Green Investors and Green Transition Efforts: Talk the Talk or Walk the Walk?*

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Abstract

Are green investors investing in activities that actually benefit the environment or only claim to benefit it? I answer this question by testing the relationship between investor decisions and a firm's substantive green transition (i.e., walk) or communication of a green corporate image (i.e., talk). I propose a novel approach to separately measure walk and talk by applying natural language processing to online job postings. Since walk and talk require workers to specialize in different tasks, I use a firm's demand for walk-relevant workers as a proxy for its efforts on walk, and the same goes for talk. I document firms that talk more are assigned better environmental ratings and are held by more sustainable funds, keeping the walk level fixed. A higher level of talk correlates with an increase in the number of institutional investors holding the firm's stock and predicts a significantly higher stock return, while a higher level of walk does not. These findings show that green investors' portfolio choices are sensitive to a firm's talk, potentially deviating from their goal of supporting substantive green transition.

JEL Classification: G11, G12, G23, M3, Q5. *Keywords*: ESG, sustainable investing, greenwashing, green marketing, green jobs.

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1 Introduction

As the demand for environmentally responsible business activities escalates rapidly, the resources held by investors who promote environmental characteristics or pursue a sustainable investment objective (i.e., green investors, as defined by the EU Sustainable Finance Disclosure Regulation) are flowing into companies that are believed to carry out these activities. However, outsiders cannot observe the effects of these activities straightforwardly or immediately. It thus becomes important to understand whether green investors know the real impact of these activities and allocate resources to support those that truly benefit the environment.

Are investors investing in activities that actually benefit the environment or merely claim to benefit it? This paper focuses on this question and its implications. Facing the increasing demand for a green corporate image, a firm can make substantive improvements in its environmental impact or use communication strategies to boost its corporate image without improving environmental impact. The goal of sustainable investment requires a sophisticated green investor to tell the two types of behaviors apart and invest in substantive improvements. If investors' asset allocation decisions are sensitive to communication strategies, firms that focus on communication can attract as much capital as firms that focus on substantive improvements, which does not necessarily contribute to environmental sustainability. The literature has not given a clear answer as to whether green investors are skilled at distinguishing "talking the talk" from "walking the walk". On the one hand, professionals are paid to discover true environmental performance. They should be sophisticated enough to spot the communication strategies and achieve the goal of investing in substantive improvements. On the other hand, we do see some cases where investors and intermediaries in green investing are not sophisticated (Berg, Fabisik, and Sautner, 2020; Rzeźnik, Hanley, and Pelizzon, 2021).

To test whether green investors are able to invest in substantive green transitions (i.e., *walk*) without being influenced by communication strategies (i.e., *talk*), a prerequisite is to measure how much a firm talks the talk and walks the walk, respectively. This is a challenge in the literature. First of all, it is difficult to clearly separate *walk* from *talk*. Most environmental information is self-reported and, thus a mixture of *walk* and *talk*. Many studies document that firms embellish their environmental disclosures (Marquis, Toffel, and Zhou, 2016; Diouf and Boiral, 2017). To tell *walk* from *talk*, we need information sources that are less susceptible to the embellishment incentive. Second, because investors invest in current or future activities, the measurements of *walk* and *talk* should also be current or forward-looking. However, most environmental information is disclosed

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with a significant time lag. Using past achievements as investment standards results in the companies with lower ESG scores often being excluded from the investment universe of ESG funds, although they are key innovators in the green patent landscape in the United States (Cohen, Gurun, and Nguyen, 2020). We need measurements that reflect firms' ongoing efforts on *walk* and *talk*.

I tackle this challenge by proposing a new approach to separately measure firms' efforts on *walk* and *talk* using their hiring decisions revealed in online job postings. As labor is a necessary production factor, a firm's current demand for certain worker expertise reflects its ongoing efforts in the corresponding area. A company conducting substantive green transitions could not implement it without relevant workers, such as environmental engineers or solar energy systems engineers. In contrast, a firm trying to communicate a green corporate image to the public needs public relations specialists or marketing personnel with knowledge of environmental issues. Since *walk* and *talk* require different types of workers, a firm's demand for walk-relevant job positions scaled by its demand for all kinds of job positions provides a proxy for its *walk* efforts, and the same goes for *talk*. Because walk-relevant job positions do not overlap with talk-relevant job positions, there is a clear division between the measured *walk* and the measured *talk*. Moreover, job postings are observed in real time, which satisfies the requirement for measuring current or future firm activities.

Walk and *talk* in this study are close to, but not limited to, greenwashing. In most studies, greenwashing refers to the intersection of poor environmental performance and positive communication about environmental performance (Delmas and Burbano, 2011). The difference between vocal green firms and silent green firms is not discussed. However, in both environmentally good and bad performers, communication strategies can influence green investors' decisions. Therefore, this paper studies *walk* and *talk* in both cases. This measurement approach is also closely related to Darendeli, Law, and Shen (2021). They measure a job posting's greenness by the proportion of green skills among all the skills required by a job position, without differentiating *walk* from *talk*, to study the connection between green skill level and profitability, patents, or environmental ratings.

The link between environmental outcomes and measured *walk* or *talk* shows that *walk* contributes to positive environmental impact while *talk* does not. Over a firm's lifetime, *walk* is associated with decreased carbon intensity and increased recycling. *Talk* is associated with deteriorated environmental outcomes or is irrelevant, keeping *walk* fixed. Comparing firms in the same industry in the same year, firms with a higher carbon intensity *walk* more, consistent with Cohen, Gurun, and Nguyen (2020), and firms with a higher ratio of hazardous waste *talk* more, consistent with the motivation to repair a

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damaged public image. Although *talk* does not help with environmental outcomes, there is an immediate, robust correlation between *talk* and an improved corporate image on the topic of greenhouse gas emissions. Interestingly, how media perceive the materiality of greenhouse gas emissions to a company is still mostly related to *walk*. Another feature distinguishing *walk* from *talk* is that *walk* involves more R&D expenses and capital expenditures, while *talk* involves more non-production costs. I also document that in the face of environmental regulatory violations, firms tend to only increase *talk* without a significant change in *walk*. In addition, I test whether *talk* and *walk* have a positive lead-lag relationship. It turns out that talk is not a leading indicator of future *walk* when controlling for past *walk*.

Armed with the measurements of *walk* and *talk*, I study how they influence investor decisions. I start by testing how *walk* and *talk* affect the environmental ratings that are widely referred to by investors. Professional rating agencies are paid to collect information and evaluate firms' environmental performance. If these ratings mostly characterize *talk*, investors who rely on them are inevitably influenced by *talk*. All three major environmental ratings from MSCI KLD, Refinitiv ASSET4, and Sustainalytics assign better evaluations to firms that *talk* more, controlling for the *walk* level. The MSCI and Refinitiv ratings are sensitive to the variation in the *walk* level. In contrast, the Sustainalytics rating does not exhibit a significant correlation with the *walk* level. Nonetheless, all three ratings are very persistent over time, indicating that either the firms have made little progress, or these ratings do not reflect their progress. My measurements of *walk* and *talk* capture information beyond these environmental ratings.

Next, I test whether a stock's popularity among sustainable funds is associated with the firm's *walk* and *talk*. If green investors aim to invest in substantive green transitions, the number of green investors holding a stock should increase with the firm's *walk* and not increase with its *talk* because *talk* does not improve environmental outcomes. Using the number of legally binding dark green, light green, or nongreen funds holding a stock, I show that the portfolio choices of light green funds, the majority of sustainable funds, are influenced by both *walk* and *talk*. Dark green funds, the funds with the strictest sustainable investing mandate, can differentiate *walk* from *talk* and invest more in firms that *walk* more, without being influenced by *talk*.

Besides green investors, nongreen investors may also integrate *walk* and *talk* into the investment process if they believe these affect pecuniary returns. I test how the broad institutional investors respond to *walk* and *talk* using the number of 13F institutional investors owning a stock. The institutional ownership breadth increases more for firms that *talk* more but not for firms that *walk* more when comparing firms in the same industry

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in the same year. Unlike green investors, who are sensitive to *walk*, broad institutional investors are only sensitive to *talk*.

I further test whether *walk* and *talk* can predict future stock returns. Consistent with the change in institutional ownership breadth, *walk* does not exhibit a significant link to stock returns in the next month, next three months, or next six months, whereas *talk* has a robust positive relationship with future returns between January 2016 and December 2021. The early years are removed due to very limited observations, and 2022 is removed due to the shock brought by the Russia–Ukraine War. The significantly higher future stock returns of firms that *talk* more rather than *walk* more, on the one hand, reflects that the market has not fully incorporated the environmental risks that only *walk* can manage. On the other hand, they justify some green investors' preference for firms that *talk* more due to their higher future returns. However, if investors are not sensitive firm's *walk*, it is questionable how much investors, especially green investors, can contribute to firms' substantive green transition, which is the mandate of green investors.

This paper makes three primary contributions to the literature. First, I provide novel evidence that most capital in green investing is sensitive to firms' *talk*. Firms that merely talk the talk can potentially attract as much capital as firms that walk the walk, although talking the talk neither associates with improved environmental outcomes nor predicts more *walk* in the future. The evidence that the portfolio choices of broad institutional investors and future stock returns are positively related to *talk* suggests a similarity between green investors and nongreen investors. It implies that most green investors do not focus on supporting substantive green transitions. This contributes to the literature on the relationship between investors and firms' sustainability pursuits and communications. Bingler, Kraus, Leippold, and Webersinke (2022) test whether various climate initiatives decrease imprecise climate commitments in annual reports. Dzieliński, Eugster, Sjöström, and Wagner (2022) and Chava, Du, and Malakar (2021) find a positive association between the discussion of environmental topics in earnings calls and environmental performance. These studies focus on whether investors motivate firms to *walk* instead of empty *talk*. My paper studies how firms' *walk* and *talk* affect investors' portfolio choices.

Second, I show that *talk* instead of *walk* predicts future stock returns. This adds to the literature on the ESG profile's cross-sectional return predictability. Previous studies debate whether the ESG profile's cross-sectional return predictability exists and where the predictability comes from (Pedersen, Fitzgibbons, and Pomorski, 2021; Pástor, Stambaugh, and Taylor, 2022; Bolton and Kacperczyk, 2021; Berk and van Binsbergen, 2021; Avramov, Lioui, Liu, and Tarelli, 2021). The lower risk premium required to hold green assets may be completely overridden by positive shifts in customers' tastes for green

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products and investors' tastes for green holdings. The empirical evidence is mixed, partly because these studies use different ESG proxies in different sample periods. Berg, Kölbel, Pavlova, and Rigobon (2021) show that the noise in existing ESG proxies makes the estimated effect of ESG performance on stock returns suffer from attenuation bias. I provide an alternative perspective in the comparison between *walk* and *talk*.

Finally, I provide a new approach to separately measure a firm's ongoing efforts in *walk* and *talk*. It complements the existing environmental information and can be used to guide investment in practice. For example, for high-stakes projects requiring high substantive efforts but without immediate successful outputs, investors can use the proportion of walk-relevant job postings as an indicator of the substantive efforts. The measurements can also be used in other studies, such as in testing whether climate-related disclosures or other initiatives motivate *walk* or *talk*. One concern is that the new hiring captured by online job postings is not representative of the entire employee structure. In the other studies using online job postings (Abis and Veldkamp, 2020; Babina, Fedyk, He, and Hodson, 2020; Darendeli, Law, and Shen, 2021), this concern has been addressed by cross-validating with other data sources. For example, Babina, Fedyk, He, and Hodson (2020) verifies that current employees (from resumes) and the demand for additional employees (from job postings) are highly correlated and have consistent trends.

The remainder of this paper is organized as follows. Section 2 describes the data. Section 3 introduces the measurement approach and descriptive features of measured walk and talk. Section 4 displays walk and talk's different associations with firm characteristics, including environmental outcomes, corporate images, financial indicators, and regulatory violations. Section 5 explores the relationship between firm green transition efforts and investor decisions, analyzing the impact of walk and talk on environmental scores, sustainable funds' holdings, overall institutional holdings, and stock returns. The conclusion follows in Section 6.

2 Data sources

Online job postings data from LinkUp. The LinkUp database is a leading provider of job market data and analyses (Campello, Kankanhalli, and Muthukrishnan, 2020). It contains the detailed contents of 165 million job records from about 60,000 companies' career sites, including private and public firms, U.S. firms, and non-U.S. firms. The first job record dates back to 2007. Once a company enters the database, it is tracked until the company disappears. For each job record, the LinkUp database lists the location of the job, the employer, the date of creation, the date of the latest update, the date of

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deletion, and the O*NET occupation code recognized by third-party software from the title of the job and the job description. LinkUp does not provide most of the job descriptions before 2016. The O*NET occupation code is an occupation classification method that follows the Standard Occupational Classification System (SOC). All O*NET codes mentioned in this study refer to the O*NET-SOC 2010 version.

This study focuses on North American firms' job postings for positions located in the United States. In spite of the concern that North American firms transfer pollution-causing sections of their operations outside of the U.S., I exclude jobs outside of the U.S. because the natural language processing algorithm I use cannot handle multiple languages.

LinkUp's linking table maps each firm's internal permanent identifier to its CUSIP and makes it possible to merge with other databases. When one Compustat company is linked to multiple LinkUp firms (e.g., due to merger and acquisition or subsidiaries), Compustat data are linked to the sum of its matched LinkUp firms. The number of companies in the Compustat universe covered by LinkUp is listed in Table 1. The sample period runs from 2007 to June 2022. As most job postings before 2016 lacked job descriptions, my sample concentrates on the recent years starting from 2016.

Although Burning Glass has a broader coverage, LinkUp has a reasonably comprehensive coverage. More importantly, LinkUp is less susceptible to duplicates and inaccurate creation dates than Burning Glass. Burning Glass collects job postings from various sources, while LinkUp collects job postings only from career pages on company websites. It is challenging for Burning Glass to determine whether there are multiple openings or duplicate postings. Duplicates can inflate the number of job postings and bias the measurements using the number of a particular type of job postings. In addition, the creation date of a job posting on the career page of a company's website is usually more accurate than the creation date from other sources. It is not easy to guarantee the accuracy and timeliness of the information on third-party platforms Burning Glass uses.

The number of EU SFDR Article 6, 8, and 9 funds holding a U.S. stock from Bloomberg. To comply with the European Union (EU) Sustainable Finance Disclosure Regulation (SFDR) 2019/2088, each fund available for sale in the EU must be classified into one of the following three categories. (1) Article 6: Where the financial product does not pursue or promote environmental or social objectives but where sustainability risks may be assessed to determine their impact on the returns of the financial product. (2) Article 8: Where a financial product promotes environmental or social characteristics or a combination of those characteristics, provided that the companies in which the investments are made follow good governance practices. (3) Article 9: Where a financial product has sustainable investment as its objective and complies with the "no significant

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harm" principle. For each stock, Bloomberg provides the latest number of Article 6, 8, or 9 funds with security exposure of more than 0% to it. My sample is cross-sectional data hand-collected in June 2022.

Environmental outcome metrics from Bloomberg. The yearly metrics include carbon intensity (the sum of carbon emissions of scope-1 and scope-2 divided by various denominators for the sake of robustness), travel emissions intensity, percentage of recycled waste, and percentage of hazardous waste. My sample spans from 2007 to 2022.

Firm-level media sentiments on environmental issues from TruValue Labs. TruValue Labs tracks daily ESG news outside of focal firms, including analyst reports, various media, advocacy groups, and government regulators. It aggregates such unstructured data and uses natural language processing to interpret semantic content to generate ESG scores that range from 0 (most negative) to 100 (most positive). Truvalue Labs classifies the data into the 26 categories defined by the Sustainability Accounting Standards Board. My study uses the category of greenhouse gas emissions because this category is material to all industries, while other categories may only be material to specific industries. My sample spans the period from January 2007 to June 2022.

Environment-related regulatory violations data from Violation Tracker. Violation Tracker covers corporate misconducts resolved by federal regulatory agencies and all parts of the Justice Department since 2000, plus cases from state attorney generals and selected state regulatory agencies. Violation Tracker has eliminated entries with penalty amounts below $5,000 as well as those with no dollar penalties at all. The Violation Tracker also provides adjusted penalties to avoid double-counting penalty amounts reported in different records by multiple facilities owned by a single company. Infractions covered by the Violation Tracker include different types of offenses. Only environmental violations are used, such as energy conservation violations, environmental violations, fuel economy (CAFE) violations, and offshore drilling violations.

