent Variables	*# Green Jobs Ln* (*t* + 1)			*# Green Jobs Ln* (*t* + 3)		
# Bad Green News (Ln)	0.019			−0.021		
	(0.66)			(−0.63)		
# Environmental Violations (Ln)		0.007			0.067*	
		(0.16)			(1.82)	
$ Environmental Violations (Ln)			−0.000			0.002
			(−0.02)			(0.67)
Control Variables/Fixed Effects	Identical to those in Panel A					
# Observations	6,511	9,185	9,185	5,302	7,690	7,690
Adjusted-R^2	0.807	0.793	0.793	0.915	0.906	0.906

This table reports the coefficient estimates of ordinary least squares regressions. Each observation is at the firm-year level. *# Bad Green News* is the number of severe environmental incidents a firm experiences in a given year. *# Environmental Violations* is the number of environmental violations by a firm in a given year. *$ Environmental Violations* is the dollar sum of environmental violations by a firm in a given year. In panel A, *Green Score* (t+3) is the cumulative sum of *Green Score* over the next three years from year t+1 to t+3. In panel B, *# Green Jobs* (t+1) is the number of green jobs in a given year. *# Green Jobs* (t+3) is the cumulative sum of *# Green Jobs* over the next three years from year t+1 to t+3. Details of other variables are in Appendix B Table 16. Standard errors are clustered at the firm level, and t-statistics are in parentheses. Intercepts are included for estimation but not tabulated. ***, **, and * indicate two-tailed t-statistics with statistical significance at the 1%, 5%, and 10% level, respectively

$$Green\ Score_{i,t+1} = \alpha + \beta_1 Green\ Shock_{i,t} + \beta_2 X_{i,t} + \lambda_i + \mu_t + \varepsilon_{i,t} \tag{3}$$

The dependent variable is the one-year-ahead *Green Score*, which captures the extent of green skills in firm *j*'s jobs in year $t + 1$. *Green Shock* refers to environmental shocks. We rely on the prior literature to guide us on two main areas that give rise to *Green Shock*: (1) negative publicity and (2) regulatory noncompliance or violation.

First, we use RepRisk to capture firms' negative environmental shocks covered in the news media. *# Bad Green News* is the number of severe environmental incidents a firm experiences in a given year. Firms with higher *# Bad Green News* have more severe environmental incidents than firms with lower *# Bad Green News*. Second, we use Violation Tracker to construct *# Environmental Violations* and *$ Environmental Violations* as proxies for firms' negative environmental shocks. *# Environmental Violations* is the number of environmental violations by a firm in a given year. *$ Environmental Violations* is the dollar sum of environmental violations by a firm in a given year. Firms with a higher *# Environmental Violations* or higher *$ Environmental Violations* should have more regulatory noncompliance than firms with a lower *# Environmental Violations* or lower *$ Environmental Violations*.

We employ the identical set of control variables as in earlier specifications with *Firm Fixed Effects* and *Year Fixed Effects*. Our main variable of interest is β_1. We predict that firms with negative environmental shocks will increase their *Green Score* (i.e., β_1 will be positive).

Table 9 summarizes the results. In panel A, columns 1–3, the estimates of *# Bad Green News* and *$ Environmental Violations* are statistically significant. The pattern suggests that firms that experience negative environmental shocks, on average, immediately increase the number of green skills (relative to the total number of skills) required per green job. The economic magnitudes of these estimates, however, are small.

Although firms do not respond to negative environmental shocks immediately, a natural question is whether they respond sluggishly. To test this conjecture, we replace the dependent variable *Green Score* with *Green Score (t + 3)*. *Green Score (t + 3)* is the cumulative sum of *Green Score* over the next three years from year $t + 1$ to $t + 3$. We re-estimate the same regression specifications with the same control variables as in columns 1–3.

Columns 4–6 summarize the results when we measure *Green Score* over a longer horizon. We continue to find that firms that experience a negative environmental shock do increase their *Green Score* over a longer horizon. In column 4, the estimate of *# Bad Green News* is positive and statistically significant. Relative to the mean of *Green Score (t + 3)* at 0.227, a one standard deviation increase in *# Bad Green News (Ln)* is associated with about a 3.2% (= 0.010 × 0.724 ÷ 0.227) increase in *Green Score (t + 3)*. In columns 5–6, we observe that the estimates of *# Environmental Violations (Ln)* and *\$ Environmental Violations (Ln)* are all positive and statistically significant. Relative to the mean of *Green Score (t + 3)*, a one standard deviation increase in *# Environmental Violations (Ln)* is associated with about a 3.6% (= 0.025 × 0.326 ÷ 0.227) increase in *Green Score (t + 3)*. Relative to the mean of *Green Score (t + 3)*, a one standard deviation increase in *\$ Environmental Violations (Ln)* is associated with about a 2.9% (= 0.002 × 3.314 ÷ 0.227) increase in *Green Score (t + 3)*. The economic magnitudes over a longer horizon are larger than those over a shorter horizon. The evidence suggests that firms tend to improve their investment in green human capital sluggishly after they experience a green shock.

Next, we examine whether firms increase the number of green jobs after experiencing green shocks. We define a job as a green job if the concentration of green skills (i.e., number of skills divided by total number of skills) is more than the sample median. We construct *# Green Jobs* as the number of green jobs in a given year and *# Green Jobs (t + 3)* as the cumulative sum of *# Green Jobs* over the next three years from year $t + 1$ to $t + 3$. We re-estimate the same regression specifications with the same control variables as in Table 9, panel A.

Table 9, panel B summarizes the results. Columns 1–4 and 6 suggest that the estimates of three green shock measures are not statistically significant. While the estimate of *# Environmental Violations (Ln)* is marginally significant in column 5, the estimate of *\$ Environmental Violations (Ln)* is not statistically significant. There is no evidence that firms significantly increase the number of green jobs after experiencing green shocks.

Overall, our analyses show that firms, on average, do not proactively increase their *Green Score* after experiencing negative shocks to their investment in green human capital. Instead, they slowly increase their *Green Score* over consecutive years in response to negative environmental shocks. In contrast, firms experiencing a green shock do not increase the number of green jobs in either the short or long term.

4.4 Do green skills cost more?

Perhaps an even more fundamental question is as follows. Why wouldn't firms with poor environmental records feign a better record by requiring more green skills in their job postings to improve their future profitability? One possible explanation is that hiring job candidates with more green skills is costly. To examine this possibility, we use the salary information in Burning Glass. Before proceeding, we should note that not all job postings contain salary information. Our empirical analyses are based on the job postings that do contain salary information; hence, they may not generalize in the real world.[27]

With this caveat in mind, we proceed to our analyses. We first construct *Salary* as the salary for a job. We then regress *Salary* on *Green Score per Job*, *# Green Skills*, *Years of Experience*, *Years of Education*, and a set of fixed effects. As mentioned in the Introduction, *Green Score per Job* is the number of green skills divided by the number of skills in each job. *# Green Skills* is the number of green skills in each job. *Years of Experience* is the minimum number of years of experience required for a job. *Years of Education* is the minimum number of years of education required for a job. As salaries are likely correlated within firms in the same county, we cluster standard errors at the firm-county level. Each observation is at the job level.

