Do Consumers Care About ESG? Evidence from Barcode-Level Sales Data*

This draft: March 19, 2024
First draft: July 31, 2022

Abstract

Using granular barcode-level sales data from retail stores, we show that environmental and social (E&S) ratings positively relate to local sales, especially in counties with more Democratic-leaning and higher-income households. Higher ratings of a firm's product market rivals negatively affect a firm's sales. Controlling for product-year-level heterogeneity, monthly product sales decline after negative firm news on E&S issues. Finally, immediately after major natural and environmental disasters, sales in counties close to the disasters become more sensitive to E&S ratings. Our study provides direct evidence that E&S investments affect consumer demand–the cash flow channel of ESG.

Keywords: Environmental, Social, and Governance (ESG), Corporate Social Responsibility (CSR), Sustainability, Household Finance, Cash Flows, Product Market Competition, Consumption

JEL classification: D12, G32, G50, M14

*Our analyses are partly based on data from Nielsen Consumer LLC and marketing databases provided through the NielsenIQ Datasets at the Kilts Center for Marketing at The University of Chicago Booth School of Business. The conclusions drawn from the NielsenIQ data are those of the researchers and do not reflect the views of NielsenIQ. NielsenIQ is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

1 Introduction

Over the past two decades, Environmental, Social, and Governance (ESG) issues have increasingly attracted the attention of business leaders, academics, policymakers, and the general public. A popular viewpoint is that firms could be "doing well by doing good," i.e., corporate investments in Environmental and Social activities (E&S) can help the firm achieve higher profits and maximize shareholder value (see Gillan, Koch, and Starks (2021) for a recent literature review and the Presidential Address by Starks (2023)). Despite a substantial number of articles on this issue, Gillan, Koch, and Starks (2021) and Starks (2023) point out that the mechanisms through which E&S activities could affect corporate performance and value creation remain poorly understood. This contrasts with a large literature on the factors affecting capital expenditures, and M&A and R&D investments and the associated valuation consequences.

There are two channels through which E&S investments could affect firm value. On the one hand, there is the discount rate channel, whereby shareholders adjust their required rate of return in consideration of firms' performance in E&S-related practices (e.g., Heinkel, Kraus, and Zechner 2001, Hong and Kacperczyk 2009, Krüger 2015, Albuquerque, Koskinen, and Zhang 2019, Bolton and Kacperczyk 2021, Pástor, Stambaugh, and Taylor 2021, 2022, Pedersen, Fitzgibbons, and Pomorski 2021). On the other hand, E&S investments could also affect firm value through the cash flow channel. For example, customers could influence a firm's revenue by adjusting their demand in response to the firm's E&S practices (Servaes and Tamayo 2013, Schiller 2018, Dai, Liang, and Ng 2021), employee productivity could be affected by the employer's E&S policies (Edmans 2011), or high E&S firms could manage to pay lower wages (Krüger, Metzger, and Wu 2023). Moreover, the response of customers and employees does not need to be constant over time but could depend on the overall level of trust in firms, markets, and institutions (Lins, Servaes, and Tamayo 2017).[1]

[1] An alternative point of view is that E&S activities are mainly due to agency problems in the firm (e.g., Masulis and Reza 2015, Cheng, Hong, and Shue 2023), which would suggest that E&S activities and profits are negatively related.

In this paper, we shed further light on the cash flow channel, and particularly on how consumers in retail markets react to a firm's E&S investments. If consumers are concerned about the social and environmental externalities of their consumption decisions, these concerns should be factored into their choices of products and services. As such, the demand for a product should depend on its perceived quality from an E&S perspective. This argument follows the reasoning of Baron (2007) that consumers consider a firm's E&S activities as a product attribute, just like they do its price or quality. Consistent with this notion, in a survey conducted by Capgemini (2020) 42% of consumers indicate having made purchase decisions based on E&S factors, and another 37% of consumers indicate that they may consider such factors in the future. In contrast, however, only 36% of companies think that their customers already consider E&S factors or might do so in the future, highlighting the need for quantitative evidence on whether consumers "put their money where their mouth is."