Environment strengths and concerns from MSCI. The MSCI ESG KLD STATS dataset assigns 0 or 1 to each firm each year for each category of strength or concern under environmental topics. For example, waste management is a category of strength, and hazardous waste is a category of concern. I calculate a net environmental score following the method of Lins, Servaes, and Tamayo (2017). Namely, for each firm each year, I divide the sum of strengths (concerns) by the maximum number of strengths (concerns) possible in that year and then subtract the concerns index from the strengths index. My sample spans from 2007 to 2018.

Environment pillar scores from Refinitiv. Refinitiv ASSET4 collects extensive, objective, quantitative, and qualitative ESG data on global companies and scores them

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on four pillars: Environmental, Social, Corporate Governance, and Economic. My study uses the environmental pillar, evaluated from three aspects, emission, innovation, and resource use. My sample spans from 2007 to 2020.

Environment scores from Sustainalytics. Sustainalytics provides monthly evaluations of several dozen environmental aspects and assigns different weights to these aspects to calculate a comprehensive weighted environmental score. These aspects include environmental policy, environmental fines and penalties, carbon intensity, green procurement policy, environmental supply chain incidents, sustainable products and services, and many others. My data sample covers monthly observations from August 2009 to August 2017.

Financial information from Compustat and stock market information from CRSP. I calculate the financial indicators and the stock characteristics following the literature, which are from the financing constraint indicators in Cohn and Wardlaw (2016) and the summary of firm characteristics in Green, Hand, and Zhang (2017).

Institutional holdings from Thomson Reuters 13F. I calculate the change in institutional ownership breadth using the equity holdings of the institutions that file 13F reports, following Lehavy and Sloan (2008).

3 Approach to measuring walk efforts and talk efforts

The gist of this approach is to quantify the proportion of employees who participate in substantive green transition and the proportion of employees who communicate a green corporate image but do not have direct impact on the environment. The ideal data source would be the detailed composition of all the employees. Unfortunately, it is not available, since firm-level information on employees has been scarce.

Online job postings reveal some information on a firm's employees. It describes in detail what type of work tasks will be performed. Appendix A gives an example of a job posting by BP for a chief sustainability officer. Based on the content, each job posting can be classified as walk-relevant, talk-relevant, or others. The proportion of walk-relevant job postings a firm creates during a period can proxy for its efforts on *walk*, and the same goes for *talk*.

Online job postings are widely used in recruitment, which makes it a comprehensive representation of the total employees and the business direction. One concern is that the online job posting is an advertisement for new hires. Some positions in online job postings may not be filled. Some positions may not be hired through job postings. The new hires may not be in proportion to existing employees. These questions are addressed by other studies using online job postings to do firm-level tests (Abis and Veldkamp, 2020; Babina,

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Fedyk, He, and Hodson, 2020; Darendeli, Law, and Shen, 2021). Babina, Fedyk, He, and Hodson (2020) show the current employees (from resumes), and the demand for additional employees (from job postings) are highly correlated, at least for AI-related workers.

Another concern is that online job postings can also be subject to greenwashing, such as claiming to be environmentally friendly to attract more talent. Unlike greenwashing targeting external stakeholders, where it is difficult to distinguish fact from fiction, future employees will eventually know the fact. It is not obvious how greenwashing in online job postings can help build a green corporate image. Online job postings are not listed as a data source of any well-known ESG rating agency. In summary, online job postings provide a valuable data source about how firms deploy the two tools, *walk* and *talk*.

3.1 Starting point

I start with the framework of the U.S. Department of Labor (DOL) to select occupations relevant to the environment. The DOL lists 204 occupations whose work and worker requirements are potentially affected by the greening of economic activities and technologies. There are three different types of impact that greening of the economy can bring to occupations. The 204 occupations are grouped correspondingly:

(1) Green Increased Demand Occupations. The impact of sustainable economic activities and technologies is an increase in employment demand for an existing occupation. However, this impact does not entail significant changes in the work and worker requirements of the occupation. The work context may change, but the tasks themselves do not.

(2) Green Enhanced Skills Occupations. The impact of sustainable economic activities and technologies results in a significant change in the work and worker requirements of an existing occupation. The essential purposes of the occupation remain the same, but tasks, skills, knowledge, and external elements, such as credentials, have been altered.

(3) Green New and Emerging Occupations. The impact of sustainable economic activities and technologies is sufficient to create the need for unique work and worker requirements, which results in the generation of a new occupation. This new occupation could be entirely novel or “born” from an existing occupation.

I conduct two steps on job postings belonging to these 204 green occupations. One step is to separate walk-relevant occupations from talk-relevant occupations. The other step is to evaluate whether the specific context of a job position is eco-friendly. A job posting in a walk-relevant (talk-relevant) occupation and employed in an eco-friendly context is a walk-relevant (talk-relevant) job posting.

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3.2 Separating walk-relevant occupations from talk-relevant occupations

Although walk-relevant and talk-relevant occupations interact closely and eventually contribute to green transition together, they specialize in tasks with distinguishable features. The most important one is that the tasks of talk-relevant occupations do not directly generate environmental impact. The influence of talk-relevant occupations can only manifest by influencing walk-relevant occupations. For example, the public relations specialist hired to handle a pollution scandal does not improve the environment if other parts of the firm stay the same. Therefore, if most tasks involved in a green occupation do not directly change the environment, it is a talk-relevant occupation. Otherwise, it is a walk-relevant occupation.

For green enhanced skills occupations or green new and emerging occupations, the DOL provides the green tasks involved in each occupation, which I use to assess whether most tasks involved in an occupation can directly change the environment. There are 1398 green tasks in total, which cover the whole process of the green transition. The areas of work are summarized in four broad themes: preparation of environment-related metrics, analysis for/and communication, implementation, and governance of implementation. Green tasks in the area "preparation of environment-related metrics" or "analysis for/and communication" do not directly affect the environment, such as emissions metrics' auditing, compliance report, and the marketing of green products. Green tasks in the area "implementation" or "governance of implementation" directly affect the environment, such as operating bioenergy machines and monitoring the operation. For occupations with less than 50% of green tasks directly influencing the environment, I consider them as talk-relevant occupations. For example, all the 16 green tasks involved in green marketers do not directly generate environmental impact. Hence green marketer is a talk-relevant occupation.

For green increased demand occupations, because work tasks remain the same regardless of whether it is employed in a sustainable economy or a traditional economy, the DOL does not provide the corresponding green tasks. However, O*NET OnLine[1], a database of O*NET occupations sponsored by the US Department of Labor, provides detailed tasks involved in each occupation. I use tasks on O*NET OnLine to evaluate whether most tasks involved in a green increased demand occupation can directly affect the environment. Only one green increased demand occupation, customer service representatives, is classified as a talk-relevant occupation. All the other green increased demand occupations are classified as walk-relevant occupations.

[1] www.onetonline.org

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As mentioned in the Data Sources section, the LinkUp database provides the standard O*NET occupation code for each job posting, which is generated by a third-party machine learning algorithm based on the job position's title and full description. Therefore, we can identify whether a job posting belongs to a walk-relevant occupation, a talk-relevant occupation, or other occupations.

Among the 204 green occupations, some occupations are always environmentally responsible whenever it appears, such as chief sustainability officers and wind energy project managers. The greenness of some occupations depends on the context, such as logistics managers and public relations specialists. Logistics managers can have a positive or negative impact on the environment depending on the way they work.

For occupations that are always green, job postings belonging to walk-relevant occupations are classified as walk-relevant job postings, and likewise for talk-relevant job postings. For occupations whose greenness is context-dependent, job postings that belong to these occupations require further evaluation of the context's greenness using natural language processing techniques.

Table A2 lists the 204 DOL green occupations, whether an occupation is walk-relevant or talk-relevant, and whether an occupation is always green or context-dependent green.

3.3 Evaluating job postings' greenness using natural language processing

For job postings in occupations whose greenness depends on the context, I use two natural language processing methods to evaluate whether the job position is eco-friendly or not. The two approaches come from divergent systems, and therefore their consistency will cross-validate each other's accuracy.

3.3.1 Method 1: green keywords

The most transparent and fundamental method is to summarize a list of keywords whose appearances signify the eco-friendly context. The list of green keywords starts from Wikipedia words and phrases under the tag "List of environmental organisations topics"[2] and "List of environmental issues"[3]. Each word or phrase on these two web pages has a dedicated Wikipedia page. On the one hand, they provide a comprehensive scope of important environmental topics. On the other hand, these words or phrases express environmental concerns and signify the word user's supportive attitude towards environmental responsibility.

[2] https://en.wikipedia.org/wiki/List_of_environmental_organisations_topics
[3] https://en.wikipedia.org/wiki/List_of_environmental_issues

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I remove words that are often used in contexts beyond the environment, such as "Population growth" and "Agricultural subsidy", and words that are related to the environment but are too general to signify the word user's attitude towards the environment, such as "Mining" and "Coal". There are still 294 seed words or phrases.

For each seed word or bigram of phrases, I select the top 40 closest synonyms with a word embedding model (details in Appendix B) and remove those that do not express environmental concerns or support based on Google search results. There are 764 green keywords in total in the combination of seed words and synonyms. Table A3 in the appendix lists the top 120 most frequent green keywords among job postings belonging to context-dependent green occupations.

3.3.2 Method 2: BERT model

Method 1 is a system with explicit signal words to recognize eco-friendly context. Because the list of signal words is fixed, the effectiveness of the recognition system depends on the quality of the signal words, which can be transparently evaluated by the readers. In comparison, in Method 2, I use a machine learning algorithm without explicit signal words to recognize eco-friendly contexts. It is a flexible program whose behavior is determined by a number of parameters. The program is applied to a manually labeled training sample to determine the best possible parameter values that improve prediction accuracy. It is difficult to interpret the parameters, which makes the recognition mechanism less transparent to the readers.

The machine learning algorithm in Method 2 is BERT, Bidirectional Encoder Representations from Transformers (details in Appendix C). The performance of the BERT classifier is evaluated on four dimensions, accuracy (0.89), precision (0.73), recall (0.96), and F1 score (0.83). These numbers are calculated by comparing the model predictions in the validation sample with their actual labels. Accuracy is the number of correct predictions divided by the number of all predictions made. 90% predictions of the BERT classifier match the actual labels. Precision is true positive divided by the sum of true positive and false positive. Recall is true positive divided by the sum of true positive and false negative. Precision (0.73) is lower than recall (0.96), which indicates that the classifier makes more type 1 errors, predicting nongreen positions as green (false positive), than type 2 errors, predicting green positions as nongreen (false negative). F1 score is the harmonic mean of precision and recall.

In comparison, Method 1 (green keywords) achieves accuracy (0.90), precision (0.84), recall (0.76), and F1 score (0.80) in the same validation sample. Method 1's better precision means that it makes fewer false positive mistakes. This is a desirable feature

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because green positions are relatively few among all job postings, making the measured green transition efforts sensitive to false positive errors. Considering that both methods achieve good accuracy, the higher precision makes Method 1 more suitable for this study. Moreover, green keywords are more transparent and accessible, as BERT requires GPU resources to be implemented.

Overall, BERT, as the state-of-the-art method and industry standard, does not perform better than the traditional keywords method. This demonstrates the good quality of the green keywords method. The following results in this study are only based on green keywords.

3.4 Summary statistics

I use the percentage of walk-relevant (talk-relevant) job postings among all job postings that a company creates during a period as a proxy for its *walk* (*talk*) efforts. To alleviate the concern that periods with very few job postings are easily affected by random noise, a firm must have more than ten job postings created in the period to be counted as a valid observation. Mechanically, the measurements of both *walk* and *talk* are bounded between 0 and 100. Since this study examines firms with environmental impacts, I restrict the sample to industries (at the 4-digit NAICS code level) where firms have violated environmental regulations and been penalized by regulators since 2000.

On average, companies post more walk-relevant job postings than talk-relevant ones. In Table 1, the average annual *walk* is 6.51, which means 6.51% of a firm's job postings are walk-relevant. This number is 1.16 for *talk*. The numbers are similar for monthly *walk* and *talk*, which are calculated with job postings in the past three months on a rolling basis. At least 25% of the annual observations do not have walk-relevant job postings. It also applies to monthly observations. For *talk*, there are at least 25% annual observations that are zero, and there are at least 50% monthly observations that are zero. In general, companies need a limited number of talk-relevant positions.

Walk and *talk* heavily depend on the industry. Figure 1 shows the average *walk* and *talk* in selected 2-digit NAICS industry in 2021. The utility industry, such as electric power, natural gas, water, and sewage, has a high *walk* level. The mining industry, such as oil and gas, coal, metal ore, and non-metallic minerals, also has a high *walk* level. However, these two are very different regarding the *talk* level. In the left part of the figure are industries with limited walk-relevant job postings, such as information and finance. Table A4 in the appendix lists the 50 industries with the highest *walk* level on average. They are industries that are known to pollute the environment. Table A5 in the appendix lists the 50 industries with the highest *talk* level on average. There are some overlaps

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between the two tables. There are also some industries ranking high on *talk* while with a very low *walk* level, such as the three industries with NAICS starting with 52, namely the finance sector.

Although the variation across industries is considerable, there is still enough variation within the industry and within a firm's lifetime, as shown in the variance statistics in Table 1 Panel D. Figure 2 gives a more straightforward illustration. It plots the measured *walk* and *talk* of selected firms in the motor vehicle manufacturing industry from 2016 to 2021. Tesla had a much higher *talk* than other companies between 2016 and 2018. General Motors has rapidly increased its *walk* since 2019.

—Insert Table 1 and Figure 1, Figure 2 here—

With the greening of the economy, a firm may need the cooperation of walk-relevant and talk-relevant workers. This cooperation can lead to a common trend between *walk* and *talk*. Table 2 shows the results of regressing contemporaneous or future *walk* on *talk* after controlling for lagged *walk*. The focused regression specification is

$$\text{walk}_{i,t+1} = \beta\text{talk}_{i,t} + \gamma\text{walk}_{i,t} + \delta\text{walk}_{i,t-1} + \text{Fixed Effect}_{j,t} + \epsilon_{i,t}, \tag{1}$$

where t indexes year, i indexes firm, and j indexes 4-digit NAICS industry. Column (4) is the estimation of this model. Other columns are the results of replacing $\text{walk}_{i,t+1}$ with $\text{walk}_{i,t}$ and using different lagged *walk* as the control variable. Columns (1) - (3) show that contemporaneous *walk* and *talk* are positively correlated. However, *talk* does not correlate with next year's *walk*. These imply that although there is a common trend between *walk* and *talk*, *talk* cannot forecast future *walk*. It rules out the possibility that investors may use *talk* as a leading indicator of future *walk*. In addition, the positive correlation between contemporaneous *walk* and *talk* suggests controlling for *walk* in the regressions using *talk* as an independent variable.

—Insert Table 2 here—

4 Walk, talk, and firm characteristics

4.1 Environmental outcomes

Suppose a firm's walk-relevant and talk-relevant job postings indeed capture its operation characteristics on green transition. In that case, measured efforts should accompany their consequences, such as changes in environmental performance or corporate image. The relationship between efforts and consequences is confounded by reverse causality, in which a firm increases its efforts due to a change in environmental performance or corpo-

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rate image. The relationship is also confounded by omitted variables affecting efforts and outcomes. No matter which channel dominates, if there are significant correlations between efforts and consequences, it demonstrates the measurements' capability to capture a firm's environment-related operation strategies.

I estimate regressions of the following form:

$$\text{Consequence}_{i,t} = \beta \text{walk}_{i,t} + \gamma \text{talk}_{i,t} + \text{Fixed Effect}_i + \text{Fixed Effect}_t + \epsilon_{i,t}, \tag{2}$$

where t indexes time, i indexes firm. I also estimate the model that replaces Fixed Effect$_i$ and Fixed Effect$_t$ with industry by time fixed effect Fixed Effect$_{j,t}$ to show the within-industry cross-sectional correlation. j indexes the 4-digit NAICS industry.

Table 3 shows the results of regressing annual environmental outcomes on contemporaneous annual green transition efforts. Panel A presents the regressions controlling for firm fixed effects. When a company increases its *walk*, the percentage of recycled waste increases, and carbon intensities calculated with various denominators decrease. When a company increases its *talk*, the carbon emission scaled by net fixed assets increases, and most other environmental performance does not change significantly. These results indicate that over a firm's lifetime, environmental performance improves with *walk* but not with *talk*.

Panel B presents the regressions without controlling for firm fixed effects. Comparing firms within the same industry in the same year, a firm that *talks* more has a higher ratio of hazardous waste. A firm that *walks* more has higher carbon intensities (carbon emissions scaled by total assets or net fixed assets). These results indicate that comparing firms cross-sectionally, the companies with higher carbon intensities or pollution make more efforts on *walk* or *talk* than other companies.