Table 10 summarizes the results. In column 1, we start with the baseline by including only *Years of Experience*, *Years of Education*, *Firm Fixed Effects*, and *Year Fixed Effects*. As expected, a higher salary premium is associated with more years of working experience and education. In column 2, we incrementally add *Green Score per Job* and find that the estimate of *Green Score per Job* is statistically significant at the 1% level. The higher salary premium is not surprising, as skill specialization in general commands a higher premium in the labor market. Switching *Green Score per Job* from zero to one is associated with about a 15.5% increase in the salary of a job.

In column 3, we estimate a more restrictive model with fixed effects capturing several time-invariant job characteristics. We incrementally include *County Fixed Effects* (based on job locations), *Education Degree Fixed Effects* (based on the minimum degree required), *Salary Type Fixed Effects* (based on the salary types), and *Job Title Fixed Effects* (based on the O*NET occupation titles). Including these high-dimensional fixed effects accounts for time-invariant job-level characteristics that could be associated with job salaries. With this extremely restrictive specification, our inferences remain unchanged. The estimate of *Green Score per Job* is still positive and statistically significant. Switching *Green Score* from zero to one is associated with about a 9.7% increase in the salary of a job.

Last, we examine the sensitivity of the regression specification in column 3 after replacing *Green Score per Job* with *# Green Skills (Ln)*. *# Green Skills (Ln)* is the natural logarithm of one plus the number of green skills required in each job. In column 4, we continue to find a positive and statistically significant estimate of *# Green Skills (Ln)*.

Overall, the evidence suggests that hiring job candidates with more green skills costs firms more. We find that the salary premium is determined by the concentration of green skills required in a job (relative to the total number of skills). Such a higher

[27] If the observable salaries of the jobs in Burning Glass are higher than the observable salaries in the real world, then our results will overestimate the wage premium of green skills. On the other hand, if the observable salaries of the jobs in Burning Glass are lower than the observable salaries in the real world, then our results will underestimate the wage premium of green skills. If there is no systematic difference in the salaries of green jobs in Burning Glass and those in the real world, our estimate will approximate the average salary premium for green skills in the real world.

Table 10 Do green skills cost more?

	Dependent Variable: *Salary (Ln)*			
Independent Variables	(1)	(2)	(3)	(4)
Green Score per Job		0.155***	0.097***	
		(3.88)	(3.11)	
# Green Skills (Ln)				0.022***
				(2.64)
Years of Experience (Ln)	0.270***	0.270***	0.144***	0.144***
	(72.19)	(71.91)	(59.68)	(59.69)
Years of Education (Ln)	0.041***	0.042***	0.006	0.006
	(19.00)	(19.59)	(0.54)	(0.53)
Firm Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
County Fixed Effects	No	No	Yes	Yes
Education Degree Fixed Effects	No	No	Yes	Yes
Salary Type Fixed Effects	No	No	Yes	Yes
Job Title Fixed Effects	No	No	Yes	Yes
# Observations	394,470	394,470	394,163	394,163
Adjusted-R^2	0.538	0.538	0.656	0.656

This table reports the coefficient estimates of ordinary least squares regressions. Each observation is at the job level. *Salary* is the salary of a job. *Green Score per Job* is the number of green skills divided by the number of skills in each green job. *# Green Skills* is the number of green skills in each job. *Years of Experience* is the minimum number of years of experience required for a job. *Years of Education* is the minimum number of years of education required for a job. *# Skills* is the number of skills in each job. *Education Degree Fixed Effects* are fixed effects based on the minimum degree required (e.g., bachelor, master). *Salary Type Fixed Effects* are fixed effects based on the salary types (e.g., base pay, commission) of a job. *Job Title Fixed Effects* are fixed effects based on the O*NET occupation titles. Standard errors are clustered at the firm-county level, and *t*-statistics are in parentheses. Intercepts are included for estimation but not tabulated. ***, **, and * indicate two-tailed *t*-statistics with statistical significance at the 1%, 5%, and 10% level, respectively

premium is consistent with anecdotal evidence that jobs requiring green skills pay more (Muro et al. 2019).[28] These results also suggest that our findings are not driven by ideology matching between firms and job candidates, because assortative matching should result in lower offered salaries.

The higher salary premium for green skills also explains why firms with poor environmental efforts do not simply feign higher environmental efforts to improve their future profitability: requiring more green skills in their job postings would cost more. Engaging in such a pooling equilibrium would be costly for firms.

4.5 Instrumental variables (IV) estimation

Our study, like others in this stream of literature, raises the obvious concern of endogeneity. Firms that expect higher profitability could increase the number of green

[28] "A Bottom-Line Case for the Green New Deal: The Jobs Pay More" (*Bloomberg* (April 24, 2019)).

jobs, and the increase in the number of green jobs would concurrently increase firms' *Green Score*. Although our research design controls for *Firm Fixed Effects,* such reverse causality could cloud the interpretations of our results.

To alleviate the endogeneity concern, we conduct IV estimations. Prior studies find that political ideology is significantly associated with attitudes on environmental issues (e.g., Costa and Kahn 2013; Gromet et al. 2013; Hoi et al. 2013; Di Giuli and Kostovetsky 2014).[29] We follow these studies to exploit the historical political voting preference of voters in the county of a firm's headquarters as an instrument (Hoi et al. 2013; Albuquerque et al. 2019). We extract firms' historical headquarters based on firms' 10-K filings and then construct *% Voting for Democrat*, the percentage of voters in a county voting for Democrats in a presidential election. Because voters' historical political voting preference varies cross-sectionally across counties, we replace *Firm Fixed Effects* with *Industry Fixed Effects* in IV estimation. Albuquerque et al. (2019) show that political preferences due to geographic clusters of industries are unlikely to be correlated with firm value after controlling for *Industry Fixed Effects*. We examine the presidential elections of 2000, 2004, and 2008. All three elections occurred well before the beginning of our sample period – as long as ten years before. With *Industry Fixed Effects*, such dated voting outcomes should be largely uncorrelated with future firm profitability, satisfying the exclusion restrictions for identification purposes.

Table 11 summarizes the results. We continue to use *Return on Assets* as the dependent variable. Columns 1, 3, and 5 instrument *Green Score* with the historical voting preference based on the 2000, 2004, and 2008 presidential elections, respectively. Across these three columns, we continue to find that the estimates of *Instrumented Green Score* are positive and statistically significant. The first-stage F-statistics are all well above the critical cutoff value of ten recommended by Stock and Yogo (2002), which suggests that the instruments are not weak. In columns 2, 4, and 6, we incrementally include *Home State Fixed Effects* to control for the state of firms' historical headquarters. Our results remain robust.[30]

In untabulated tests, we also construct an alternative IV based on the local green culture. We construct *Local Green Culture*, which is the average *Green Score* of all peer firms (with the firm itself excluded) in the same county-industry-year. The first-stage F-statistic well exceeds ten, indicating that *Local Green Culture* is not a weak IV. We use *Local Green Culture* to instrument *Green Score* and include the same set of control variables, *Firm Fixed Effects*, and *Year Fixed Effects*. We continue to observe a positive and statistically significant *Instrumented Green Score*.