We approach this question using Nielsen Retail Scanner Data. The advantage of our setting over prior work is that we have detailed barcode-level sales data on specific products sold at the US county level. The granularity of our data enables us to compare very similar products sold in the same location at the same time by companies with different levels of E&S activities. Using these barcode-level sales data in local markets over the period of 2008 to 2016 and a brand owner's E&S rating as an empirical proxy for its perceived E&S performance, we find that a brand owner's E&S performance is positively related to local product sales. Based on our estimates, a one-standard-deviation increase in the owner's E&S rating is related to an increase in sales of 9.2% in the subsequent year for the average product sold in the same county (about half the variation in E&S scores results from within-firm variation, the other half of the variation is between firms). This estimate is robust to controlling for a battery of high-dimensional fixed effects. Specifically, in our baseline regressions where we investigate product sales at the firm-product category-county-year level, we include firm×county×product category fixed effects, county×year fixed effects, and product category×year fixed effects. Thus, our empirical setting significantly limits the scope of potentially omitted variables. Nevertheless, we

show that our findings are robust to the inclusion of various controls that could be correlated with sales and E&S activities, such as advertising, corporate governance, or the product quality of the firm.

Next, we investigate different demographic characteristics that may explain local consumer responses to corporate E&S investments. Previous studies have shown that people with different demographic characteristics view and respond differently to E&S activities (e.g., Di Giuli and Kostovetsky 2014, Lins, Servaes, and Tamayo 2017, Dyck, Lins, Roth, and Wagner 2019). Specifically, we examine whether Democratic voters and consumers with higher income and education respond differently to a firm's E&S activities. We find positive and significant point estimates for the interactions between E&S scores and both the share of Democratic voters and average income in a county. These findings are consistent with the role of consumers' political leaning and financial conditions in shaping their preferences to consume the products of more socially responsible companies.

We also assess whether local product market competition affects the consumer's response to E&S policies as consumers can choose between different brands based on their social preferences. Cao, Liang, and Zhan (2019) find that the peers of firms that pass an E&S proposal experience negative announcement returns, suggesting that firms face E&S peer pressure. If a firm's relative E&S performance influences local product market competition, then local product sales should be negatively correlated with the E&S rating of local rivals. This is the case: a firm's product sales in a county are *negatively* related to the E&S performance of local rivals that sell the same types of products in the same county. These results indicate that consumers choose between alternative products based on the relative E&S performance of the companies, creating further competitive pressure on firms to improve their E&S standards.

Given the granularity of our data, which allows for the inclusion of many high-dimensional fixed effects, our results are unlikely to be spurious due to the lack of sufficient controls. Nevertheless, we

conduct two additional analyses where omitted variable bias or endogeneity concerns are less applicable. First, we analyze the time-series lead-lag relation between time-stamped negative corporate E&S news and product sales at the monthly level. We find that the release of negative firm news on E&S-related issues precedes but does not follow product sales declines. This evidence is consistent with consumers reducing the product demand in response to bad news related to the firms' E&S practices. With the monthly sales data in this analysis, we can control for product×year fixed effects, which further alleviates the concern about omitted explanatory variables.

Second, we exploit a series of major natural and environmental disasters as shocks to the salience of E&S activities for consumers from neighboring counties unaffected by the disaster. Such events are exogenous to firms' choice of E&S policies and product characteristics since we lag E&S scores by one year. Holding fixed the perceived level of a firm's E&S performance and product characteristics, an exogenous increase in consumer awareness of E&S issues could increase the sensitivity of their consumption decisions to a firm's E&S performance, as reflected by the E&S metrics of the brand owner. Measuring the salience of the events to local consumers based on geographic distance, we find that sales become more sensitive to E&S ratings after the disasters, particularly for environmental and community ratings. We also find that this effect dissipates with distance to the disaster counties and over time.

We also address various concerns about the interpretation of our results. One concern is that our findings could be driven by supply effects rather than changes in consumer demand. Many of our findings are inconsistent with supply effects, however. First, there is no clear reason why improvements in E&S activities would lead firms to increase supply more in high-income and/or Democratic-leaning counties, except to meet increased demand. Second, the stronger effect of E&S policies on sales in unaffected counties closer to disaster areas is also unlikely to be driven by changes in supply. That is, why would high E&S companies supply more to unaffected nearby counties compared to low E&S firms? Finally, it is unlikely that a firm's sales depend on the E&S efforts of

its rival firms due to supply effects.