The striking difference between Panel A and Panel B can be explained by the difficulty of transforming a brown firm into a green firm. A brown firm makes more green transition efforts, improving its environmental outcomes. However, this improvement has not been large enough to turn the brown firm into a green firm when comparing firms cross-sectionally.

In summary, the results show that companies with higher carbon intensities or pollution make more green transition efforts than other companies. When they increase *walk*, their environmental outcomes improve. When they increase *talk* while keeping *walk* fixed, their environmental outcomes deteriorate or do not change significantly.

—Insert Table 3 here—

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4.2 Media images

Table 4 Panel A lists the results of regressing monthly TruValue Labs media scores on contemporaneous monthly green transition efforts using the specification of Equation 2. Panel B replaces Fixed Effect$_i$ and Fixed Effect$_t$ with industry by time fixed effect Fixed Effect$_{j,t}$ to show the within-industry cross-sectional correlation.

TruValue Labs constructs the scores by tracking news outside focal firms, including analyst reports, media, advocacy groups, and government regulators. Then it uses natural language processing to interpret semantic contents to generate scores under different topics. In this study, I use the scores under the topic of greenhouse gas emissions because it is an influential environmental topic for all industries. There are five different scores under this topic. *image_recent*, ranging from 0 to 100, reflects how positive a firm's image is in recent media texts. *image_medium* is the exponentially weighted moving average of *image_recent* in a longer period (the TruValue Labs does not specify the period it uses to calculate the moving average). *image_long* is the slope of *image_medium* over the past 12 months, showing whether a firm's media image has been improving or deteriorating in the past 12 months. *no. article* is the number of articles tagged to the topic of greenhouse gas emissions in the past 12 months. *materiality* measures how much stakeholders consider a topic to be material for a firm. In other words, *image_recent*, *image_medium*, and *image_long* measure the short-, medium-, and long-term media image, respectively. *no. article* measures the number of articles and *materiality* measures how material greenhouse gas emissions are to a firm's stakeholders.

Panel A and Panel B are consistent. *Talk* increases with all short-, medium-, and long-term media images on greenhouse gas emissions, while *walk* does not exhibit significant associations. It demonstrates the effectiveness of using *talk* to gain a green corporate image, even though it does not directly link to a firm's environmental performance. The results that *walk* does not explain the variation of firm images is consistent with the significant time lag of environmental disclosures. When a firm increases *talk*, its number of articles on greenhouse emissions increases in panel A, which is not significant when comparing firms within the same industry in the same year.

Interestingly, in column (5) of Panel A and Panel B, the relationship between materiality and *walk* or *talk* is similar to the relationship between environmental outcomes and green transition efforts in Table 3. In Panel A, when a firm increases *walk*, its stakeholders think that greenhouse gas emissions are less material to the firm. In Panel B, greenhouse gas emissions are more material for the firms that *walk* more. *talk* does not correlate with the materiality score. It implies that stakeholders understand the different consequences of *walk* and *talk*, and they evaluate the materiality score and media images (*image_recent*,

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image_medium, and *image_long*) in different ways.

—Insert Table 4 here—

4.3 Cost structure

Besides that *talk* does not directly affect the environment, another key characteristic that distinguishes *talk* from *walk* is that *talk* requires a lower input on associated fixed assets. Substantive green transition usually involves adjustments on the production line, such as using new equipment. In contrast, communication of a green corporate image involves mostly non-production costs, such as advertisement and marketing expenses. A firm's choice between *walk* and *talk* results in different cost structures.

I focus on comparing firms in the same industry in the same year. My main regression is of the following form:

$$\text{Financial Indicator}_{i,t} = \beta\text{Walk}_{i,t} + \gamma\text{rTalk}_{i,t} + \text{Fixed Effect}_{j,t} + \epsilon_{i,t}, \tag{3}$$

where t indexes time, i indexes firm, and j indexes the 4-digit industry. To test the lead-lag relationship, I replace the dependent variable Financial Indicator$_{i,t}$ with its lag or future value.

The financial indicators revealing a firm's cost structure include capital expenditures, research and development expenses, advertising expenses scaled, and organization capital. Financial indicators are tested as dependent variables, following the majority of literature summarized in Gillan, Koch, and Starks (2021). *rd/sale* is the R&D expenses scaled by sales. Many firms have missing R&D expenses. *capx/asset* and *ad/asset* are capital expenditures and advertising expenses scaled by average total assets, respectively. Advertising expenses are not available for many companies, including all utility companies. I add a robustness check on a related variable, intangible capital *orgcap*. *orgcap* is capitalized SG&A expenses (xsga) scaled by average total assets, following Eisfeldt and Papanikolaou (2013). Table 5 presents the relationship between a firm's annual green transition efforts and its lagged, contemporaneous, and future financial indicators.

—Insert Table 5 here—

Table 5 shows that companies that *walk* more persistently have a higher R&D expense ratio, capital expenditure ratio, lower advertising expense ratio, and lower organization capital. Companies that *talk* more have a lower R&D expense ratio contemporaneously and in the future. *talk* is also positively correlated with organization capital in the next year. These results fit the expected cost structures associated with *walk* and *talk*.

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4.4 Peers' regulatory violations

It is well documented that regulation violations have spillover effects. For example, Johnson (2020) shows that publicizing a facility's violations of safety and health regulations led other facilities to improve their compliance substantially. Chu, Liu, and Tian (2021) show that companies increase environmental innovation in response to nearby environmental spills. Peers' regulatory violations may make the whole group's environmental risk more salient to the public and induce a revolution.

However, it is puzzling that if regulations are indeed influential, why do we observe violations by the same industry or even the same firm again and again after they were penalized? Figure 4 shows the environmental penalties imposed on the motor vehicle manufacturing industry. Firms are punished every year. Is it possible that firms resort to communication strategies rather than substantive environmental improvement when violations occur? The *walk* and *talk* efforts proposed in this study provide the necessary measurements to answer this question. As neither peer firms nor regulators are under the control of the studied firm and vice versa, peers' violation can be considered irrelevant to the studied firm's unobserved characteristics. This setting can causally identify how peers influence a firm's green transition efforts.

I focus on industry peers instead of location peers for two reasons. First, many firms operate in multiple areas, making it tricky to classify location peers. Second, it is natural for stakeholders to compare firms in the same industry. For example, Bachmann, Ehrlich, and Ruzic (2017) document that after the 2015 Volkswagen emissions scandal, BMW, Mercedes-Benz, and Smart experience declines in sales, stock return, and public sentiment. To identify peers, the text-based product market peer database (Text-Based Network Industry Classifications or TNIC) by Hoberg and Phillips (2016) is widely used. Unfortunately, TNIC is only available until 2015, while most online job postings in LinkUp are created after 2015.

—Insert Figure 4 here—

To provide a benchmark for evaluating the influence of peers, Table 6 Panel A presents the relationship between a firm's own environmental penalties and its green transition efforts. I estimate regressions of the following form:

$$\text{walk}_{i,t} = \beta \text{penalty}_{i,t} + \text{Fixed Effect}_i + \text{Fixed Effect}_t + \epsilon_{i,t}, \tag{4}$$

where t indexes time, i indexes firm. The dependent variable is replaced with $\text{talk}_{i,t}$ as well. Firms in the years when they are not documented with any environmental penalty are considered with zero penalty. Panel B tests the relationship between the total

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environmental penalty at the industry level and the green transition efforts of firms that have never been documented with environmental penalties since 2000.

Panel A shows that over a firm's lifetime, when the penalty increases by one standard deviation, the firm increases *talk* by around 0.022 percentage points. *Walk* efforts are not significantly affected. Panel B's coefficients are in the same direction as Panel A, indicating that peer effects are in the same direction as a penalty's influence on the violator. Column (2) in Panel B shows that within an industry over time, when the total penalty of peers increases by one standard deviation, firms that are not directly penalized would, on average, increase *talk* by 0.0208 percentage points.

The results in Table 6 are consistent with the puzzle that industries are punished over and over again. There is no significant change in *walk* for both the violators and their peers. *Talk* is significantly correlated with penalties. This also validates that my measurements capture the difference between *walk* and *talk*.

In summary, firms immediately resort to *talk* rather than *walk* to manage the damaged corporate image when environment-related penalties on themselves or their industry peers are announced.

—Insert Table 6 here—

5 Walk, talk, and investor decisions

In this section, I examine how much investors, especially green investors, are influenced by *walk* and *talk*, respectively. Sophisticated green investors should be able to distinguish a firm's communication strategies from its substantive green transition. They should not be affected by the idiosyncratic part of *talk* because *talk* neither improves the environment in Table 3 nor indicates a higher *walk* in the future in Table 2. In four steps, I evaluate *walk* and *talk*'s influences on investors.

First, green investors commonly refer to environmental ratings as their investment basis. These environmental ratings are well-known for their quality issues. A widely-used environmental rating adjusts retroactively to create a mechanical correlation with stock returns (Berg, Fabisik, and Sautner, 2020), and the ratings are not consistent with each other (Gibson Brandon, Krueger, and Schmidt, 2021). Does *talk* affect a firm's environmental rating? If so, the influence is likely to pass on to investors.

Second, I directly test whether a stock's popularity among sustainable funds is associated with its *walk* and *talk*. Many self-claimed sustainable funds do not align their investment with their claims. Morningstar removed the sustainable label from 1200 self-classified sustainable funds after checking fund documents under the rules of the European

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Union Sustainable Finance Disclosure Regulation[4]. The greenwashing of funds is a separate research question from whether truly green funds are affected by *talk*. To mitigate the confusion caused by funds' greenwashing behaviors, I hand-collect the number of the legally binding sustainable funds (i.e., funds regulated by the EU Sustainable Finance Disclosure Regulation) holding a stock. Based on these numbers, I calculate two proxies for a stock's relative popularity among dark green and light green funds.

Third, beyond green investors, the stock market has many other participants. Non-green investors may or may not care about green transition efforts, depending on their beliefs about how green transition efforts affect a stock's pecuniary return. How do broader investors respond to *walk* and *talk*? I study this by testing whether the change in a stock's institutional ownership breadth is related to its *walk* and *talk*.

Fourth, investor decisions may impact corporate behaviors and asset prices. The effects on the environment may take years to manifest. The price impact in financial markets is immediately observable. Because *talk* neither improves the environment nor represents actual exposure to environmental risk, it should not be associated with the premium that firm stakeholders pay for environmental considerations. I test whether a firm's *talk* or *walk* can explain its stock return, which reflects various stakeholders' perceptions of the firm.

5.1 Environmental scores

I use environmental scores from three rating agencies, MSCI KLD, Refinitiv ASSET4, and Sustainalytics. *MSCI* is the annual net environmental score calculated with MSCI KLD data following the method of Lins, Servaes, and Tamayo (2017), in percentage. *Refinitiv* is the annual environmental pillar score in Refinitiv ASSET4 ESG data. *Sustainalytics* is the monthly environment score provided by Sustainalytics.

Table 7 presents how much *walk* and *talk* explain the variation of environmental scores. The regression specification is the same as Equation 2, except for replacing Consequence with Environmental Score. The first feature of Table 7 is that the adjusted R-squared increases substantially for all three dependent variables when adding the firm fixed effects. It implies that environmental scores are very persistent. There is not much variation over a firm's lifetime, indicating that either firms have made little progress on green transition or environmental scores do not reflect their progress. If firms have made little progress, green investing is effective. If the score is inaccurate, it should not be used as guidance for green investing.

[4]https://www.ft.com/content/9cf8c788-6cad-4737-bc2a-2e85ac4aef7d

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The second feature is that in Panel B, *MSCI* and *Refinitiv* significantly increase with both *walk* and *talk*, while *Sustainalytics* only increases with *talk*. Surprisingly, for companies in the same industry in the same period, all three ESG rating agencies assign a higher score to companies that *talk* more, keeping *walk* fixed. Sustainalytics cannot even capture the variation of *walk*. The comparison between *walk*'s coefficient and *talk*'s rules out explanations such as limited sample length because the coefficient of *talk* is significant.

The third feature is that in Panel A, only *MSCI* is sensitive to a firm's improvement on *walk*. The other two ESG rating agencies do not capture the time-variation of firms' substantive green transition efforts. The high stickiness of *Refinitiv* and *Sustainalytics* could be a possible explanation, considering that the only sensitive score *MSCI* has a lower adjusted R-squared.

In summary, all three ESG rating agencies give a better environmental evaluation for firms that *talk* more, keeping *walk* fixed. All three environmental scores are highly persistent, reflecting either little green transition progress or lagged environmental information.

—Insert Table 7 here—

5.2 Holdings of sustainable funds

As mentioned above, the greenwashing of self-claimed sustainable funds is often mingled with examining whether genuinely sustainable funds have the skills to identify and support green activities. So I narrow the scope of sustainable funds to funds regulated by the EU Sustainable Finance Disclosure Regulation to mitigate the confusion. Since 10 March 2021, the European Union has introduced a Sustainable Finance Disclosure Regulation, which requires financial products available for sale in the EU to be classified into three categories:

- Products with a sustainable investment objective (Article 9, dark green)
- Products promoting environmental or social characteristics (Article 8, light green)
- Non-sustainable products (Article 6, nongreen)

Financial products' sustainability characteristics or objectives must be disclosed in precontractual periodic documentation and websites. Whether this regulation successfully prevents funds from pretending to be green is still unknown. Nevertheless, the sustainable goal of the dark green or light green fund is legally binding. For each stock, Bloomberg provides the latest count of all SFDR dark green (or light green, nongreen) funds with a holding exposure $> 0\%$ in this stock. I hand-collected cross-sectional data for all U.S. stocks in June 2022. U.S. stocks that are popular among funds for sale in the EU are expected to have some particular characteristics, such as higher market capitalization. Because dark green, light green, and nongreen funds only differ in their attitudes toward

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sustainability, characteristics other than sustainability should equally affect dark green, light green, and nongreen funds. If sustainability is not considered, a stock's popularity in dark green or light green funds should not differ significantly from its popularity in nongreen funds. The variation in popularity reflects the difference between dark green or light green funds and nongreen funds due to the sustainability mandate.

Table 8 estimates the cross-sectional correlation between a firm's green transition efforts and its relative popularity among dark green or light green funds. The regression specification is the same as Equation 2, except for replacing Consequence with Popularity in Green Funds and removing firm fixed effect because this sample is cross-sectional. *ratio dark* is a stock's popularity in dark green funds scaled by its popularity in nongreen funds. When this value exceeds one, the stock is preferred by light green funds, compared with its popularity in nongreen funds. The same applies to *ratio light*.

In both panels, no matter the regression controls for industry fixed effect or not, a firm with a higher *walk* is more popular in dark green or light green funds than in nongreen funds. One percentage increase in the proportion of walk-relevant job postings is associated with a 0.230 increase in *ratio dark*, which is large compared to its mean of 0.24 and standard deviation of 0.32. The magnitude is similar in the case of *ratio light*.

The two panels differ in the coefficient of *talk*. In panel B, one percentage increase in the proportion of talk-relevant job postings is associated with a 0.692 increase in *ratio light*, which is also large compared to its mean of 0.40 and standard deviation of 0.44. The coefficient of *talk* is larger than the coefficient of *walk*, possibly because *talk* are usually much lower than *walk*. After controlling for the industry fixed effects, the coefficient decreases to 0.443, remaining significant. This result suggests that the industries that on average *talk* more are more popular in light green funds than in nongreen funds. Within the same industry, firms that *talk* more are still favored by light green funds compared to nongreen funds.

In panel A, *talk* positively correlates with *ratio dark* if not including the industry fixed effects. Industries that *talk* more on average are also more popular in dark green funds. However, in column (1), when comparing within the same industry, firms that *talk* more are not significantly preferred by dark green funds.

The comparison between Panel A and Panel B shows that light green funds are influenced by both *walk* and *talk*, but dark green funds can invest in *walk* without being influenced by *talk*. It is consistent with the fact that dark green funds have a stricter sustainable investing mandate than light green funds. In the cross-sectional sample I collected, the stock most popular in dark green funds, light green funds, or nongreen funds is held by 134 dark green funds, 1451 light green funds, or 4246 nongreen funds, respectively.

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—Insert Table 8 here—

5.3 Change in institutional ownership breadth

Beyond green investors, how influential *walk* and *talk* are in the financial market also depends on other investors' portfolio size and investment strategies. Nongreen investors' attitudes toward green transition efforts may differ. Some nongreen investors who believe that green transition positively or negatively affects pecuniary returns would still be sensitive to it. Some investors may not take environmental information into account at all. It is not obvious whether the influence of *talk* on green investors is still important when tested in a broader investor group. Therefore, I test the relationship between a stock's institutional ownership breadth and its *walk* and *talk*.