Overall, our IV results mitigate the concern that our results are driven by endogeneity.

[29] Hong and Kostovetsky (2012) show that mutual fund managers who donate to Democrats hold less of their portfolios (relative to nondonors or donors to Republicans) in companies that are deemed socially irresponsible.

[30] We also follow Di Giuli and Kostovetsky (2014) to use the political preference of the state where the founders were born. We collect the birth states of chief executive officers (CEOs) from *Marquis Who's Who*. We continue to find positive estimates of *Instrumented Green Score*. The estimates, however, are not statistically significant because of the small matched sample.

Table 11 Instrumental variables (IV) estimations

	Dependent Variable: *Return on Assets* (t+1)					
Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)
Instrumented Green Score						
- 2000: Bush vs. Gore	0.986**	0.779**				
	(2.24)	(2.48)				
- 2004: Bush vs. Kerry			1.258**	0.946***		
			(2.30)	(2.66)		
- 2008: McCain vs. Obama					1.179**	0.981**
					(2.14)	(2.46)
Control Variables	Identical to those in Table 4, column 2					
Home State Fixed Effects	No	Yes	No	Yes	No	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
# Observations	12,627	12,614	12,628	12,615	12,628	12,615
Adjusted-R^2	0.243	0.326	0.076	0.247	0.129	0.228
First-stage F-statistic	22.19	34.32	20.79	34.93	19.17	29.89

This table reports the coefficient estimates of instrumental variables (IV) regressions. Each observation is at the firm-year level. In columns 1–2, *Green Score* is instrumented by *% Voting for Democrat*, the percentage of voters in a county voting for Gore in the 2000 presidential election. In columns 3–4, *Green Score* is instrumented by *% Voting for Democrat*, the percentage of voters in a county voting for Kerry in the 2004 presidential election. In columns 5–6, *Green Score* is instrumented by *% Voting for Democrat*, the percentage of voters in a county voting for Obama in the 2008 presidential election. *Home State Fixed Effects* are based on firms' historical headquarter states. *Industry Fixed Effects* are based on Fama-French 48 industry classifications. *First-Stage F-statistic* represents the first-stage Cragg-Donald Wald F-statistic. Standard errors are clustered at the firm level, and t-statistics are in parentheses. ***, **, and * indicate two-tailed t-statistics with statistical significance at the 1%, 5%, and 10% level, respectively

4.6 Hiring intensity?

An obvious concern is that *Green Score* could be associated with a concurrent increase in a firm's hiring intensity. Gutiérrez et al. (2020) find that changes in firms' online job postings are positively associated with firms' future operating performance. If firms' overall hiring intensity drives our result, we should not observe the effect of *Green Score* on firms' profitability after controlling for overall hiring intensity. To examine this possibility, we follow Gutiérrez et al. (2020) to construct two measures of firms' hiring intensity. *# Jobs* is the number of job postings of a firm in the first three months of the fiscal year t + 1. *# Green Jobs* is the number of green jobs of a firm in a given year. We separately include *# Jobs (Ln)* or *# Green Jobs (Ln)* in our baseline regression and re-estimate it.

Online Appendix Table 6, panel A summarizes the results. In column 1, we find that *# Jobs (Ln)* is positively associated with *Return on Assets*, which is consistent with the

[0] Although we do not have the job postings data from Eagle Alpha used in Gutiérrez et al. (2020), we used job postings data from Burning Glass. We replicated the main findings in their Table 3.

findings in Gutiérrez et al. (2020).[31] In column 2, we find that our main results remain robust after controlling for *# Jobs (Ln)*. The economic magnitude of *Green Score* barely changes after we include *# Jobs (Ln)*. In column 3, we find that *# Green Jobs (Ln)* is not associated with *Return on Assets* at the conventional level. In column 4, we find that the estimate of *Green Score* remains robust after we control for *# Green Jobs (Ln)*.

We also alternatively construct two versions of green jobs. Burning Glass has conducted in-house analyses based on job titles to identify green jobs. We obtain the list of green job titles shared by Burning Glass and list the detailed Standard Occupational Classification (SOC) codes for each title in Online Appendix Table 7. We use the information to construct two new variables. The first variable is *# Green Jobs (Titles)*, the number of jobs with titles containing the term(s) "climate," "nuclear," "recycling," "biofuel," "energy," "hydrolo," or "solar" of a firm in a given year. The second variable is *# Green Jobs (O*NET)*, the number of jobs with titles that match any of the O*NET green job titles in Online Appendix Table 7 of a firm in a given year.

We include these two new variables and re-estimate our baseline regression. Online Appendix Table 6, panel B, columns 1–3 summarize the estimation results. The results remain robust even after we control for alternative measures of green jobs.[32] As mentioned earlier, Burning Glass does not consider job titles to classify job skills; still, these results also mitigate the concern that an increase in new green job titles drives our main results.

Last, we ask whether the increase in *Green Score* could be associated with firms' efforts to manage their CSR image. To the extent that such impression management correlates with firms' overall marketing strategies, our baseline specification has already controlled for firms' advertising expenses.

An increase in *Green Score*, however, may still coincide with an increase in the hiring of public relations officers, and advertising expenses may not fully capture the increased hiring. To examine this possibility, we construct the variable *# Public Relations*, which is the number of jobs with titles containing the term(s) "public relations," "public affairs," "media relations," or "corporate communications." We include this variable and re-estimate our baseline specification. Our results in Online Appendix Table 6, panel B, column 4 remain robust.

Overall, these findings suggest that a concurrent increase in a firm's hiring intensity cannot explain our main results.

4.7 What about other skills?

One possible concern is that *Green Score* could simply be capturing the intensity of specialized skills (e.g., IT skills) specified in firms' job postings. To rule out this possibility, we first identify the top five skill categories specified in firms' job postings: *Information Technology (IT)*, *Sales*, *Business*, *Customer Services*, and *Supply Chain*. These five specializations represent the five most common families of skills in Burning Glass (i.e., the five most frequent skill cluster families in Burning Glass's taxonomy). Next, we follow the same methodology of computing *Green Score* to construct the following five specialization scores: *IT Score*, *Sales Score*, *Business Score*, *Customer*

[32] Our results remain robust if we incrementally control for the percentage of green jobs, as in Table 13, Panel B, column 4.