Another concern is that all consumers may not be aware of a firm's E&S rating or that they may not be able to link specific brands to certain firms. We do not contend, however, that consumers know the exact rating for each firm; the rating is simply a proxy for the consumer's perception of a company's E&S performance. Moreover, our results do not rely on the assumption that the average consumer cares about E&S performance or knows a firm's E&S score. As long as there are some consumers, even if they are in the minority, who care about E&S performance and make it their mission to find out about a firm's E&S activities, then their purchase decisions are sufficient to lead to our findings. This argument is also supported by our cross-sectional results, which show that counties with more consumers who care about E&S performance (Democratic voters) exhibit a stronger relationship between E&S scores and subsequent sales.

This study contributes to the literature on ESG/CSR by providing direct evidence that E&S investments affect consumer demand–the cash flow channel of ESG. Our hypotheses and economic interpretation build on earlier work by Servaes and Tamayo (2013), which suggests that customer awareness is an important factor that explains the relation between ESG performance and both profits and firm value. Our detailed data at the firm-product category-county-year level allows for a more refined apples-to-apples comparison, thereby reducing the likelihood that the results are due to omitted variable bias. Hence, our setting allows us to provide more direct evidence for the effect of ESG/CSR on consumer demand, as well as to uncover socioeconomic factors that explain consumers' heterogeneous preferences to purchase products from more socially and environmentally responsible firms–consumer heterogeneities that can be uncovered using our granular firm-product-county-level data but not by firm-level data. As such we also contribute to the value vs values discussion highlighted by Starks (2023) in her Presidential Address by showing that ESG activities affect sales, an important driver of cash flows and corporate value.

While several articles have studied the discount rate channel by examining the relation between ESG/CSR and stock returns and discussing E&S investing from a shareholder's perspective (e.g., Hong and Kacperczyk 2009, Riedl and Smeets 2017, Pástor, Stambaugh, and Taylor 2021, 2022, Pedersen, Fitzgibbons, and Pomorski 2021), there is less evidence on the cash flow channel, and the available evidence is inconclusive. For example, while Di Giuli and Kostovetsky (2014) find that CSR measures are negatively related to profitability and unrelated to revenues, Gillan, Hartzell, Koch, and Starks (2010) show a positive relation between CSR and profits.

More recent contemporaneous work on the cash flow channel is by Derrien, Krüger, Landier, and Yao (2023), Houston, Lin, Shan, and Shen (2023), Christensen, De George, Joffre, and Macciocchi (2023), Cen, Han, Liu, and Wu (2023), Duan, Li, and Michaely (2023), Dube, Lee, and Wang (2023), and Xiao, Zheng, and Zheng (2023). A common theme among these articles, except for Christensen, De George, Joffre, and Macciocchi (2023) and Cen, Han, Liu, and Wu (2023), is that they focus exclusively on the impact of ESG incidents on either household-level consumption decisions based on survey data or on anticipated sales based on store visits or analyst forecasts. Their findings are generally consistent with those of our news test, which illustrates that sales decline after ESG incidents. Specifically, Derrien, Krüger, Landier, and Yao (2023) report reductions in analyst forecasts at the firm level, Houston, Lin, Shan, and Shen (2023) report reductions in household purchases in a survey sample, and Dube, Lee, and Wang (2023), Duan, Li, and Michaely (2023) and Xiao, Zheng, and Zheng (2023) all find reduced foot traffic in stores with ESG incidents. Our paper differs from the aforementioned studies in several ways. First, we examine county-level product sales using a comprehensive sample of US retail stores. Thus, our findings provide a more representative view of consumer behavior and the direct impact of firms' E&S investments on revenues relative to evidence based on survey data, foot traffic data, or analyst forecasts. Second, in addition to examining the impact of negative E&S incidents, our study also examines the relation between product sales and various ratings of firms' overall E&S performance. These ratings not only capture the adverse effect

of negative incidents about firms' E&S practices but also the positive effects of firms' efforts in improving their E&S performance. This is particularly relevant because most firms' E&S strategies go beyond just avoiding negative events.

Christensen, De George, Joffre, and Macciocchi (2023) use the same store-level product sales data as we do to examine cash flow outcomes after negative news events; however, their focus is exclusively on "S"-related events. They also find a negative sales effect, but it is limited to only a small subset of highly visible news events. The only contemporaneous piece that does not focus on negative E&S news is Cen, Han, Liu, and Wu (2023), which uses household survey data (as in Houston, Lin, Shan, and Shen (2023)) to examine the relation between household consumption decisions and workplace equality, one of the ingredients of the overall E&S score that we study. Cen, Han, Liu, and Wu (2023) find a positive relation.