Table 9 presents the results of regressing the change in a firm's institutional ownership breadth on its green transition efforts. The regression specification is the same as Equation 2, except for replacing Consequence with Change in institutional ownership breadth. I calculate the percentage change in Institutional Ownership Breadth following Lehavy and Sloan (2008) using Thomson-Reuters 13F data. Institutional Ownership Breadth represents the number of institutions that own the stock during the quarter. To capture changes in the breadth of ownership rather than changes in the universe of institutions covered by the database, the percentage change is calculated using only 13F filers that exist in the database in both quarters T and T-1.

In column (2), firms that *talk* more have seen a higher increase of the number of institutions owning it. In contrast, the coefficient of *walk* is not significant. It suggests that comparing firms within the same industry in the same period, the number of institutional investors holding a stock increases more when the firm *talks* more, but this is not obvious for firms that *walk* more.

In column (1), the coefficient of *talk* becomes insignificant. It is consistent with that increasing popularity is a persistent phenomenon for firms that *talk* more. The fluctuation of their *talk* is not large enough to turn a good talker into a bad talker, as shown in Figure 2. In addition, compared to Table 8, broad institutional investors care less about *walk* than green investors.

In summary, the number of 13F institutional investors owning a stock increases more for firms that *talk* more in the cross-sectional comparison. It indicates *talk* attracts institutional investors to invest in a firm's stock.

—Insert Table 9 here—

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5.4 Asset pricing implications

Modern asset pricing models are built on optimal portfolio choice and market clearing. As I document that investors' portfolio choices are sensitive to firms' *talk* efforts, a natural extension is to test whether stock returns are also sensitive to *talk*.

The literature does not separate *walk* from *talk*, although many ESG proxies have been used to test cross-sectional return predictability. Among the previous studies, Bolton and Kacperczyk (2021) find that stocks of firms with higher carbon emissions earn higher risk-adjusted returns, consistent with the lower risk compensation required by green assets because they are less exposed to environmental risks. Pástor, Stambaugh, and Taylor (2022) define green and brown stocks with MSCI environmental scores and find that green stocks strongly outperformed brown stocks, indicating a higher realized return of green assets due to positive shocks to investors' sustainability preference. The two studies are not contradictory since they use different definitions of green versus brown and different sample periods. I provide an alternative angle by running a horse-race test between *walk* and *talk*.

Table 10 presents the panel regression of stock return in month T+1, cumulative return from month T+1 to month T+3, or cumulative return from month T+1 to month T+6 on firm green transition efforts in month T, controlling for other stock characteristics in month T, in the period between January 2016 and December 2021. The sample period before 2016 is removed because LinkUp provides very limited full job descriptions in the early years, as shown in Table 1 panel A. The sample period in 2022 is not included because the 2022 Russia-Ukraine war is closely related to the energy price, causing a tremendous shock to investor behaviors. When the dependent variable is any of the cumulative return variables, the observations in adjacent months overlap. To avoid mechanical correlation, I select observations with 3-month or 6-month intervals to conduct the model estimation. Standard errors are clustered at the firm and time level as recommended by Petersen (2009).

For all four investment horizons, *walk* can not forecast future stock returns. In contrast, *talk* predicts positive stock returns in the next month and the next three months. The significance level is 5% for the 1-month return and 1% for the 3-month return, comparable to the significance level of gross profitability. Although surprising, this result is consistent with the regression of the change in institutional ownership breadth in Table 9 in which firms that *talk* more gain an increase in the number of institutions holding it, and firms that *walk* more do not.

This predictability supports the theory in Pástor, Stambaugh, and Taylor (2021) that positive shifts in customers' tastes for green products and investors' tastes for green hold-

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ings lead to the outperformance of green assets. However, the green assets perceived by customers and investors are not the firms that make more efforts in substantive green practices but those making more efforts in communicating a green corporate image.

Are investors not sophisticated enough to identify and support substantive green transition? As we see in Table 4, even though communications effectively improve a firm's corporate image, stakeholders' perception of how material greenhouse gas emissions are to a firm only correlates with *walk*. This evidence implies that investors are aware of the difference between *walk* and *talk* but still invest in *talk*.

The positive future stock returns of firms that *talk* more also explains its influence on light green funds in Table 8. Light green funds may prefer good talkers out of the consideration of pecuniary return. Nonetheless, it is important to understand how devoted green investors are to pursuing substantive environmental improvements and how devoted they are to pursuing pecuniary returns linked to a green corporate image.

—Insert Table 10 here—

6 Conclusion

The concern that self-claimed sustainable funds do not implement what they say has motivated regulators to require or propose detailed disclosure on how sustainable funds implement their sustainability goals. However, this does not solve the problem that some sustainable funds may lack the skills to identify and support truly green activities. There is no evaluation standard to keep green investing accountable. I propose evaluating green investors by whether their investment decisions depend on firms' substantive green transition or communication of a green corporate image.

I document that all three commonly-used environmental rating agencies assign a better score to firms hiring more staff to engage in environment-related communication strategies. The legally binding green investors also favor these good talkers, although communications influence dark green funds less than light green funds. The broad institutional investors are sensitive to communication strategies while not sensitive to substantive green practices. Stock returns also confirm this phenomenon. Firm efforts in environmental-related communication predict a significantly higher return after controlling for other firm characteristics, but efforts in substantive green transition cannot predict stock returns. Above all, my findings suggest that professionals in green investing allocate more resources to good talkers, potentially deviating from their original goal of supporting substantive green practices.

The possible explanations for this phenomenon are diverse. On the one hand, eval-

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uating a firm's environmental performance is difficult when it involves many aspects of the environment but limited, embellished information. On the other hand, if consumers or the general public are not sophisticated and perceive a firm's greenness based on its communication, sophisticated investment professionals are not incentivized to invest in the substantive green transition. The tendency for professionals to swim with the tide is not new in finance history.

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Figure 1: *walk* and *talk* of selected 2-digit NAICS industries in 2021.
walk of an industry in 2021 is the average *walk* of firms within the 2-digit NAICS industry in 2021. For each firm, *walk* is the percentage of job postings that are classified as walk-relevant among all job postings the company creates during the period. The same applies for *talk*.

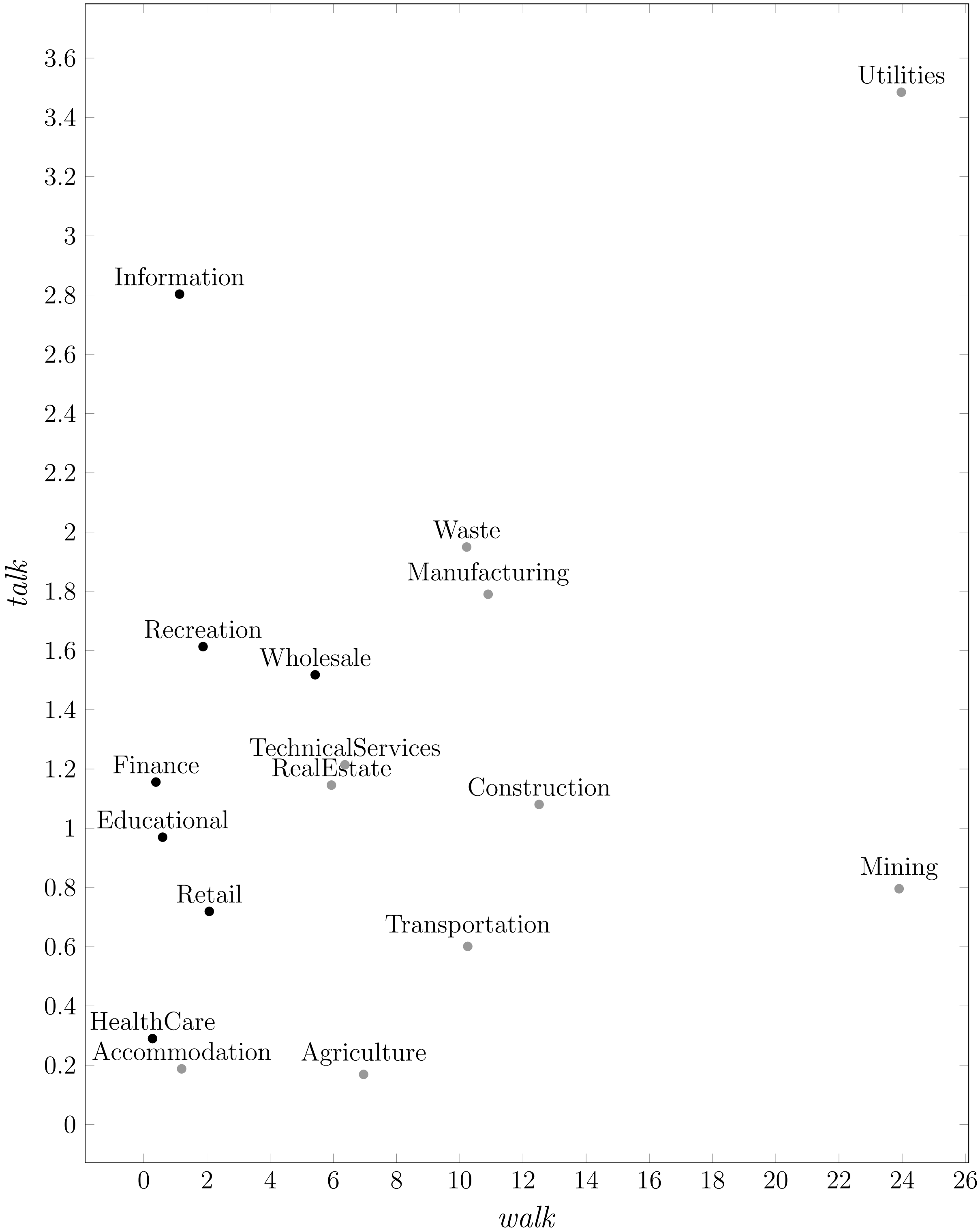

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Figure 2: *walk* and *talk* of selected firms in the motor vehicle manufacturing industry. *walk* is the percentage of job postings that are classified as walk-relevant among all job postings the company creates during the period. The same applies for *talk*.

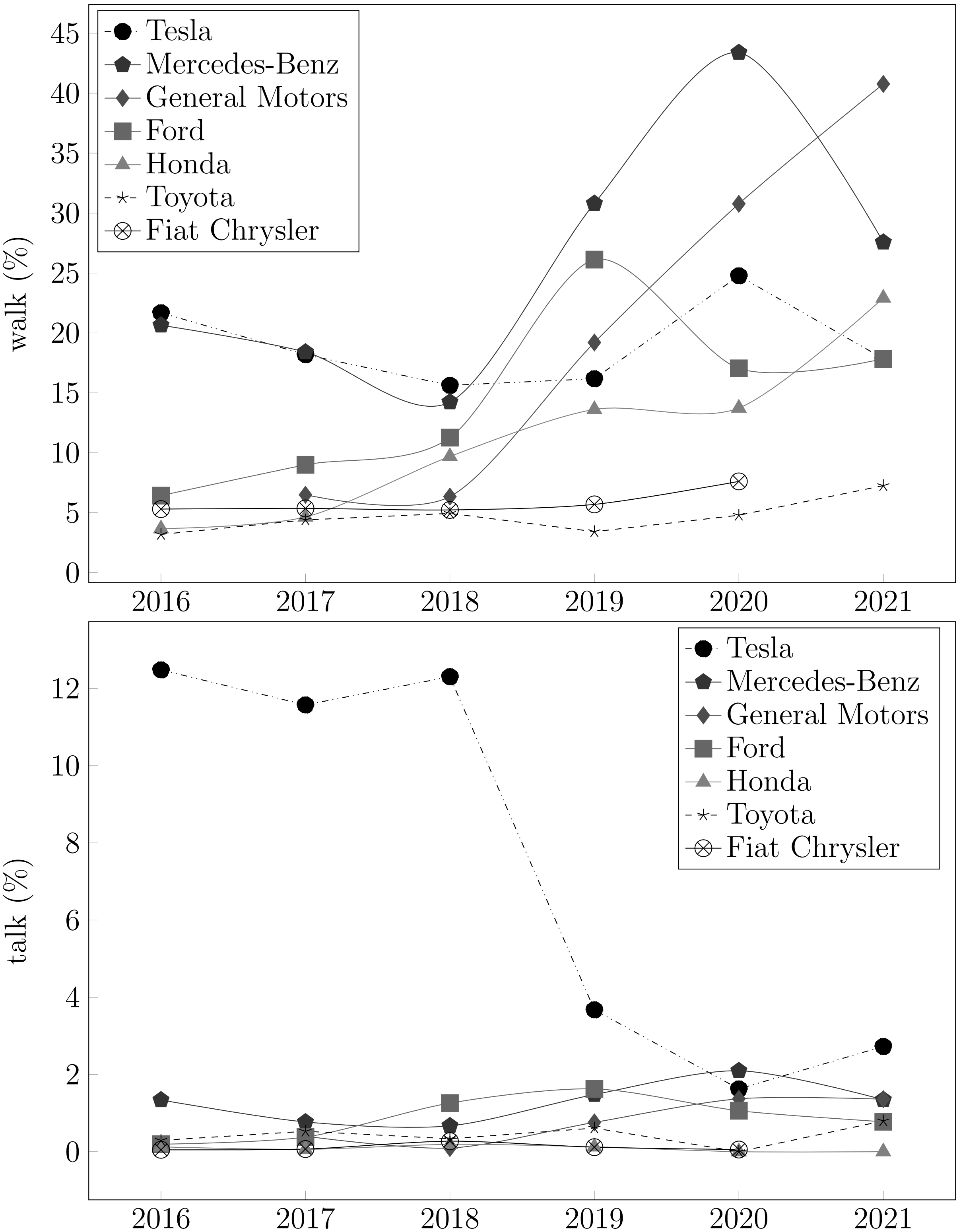

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Figure 3: *walk* and *talk* of selected firms in Petroleum and Coal Products Manufacturing industry.
walk is the percentage of job postings that are classified as walk-relevant among all job postings the company creates during the period. The same applies for *talk*.

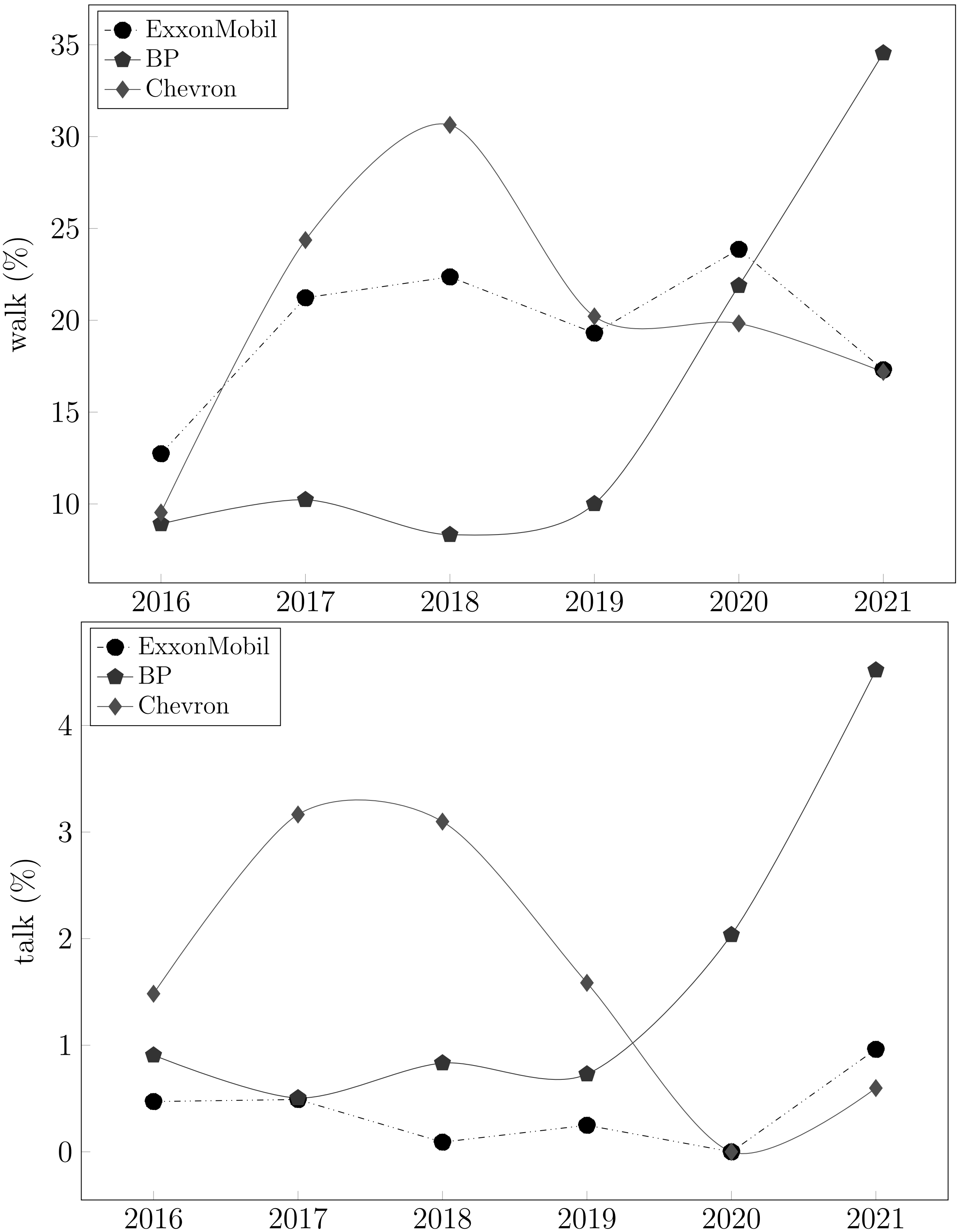

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Figure 4: Number of violations and sum of penalties in motor vehicle manufacturing industry by year