Services Score, and *Supply Chain Score*. For example, to compute *IT Score*, we first compute the *IT Score per Job*, which is the number of IT skills divided by the number of skills in each job. Then we take an average of *IT Score per Job* for all IT jobs of a firm in a given year. Table 12, panel A reports the distribution of such skill specializations by industry. On average, these five skill specializations are more prevalent than *Green Score*, as they are more general skills. If the skill concentrations could explain the effect of *Green Score* on firms' future performance, we would not observe a similar finding after controlling for these skill concentration measures.

We augment our baseline specification with each of these five specialization scores. Table 12, panel B summarizes the results. None of the other specialization scores are associated with future firm profitability. This suggests that our results do not reflect a firm-wide strategy of hiring specialized employees across other domains. We note, however, that our research design is not sharp enough to completely eliminate this competing mechanism, because there may be other specialization skills not captured by Burning Glass.

4.8 More robustness tests

In this section, we conduct a battery of robustness checks. First, we confirm our main results by alternatively measuring *Return on Assets* and *Green Score*. Table 13, panel A summarizes the results. In column 1, we reconstruct *Return on Assets* as sales (*SALE*) minus the costs of goods sold (*COGS*) and selling, general, and administrative expenses (*XSGA*), divided by total assets (*AT*). The estimate of *Green Score* remains robust. In column 2, we extend the measurement window of *Green Score* and construct *Green Score (Long Run)* as the cumulative sum of *Green Score* over the last three years from year *t*-3 to year *t*-1. Our main result remains robust. In column 3, *Green Score (Fiscal)* is the average *Green Score per Job* across all of a firm's jobs that require green skills in a fiscal year period. For example, if a firm's fiscal year ends on December 31, *Green Score (Fiscal)* is based on all job postings from January 1 to December 31. Column 3 shows that our results remain robust.

It is possible that firms repost the same job posting over a longer horizon (e.g., across years) and that the reposting affects the measurement of *Green Score*. To alleviate this concern, we conduct three additional analyses to mitigate the effect of such measurement error on *Green Score*. First, we use only the jobs in the first three months of a given year to calculate *Green Score*. In column 4, *Green Score (First Instance: Year)* is the average *Green Score per Job* across a firm's jobs that require green skills in the first three months of a given year. Second, to calculate *Green Score*, we use the jobs only when they first appear. For a given firm, we do not count any jobs with identical job titles after their first appearance. In column 5, *Green Score (First Instance: Firm)* is the average *Green Score per Job* across a firm's jobs that require green skills when they first appear. Last, we deflate *Green Score* using the inverse weight of the frequency of job titles. In column 6, *Green Score (Inversely Weighted)* is the average *Green Score per Job* across a firm's jobs that require green skills in a given year, inversely weighted by the frequency of job titles. The results in columns 4–6 suggest that our main results are robust to using these three alternative measures of *Green Score*. In column 7, *Green Score (All Jobs)* is the average *Green Score per Job* across all of a firm's jobs (not just green jobs that require green skills) in a given year, and our main results remain robust.

Table 12 What about other skills?

Panel A: Distribution by industry

Industries	***IT Score***	***Sales Score***	***Business Score***	***Customer Services Score***	***Supply Chain Score***
Consumer Nondurables	0.167	0.208	0.137	0.110	0.163
Consumer Durables	0.200	0.204	0.146	0.113	0.169
Manufacturing	0.180	0.172	0.149	0.101	0.167
Oil and Gas	0.196	0.108	0.149	0.087	0.144
Chemicals and Allied Products	0.149	0.168	0.145	0.092	0.154
Business Equipment	0.311	0.174	0.136	0.088	0.109
Wholesale and Retail	0.197	0.245	0.163	0.168	0.187
Healthcare	0.146	0.138	0.120	0.068	0.106
Others	0.195	0.179	0.152	0.128	0.141
Average	0.212	0.178	0.142	0.104	0.140

Panel B: Firm performance

	Dependent Variable: *Return on Assets* (t+1)					
Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)
Green Score						0.039***
						(3.32)
IT Score	−0.002					−0.006
	(−0.23)					(−0.58)
Sales Score		0.007				0.005
		(0.83)				(0.56)
Business Score			0.023*			0.023
			(1.66)			(1.57)
Customer Services Score				−0.001		−0.009
				(−0.06)		(−0.72)
Supply Chain Score					0.006	0.001
					(0.62)	(0.13)
Control Variables	Identical to those in Table 4, column 2					
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
# Observations	14,583	14,583	14,583	14,583	14,583	14,583
Adjusted-R^2	0.681	0.681	0.681	0.681	0.681	0.682

Panel A reports the distribution of other skill concentrations by industry. Panel B reports the coefficient estimates of ordinary least squares regressions. Each observation is at the firm-year level. *Green Score* is the average *Green Score per Job* across a firm's jobs that require green skills in a given year. *IT Score* is the average *IT Score per Job* across a firm's jobs that require IT skills in a given year. *Sales Score* is the average *Sales Score per Job* across a firm's jobs that require sales skills in a given year. *Business Score* is the average *Business Score per Job* across a firm's jobs that require business skills in a given year. *Customer Services Score* is the average *Customer Services Score per Job* across a firm's jobs that require customer services skills in a given year. *Supply Chain Score* is the average *Supply Chain Score per Job* across a firm's jobs that require supply chain skills in a given year. Standard errors are clustered at the firm level, and *t*-statistics are in parentheses. Intercepts are included for estimation but not tabulated. ***, **, and * indicate two-tailed *t*-statistics with statistical significance at the 1%, 5%, and 10% level, respectively

Table 13 More robustness tests

Panel A: Alternative measures of *Return on Assets* and *Green Score*

		Alternative *Green Score*:					
	Alternative *Return on Assets*	Long Run	Fiscal Period	First Instance: Year	First Instance: Firm	Inversely Weighted	All Jobs
	Dependent Variable: *Return on Assets* (t+1)						
Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Green Score	0.033^{**}						
	(2.36)						
Green Score (Long Run)		0.025^{***}					
		(3.34)					
Green Score (Fiscal)			0.036^{***}				
			(2.78)				
Green Score (First Instance: Year)				0.041^{***}			
				(3.48)			
Green Score (First Instance: Firm)					0.038^{***}		
					(3.30)		
Green Score (Inversely Weighted)						0.042^{***}	
						(2.83)	
Green Score (All Jobs)							0.234^{***}
							(2.86)
Control Variables/FEs	Identical to those in Table 4, column 2						
# Observations	14,595	13,120	14,583	14,583	14,583	14,583	14,583
Adjusted-R^2	0.720	0.682	0.681	0.682	0.682	0.682	0.682

Table 13 (continued)

Panel B: Alternative specifications

	Clustering of S.E. by Industry	Double Clustering of S.E. by Firm and Year	Controlling for Local Economic Conditions	Kitchen Sink
	Dependent Variable: *Return on Assets* (t+1)			
Independent Variables	(1)	(2)	(3)	(4)
Green Score	0.040**	0.040**	0.041***	0.045***
	(2.45)	(3.04)	(3.19)	(3.12)
Control Variables	Identical to those in Table 4, column 2			
Firm Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	No
State-Year FEs	No	No	Yes	Yes
# Observations	14,583	14,583	12,755	11,252
Adjusted-R^2	0.682	0.682	0.689	0.706