Compared to all contemporaneous work, our study is the least subject to external validity concerns because of our precise and comprehensive measurement of both the sales outcomes and firms' perceived E&S performance. Moreover, our quasi-natural experiment around natural and environmental disasters (together with the E&S news test) helps to alleviate identification concerns.

2 Data

2.1 Retail sales data

Our main data source is the Nielsen Retail Scanner Database, which provides comprehensive information on the quantity and price of product sales at the retail store level at a weekly frequency. We employ data over the 2008-2016 period. There are approximately 30,000-35,000 participating grocery, drug, mass merchandiser, and other stores (varying by year) from 90 retail chains that voluntarily contribute these sales data. The coverage is very extensive. For example, in 2011, the Nielsen Retail Scanner Database covered 55% of the total US drug store sales, 53% of the US grocery

store sales, and 32% of the US mass merchandiser sales. Each product is uniquely identified with a Universal Product Code (UPC code), with the first 6-9 digits representing a unique identifier of the company (GCP code) that manufactures the product as assigned by GS1 US (the organization assigning barcodes).

Nielsen classifies products into three nested layers of aggregation: 10 departments, 124 product groups, and 1,404 product categories (called modules) (see Figure 1). Table 1 provides a description of the ten departments and some of the product groups included in those departments. Table 2 provides some examples of product modules. For example, module code 1,323 represents "Snacks – potato chips", which falls under the product group of "Snacks" (group code 1,507), and the product department of "Dry Grocery" (department code 1). This specific type of snack is differentiated by the database from other similar snacks, such as "Snacks – tortilla chips," which belong to product module 1,326 under the same product group and department. As this example illustrates, the products we compare across companies are very similar in nature.

We link the product owners to public firms from other financial databases based on fuzzy name matching. Specifically, we first match the company names associated with the GCP codes with the names of public firms from the CRSP database, which contains historical information on company names and stock returns. Next, we supplement the GCP-CRSP matches with another round of name matching between the company names associated with the GCP codes and establishments from the National Establishment Time-Series Database (NETS). Using the information on the ownership links between the establishments and their parent firms, we can trace the parent firms of each matched product owner. We then match the NETS parent firms with public firms from the CRSP database.

We further merge the above data with other sources. These include financial statement information from Compustat, E&S news from the RepRisk database, and the ESG ratings from the MSCI ESG Stats database (formerly called KLD). Finally, Nielsen Retail Scanner Data also provides in-

formation on the location of each retail store at the county level. This allows us to aggregate firm product sales to the county level and measure local demographic characteristics using county-level statistics from the Census Bureau. The final sample for the analysis of the relation between sales and E&S ratings includes 192 firms with products in 886 product categories (modules), covering 2,641 counties. The final sample for the analysis using E&S news includes 97,598 unique products in 844 modules produced by 171 firms. The sample period for our analysis is from 2008 to 2016 because data on E&S news events are available from 2007 onwards.

2.2 E&S data

We obtain firms' E&S scores from MSCI ESG Stats (formerly called KLD). This dataset has the longest time series of any of the available ESG datasets and has been used extensively in academic research (see, e.g., Deng, Kang, and Low (2013) and Lins, Servaes, and Tamayo (2017)). It also has the widest cross-sectional coverage of any of the ESG databases, particularly at the start of our sample period. However, given the concern about the lack of consistency among ESG databases (Berg, Koelbel, and Rigobon 2022), we also conduct sensitivity tests using ratings from Sustainalytics, while our tests on negative E&S news rely on data from the RepRisk database. The analyses conducted using all three datasets yield consistent results on the relation between firms' perceived E&S performance and subsequent sales, which attests to the robustness of our findings.

The MSCI ESG Stats database consists of positive and negative performance indicators for publicly traded companies on seven elements related to ESG: employee relations, community, environment, diversity, human rights, product, and corporate governance. Since corporate governance and product are generally not considered part of E&S activities, we follow the literature (e.g., Servaes and Tamayo 2013) and exclude corporate governance and product indicators from the measurement of E&S performance. Of course, the governance element of ESG could be important in its own right and we will use it as a control variable in various specifications. Similarly, various elements of the

product category are related to product quality or safety, and finding that these issues affect future sales would not be surprising. Therefore, we will also control for the product measure in some of our models to ensure that we are not simply picking up variations in product quality.