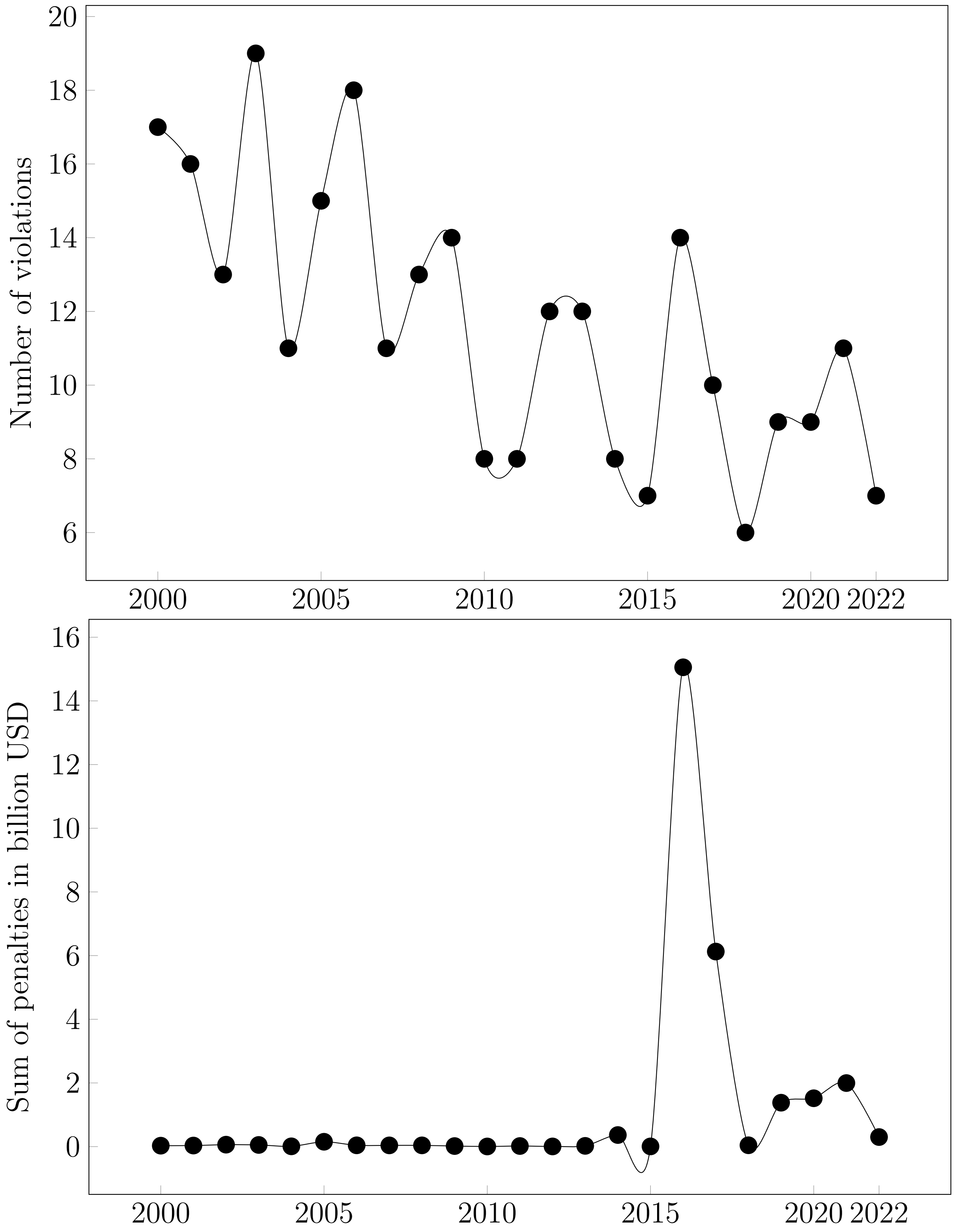

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Table 1: Summary Statistics

This table presents summary statistics of variables used in this study from January 2007 to June 2022. Variables are defined in Table A1 in the appendix. Panel A lists the number of observations in each fiscal year. Only observations with the full text of the job postings are used in this study. Panel B shows the summary statistics of annual variables.

Panel A: Observations by year in the Compustat-LinkUp merged universe

fiscal year	obs w. job title	obs w. full text	fiscal year	obs w. job title	obs w. full text
2007	58	5	2015	1672	141
2008	562	36	2016	1674	1330
2009	770	74	2017	1874	1841
2010	801	65	2018	2452	2388
2011	942	55	2019	2537	2467
2012	1073	48	2020	2567	2524
2013	1416	81	2021	2884	2862
2014	1636	112			

Panel B: Summary statistics of annual variables

	mean	sd	p1	p25	p50	p75	p99	N
walk	6.51	12.02	0	0	0.83	7.14	55.43	14029
talk	1.16	2.97	0	0	0.03	0.96	14.67	14029
recycled	52.85	31.95	0.00	32	55.28	75.40	99.32	1243
hazardous	14.42	21.43	0	0.4	4.53	19.14	98.78	1003
carbon/ppe	238.15	806.00	3.18	37.28	82.36	184.36	2256.64	2432
carbon/asset	157.61	384.36	0.06	5.04	25.91	128.21	2013.76	2811
carbon/ebitda	1032.56	28842.51	-5295.98	57.30	252.35	1215.87	23908.05	2544
capx/asset	3.15	3.86	0	0.63	2.00	4.21	18.84	13589
ad/asset	2.35	4.80	0	0.12	0.66	2.35	27.72	6230
org cap	0.47	0.55	0.01	0.12	0.32	0.62	2.50	10453
cash	17.53	21.02	0.16	3.64	9.06	21.84	90.49	14017
log(assets)	8.12	1.95	3.74	6.80	8.02	9.41	12.66	13986
roe	3.97	105.02	-324.36	-1.87	9.41	18.34	258.30	13576
dividend yield	1.68	2.79	0	0	0.70	2.48	13.78	13926
b/m	46.86	77.90	-90.26	18.01	38.82	70.63	251.88	13965
penalty	8.35E+05	2.68E+07	0	0	0	0	1.40E+06	13961
ind_penalty	2.71E+07	4.45E+08	0	5000	1.45E+05	8.06E+05	3.27E+08	10283
MSCI	11.41	21.63	0	0	0	20	100	4172
Refinitiv	24.39	27.87	0	0	12.155	44.58	90.17	6452
No. nongreen	805.99	827.88	2	335	462	855	3149	2419
No. light	153.42	223.18	0	19	54	142	903	2419
No. dark	10.62	18.92	0	1	2	8	80	2419
ratio light	0.40	0.44	0	0.18	0.34	0.57	1.12	2415
ratio dark	0.24	0.32	0	0.06	0.15	0.36	1.16	2415

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Table 1: Summary Statistics (Continued)

Panel C shows the summary statistics of monthly, quarterly, and semi-annual variables. Panel D presents a summary of the relative variation of *walk* and *talk* between and within industry and firm. The first two rows report the mean and standard deviation of the variable for the full sample. The second set of rows reports the standard deviation across different industries controlling for the time-series mean and within each industry controlling for the industry mean.

Panel C: Summary statistics of monthly, quarterly, and semi-annual variables

	mean	sd	p1	p25	p50	p75	p99	N
walk	6.63	12.91	0	0	0.15	7.14	60.91	127321
talk	1.20	3.61	0	0	0	0.41	17.24	127321
image_recent	62.82	15.87	21.63	50	60.69	73.77	97.19	77583
image_medium	62.59	12.75	27.79	52.96	61.98	70.61	92.96	77430
image_long	50.84	22.50	8.2	33.05	50	69.93	92.54	77389
no. article	17.22	121.30	0	0	0	3	339	123552
materiality	14.11	16.19	0.31	3.33	7.95	18.92	75	47952
Sustainalytics	54.69	13.37	31.67	44.17	53.55	64	88	8678
market beta	1.20	0.53	0.12	0.86	1.14	1.48	2.79	118465
book-to-market	0.46	0.46	-0.74	0.18	0.38	0.67	2.16	118997
size	14.79	1.84	10.44	13.60	14.76	16.02	18.82	118997
reversal	0.01	0.13	-0.33	-0.05	0.01	0.07	0.43	118997
momentum	0.19	0.60	-0.71	-0.12	0.10	0.35	2.37	115243
asset growth	0.13	0.35	-0.34	-0.01	0.05	0.16	1.77	115287
gross profitability	0.31	0.29	-0.46	0.11	0.27	0.45	1.26	115287
capx growth	0.48	1.88	-0.88	-0.22	0.11	0.55	8.19	109515
illiquidity	1.21E-07	1.69E-06	8.15E-12	1.54E-10	7.21E-10	3.50E-09	1.53E-06	118993
unexpected earnings	-7.16E-04	7.28E-02	-1.59E-01	-5.97E-04	6.23E-04	2.74E-03	1.14E-01	118773
ret	1.46	16.49	-34.80	-5.09	1.01	7.10	45.04	138274
ret3	4.61	29.40	-56.97	-8.39	3.07	14.86	92.98	44274
ret6	8.17	43.92	-65.97	-11.71	5.38	22.56	128.03	20797
dbreadth	0.08	0.71	-1.45	-0.14	0.04	0.27	1.82	46664

Panel D: Panel variance statistics

	walk-annual	talk-annual	walk-monthly	talk-monthly
Overall Mean	6.511	1.164	6.632	1.200
Overall Std. Dev.	12.019	2.967	12.913	3.612
Between Industry	9.310	1.101	9.747	1.232
Within Industry	8.704	2.832	9.713	3.482
Between Firm	11.642	2.705	11.888	2.881
Within Firm	4.128	1.658	6.211	2.729

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Table 2: Correlation between talk and walk

This table shows regressions of a company's annual walk on its contemporaneous or lagged talk, controlling for the lagged walk. *walk* and *talk* are the proportion of job postings that are classified as walk-relevant and talk-relevant among all the job postings the company creates during the year, respectively. The lagged value of *walk* in year T-1 or year T-2 is *walk lag* or *walk lag2*. The future value of *walk* in year T+1 is *walk lead*. T-statistics (with standard errors clustered by firm and time) are in parentheses, and *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The overall adjusted R^2 is reported.

Panel A: walk as dependent variable				
	(1)	(2)	(3)	(4)
	walk	walk	walk	walk lead
talk	0.559***	0.162***	0.183***	0.0298
	(8.462)	(5.936)	(4.983)	(0.695)
walk				0.745***
				(26.64)
walk lag		0.820***	0.738***	0.124***
		(37.82)	(16.85)	(5.293)
walk lag2			0.123***	
			(3.039)	
Industry*Year FE	Yes	Yes	Yes	Yes
Observations	13,616	9,680	6,708	6,704
Adj. R^2	0.478	0.817	0.834	0.833
Panel B: talk as dependent variable				
	(1)	(2)	(3)	(4)
	talk	talk	talk	talk lead
walk	0.0600***	0.0251***	0.0242***	0.00917***
	(9.673)	(5.358)	(4.220)	(3.551)
talk				0.606***
				(9.429)
talk lag		0.677***	0.600***	0.151***
		(17.22)	(10.22)	(3.909)
talk lag2			0.149***	
			(3.628)	
Industry*Year FE	Yes	Yes	Yes	Yes
Observations	13,616	9,680	6,708	6,704
Adj. R^2	0.088	0.475	0.519	0.515

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Table 3: Green transition efforts and environmental outcomes

This table examines the regressions of annual environmental outcomes on a firm's annual *walk* and *talk*. *recycled* is the percentage of waste that is recycled. *hazardous* is the percentage of hazardous waste. *carbon/asset* is carbon emissions scaled by assets. *carbon/ebitda* is carbon emissions scaled by EBITDA. *carbon/ppe* is carbon emissions scaled by net property, plant, and equipment. T-statistics (with standard errors clustered by firm and time) are in parentheses, and *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The overall adjusted R^2 is reported.

Panel A: with firm fixed effects					
	(1)	(2)	(3)	(4)	(5)
	recycled	hazardous	carbon/asset	carbon/ebitda	carbon/ppe
walk	0.287**	-0.0536	-1.345*	-311.5**	-3.409*
	(2.761)	(-1.159)	(-1.989)	(-2.292)	(-2.051)
talk	0.1000	0.218	2.132	-109.8	8.565*
	(0.448)	(0.867)	(1.603)	(-0.404)	(1.767)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	1,178	957	2,747	2,478	2,681
Adj. R^2	0.633	0.908	0.945	-0.020	0.971
Panel B: without firm fixed effects					
	(1)	(2)	(3)	(4)	(5)
	recycled	hazardous	carbon/asset	carbon/ebitda	carbon/ppe
walk	0.00286	-0.0446	5.313*	-17.27	8.839*
	(0.0234)	(-0.589)	(2.088)	(-0.312)	(2.156)
talk	-0.0615	1.369***	-8.650	-1,335	4.463
	(-0.0933)	(3.917)	(-1.044)	(-1.269)	(0.142)
Industry*Year FE	Yes	Yes	Yes	Yes	Yes
Observations	977	810	2,540	2,267	2,471
Adj. R^2	0.218	0.202	0.421	-0.174	0.241

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Table 4: Green transition efforts and media images

This table examines the regressions of monthly media images on a firm's monthly *walk* and *talk*. *image_recent*, *image_medium*, and *image_long*, ranging from 0 to 100, reflect how positive a firm's corporate image is in short-term, mid-term, and long-term media texts under the topic of greenhouse gas emissions, respectively. *no. article* is the number of articles tagged to the greenhouse gas emissions topic in the past 12 months. *materiality* measures how much stakeholders consider the greenhouse gas emissions topic to be material for a firm. T-statistics (with standard errors clustered by firm and time) are in parentheses, and *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The overall adjusted R^2 is reported.

Panel A: with firm fixed effects					
	(1) image_recent	(2) image_medium	(3) image_long	(4) no. article	(5) materiality
walk	-0.00505	0.00520	-0.00892	0.264	-0.0301*
	(-0.439)	(0.573)	(-0.331)	(0.989)	(-1.941)
talk	0.0697**	0.0483***	0.160***	0.349*	0.0254
	(2.441)	(2.668)	(2.845)	(1.691)	(0.962)
Firm FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Observations	77,481	77,327	77,287	123,239	47,836
Adj. R^2	0.451	0.715	0.131	0.475	0.768
Panel B: without firm fixed effects					
	(1) image_recent	(2) image_medium	(3) image_long	(4) no. article	(5) materiality
walk	0.000343	0.00440	-0.00860	0.0797	0.0720***
	(0.0214)	(0.271)	(-0.458)	(0.553)	(2.832)
talk	0.0918**	0.0723*	0.125***	0.197	-0.0103
	(2.140)	(1.790)	(2.718)	(0.350)	(-0.165)
Industry*Month FE	Yes	Yes	Yes	Yes	Yes
Observations	72,475	72,322	72,293	118,490	43,181
Adj. R^2	0.068	0.111	0.012	0.166	0.449

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Table 5: Green transition efforts and lagged, contemporaneous, and future financial indicators.

This table presents the relationship between a firm's annual green transition efforts and its lagged, contemporaneous, and future financial indicators. *rd/sale* is R&D expenses scaled by sales in percentage. *capx/asset* is capital expenditures scaled by average total assets in percentage. *ad/asset* is advertising expenses scaled by average total assets in percentage. *org cap* is capitalized SG&A expenses (xsga) scaled by average total assets in percentage. T-statistics (with standard errors clustered by firm and time) are in parentheses, and *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The overall adjusted R^2 is reported.