This table reports the coefficient estimates of ordinary least squares regressions. Each observation is at the firm-year level. Panel A alternatively measures *Return on Assets* and *Green Score*. Column 1 reconstructs *Return on Assets* as sales (*SALE*) minus the costs of goods sold (*COGS*) and selling, general, and administrative expenses (*XSGA*), divided by total assets (AT). In column 2, *Green Score (Long Run)* is the cumulative sum of *Green Score* over the last three years from year t-3 to year t-1. In column 3, *Green Score (Fiscal)* is the average *Green Score per Job* across a firm's jobs that require green skills in a fiscal year period. In column 4, *Green Score (First Instance: Year)* is the average *Green Score per Job* across a firm's jobs that require green skills in the first three months of a given year. In column 5, *Green Score (First Instance: Firm)* is the average *Green Score per Job* across a firm's jobs that require green skills when they first appear. For a given firm, we do not count any jobs with identical job titles after their first appearance. In column 6, *Green Score (Inversely Weighted)* is the average *Green Score per Job* across a firm's jobs that require green skills in a given year, inversely weighted by the frequency of job titles. In column 7, *Green Score (All Jobs)* is the average *Green Score per Job* across all of a firm's jobs in a given year. Panel B uses alternative specifications of our main model. Column 1 clusters standard errors by Fama-French 48 industries. Column 2 double-clusters standard errors by firm and year. In column 3, we incrementally control for local economic conditions by including state-year fixed effects. In column 4, we add ten control variables: *CSR 1*, *# Jobs (Ln)*, *# Green Jobs (Ln)*, *IT Score*, *Sales Score*, *Business Score*, *Customer Services Score*, *Supply Chain Score*, *% Green Job Titles*, and *% Green Job Functions*. Except in columns 1–2 of panel B, standard errors are clustered at the firm level, and t-statistics are in parentheses. Intercepts are included for estimation but not tabulated. ***, **, and * indicate two-tailed t-statistics with statistical significance at the 1%, 5%, and 10% level, respectively

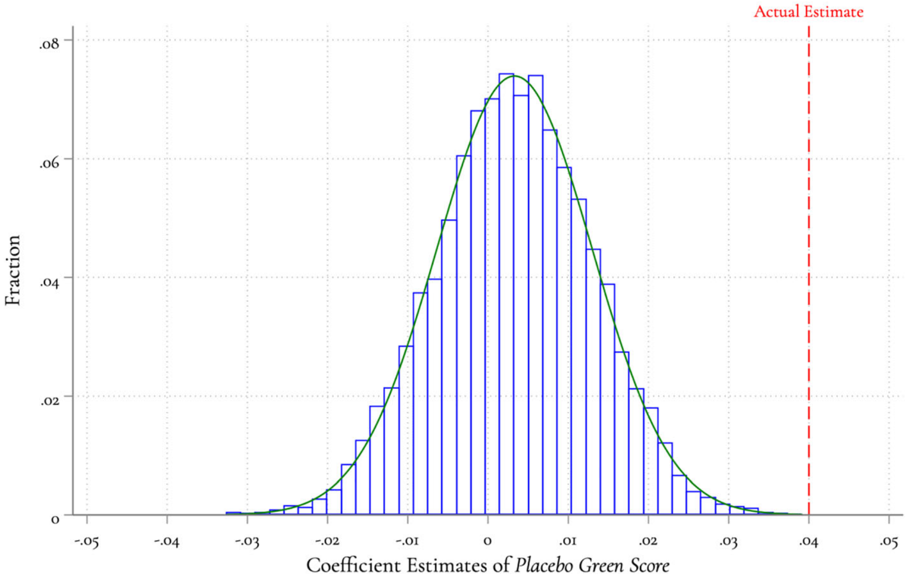

Fig. 3 Falsification test. This figure plots the distribution of the estimate of *Placebo Green Score*. The steps are as follows. First, we randomly shuffle *Green Score* for each firm-year within the same state-year during our sample period and label this variable *Placebo Green Score*. We then re-estimate the baseline specification from Table 3, column 2 by replacing *Green Score* with *Placebo Green Score*. After repeating the procedure 10,000 times, we summarize the estimates of *Placebo Green Score* in the bars below. The red dotted line represents the value of our actual estimate of *Green Score* from the baseline specification. We superimpose a line of normal density for reference

Panel B uses alternative specifications of our main model. Column 1 clusters standard errors by Fama-French 48 industries. Column 2 double-clusters standard errors by firm and year. This alternative clustering helps mitigate the concern that the standard errors of our *Green Score* estimates are underestimated because of repeated job postings across years. Our results remain robust.

In column 3, we incrementally control for the local economy by including state-year fixed effects. Our results remain robust. We also conduct a simple falsification test to address the potential concern that our measure of *Green Score* captures local economic conditions. The steps are as follows. First, we randomly shuffle *Green Score* for each firm-year within the same state-year during our sample period and label this variable *Placebo Green Score*. We then re-estimate the baseline specification in Table 4, column 2 after replacing *Green Score* with *Placebo Green Score*. After repeating the procedure 10,000 times, we summarize the estimates of *the Placebo Green Score* and plot the distribution of the estimate of *Placebo Green Score in* Fig. *3*. The red dotted line represents the value of our actual estimate of *Green Score* from the baseline specification in Table 4, column 2. There are two findings here. First, we do not find any systematic pattern showing that the *Placebo Green Score* can predict firms' future profitability. Second, the main effect reported in Table 4 is positioned far to the right of the entire distribution of estimates from the falsification test. Hence, the results suggest that the measure is not simply capturing local economic conditions.

In column 4, we add ten control variables on top of the variables in our baseline regressions (21 variables and three sets of fixed effects in total). Our results remain robust in all these robustness tests.

5 How to use *Green Score*? An application

In this section, we offer a simple application of our *Green Score* to detect greenwashing firms. As mentioned in the Introduction, firms may strategically distort their environmental disclosure without increasing their investment in green human capital. Such greenwashing improves a firm's environmental rating without requiring a corresponding increase in the firm's investment in green human capital. To help identify greenwashing firms, we construct *Greenwashing*, an indicator variable equal to one if the increase in *Green Score* is less than the increase in KLD strengths.[33] *Greenwashing* captures the difference between the concurrent increases in firms' environmental ratings and investment in green human capital. Thus, a firm that improves its environmental rating without a corresponding increase in its green human capital is likely to engage in greenwashing and have a higher value of *Greenwashing*. Online Appendix Table 8 tabulates a sample list of firms whose *Green Score* diverges significantly from their KLD environmental strengths.