For each category and year, the database reports the number of "strengths" and "concerns", i.e., the number of positive and negative aspects of a firm's policies in a category. Since the scope of strengths and concerns considered by the database varies over time, we standardize the scores to account for this time-series variation in the number of strengths and concerns. Specifically, we follow Albuquerque, Koskinen, and Zhang (2019) in using a standardized score as our main measure: we first sum up the number of strengths (concerns) across all five categories including employee relations, community, environment, diversity, and human rights for each firm and year. We then standardize both the number of strengths and concerns by the maximum number of strengths plus the maximum number of concerns among all firms in a given year. A firm's E&S performance is then measured by the standardized number of strengths minus the standardized number of concerns. This measure ranges from -1 to 1. In our robustness tests, we also use two alternative ways of standardizing the E&S ratings. Details about the construction of these measures are in Appendix A.

2.3 E&S news and rating measures

We obtain data on E&S-related news from 2007 to 2016 from the RepRisk database. RepRisk collects news from a wide range of sources and covers firm-specific ESG news worldwide and in different languages. The raw data set divides corporate news into four categories, namely environmental (E), social (S), governance (G), and cross-cutting (C). The database also assigns a novelty score for each news incident, with a score of 1 for re-occurring issues and 2 for new issues. For our analysis, we use the novel news incidents (i.e., novelty score = 2) to more precisely identify consumers' first response to news releases in the time series. When multiple news stories about a firm are reported on the same day, we count them as one news incident as they are likely related. We exclude governance

news from the analysis.

For each product-month observation, we aggregate the number of unique news stories from month -6 to month -4, month -3 to month -1, and month 1 to month 3 for each category to identify the lead-lag relation between ESG news releases and consumer demand. We include all the firms that have appeared in the RepRisk dataset at least once during the sample period and create a panel dataset of these firms including the no-news months. Table B1 shows the list of topics for each news category. For example, news about overuse and waste of resources is classified as E news; news about child labor is classified as S news; news about product-related health and environmental issues is classified as C news.

Table 3 presents the summary statistics of our main variables. We provide a detailed description of all variables in Appendix A. Panel A of Table 3 shows variables in the firm-module-county-year level sample, which is used for the baseline analysis. Our baseline regression includes approximately 15 million observations. After adding the firm-level controls, we still have more than 11 million observations. The average E&S score is 0.08 with a standard deviation of 0.10. The (untabulated) within-firm standard deviation of the E&S score is 0.06, and the (untabulated) between-firm standard deviation for the E&S score is also 0.06. *Sustainalytics* is the average of the environmental and social pillar scores provided by the Sustainalytics database. The average *Sustainalytics* rating is 64.19 and the standard deviation is 8.88 for our sample firms. *RepRisk* is the negative value of the number of a firm's E&S-related incidents in the previous year. It averages -9.17 with a standard deviation of 10.06. The average firm in our sample has total assets of \$14.91 billion, leverage of 0.31, Tobin's Q of 2.13, *ROA* of 17%, and advertising and R&D expenditures that amount to 5% and 2% of total assets.

Panel B presents the summary statistics of variables in the firm-product-month sample, which we use to examine the effect of negative E&S news on total monthly product sales. The average product

has 0.90 negative E&S news incidents in months $m-3$ to $m-1$. Within these 0.90 incidents, 0.42 are categorized as environmental issues, 0.52 are categorized as social issues, and 0.70 are categorized as cross-cutting issues. The news counts for different categories do not add up to the total number of news incidents because one news story can be simultaneously considered as an environmental, social, and cross-cutting issue. Panel C presents the summary statistics of variables in the firm-department-county-month level sample, which we use to examine the effect of natural and environmental disasters on consumer behavior. 28% of the observations have an environmental disaster that occurred within 500 miles of the county in the past 12 months.

There is substantial cross-sectional variation in E&S scores even within an industry. For example, Tyson Foods and Hormel Foods, which are both in the food processing industry and S&P500 constituents, are both in our sample. On average, over our sample period, Tyson Foods is ranked in the first (worst) decile of E&S scores, while Hormel Foods is in the ninth decile. Moreover, Tyson Foods has a long history of negative E&S news, ranging from pollution issues to labor abuses. Its annual average number of negative news stories in our sample is 15, compared to 3 for Hormel Foods.