Panel A: last year's financial indicators				
	(1)	(2)	(3)	(4)
	rd/sale	capx/asset	ad/asset	org cap
walk	1.353	0.0151***	-0.0152	-0.00349***
	(0.801)	(3.114)	(-1.554)	(-3.809)
talk	-2.112	-0.0129	-0.0415	0.00834
	(-0.389)	(-0.727)	(-1.174)	(1.613)
Industry*Year FE	Yes	Yes	Yes	Yes
Observations	5,832	10,695	4,900	8,184
Adj. R^2	-0.061	0.457	0.290	0.310
Panel B: contemporaneous financial indicators				
	(1)	(2)	(3)	(4)
	rd/sale	capx/asset	ad/asset	org cap
walk	2.326*	0.0159***	-0.0206**	-0.00343***
	(1.701)	(3.779)	(-2.365)	(-3.599)
talk	-6.317*	-0.00232	-0.0137	0.00837
	(-1.843)	(-0.121)	(-0.313)	(1.219)
Industry*Year FE	Yes	Yes	Yes	Yes
Observations	7,237	13,173	5,858	10,029
Adj. R^2	-0.031	0.455	0.292	0.291
Panel C: next year's financial indicators				
	(1)	(2)	(3)	(4)
	rd/sale	capx/asset	ad/asset	org cap
walk	-0.164	0.0165***	-0.0169	-0.00346***
	(-0.151)	(3.217)	(-1.609)	(-3.416)
talk	-4.483**	0.00451	-0.0237	0.00883*
	(-2.087)	(0.289)	(-0.572)	(1.919)
Industry*Year FE	Yes	Yes	Yes	Yes
Observations	5,105	9,638	4,377	7,380
Adj. R^2	-0.067	0.476	0.286	0.287

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Table 6: Penalty on environmental regulatory violations and green transition efforts

This table presents the correlation between environmental penalty and annual green transition efforts. Panel A shows how a firm's own penalty correlates with its efforts. Panel B shows for firms without environmental penalty during 2000 and 2022, how the sum of penalties of its 4-digit NAICS peers correlates with its efforts. *penalty* is the sum of adjusted environment-related violation penalties imposed on the company during the period. *ind_penalty* is the sum of adjusted environment-related violation penalties imposed on the industry (at 4-digit NAICS code level) during the period. The amount of adjusted penalty is provided by Violation Tracker. T-statistics (with standard errors clustered by firm and time) are in parentheses, and *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The overall adjusted R^2 is reported.

Panel A: firm-level penalty		
	(1)	(2)
	walk	talk
Standardized penalty	0.134	0.0220***
	(1.009)	(2.635)
Firm FE	Yes	Yes
Time FE	Yes	Yes
Observations	13,152	13,152
Adj. R^2	0.840	0.574
Panel B: industry-level penalty in non-violator subsample		
	(1)	(2)
	walk	talk
Standardized ind_penalty	-0.0559	0.0208**
	(-0.892)	(2.462)
Firm FE	Yes	Yes
Time FE	Yes	Yes
Observations	9,508	9,508
Adj. R^2	0.830	0.553

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Table 7: Green transition efforts and environmental scores

This table presents the environmental scores' sensitivity to firm green transition efforts. *MSCI* is the annual net environmental score calculated with MSCI KLD data following the method of Lins, Servaes, and Tamayo (2017), in percentage. *Refinitiv* is the annual environmental pillar score in Refinitiv ASSET4 ESG data. *Sustainalytics* is the monthly environment score provided by Sustainalytics. T-statistics (with standard errors clustered by firm and time) are in parentheses, and *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The overall adjusted R^2 is reported.

Panel A: with firm fixed effect			
	(1) MSCI	(2) Refinitiv	(3) Sustainalytics
walk	0.157**	-0.0310	-0.00710
	(2.616)	(-1.175)	(-0.844)
talk	-0.0970	-0.148	0.0305
	(-0.551)	(-1.079)	(1.270)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	3,593	5,955	8,658
Adj. R^2	0.743	0.933	0.945
Panel B: without firm fixed effect			
	(1) MSCI	(2) Refinitiv	(3) Sustainalytics
walk	0.149***	0.107*	-0.0142
	(3.210)	(2.013)	(-0.278)
talk	0.770***	0.802***	0.327**
	(4.433)	(3.432)	(1.992)
Industry*Year FE	Yes	Yes	Yes
Observations	3,872	6,118	6,984
Adj. R^2	0.112	0.181	0.184

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Table 8: Green transition efforts and popularity among EU SFDR funds

This table presents the cross-section regression of a firm's relative popularity in dark green funds or light green funds on its green transition efforts. *ratio dark* is the popularity in dark green funds scaled by its popularity in nongreen funds. *ratio light* is the popularity in light green funds scaled by its popularity in nongreen funds. T-statistics (with standard errors clustered by firm and 4-digit industry) are in parentheses, and *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The overall adjusted R^2 is reported.

Panel A: relative popularity in dark green funds		
	(1)	(2)
	ratio dark	ratio dark
walk	0.230**	0.212**
	(2.162)	(2.169)
talk	0.557	0.940***
	(1.517)	(3.202)
Industry FE	Yes	No
Observations	2,386	2,415
Adj. R^2	0.203	0.020
Panel B: relative popularity in light green funds		
	(1)	(2)
	ratio light	ratio light
walk	0.251**	0.245**
	(2.461)	(2.448)
talk	0.443**	0.692***
	(2.137)	(3.402)
Industry FE	Yes	No
Observations	2,386	2,415
Adj. R^2	0.058	0.009

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Table 9: Green transition efforts and the change in institutional ownership breadth

This table presents the panel regression of the change in institutional ownership breadth on green transition efforts. *dbreadth* is the percentage change in Institutional Ownership Breadth following Lehavy and Sloan (2008) using Thomson-Reuters 13F data. Institutional Ownership Breadth represents the number of institutions that own the stock during the quarter. T-statistics (with standard errors clustered by firm and time) are in parentheses, and *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The overall adjusted R^2 is reported.

	(1) dbreadth	(2) dbreadth
walk	0.000619	0.000431
	(1.138)	(1.115)
talk	-0.000767	0.00252**
	(-0.731)	(2.389)
Firm FE	Yes	
Time FE	Yes	
Industry*Time FE		Yes
Observations	46,323	44,141
Adj. R^2	0.121	0.181

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Table 10: Green transition efforts and future stock returns

This table presents the panel regression of stock returns in the next month, next 3 months, or next 6 months on firm green transition efforts, controlling for other stock characteristics that are documented to predict returns. T-statistics (with standard errors clustered by firm and time) are in parentheses, and *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The overall adjusted R^2 is reported.

	(1) ret	(2) ret3	(3) ret6
walk	0.00466	0.0191	-0.0139
	(0.765)	(0.951)	(-0.437)
talk	0.0350**	0.145***	0.162
	(2.083)	(3.024)	(1.348)
market beta	0.549	2.850	5.321
	(1.033)	(1.437)	(1.532)
book-to-market	0.403	0.933	1.314
	(0.866)	(0.560)	(0.313)
size	-0.0466	-0.128	-0.00504
	(-0.560)	(-0.471)	(-0.00814)
reversal	-2.477	-35.06*	-4.001
	(-0.416)	(-1.836)	(-0.260)
momentum	-0.483	-1.985	-7.756**
	(-0.877)	(-1.292)	(-2.412)
asset growth	0.113	0.468	1.568
	(0.336)	(0.373)	(0.433)
gross profitability	1.147**	3.841*	7.570***
	(2.447)	(1.955)	(3.990)
capx growth	0.0289	0.0448	-0.270
	(0.647)	(0.342)	(-1.067)
illiquidity	83,642	865,755	491,989
	(1.006)	(1.338)	(1.229)
unexpected earnings	-3.256	-4.033	-5.683
	(-0.948)	(-0.674)	(-0.753)
Observations	108,477	34,305	15,720
Adj. R^2	0.002	0.032	0.014

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Appendix A: An excerpt of a sample job posting

This excerpt comes from a job posting by the company BP for the work location “Chicago, Illinois, United States”, created on September 29, 2022, under the job title “Sustainability Manager - Bio Feeds”. The LinkUp database assigns the O*NET code “11-1011.03” and the O*NET title “chief sustainability officers” to it.

Sustainability Manager - Bio Feeds

Key accountabilities

- Take lead role in executing and continuously improving the bp sustainability compliance programme in RPT-A, including certification under various schemes, procedures, processes, systems, GHG tools, training and communications.
- Support surveillance audits, working with the trading operations teams to ensure all sustainability management requirements are kept timely and with the appropriate control process.
- Collaborate with the central Regulatory Affairs team in communicating with CARB/EPA/etc and to get support when applying for pathways/ISCC certs as needed.
- Identify new market opportunities, advising analytics/traders on reg changes or competitor activity, and being the bench point person on reg advocacy discussions.
- Provide cross bench support to the biofuels trading teams with daily regulatory queries, focusing on GHG optimisation.
- Proactively identify and communicate possible risks faced by the business, proactively putting steps in place to effectively mitigate them in coordination with Global biofuel sustainability manager.
- Provide support to T&S low carbon growth agenda, including implementation of certified supply chains in the region.
- Develop intelligence and expertise around advanced/development feedstocks and biofuels legislation.

Essential Education:

- Degree in engineering, finance or a commercial field.
- Educational profile is less important than behaviours and a track history of high relationship management and performance.

Essential experience and job requirements:

The successful candidate will have:

- Extensive commercial and leadership skills. Experience and knowledge of trading and/or supply business and operations in energy value chains.
- Background on certification/auditing programmes, in particular ISCC system and

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similar would be highly beneficial.

- Experience guiding deals through pathway processes with regulatory bodies such as CARB, DEQ, EPA, etc.
- Strong track record of delivering projects and/or working to deadlines; Willing to speak-up and be able to lead and influence a broad range of collaborators both internally and externally.
- Strong background in Commercial/Operations or Finance & Risk subject area, with breadth of experience.
- Must be a great teammate able to operate within a complex and dynamic trading business, possessing the interpersonal and decision-making skills, coupled with sound commercial judgement to build credible relationships across T&S and 3rd parties.
- Self-motivated and highly drive.
- Understanding of BP's reputational risks, the intent of BP's Code of Conduct, and compliance commitments demonstrated by a track record of supporting actions.

Desirable criteria and qualifications

The successful candidate will also be expected to demonstrate the following:

- Commercially astute and innovative
- Performance bias, with an ability to overcome obstacles and inspire change. Strategically aware, with an ability to translate strategies into actions and the timely delivery of business results
- Experience with life-cycle greenhouse gas analysis
- Strong influencing skills, with an ability to build consensus and engagement across teams, functions and geographies
- Strong customer relationship building and management skills. Able to build relationships in a short period of time with new external parties

Appendix B: Word embedding model

Word embeddings are learned vector representations of each particular word or phrase. It allows words and phrases with similar meaning to have a similar representation. For example, "sustainable investing" and "ESG investing" have very similar meanings and should have very similar vector representations. Word embedding models learn these vector representations from a corpus of text through machine learning tasks, and then the similarity between vectors represents the semantic similarity between words.

In this study, I apply a widely-used algorithm based on neural networks, Word2vec,

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with the Gensim package. The semantic similarity between words in a corpus can be learned by two ways, Continuous-bag-of-words (CBOW) or Skip-grams (SG). CBOW method takes the context of each word as the input and tries to predict the word corresponding to the context. For example, in the sentence "Sustainable investing makes contribution to green transition", the word "sustainable" is covered in the input and the output is the covered word "sustainable". A Neural Network model is trained to generate the output from the input. During the process, the model learns the vector representations. The SG method flips the input and output of the CBOW method. The word "sustainable" is the input and the model tries to predict the context words of "sustainable". According to Mikolov, Sutskever, Chen, Corrado, and Dean (2013), the SG method represents rare words well, while the CBOW method represents better for more frequent words. As environment-related words are relatively rare in online job postings, I use the SG method.

As the model's goal is to predict a target word's context words, what we care is not whether the model can accurately predict the context but whether the parameters trained during the process can capture words' semantic similarities. Therefore, I test the model by giving it a particular word and asking for the Top 40 closest synonyms in the corpus. As we can see from the examples below, the model functions well. "gri" is the acronym for "Global Reporting Initiative". "sbti" is the acronym for "Science-Based Targets Initiative". Although there are unrelated phrases such as "mergers acquisitions" and "macroeconomic", these will be removed in the step of manually checking the meaning of the words and phrases using Google search results.

Top 40 closest synonyms to "sustainability": sustainable, gri aca, ghg emissions, greenhouse gas, carbon neutrality, ghg emission, circularity, esg, sbti, tcfd sasb, ghg carbon, ghg reduction, biodiversity, conservation, ghg, gri cdp, decarbonization, higg, green, ghg protocol, tcfd cdp, roots theinvention, carbon, djsi, index ftsegood, calculator forscherwelt, environmental stewardship, cdp gri, sedex, cdp tcfd, disclosures tcfd, climate, global, breeam, ecovadis, tcfd, dcehs, resiliency watershed, modern slavery, gri sasb.

Top 40 closest synonyms to "esg": tcfd, sasb, sasb gri, gri sasb, sdgs, tcfd sasb, frameworks sasb, gri cdp, sustainalytics, corporates, ungc, mergers acquisitions, tcfd cdp, disclosures tcfd, iss esg, cdp tcfd, sbti, gresb gri, greenhouse gas, ghg emissions, msci esg, ecovadis, sasb tcfd, ghg, advisory, msci sustainalytics, iss msci, strategist, trucost, lob, governance, blackrock, materiality, cdp gri, decarbonization, issuer, restructuring, macroeconomic, valuation, dji.

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Appendix C: BERT model

Bidirectional Encoder Representations from Transformers (BERT) is a natural language processing method widely adopted in industry since its birth in 2017 (Vaswani, Shazeer, Parmar, Uszkoreit, Jones, Gomez, Kaiser, and Polosukhin, 2017). It is a deep learning model in which every output element is connected to every input element and the weightings between them are dynamically calculated based on their connection. Training a BERT model requires very large training samples and a long processing time. Fortunately, it can be pre-trained with texts that are not specific to a classification problem. Based on the pre-trained model, fine-tuning with a small set of training samples in a specific problem can achieve satisfying accuracy. In this study, I use the widely used transformer package from Hugging Face, which provides pretrained BERT models of various sizes for several languages. Specifically, I use the "bert-base-uncased" model as the initial BERT model to fine-tune.

The training sample for fine-tuning directly affects model parameters and prediction quality. I expect environment-related jobs to be much fewer than irrelevant ones, as our economy is still in a transition stage. If a random group of job postings is used as a training sample, one class will dominate the other, and the model is tempted to always predict the dominant class. Furthermore, for occupations such as logistics manager, where the greenness of the job position depends on the context, some work tasks are not related to environmental responsibility. The same applies to many sentences in its job description. Fine-tuning could be more effective if positive training samples are more distinct from negative training samples. Therefore, in the training sample, the descriptions of green tasks (nongreen tasks) are used as a positive sample (negative sample). As I mentioned earlier that the DOL lists the green tasks and nongreen tasks involved in every green enhanced skills occupation and green new and emerging occupation, there are 1398 green tasks and 1705 nongreen tasks in total. This training sample with a balanced proportion between positive sample and negative sample can help relieve the over-fitting concern. The DOL also provides a general description of each green occupation. For occupations whose greenness depends on the context, the general description does not indicate environmental responsibility, while the description of an always-green occupation does. So, I use the general descriptions of always-green occupations (context-dependent green occupations) as the positive sample (negative sample) in the validation sample.