Table 14 tabulates the results. First, we examine the determinants of firms' *Greenwashing* in column 1. We regress *Greenwashing* on the same control variables and fixed effects used in Table 4. We find that large firms, growth firms, and firms with high institutional ownership are more likely to engage in greenwashing.

Next, we examine whether *Greenwashing* is associated with future performance. Column 2 regresses *Return on Assets* on *Greenwashing* and the same control variables and fixed effects. We use all six ESG categories (i.e., diversity, employee relations, environment, product, community, and human rights) in KLD to measure *Greenwashing* in column 2. The estimate of *Greenwashing* is negative and statistically significant. The results suggest that firms that choose to greenwash have lower future profitability.

In columns 3–4, we further decompose KLD strengths into environmental strengths (column 3) and non-environmental strengths (column 4). We find that the main effect is only observed when firms greenwash their environmental strengths (column 3) but improve their other strengths (column 4). In other words, firms that choose to greenwash without correspondingly stepping up their environmental inputs have lower future profitability.

Overall, the results in this section suggest that *Green Score* can detect firms' greenwashing behaviors. We demonstrate one potential application of *Green Score* and encourage researchers to explore other applications in their future research.

6 Conclusion

In this paper, we use novel labor data to measure a firm's environmental efforts. Our idea builds upon a simple premise: a firm that puts in environmental efforts needs people to execute them. Specifically, we exploit firms' demand for green skills in their job postings as a proxy for their investment in green human capital – a type of environmental effort. In our context, green human capital is the set of green skills in

[33] This measure is similar to the "speak-in-two-tongues" measure proposed by Malmendier and Shanthikumar (2014). They use the distance between forecast optimism and recommendation optimism to measure an analyst's strategic distortion to issue an overly positive recommendation but a less optimistic forecast.

Table 14 How to use *Green Score*? An application

	Dependent Variables:			
		Return on Assets (*t*+1)		
Independent Variables	*Greenwashing* (1/0) (1)	All ESG Pillars (2)	Environmental Pillar (3)	Non-Environmental Pillars (4)
Greenwashing (1/0)		−0.008**	−0.007**	−0.005
		(−2.58)	(−2.28)	(−1.53)
Return on Assets	−0.210	0.186***	0.186***	0.186***
	(−0.48)	(7.94)	(7.94)	(7.94)
Firm Size (Ln)	0.505***	0.001	0.001	0.001
	(17.39)	(0.26)	(0.25)	(0.26)
Property, Plant, & Equip.	−0.216	0.072*	0.072*	0.072*
	(−0.61)	(1.90)	(1.91)	(1.90)
Leverage	−0.384	−0.064***	−0.064***	−0.064***
	(−1.52)	(−3.42)	(−3.42)	(−3.43)
Book-to-Market (Ln)	−0.273***	−0.054***	−0.054***	−0.054***
	(−5.51)	(−14.98)	(−15.01)	(−14.99)
R&D	1.107	−0.049	−0.048	−0.048
	(0.64)	(−0.68)	(−0.68)	(−0.68)
Loss	0.049	0.005	0.005	0.005
	(0.40)	(1.33)	(1.33)	(1.33)
Dividend	0.347***	−0.002	−0.002	−0.002
	(3.40)	(−0.40)	(−0.41)	(−0.40)
Institutional Ownership	1.377***	0.007	0.007	0.007
	(8.94)	(0.94)	(0.95)	(0.93)
CapEx	0.302	−0.026	−0.0264	−0.027
	(0.20)	(−0.47)	(−0.47)	(−0.47)
Advertising	1.340	−0.143	−0.142	−0.143
	(0.84)	(−0.69)	(−0.68)	(−0.69)
Industry Fixed Effects	Yes	No	No	No
Firm Fixed Effects	No	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
# Observations	14,055	14,583	14,583	14,583
Pseudo-R^2/Adjusted-R^2	0.204	0.681	0.681	0.681

This table reports the coefficient estimates of logistic regression (column 1) and ordinary least squares regressions (columns 2–4). Each observation is at the firm-year level. *Greenwashing* is an indicator variable equal to one if the increase in *Green Score* is less than the increase in KLD strengths. In column 2, the KLD strengths are based on all six ESG pillars: diversity, employee relations, environment, product, community, and human rights. In column 3, only strengths from the environmental pillar are used to construct *Greenwashing*. In column 4, only strengths from the non-environmental pillars are used to construct *Greenwashing*. Details of other variables are in Appendix B Table 16. Standard errors are clustered at the firm level, and *t*-statistics are in parentheses. Intercepts are included for estimation but not tabulated. ***, **, and * indicate two-tailed *t*-statistics with statistical significance at the 1%, 5%, and 10% level, respectively a firm's workforce, and green skills are environment-related skills (e.g., environmental science skills). We propose a new measure, *Green Score*, based on the concentration of green skills required in firms' job postings.

Our main findings are as follows. First, we find that firms that increase their *Green Score* have higher future profitability. Second, we find that firms that increase their *Green Score* generate more green patents, and those green patents are of higher quality and receive more citations. Third, we show that the KLD ratings that are widely used to evaluate firms' environmental efforts do not consider firms' *Green Score*. Fourth, we find that firms do not proactively increase their *Green Score*. Instead, they sluggishly increase their *Green Score* over consecutive years in response to negative environmental shocks (e.g., negative publicity on environmental efforts, regulatory noncompliance). Fifth, we find that hiring job candidates who have green skills costs firms more. Last, we offer a simple application of our *Green Score* to detect greenwashing firms. We find that these greenwashing firms have lower future profitability.

Our main contributions are as follows. First, we propose a new action-based measure to quantify firms' investment in human capital and, more specifically, investment in green human capital. *Green score* is simple to measure. It is less subjective and offers a larger time-series variation than traditional disclosure-based environmental ratings, which typically rely on firm disclosure. It also covers a much wider set of firms than traditional rating agencies, including firms in both polluting and non-polluting industries. Second, our findings contribute to the CSR literature. We find that firms' investment in green human capital proxied by the concentration of green skills required in firms' job postings is associated with future profitability after we control for KLD ratings. Our results on green patents also reveal a mechanism whereby *Green Score* is associated with better firm performance. Our results will inform firm executives – especially those with the worst environmental track records – by suggesting that firms could step up their investment in green human capital more proactively and thereby increase their future profitability.

We provide a simple application of our *Green Score* to detect greenwashing firms. We encourage researchers to consider using *Green Score* to answer a broad set of questions on firms' CSR performance (e.g., whether an increase in *Green Score* leads to better employee satisfaction and lower workplace injury). The methodology we use to construct *Green Score* could also be extended to other ESG pillars (e.g., it could be used to construct a skill-based score to capture firms' governance performance).

Appendix A

Job Description of a Sample Green Job

JOB TITLE:

Environmental Engineer/Scientist (Maplewood, MN) at 3M.

TYPE:

Full-Time.

LOCATION:

Maplewood, Minnesota.