3 Corporate E&S ratings and annual product sales in local markets

3.1 Baseline analyses

As described in Section 2, Nielsen Retail Scanner Data consist of quantity and price data of individual products sold at the store level on a weekly basis. To balance the trade-off between data granularity and computational workload, we collapse the original data into various levels when testing different hypotheses. In our baseline analyses, we investigate the relation between companies' perceived E&S performance and subsequent sales levels. In these models, we collapse the retail sales data to the firm-product module-county-year level. Specifically, for all the products that are under the same product category (i.e., product module) and produced by the same firm, we calculate the total annual dollar

sales and unit sales by summing up the weekly sales in the same calendar year across stores located in the same county. We calculate the per unit price for each product by dividing its county-year dollar sales by unit sales and then compute the average unit price across all products in the same firm-module group. Using these data, we estimate the following regression:

$$Log\_sales_{i,d,c,y} = \alpha + \beta_1 E\&S_{i,y-1} + \delta' CONTROL_{i,y-1} + \gamma_{i,c,d} + \lambda_{c,y} + \eta_{d,y} + \varepsilon_{i,d,c,y}. \quad (1)$$

$Log\_sales_{i,d,c,y}$ is the natural logarithm of dollar sales of product module d for firm i in county c and year y. Our main independent variable is the E&S score of firm i in year $y-1$. $CONTROL_{i,y-1}$ refers to a vector of lagged firm-level characteristics that are possibly correlated with a firm's E&S performance, including *Log_assets*, *Leverage*, *Q*, *ROA*, *Advertising*, and *R&D*. Benefiting from the granularity of our data, we can include a number of high-dimensional fixed effects to control for potentially unobservable factors that could drive our results. Specifically, we include firm×county×product module fixed effects ($\gamma_{i,c,d}$), county×year fixed effects ($\lambda_{c,y}$), and product module×year ($\eta_{d,y}$) fixed effects in Equation (1). We estimate the standard errors with three-way clustering at the firm, product module, and county levels.

Column (1) of Table 4 reports the estimates of Equation (1) without the firm control variables. The coefficient on the lagged E&S score is positive and statistically significant, suggesting that a higher E&S score is associated with higher local product sales in the following year. The relation between a firm's E&S score and local retail sales is also economically significant: a one standard deviation increase in the E&S score (0.10) is associated with an increase in local product sales by 9.2% in the following year.

The tightness of the fixed effects in column (1) of Table 4 is highlighted by the number of fixed effects estimated. In this model with 14,947,562 observations, we estimate 2,618,255 firm×county×product module fixed effects, 22,831 county×year fixed effects, and 6,972 product module×year fixed effects. These fixed effects greatly limit the scope of potentially omitted variables. Estimating these models

at the firm level could result in any outcome without yielding a clear interpretation of the results because changes in E&S efforts could be related to various factors. For example, a firm may change its product mix, or there may be changes in the demographics of the counties where the firm's products are sold.

The economic significance of the above estimates appears very large, but that is because we computed this signifance based on the overall standard deviation of the firm's E&S score for the entire panel. The (untabulated) within-firm standard deviation of the E&S score is 0.06, and the (untabulated) between-firm standard deviation of the E&S score is also 0.06. Thus, the within-firm and between-firm variations in E&S ratings contribute about equally to the estimated effects.

We repeat the estimation of Equation (1) by decomposing sales into unit sales and price per unit. Columns (2) and (3) of Table 4 present the estimates of the regressions with the dependent variables $Log\_units_{i,d,c,y}$ and $Log\_price_{i,d,c,y}$. The estimates in column (2) show that the number of products sold is positively related to the corporate E&S rating. A one-standard-deviation increase in the E&S score is related to an increase in unit sales by 9.1% in the following year, similar to the magnitude of changes in dollar sales from column (1). Thus, when a firm has a better E&S performance as reflected by third-party ratings, there is a higher consumer demand for the firm's products. By contrast, the estimates in column (3) do not show a significant relation between the average product unit price and the E&S rating. Thus, a better firm E&S profile contributes to higher revenues mainly through higher consumer demand for the product at a given price but is not associated with increases in the product price. It should be noted that the total units and average price of products sold in these two specifications are calculated across different products of the same module. For example, if a firm has sold a can of soda for \$1 and a six-pack of the same soda for \$6 in a county, then the calculated total sales quantity is 2, and the average price is \$3.5. Therefore, variations in *Log_units* and *Log_price* could be driven by changes in the product mix that are unrelated to consumer demand, thereby confounding our estimated effect of E&S performance on consumer demand in columns (2) and