Appendix D: Additional tables

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Table A1: List of variables and definitions

Variables	Definition
	Green transition efforts
walk	Percentage of job postings that are classified as walk-relevant among all the job postings the company creates during the period. The period is either a year or a month. For annual walk, its lagged value in T-1 is walk lag, its lagged value in T-2 is walk lag2, and its future value in T+1 is walk lead.
talk	Percentage of job postings that are classified as talk-relevant among all the job postings the company creates during the period. The period is either a year or a month. For annual talk, its lagged value in T-1 is talk lag, its lagged value in T-2 is talk lag2, and its future value in T+1 is talk lead.
	Environmental outcomes
recycled	Percentage of waste that is recycled out of the total waste the company discards in the reporting year. The value is taken as reported by the company, or if not disclosed, calculated by Bloomberg as: (Waste Recycled / Total Waste) * 100.
hazardous	Percentage of hazardous waste out of total waste the company discards in the reporting year. The value is taken as reported by the company, or if not disclosed, calculated by Bloomberg as: (Hazardous Waste / Total Waste) * 100.
carbon/asset	Metric tonnes of total greenhouse gas (GHG) emitted per million of assets in the company's reporting currency. If total GHG emitted is not available, Bloomberg substitutes it with total carbon dioxide (CO2) emitted. Total assets are the sum of all short and long-term assets as reported on the balance sheet. The value is calculated by Bloomberg as: Total GHG Emissions*1000 / Total Assets, or Total CO2 Emissions*1000 / Total Assets. The former is shown in the priority.
carbon/ebitda	Metric tonnes of total greenhouse gas (GHG) emitted per million of Earnings Before Interest, Taxes, Depreciation and Amortization (EBITDA) in the company's reporting currency. If total GHG emitted is not available, Bloomberg substitutes it with total carbon dioxide (CO2) emitted. Total assets are the sum of all short and long-term assets as reported on the balance sheet. The value is calculated by Bloomberg as: Total GHG Emissions*1000 / EBITDA, or Total CO2 Emissions*1000 / EBITDA. The former is shown in the priority.
carbon/ppe	Metric tonnes of total greenhouse gas (GHG) emitted per million of net property, plant and equipment in the company's reporting currency. If total GHG emitted is not available, Bloomberg substitutes it with total carbon dioxide (CO2) emitted. Gross property, plant and equipment is prior to depreciation. The value is calculated by Bloomberg as: Total GHG Emissions*1000 / Gross Property Plant and Equip (PP&E), or Total CO2 Emissions*1000 / Gross PP&E. The former is shown in the priority.

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Table A1: List of variables and definitions (continued).

Variables	Definition
	Media images
image_recent	Recent firm image for the greenhouse gas emissions topic, ranging from 0 to 100. It reflects how positive a firm's image is in recent media texts that are related to greenhouse gas emission.
image_medium	Medium-term firm image for the greenhouse gas emissions topic. It is the exponentially weighted moving average of image_recent, providing rating equivalents for longer-term investors (the TruValue Labs does not specify the period it uses to calculate the moving average).
image_long	Long-term firm image for the greenhouse gas emissions topic. It is the slope of image_medium over the past trailing 12 months. It shows whether a firm's media image has been improving or deteriorating in the past trailing 12 months.
no. article	Number of articles tagged to the greenhouse gas emissions topic in the past 12 months.
materiality	Materiality score for the greenhouse gas emissions topic. It measures how much stakeholders consider the greenhouse gas emissions topic to be material for a firm.
	Financial indicators
rd/sale	Research and Development expenses divided by sales in percentage, calculated as xrd/sale.
capx/asset	Capital Expenditures scaled by average total assets in percentage, calculated as 100*capx/((at+lag(at))/2), capx represents the funds used for additions to property, plant, and equipment, excluding amounts arising from acquisitions (for example, fixed assets of purchased companies).
ad/asset	Advertising Expenses scaled by average total assets in percentage, calculated as 100*xad/((at+lag(at))/2), xad represents the cost of advertising media (i.e., radio, television, and periodicals) and promotional expenses. This item is not available for utility companies.
org cap	Organization capital calculated following Eisfeldt and Papanikolaou (2013), which is capitalized SG&A expenses (xsga) scaled by average total assets in percentage. xsga represents all commercial expenses of operation (i.e., expenses not directly related to product production) incurred in the regular course of business pertaining to the securing of operating income.
cash	Cash holdings scaled by average total assets in percentage, calculated with cash and cash equivalents multiplied by 100 and then divided by average total assets.
log(assets)	Natural logarithm of total assets (at).
roe	Return on equity in percentage, calculated with earnings before extraordinary items multiplied by 100 and then divided by lagged common shareholders' equity.
dividend yield	Dividend to price in percentage, total dividends (dvt) multiplied by 100 and then divided by market capitalization at fiscal year-end.
b/m	Book-to-market ratio in percentage, calculated with book value of equity (ceq) multiplied by 100 and then divided by end of fiscal year-end market capitalization.

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Table A1: List of variables and definitions (continued).

Variables	Definition
	Incentive program
incentive	Binary value 1 if the answer is "Yes" to CDP annual survey question "Do you provide incentives for the management of climate change issues, including the attainment of targets?", otherwise 0.
benefit	Binary value 0 if the answer is "Question not applicable" to CDP annual survey question "Provide further details on the incentives provided for the management of climate-related issues (do not include the names of individuals). - Who is entitled to benefit from these incentives?", otherwise 1.
publication	Binary value 1 if the answer is "Yes" to CDP annual survey question 4.1. "Have you published information about your company's response to climate change and GHG emissions performance for this reporting year in places other than in your CDP response? If so, please attach the publication(s).", otherwise 0.
	Environment-related violations
penalty	Sum of adjusted environment-related violation penalties imposed on the company during the period. The amount of adjusted penalty is provided by Violation Tracker. Standardized penalty is to standardize penalty into the mean equal to zero and variance equal to one.
ind_penalty	Sum of adjusted environment-related violation penalties imposed on the industry (at 4-digit NAICS code level) during the period. The amount of adjusted penalty is provided by Violation Tracker. Standardized ind_penalty is to standardize ind_penalty into the mean equal to zero and variance equal to one.
	Environmental ratings
MSCI	Net environmental score calculated with MSCI KLD data following the method of Lins, Servaes, and Tamayo (2017), which first divides the sum of strengths (concerns) by the maximum number of strengths (concerns) possible in reporting year and then subtracts the concerns index from the strengths index. The value is in percentage, ranging from -100 to 100.
Refinitiv	Environmental pillar score in Refinitiv ASSET4 ESG data, which is evaluated from three aspects, emission, innovation, and resource use. The value ranges from 0 to 100.
Sustainalytics	Weighted comprehensive environment score provided by Sustainalytics. Different from the annual MSCI or Refinitiv data, this variable is monthly. It is a weighted average score on aspects including environmental policy, environmental fines & penalties, carbon intensity, green procurement policy, environmental supply chain incidents, sustainable products & services and many others. The value ranges from 0 to 100.

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Table A1: List of variables and definitions (continued).

Variables	Definition
	Sustainability investors
No. nongreen	Count of all SFDR Article 6 Funds with holding exposure >0% on this security, shown on Bloomberg. Article 6 Funds: funds marketed in EU that do not integrate sustainability in investment process. By the sustainability classification under European Union (EU) Sustainable Finance Disclosure Regulation (SFDR) 2019/2088, where the financial product does not pursue or promote environmental or social objectives, but where sustainability risks may be assessed to determine their impact on the returns of the financial product.
No. light	Count of all SFDR Article 8 Funds with holding exposure >0% on this security, shown on Bloomberg. Article 8 Funds: "light green" funds marketed in EU. By the sustainability classification under European Union (EU) Sustainable Finance Disclosure Regulation (SFDR) 2019/2088, where a financial product promotes environmental or social characteristics, or a combination of those characteristics, provided that the companies in which the investments are made follow good governance practices.
No. dark	Count of all SFDR Article 9 Funds with holding exposure >0% on this security, shown on Bloomberg. Article 9 Funds: "dark green" funds marketed in EU. By the sustainability classification under European Union (EU) Sustainable Finance Disclosure Regulation (SFDR) 2019/2088, where a financial product has sustainable investment as its objective and complies with the "no significant harm principle" .
ratio light	Popularity in light green funds scaled by its popularity in nongreen funds, calculated with (No. light of this firm/maximum of No. light)/(No. nongreen of this firm/maximum of No. nongreen). When the value is larger than one, the stock is preferred by light green funds.
ratio dark	Popularity in dark green funds scaled by its popularity in nongreen funds, calculated with (No. dark of this firm/maximum of No. dark)/(No. nongreen of this firm/maximum of No. nongreen). When the value is larger than one, the stock is preferred by dark green funds.
	Institutional investors
dbreadth	Percentage change in Institutional Ownership Breadth following Lehavy and Sloan (2008) using Thomson-Reuters 13F data. Institutional Ownership Breadth represents the number of institutions that own the stock during the quarter. The percentage change is calculated using only 13F filers that exist in the database in both quarters T and T-1, to capture changes in the breadth of ownership rather than changes in the universe of institutions covered by the database.

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Table A1: List of variables and definitions (continued).

Variables	Definition
	Stock characteristics
ret	Excess return in the month after the month end when independent variables are recorded, in percentage.
ret3	Cumulative excess return in the 3 months after the month end when independent variables are recorded, in percentage.
ret6	Cumulative excess return in the 6 months after the month end when independent variables are recorded, in percentage.
market beta	Estimated market beta from weekly returns and equal weighted market returns in the past 3 years with at least 52 weeks of returns.
book-to-market	Book-to-market ratio. Its difference from variable b/m in the financial indicator part is *book-to-market* is monthly and in unit while b/m is annual and in percentage.
size	Natural log of market capitalization.
reversal	Short-term reversal, calculated with 1-month return.
momentum	1-year momentum, calculated with 11-month cumulative returns ending one month before the report month end.
asset growth	Annual percent change in total assets (at).
gross profitability	Revenues (revt) minus cost of goods sold (cogs) divided by lagged total assets (at).
capx growth	Growth in capital expenditures, calculated with percent change in capital expenditures from year T-2 to year T.
illiquidity	Average of daily (absolute return / dollar volume).
unexpected earnings	Unexpected quarterly earnings divided by fiscal-quarter-end market cap. Unexpected earnings is I/B/E/S actual earnings minus median forecasted earnings if available, else it is the seasonally differenced quarterly earnings before extraordinary items from Compustat quarterly file.

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Table A2: List of 204 green occupations.

Efforts	Always	O*NET Title	O*NET code
Talk	0	marketing managers	11-2021.00
Talk	0	regulatory affairs managers	11-9199.01
Talk	0	regulatory affairs specialists	13-1041.07
Talk	0	financial analysts	13-2051.00
Talk	0	personal financial advisors	13-2052.00
Talk	0	financial quantitative analysts	13-2099.01
Talk	0	risk management specialists	13-2099.02
Talk	0	investment underwriters	13-2099.03
Talk	0	reporters and correspondents	27-3022.00
Talk	0	public relations specialists	27-3031.00
Talk	0	energy brokers	41-3099.01
Talk	0	sales representatives wholesale and manufacturing technical and scientific products	41-4011.00
Talk	0	customer service representatives	43-4051.00
Talk	0	shipping receiving and traffic clerks	43-5071.00
Talk	1	green marketers	11-2011.01
Talk	1	energy auditors	13-1199.01
Talk	1	environmental economists	19-3011.01
Talk	1	solar sales representatives and assessors	41-4011.07
Walk	0	general and operations managers	11-1021.00
Walk	0	industrial production managers	11-3051.00
Walk	0	transportation managers	11-3071.01
Walk	0	storage and distribution managers	11-3071.02
Walk	0	logistics managers	11-3071.03
Walk	0	farm and ranch managers	11-9013.02
Walk	0	construction managers	11-9021.00
Walk	0	architectural and engineering managers	11-9041.00
Walk	0	natural sciences managers	11-9121.00
Walk	0	compliance managers	11-9199.02
Walk	0	supply chain managers	11-9199.04
Walk	0	buyers and purchasing agents farm products	13-1021.00
Walk	0	wholesale and retail buyers except farm products	13-1022.00
Walk	0	logistics engineers	13-1081.01
Walk	0	logistics analysts	13-1081.02
Walk	0	training and development specialists	13-1151.00
Walk	0	software developers systems software	15-1133.00
Walk	0	geospatial information scientists and technologists	15-1199.04
Walk	0	geographic information systems technicians	15-1199.05
Walk	0	architects except landscape and naval	17-1011.00
Walk	0	landscape architects	17-1012.00
Walk	0	aerospace engineers	17-2011.00
Walk	0	chemical engineers	17-2041.00
Walk	0	civil engineers	17-2051.00
Walk	0	transportation engineers	17-2051.01
Walk	0	electrical engineers	17-2071.00

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Table A2: The list of 204 green jobs (continued).

Efforts	Always	O*NET Title	O*NET code
Walk	0	electronics engineers except computer	17-2072.00
Walk	0	industrial engineers	17-2112.00
Walk	0	mechanical engineers	17-2141.00
Walk	0	fuel cell engineers	17-2141.01
Walk	0	automotive engineers	17-2141.02
Walk	0	biochemical engineers	17-2199.01
Walk	0	validation engineers	17-2199.02
Walk	0	manufacturing engineers	17-2199.04
Walk	0	mechatronics engineers	17-2199.05
Walk	0	microsystems engineers	17-2199.06
Walk	0	photonics engineers	17-2199.07
Walk	0	robotics engineers	17-2199.08
Walk	0	nanosystems engineers	17-2199.09
Walk	0	architectural drafters	17-3011.01
Walk	0	electronics engineering technicians	17-3023.01
Walk	0	electrical engineering technicians	17-3023.03
Walk	0	electromechanical technicians	17-3024.00
Walk	0	robotics technicians	17-3024.01
Walk	0	industrial engineering technicians	17-3026.00
Walk	0	automotive engineering technicians	17-3027.01
Walk	0	electrical engineering technologists	17-3029.02
Walk	0	electromechanical engineering technologists	17-3029.03
Walk	0	electronics engineering technologists	17-3029.04
Walk	0	industrial engineering technologists	17-3029.05
Walk	0	manufacturing engineering technologists	17-3029.06
Walk	0	mechanical engineering technologists	17-3029.07
Walk	0	photonics technicians	17-3029.08
Walk	0	manufacturing production technicians	17-3029.09
Walk	0	fuel cell technicians	17-3029.10
Walk	0	nanotechnology engineering technologists	17-3029.11
Walk	0	nanotechnology engineering technicians	17-3029.12
Walk	0	chemists	19-2031.00
Walk	0	materials scientists	19-2032.00
Walk	0	geoscientists except hydrologists and geographers	19-2042.00
Walk	0	remote sensing scientists and technologists	19-2099.01
Walk	0	urban and regional planners	19-3051.00
Walk	0	transportation planners	19-3099.01
Walk	0	agricultural technicians	19-4011.01
Walk	0	chemical technicians	19-4031.00
Walk	0	geophysical data technicians	19-4041.01
Walk	0	geological sample test technicians	19-4041.02
Walk	0	remote sensing technicians	19-4099.03
Walk	0	arbitrators mediators and conciliators	23-1022.00
Walk	0	farm and home management advisors	25-9021.00
Walk	0	commercial and industrial designers	27-1021.00

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Table A2: The list of 204 green jobs (continued).

Efforts	Always	O*NET Title	O*NET code
Walk	0	occupational health and safety specialists	29-9011.00
Walk	0	occupational health and safety technicians	29-9012.00
Walk	0	securities and commodities traders	41-3031.03
Walk	0	freight forwarders	43-5011.01
Walk	0	dispatchers except police fire and ambulance	43-5032.00
Walk	0	production planning and expediting clerks	43-5061.00
Walk	0	firstline supervisors of logging workers	45-1011.05
Walk	0	firstline supervisors of agricultural crop and horticultural workers	45-1011.07
Walk	0	agricultural inspectors	45-2011.00
Walk	0	boilermakers	47-2011.00
Walk	0	construction carpenters	47-2031.01
Walk	0	rough carpenters	47-2031.02
Walk	0	cement masons and concrete finishers	47-2051.00
Walk	0	construction laborers	47-2061.00
Walk	0	operating engineers and other construction equipment operators	47-2073.00
Walk	0	electricians	47-2111.00
Walk	0	pipe fitters and steamfitters	47-2152.01
Walk	0	plumbers	47-2152.02
Walk	0	roofers	47-2181.00
Walk	0	sheet metal workers	47-2211.00
Walk	0	structural iron and steel workers	47-2221.00
Walk	0	helperscarpenters	47-3012.00
Walk	0	construction and building inspectors	47-4011.00
Walk	0	railtrack laying and maintenance equipment operators	47-4061.00
Walk	0	service unit operators oil gas and mining	47-5013.00
Walk	0	continuous mining machine operators	47-5041.00
Walk	0	firstline supervisors of mechanics installers and repairers	49-1011.00
Walk	0	electrical and electronics repairers commercial and industrial equipment	49-2094.00
Walk	0	automotive specialty technicians	49-3023.02
Walk	0	bus and truck mechanics and diesel engine specialists	49-3031.00
Walk	0	heating and air conditioning mechanics and installers	49-9021.01
Walk	0	refrigeration mechanics and installers	49-9021.02
Walk	0	industrial machinery mechanics	49-9041.00
Walk	0	millwrights	49-9044.00
Walk	0	electrical powerline installers and repairers	49-9051.00
Walk	0	maintenance and repair workers general	49-9071.00
Walk	0	helpersinstallation maintenance and repair workers	49-9098.00
Walk	0	firstline supervisors of production and operating workers	51-1011.00
Walk	0	aircraft structure surfaces rigging and systems assemblers	51-2011.00
Walk	0	electrical and electronic equipment assemblers	51-2022.00

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Table A2: The list of 204 green jobs (continued).