JOB DESCRIPTION:

3M is seeking an Environmental Engineer/Scientist for Corporate Environment, Health, Safety &amp [sic]; Sustainability located in Maplewood, MN. At 3M, you can apply your talent in bold ways that matter. Here, you go.

JOB SUMMARY:

The person hired for the position of Environmental Engineer/Scientist will primarily be responsible for supporting and leading environmental remediation projects involving cross functional teams for various sites around the world. For additional information, please visit: https://www.3m.com/3M/en_US/sustainability-us/ This position provides an opportunity to transition from other private, public, government or military environments to a 3M career. Primary Responsibilities include but are not limited to the following:

- Serve as project engineer/scientist and/or project manager for assigned remediation projects.
- Manage financial aspects of remediation project spending.
- Direct external contractors involved in remediation projects.
- Assess regulatory requirements and establish remediation strategy for assigned projects.
- Communicate with internal and external stakeholders regarding relative aspects of assigned projects.
- Optimize remediation project effectiveness at various phases of implementation.
- Assist internal stakeholders with projects related to property acquisition, divestiture and/or closure.

BASIC QUALIFICATIONS:

Possess a Bachelor's degree or higher in engineering or science discipline (completed and verified prior to start) from an accredited university. Minimum of one (1) year of environmental experience in a private, public, government or military environment.

PREFERRED QUALIFICATIONS:

- Project management experience
- Training and/or experience with Geographic Information Systems (GIS)
- Environmental regulatory knowledge (with a basic understanding of waste and remediation concepts and regulations), with experience working with regulatory agencies in interactions and/or negotiations
- Previous experience in waste characterization, geology/hydrogeology, environmental site assessments and/or asbestos regulations
- Strategic thinker, high attention to detail, process-oriented, ability to develop and maintain good working relations with clients, effective listening abilities, ability to communicate with varying levels and in one-on-one, small group and large audience settings, clear and concise writing and data documentation style, and a self-starter with the ability to multi-task.
- Knowledge and experience related to auditing and health and safety regulations a plus
- Microsoft Office proficient

TRAVEL:

May include up to 20% domestic/international.

RELOCATION:

Must be legally authorized to work in country of employment without sponsorship for employment visa status (e.g., H1B status).

Responsibilities of this position may include direct and/or indirect physical or logical access to information, systems, technologies subjected to the regulations/compliance with U.S. Export Control Laws. U.S. Export Control laws and U.S. Government Department of Defense contracts and sub-contracts impose certain restrictions on companies and their ability to share export-controlled and other technology and services with certain "non-U.S. persons" (persons who are not U.S. citizens or nationals, lawful permanent residents of the U.S., refugees, "Temporary Residents" (granted Amnesty or Special Agricultural Worker provisions), or persons granted asylum (but excluding persons in nonimmigrant status such as H-1B, L-1, F-1, etc.) or non-U.S. citizens. To comply with these laws, and in conjunction with the review of candidates for those positions within 3M that may present access to export controlled technical data, 3M must assess employees' U.S. person status, as well as citizenship(s). The questions asked in this application are intended to assess this and will be used for evaluation purposes only. Failure to provide the necessary information in this regard will result in our inability to consider you further for this particular position. The decision whether or not to file or pursue an export license application is at 3M Company's sole election.

Table 15 Job Description of a Sample Green Job

Skill
1. Geographic Information System (GIS)
2. Writing
3. **Environmental remediation**
4. Multi-tasking
5. Detail-oriented
6. **Hydrogeology**
7. Information systems
8. **Site assessments**
9. Microsoft Office
10. Project management
11. Self-starter
12. **Environmental engineering**
13. Listening
14. Data documentation

Burning Glass has identified 14 skills for the green job. The *Green Score per Job* is 0.286 (= 4 green skills ÷ 14 skills)

Appendix B

Table 16 Variable Definitions

Main Variables	Descriptions
Green Score per Job	Number of green skills divided by the number of skills in each job. For example, if a job requires five sets of skills and one set of skills is green skills, then the *Green Score per Job* is 0.20. [Source: Burning Glass]
Green Score	Average *Green Score per Job* across a firm's jobs that require green skills in a given year. [Source: Burning Glass]
Green Score (*t*+ *3*)	Cumulative sum of *Green Score* over the next three years from year $t+1$ to $t+3$. [Source: Burning Glass]
# Green Skills	Number of green skills in each job. [Source: Burning Glass]
# Green Jobs	Number of green jobs in a given year. A job is a green job if the concentration of green skills is more than the sample median. [Source: Burning Glass]
# Green Jobs (*t*+ *3*)	Cumulative sum of # *Green Jobs* over the next three years from year $t+1$ to $t+3$. [Source: Burning Glass]
Greenwashing	An indicator variable equal to one if the increase in *Green Score* is less than the increase in KLD strengths. [Source: Burning Glass and KLD]
Return on Assets	Net income or loss (*NI*) divided by total assets (*AT*). It is winsorized at the 1st and 99th percentiles. [Source: Compustat]
Net Profit Margin	Net income (*NI*) divided by sales (*SALE*). It is winsorized at the 1st and 99th percentiles. [Source: Compustat]
Asset Turnover	Sales (*SALE*) divided by total assets (*AT*). It is winsorized at the 1st and 99th percentiles. [Source: Compustat]
Gross Profit Margin	Sales (*SALE*) minus cost of goods sold (*COGS*), divided by sales (*SALE*). It is winsorized at the 1st and 99th percentiles. [Source: Compustat]
Sales	Sales (*SALE*). [Source: Compustat]
Cost of Goods Sold	Cost of goods sold (*COGS*) divided by sales (*SALE*). It is winsorized at the 1st and 99th percentiles. [Source: Compustat]
SGA Expenses	Selling, general, and administrative expense (*XSGA*) divided by total assets (*AT*). It is winsorized at the 1st and 99th percentiles. [Source: Compustat]
# Patents	Number of patents applied for and eventually granted from year $t+1$ to year $t+3$. [Source: United States Patent and Trademark Office and WRDS US Patents]
# Green Patents	Number of green patents applied for and eventually granted from year $t+1$ to year $t+3$. [Source: United States Patent and Trademark Office and WRDS US Patents]
# Green Patents (Environmental Management Technologies)	Number of green patents on environmental management technologies applied for and eventually granted from year $t+1$ to year $t+3$. [Source: United States Patent and Trademark Office and WRDS US Patents]

Table 16 (continued)

Main Variables	Descriptions
# Green Patents (Water-Related Adaptation Technologies)	Number of green patents on water-related adaptation technologies applied for and eventually granted from year $t+1$ to year $t+3$. [Source: United States Patent and Trademark Office and WRDS US Patents]
# Green Patents (Greenhouse Gases Technologies)	Number of green patents on greenhouse gases technologies applied for and eventually granted from year $t+1$ to year $t+3$. [Source: United States Patent and Trademark Office and WRDS US Patents]
# Green Patents (Climate Change Mitigation Technologies)	Number of green patents on climate change mitigation technologies applied for and eventually granted from year $t+1$ to year $t+3$. [Source: United States Patent and Trademark Office and WRDS US Patents]
# Citations	Number of citations of applied-for and granted patents from year $t+1$ to $t+3$. [Source: United States Patent and Trademark Office and WRDS US Patents]
# Green Citations	Number of citations of applied-for and granted green patents from year $t+1$ to $t+3$. [Source: United States Patent and Trademark Office and WRDS US Patents]
CSR 1	The difference between *STR 1* and *CON 1*. *STR 1* is the sum of strengths across all six CSR categories (i.e., community, diversity, employee relations, environment, product, and human rights), divided by the sum of the maximum possible strengths across the six CSR categories. *CON 1* is the sum of concerns across the six CSR categories, divided by the sum of the maximum possible concerns across the six CSR categories for each firm-year. Missing values are assigned to be zero. [Source: KLD]
CSR 2	The difference between *STR 2* and *CON 2*, divided by the sum of the maximum possible strengths and the maximum possible concerns across all six CSR categories (i.e., community, diversity, employee relations, environment, product, and human rights) for each firm-year. *STR 2* is the sum of strengths across the six CSR categories. *CON 2* is the sum of concerns across the six CSR categories. Missing values are assigned to be zero. [Source: KLD]
CSR 3	The difference between *STR 3* and *CON 3*. *STR 3* is the sum of strengths of each CSR category (i.e., community, diversity, employee relations, environment, product, and human rights), divided by the maximum possible strengths of each of the six CSR categories for each firm-year. *CON 3* is the sum of concerns of each CSR category, divided by the maximum possible concerns of each of the six CSR categories for each firm-year. Missing values are assigned to be zero. [Source: KLD]
ENV 1	The difference between *ENV STR* and *ENV CON*. *ENV STR* is the sum of environmental strengths, divided by the maximum possible strengths in the environment category. *ENV CON* is the sum of environmental concerns, divided by the maximum possible concerns in the environment category for each firm-year. Missing values are assigned to be zero. [Source: KLD]
ENV 2	The difference between the sum of environmental strengths and the sum of environmental concerns, divided by the sum of the maximum possible strengths and concerns in the environment category for each firm-year. Missing values are assigned to be zero. [Source: KLD]

Table 16 (continued)

Main Variables	Descriptions
# Bad Green News	Number of severe environmental incidents a firm experiences in a given year. [Source: RepRisk]
# Environmental Violations	Number of environmental violations by a firm in a given year. [Source: Violation Tracker]
$ Environmental Violations	Dollar sum of environmental violations by a firm in a given year. [Source: Violation Tracker]
Firm Size	Total assets (*AT*). [Source: Compustat]
Property, Plant, & Equipment	Property, plant and equipment (*PPENT*) divided by total assets (*AT*). It is winsorized at the 1st and 99th percentiles. [Source: Compustat]
Leverage	Sum of long-term debt (*DLTT*) and short-term debt (*DLC*), divided by total assets (*AT*). It is winsorized at the 1st and 99th percentiles. [Source: Compustat]
Book-to-Market	The ratio of book value to market capitalization. Book value is the sum of common equity (*CEQ*) plus deferred taxed and investment credit (*TXDITC*) minus the book value of preferred stock (depending on availability, *PSTKRV PSTKL PSTK*, in that order). Market capitalization is the number of shares outstanding (*CSHO*) multiplied by share price (*PRCC_F*). [Source: Compustat]
R&D	Research and development expenses (*RD*) divided by total assets (*AT*). It is winsorized at the 1st and 99th percentiles. [Source: Compustat]
Loss	An indicator variable equal to one if a firm's *Return on Assets* in year *t*-1 is negative. [Source: Compustat]
Dividend	An indicator variable equal to one if a firm pays dividends (*DVC*). [Source: Compustat]
Institutional Ownership	Percentage of total institutional ownership in a firm. It is winsorized at the 1st and 99th percentiles. [Source: WRDS 13F dataset]
CapEx	Capital expenditures (*CAPX*) divided by total assets (*AT*). It is winsorized at the 1st and 99th percentiles. [Source: Compustat]
Advertising	Advertising expenses (*XAD*) divided by sales (*SALE*). It is winsorized at the 1st and 99th percentiles. [Source: Compustat]
Salary	Salary of a job. [Source: Burning Glass]
Years of Experience	Minimum number of years of experience required for a job. [Source: Burning Glass]
Years of Education	Minimum number of years of education required for a job. [Source: Burning Glass]
# Jobs	Number of job postings of a firm in the first three months of the fiscal year *t*+1. [Source: Burning Glass]
% Voting for Democrat	Percentage of voters in a county voting for Democrats in a presidential election. [Source: MIT Election Lab]
IT Score	Average *IT Score per Job* across a firm's jobs that require IT skills in a given year. *IT Score per Job* is the number of information technology (IT) skills (Microsoft Office, technical support, SAP) divided by the number of skills in each IT job. [Source: Burning Glass]

Table 16 (continued)

Main Variables	Descriptions
Sales Score	Average *Sales Score per Job* across a firm's jobs that require sales skills in a given year. *Sales Score per Job* is the number of sales skills (e.g., business development, merchandising, negotiation skills) divided by the number of skills in each sales job. [Source: Burning Glass]
Business Score	Average *Business Score per Job* across a firm's jobs that require business skills in a given year. *Business Score per Job* is the number of general business skills (e.g., project management, supervisory skills, and staff management) divided by the number of skills in each general business-related job. [Source: Burning Glass]
Customer Services Score	Average *Customer Services Score per Job* across a firm's jobs that require customer services skills in a given year. *Customer Score per Job* is the number of customer service skills (e.g., customer contact, refunds and exchanges, and customer accounts) divided by the number of skills in each customer services job. [Source: Burning Glass]
Supply Chain Score	Average *Supply Chain Score per Job* across a firm's jobs that require supply chain skills in a given year. *Supply Chain Score per Job* is the number of supply chain skills (e.g., forklift operation, commercial driving, and truck driving) divided by the number of skills in each supply chain job. [Source: Burning Glass]
Green Score (Long Run)	Cumulative sum of *Green Score* over the last three years from year *t*-3 to year *t*-1. [Source: Burning Glass]
Green Score (Fiscal)	Average *Green Score per Job* across a firm's jobs that require green skills in a fiscal year period. [Source: Burning Glass]
Green Score (First Instance: Year)	Average *Green Score per Job* across a firm's jobs that require green skills in the first three months of a given year. [Source: Burning Glass]
Green Score (First Instance: Firm)	Average *Green Score per Job* across a firm's jobs that require green skills when they first appear. [Source: Burning Glass]
Green Score (Inversely Weighted)	Average *Green Score per Job* across a firm's jobs that require green skills in a given year, inversely weighted by the frequency of job titles. [Source: Burning Glass]
Green Score (All Jobs)	Average *Green Score per Job* across all a firm's jobs in a given year. [Source: Burning Glass]

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