Efforts	Always	O*NET Title	O*NET code
Walk	0	engine and other machine assemblers	51-2031.00
Walk	0	structural metal fabricators and fitters	51-2041.00
Walk	0	team assemblers	51-2092.00
Walk	0	computer controlled machine tool operators metal and plastic	51-4011.00
Walk	0	cutting punching and press machine setters operators and tenders metal and plastic	51-4031.00
Walk	0	drilling and boring machine tool setters operators and tenders metal and plastic	51-4032.00
Walk	0	machinists	51-4041.00
Walk	0	welders cutters and welder fitters	51-4121.06
Walk	0	solderers and brazers	51-4121.07
Walk	0	power distributors and dispatchers	51-8012.00
Walk	0	power plant operators	51-8013.00
Walk	0	stationary engineers and boiler operators	51-8021.00
Walk	0	chemical plant and system operators	51-8091.00
Walk	0	chemical equipment operators and tenders	51-9011.00
Walk	0	separating filtering clarifying precipitating and still machine setters operators and tenders	51-9012.00
Walk	0	mixing and blending machine setters operators and tenders	51-9023.00
Walk	0	inspectors testers sorters samplers and weighers	51-9061.00
Walk	0	bus drivers transit and intercity	53-3021.00
Walk	0	heavy and tractortrailer truck drivers	53-3032.00
Walk	0	locomotive engineers	53-4011.00
Walk	0	railroad conductors and yardmasters	53-4031.00
Walk	0	transportation vehicle equipment and systems inspectors except aviation	53-6051.07
Walk	0	industrial truck and tractor operators	53-7051.00
Walk	0	laborers and freight stock and material movers hand	53-7062.00
Walk	1	chief sustainability officers	11-1011.03
Walk	1	geothermal production managers	11-3051.02
Walk	1	biofuels production managers	11-3051.03
Walk	1	biomass power plant managers	11-3051.04
Walk	1	methanel and fill gas collection system operators	11-3051.05
Walk	1	hydroelectric production managers	11-3051.06
Walk	1	biofuelsbiodiesel technology and product development managers	11-9041.01
Walk	1	water resource specialists	11-9121.02
Walk	1	wind energy operations managers	11-9199.09
Walk	1	wind energy project managers	11-9199.10
Walk	1	brownfield redevelopment specialists and site managers	11-9199.11
Walk	1	sustainability specialists	13-1199.05

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Table A2: The list of 204 green jobs (continued).

Efforts	Always	O*NET Title	O*NET code
Walk	1	environmental engineers	17-2081.00
Walk	1	waterwastewater engineers	17-2081.01
Walk	1	industrial safety and health engineers	17-2111.01
Walk	1	nuclear engineers	17-2161.00
Walk	1	energy engineers	17-2199.03
Walk	1	wind energy engineers	17-2199.10
Walk	1	solar energy systems engineers	17-2199.11
Walk	1	environmental engineering technicians	17-3025.00
Walk	1	soil and plant scientists	19-1013.00
Walk	1	zoologists and wildlife biologists	19-1023.00
Walk	1	soil and water conservationists	19-1031.01
Walk	1	atmospheric and space scientists	19-2021.00
Walk	1	environmental scientists and specialists including health	19-2041.00
Walk	1	climate change analysts	19-2041.01
Walk	1	environmental restoration planners	19-2041.02
Walk	1	industrial ecologists	19-2041.03
Walk	1	hydrologists	19-2043.00
Walk	1	nuclear equipment operation technicians	19-4051.01
Walk	1	environmental science and protection technicians including health	19-4091.00
Walk	1	forest and conservation technicians	19-4093.00
Walk	1	precision agriculture technicians	19-4099.02
Walk	1	fish and game wardens	33-3031.00
Walk	1	forest and conservation workers	45-4011.00
Walk	1	solar energy installation managers	47-1011.03
Walk	1	insulation workers floor ceiling and wall	47-2131.00
Walk	1	solar photovoltaic installers	47-2231.00
Walk	1	hazardous materials removal workers	47-4041.00
Walk	1	solar thermal installers and technicians	47-4099.02
Walk	1	weatherization installers and technicians	47-4099.03
Walk	1	wind turbine service technicians	49-9081.00
Walk	1	geothermal technicians	49-9099.01
Walk	1	nuclear power reactor operators	51-8011.00
Walk	1	biofuels processing technicians	51-8099.01
Walk	1	methanelandfill gas generation system technicians	51-8099.02
Walk	1	biomass plant technicians	51-8099.03
Walk	1	hydroelectric plant technicians	51-8099.04
Walk	1	recycling and reclamation workers	51-9199.01
Walk	1	recycling coordinators	53-1021.01
Walk	1	refuse and recyclable material collectors	53-7081.00

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Table A3: 120 most frequent green keywords in job postings of the occupations whose greenness depends on context.

keyword	frequency	keyword	frequency	keyword	frequency
environmental	1397862	recyclable material	19981	renewable electricity	5256
sustainable	546296	water quality	19149	conserving resource	5173
hazardous material	310092	wind turbine	18720	chlorine	4962
sustainability	309438	wastewater treatment	18617	phmsa	4815
waste management	259732	hazwoper	18601	solar wind	4652
recycling	256332	rcra	15365	agronomic	4533
ecosystem	230866	climate change	13601	gmp haccp	4358
ehs	179422	air quality	13267	beryllium	4225
solar	145918	pollution	12848	ghg	3943
landfill	139006	environmental stewardship	12539	home recycle	3910
toxic	120598	solar energy	11037	niosh	3696
wastewater	95714	drinking water	10893	gas renewables	3445
hazardous waste	90606	efficient energy use	10638	nuclear safety	3398
renewable	90154	green building	10519	chemical spill	3386
cleaner safer	86425	asbestos	10503	hydroelectric	3385
occupational safety	80112	waste reduction	10359	sludge	3288
environmentally	79899	zero emission	9985	spcc	3158
pcb	77149	pcbs	9701	urethane	3145
radiation	68988	ferc	9223	harmful chemical	3047
waste disposal	68039	wildlife	9100	greenhouse gas	3002
water wastewater	60348	wind farm	8505	watershed	2798
renewable energy	58137	pesticide	8331	oil spill	2766
covanta	54535	nuclear weapon	7996	spray hazardous	2763
conservation	51090	animal husbandry	7928	cgmp glp	2753
water treatment	47097	wind energy	7657	ghg emission	2720
recycle	44992	mrf	7403	radiation effect	2650
fostering sustainable	42432	toxin	7382	sdg	2637
forest	37958	contaminant	7256	biosecurity	2596
cng	32945	landfill transfer	7189	hydropower	2566
renewables	31760	water filtration	7091	tailing	2524
esg	29764	natural disaster	7052	amine	2522
energy conservation	27058	nnsa	6902	fossil fuel	2519
natural resource	26265	nanotechnology	6807	facility mrf	2496
marsh	26089	litter	6796	radon	2492
recyclable	25460	disposal recycling	6655	microplastics	2485
leed	25216	wind solar	6259	petro chemical	2485
sustainably	24813	chemical petrochemical	5954	naval nuclear	2466
nuclear power	21969	carbon dioxide	5879	pollution prevention	2439
hydrocarbon	20294	incinerator	5565	nepa	2386
fuel cell	20127	alternative fuel	5327	vehicle emission	2345

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Table A4: 50 industries with the highest average walk

This table presents the 4-digit NAICS code, industry name, average walk, average talk, and average number of job postings posted in a year for firms within each of the 50 industries with the highest average walk. The industry with the highest percentage of talk jobs is of 4-digit NAICS code 5621, including solid waste collection, hazardous waste collection and others.

4-digit NAICS	Industry Name	Walk	Talk	Avg Job postings
5621	Waste Collection	44.45	1.67	5624.02
5622	Waste Treatment and Disposal	43.15	3.08	3245.94
4862	Pipeline Transportation of Natural Gas	40.60	0.84	552.41
2122	Metal Ore Mining	37.59	0.74	487.68
2213	Water, Sewage and Other Systems	37.07	5.04	511.92
3252	Resin, Synthetic Rubber, and Artificial and Synthetic Fibers and Filaments Manufacturing	30.86	1.80	490.74
3251	Basic Chemical Manufacturing	30.60	2.62	771.70
3312	Steel Product Manufacturing from Purchased Steel	29.08	0.87	252.70
3313	Alumina and Aluminum Production and Processing	28.88	1.75	166.69
3253	Pesticide, Fertilizer, and Other Agricultural Chemical Manufacturing	27.81	3.76	488.12
3212	Veneer, Plywood, and Engineered Wood Product Manufacturing	27.36	1.84	232.79
3221	Pulp, Paper, and Paperboard Mills	26.34	3.11	602.22
3365	Railroad Rolling Stock Manufacturing	25.81	0.95	955.11
2123	Nonmetallic Mineral Mining and Quarrying	25.57	0.89	679.76
3326	Spring and Wire Product Manufacturing	25.01	0.09	715.50
3311	Iron and Steel Mills and Ferroalloy Manufacturing	24.84	1.11	442.89
4239	Miscellaneous Durable Goods Merchant Wholesalers	24.17	6.32	896.90
3241	Petroleum and Coal Products Manufacturing	23.93	2.42	809.36
2121	Coal Mining	23.27	0.03	87.88
2211	Electric Power Generation, Transmission and Distribution	22.86	2.59	827.57
2131	Support Activities for Mining	22.84	0.58	625.26
5413	Architectural, Engineering, and Related Services	22.41	0.45	2499.03
2111	Oil and Gas Extraction	22.10	0.71	284.42
3324	Boiler, Tank, and Shipping Container Manufacturing	21.26	0.64	597.04
3211	Sawmills and Wood Preservation	20.82	0.00	112.00
3272	Glass and Glass Product Manufacturing	20.77	1.16	171.77
3321	Forging and Stamping	20.06	0.13	184.12
4869	Other Pipeline Transportation	19.90	0.41	165.30
3328	Coating, Engraving, Heat Treating, and Allied Activities	19.57	0.00	123.00
3334	Ventilation, Heating, Air-Conditioning, and Commercial Refrigeration Equipment Manufacturing	19.31	3.57	2954.85
3279	Other Nonmetallic Mineral Product Manufacturing	19.30	2.57	287.17
4861	Pipeline Transportation of Crude Oil	19.23	0.52	202.94
2371	Utility System Construction	18.07	1.63	665.57
3261	Plastics Product Manufacturing	17.95	2.46	715.53
3359	Other Electrical Equipment and Component Manufacturing	17.89	3.20	758.77
3255	Paint, Coating, and Adhesive Manufacturing	17.59	3.94	2592.58
3314	Nonferrous Metal (except Aluminum) Production and Processing	17.31	1.00	232.18
2382	Building Equipment Contractors	16.94	0.35	1700.08
3222	Converted Paper Product Manufacturing	16.05	1.35	1924.49
2212	Natural Gas Distribution	16.02	1.53	414.65
3362	Motor Vehicle Body and Trailer Manufacturing	15.98	0.40	363.83
4246	Chemical and Allied Products Merchant Wholesalers	15.69	4.24	1074.69
3112	Grain and Oilseed Milling	15.68	1.67	1341.89
2373	Highway, Street, and Bridge Construction	15.54	0.30	396.58
3141	Textile Furnishings Mills	15.28	2.31	1867.57
3323	Architectural and Structural Metals Manufacturing	15.24	1.12	619.67
2379	Other Heavy and Civil Engineering Construction	15.07	0.14	1243.17
3331	Agriculture, Construction, and Mining Machinery Manufacturing	14.99	0.68	603.91
5416	Management, Scientific, and Technical Consulting Services	14.79	1.16	5716.20
5612	Facilities Support Services	14.71	0.89	753.00

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Table A5: 50 industries with the highest average talk.

This table presents the 4-digit NAICS code, industry name, average walk, average talk, and average number of job postings posted in a year for firms within each of the 50 industries with the highest average talk. The industry with the highest percentage of talk jobs is of 4-digit NAICS code 7139, including golf courses and country clubs, skiing facilities, marinas, fitness and recreational sports centers, bowling centers and others.

4-digit NAICS	Industry Name	Walk	Talk	Avg Job postings
7139	Other Amusement and Recreation Industries	1.22	6.42	3627.84
4239	Miscellaneous Durable Goods Merchant Wholesalers	24.17	6.32	896.90
2213	Water, Sewage and Other Systems	37.07	5.04	511.92
4246	Chemical and Allied Products Merchant Wholesalers	15.69	4.24	1074.69
3255	Paint, Coating, and Adhesive Manufacturing	17.59	3.94	2592.58
3253	Pesticide, Fertilizer, and Other Agricultural Chemical Manufacturing	27.81	3.76	488.12
4237	Hardware, and Plumbing and Heating Equipment and Supplies Merchant Wholesalers	2.42	3.70	982.48
8129	Other Personal Services	3.33	3.64	3216.91
3334	Ventilation, Heating, Air-Conditioning, and Commercial Refrigeration Equipment Manufacturing	19.31	3.57	2954.85
5616	Investigation and Security Services	3.13	3.45	2507.94
3372	Office Furniture (including Fixtures) Manufacturing	7.80	3.28	483.60
3359	Other Electrical Equipment and Component Manufacturing	17.89	3.20	758.77
3221	Pulp, Paper, and Paperboard Mills	26.34	3.11	602.22
5622	Waste Treatment and Disposal	43.15	3.08	3245.94
3256	Soap, Cleaning Compound, and Toilet Preparation Manufacturing	8.64	2.92	1422.78
3343	Audio and Video Equipment Manufacturing	7.09	2.77	323.94
4247	Petroleum and Petroleum Products Merchant Wholesalers	13.32	2.66	313.00
3251	Basic Chemical Manufacturing	30.60	2.62	771.70
4234	Professional and Commercial Equipment and Supplies Merchant Wholesalers	1.05	2.62	929.72
2211	Electric Power Generation, Transmission and Distribution	22.86	2.59	827.57
3279	Other Nonmetallic Mineral Product Manufacturing	19.30	2.57	287.17
2372	Land Subdivision	6.28	2.54	200.20
3261	Plastics Product Manufacturing	17.95	2.46	715.53
3241	Petroleum and Coal Products Manufacturing	23.93	2.42	809.36
3141	Textile Furnishings Mills	15.28	2.31	1867.57
5112	Software Publishers	1.23	2.28	1344.27
4853	Taxi and Limousine Service	4.84	2.28	2116.29
3333	Commercial and Service Industry Machinery Manufacturing	10.27	2.18	1252.86
6116	Other Schools and Instruction	0.52	2.15	325.40
5182	Data Processing, Hosting, and Related Services	0.43	2.06	1204.28
3345	Navigational, Measuring, Electromedical, and Control Instruments Manufacturing	8.37	2.05	1938.19
5239	Other Financial Investment Activities	0.47	2.00	637.14
3353	Electrical Equipment Manufacturing	11.58	1.95	1290.00
5122	Sound Recording Industries	0.47	1.92	357.00
3352	Household Appliance Manufacturing	7.78	1.89	960.50
3339	Other General Purpose Machinery Manufacturing	12.76	1.88	1342.22
5191	Other Information Services	0.56	1.85	913.63
3212	Veneer, Plywood, and Engineered Wood Product Manufacturing	27.36	1.84	232.79
5412	Accounting, Tax Preparation, Bookkeeping, and Payroll Services	0.53	1.84	8091.77
4411	Automobile Dealers	3.67	1.84	5478.85
3252	Resin, Synthetic Rubber, and Artificial and Synthetic Fibers and Filaments Manufacturing	30.86	1.80	490.74
5231	Securities and Commodity Contracts Intermediation and Brokerage	0.45	1.76	1149.90
3313	Alumina and Aluminum Production and Processing	28.88	1.75	166.69
3391	Medical Equipment and Supplies Manufacturing	4.90	1.74	992.97
3341	Computer and Peripheral Equipment Manufacturing	2.63	1.73	1421.00
5242	Agencies, Brokerages, and Other Insurance Related Activities	0.73	1.69	2075.11
3122	Tobacco Manufacturing	3.20	1.68	344.17
3112	Grain and Oilseed Milling	15.68	1.67	1341.89
5621	Waste Collection	44.45	1.67	5624.02
2371	Utility System Construction	18.07	1.63	665.57

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