columns (3). Consequently, the specifications with *Log_sales* as dependent variable are the preferred specifications, since there are no concerns about combining different products in these models.

One issue with the models reported in columns (1) through (3) is that E&S activities measured at the firm level are correlated with other time-varying firm-level variables that could influence county-level sales. For example, a firm may decide to increase advertising with the goal of improving sales levels. To address this concern, we re-estimate these models after including the control variables listed previously. Our inferences remain unchanged, as reported in columns (4) to (6). The coefficients on the E&S variable decline only slightly in magnitude and remain statistically and economically significant. For example, based on the estimates in column (4), a one-standard-deviation increase in the E&S score is related to an increase in dollar sales by 8.6% in the following year. None of the control variables are significant, except for lagged profitability, which is positively related to product sales levels.

Overall, our results indicate that firms with better perceived E&S performance experience higher sales, holding the product category, time, and place where the product is sold constant. This effect is due to increases in unit sales, while price levels remain constant. This result attests to the importance of the consumer demand channel in explaining how E&S investments can potentially impact cash flows and firm value. While the high-dimensional fixed effects alleviate some concerns about omitted variables, potentially remaining identification concerns are addressed in further tests below.

3.2 Robustness tests

The number of observations declines by 26% in columns (4) through (6) of Table 4 compared to columns (1) through (3). This is because advertising and R&D expenses are often missing on Compustat, and these observations are therefore removed from our analysis. The alternative would be to set these variables equal to zero when missing, based on the assumption that missing values reflect negligible amounts. However, we believe that such an adjustment is not necessarily appropriate. The

firms in our sample have a business-to-consumer business model and are publicly listed firms and, consequentially, large firms. Thus, it seems implausible that any of these firms has zero advertising. With regards to R&D expenses, Koh and Reeb (2015) document that a significant share of firms that report no R&D expenses are filing patents, and they demonstrate that imputing R&D expenses for these firms is problematic. Nevertheless, we verify in column (1) of Table B3, that our findings persist if we set missing R&D and advertising expenses equal to zero. In column (2) of Table B3, we also show that our findings are unaffected if we scale R&D and advertising by sales instead of by assets, and in column (3) we show that the results also hold when we set R&D and advertising scaled by sales equal to zero when missing.

While our main focus is on the relation between E&S investments and firm sales, we also investigate whether measures of corporate governance are related to firm sales. For consistency, we employ the governance strengths and concerns from the MSCI ESG Stats database, from which we also source the E&S ratings. As with the E&S ratings, we sum the number of governance strengths (concerns) and then standardize both by the maximum number of strengths plus the maximum number of concerns among all firms in a given year. We then subtract the standardized concerns from the standardized strengths to obtain a governance index that ranges from -1 to +1. The results after controlling for governance are displayed in column (1) of Table 5. Improvements in the corporate governance rating are also associated with a higher subsequent sales level of a given product in a specific county, but the positive effect of E&S investments on sales persists.

Since several studies (e.g., Hartzell and Starks 2003, McCahery, Sautner, and Starks 2016, Chung and Zhang 2011, Fich, Harford, and Tran 2015) have pointed out that institutional ownership is associated with good governance, we use it as an alternative measure of corporate governance in column (2) of Table 5. We collect information on quarterly institutional holdings from Thomson Reuters and include a firm's institutional ownership as of the last quarter of the previous year as an additional control variable. We do not find it to be associated with higher sales levels. Importantly, however,

the effect of our E&S measure on subsequent sales remains highly significant in this specification as well.

In column (3) of Table 5, we control for a firm's product quality based on its product strengths and concerns from the MSCI ESG Stats database. The index is computed in the same way as the governance index discussed above. We find no significant relation between the product rating and subsequent local product sales, while the effect of our E&S measure remains significant. Thus, the relation between E&S activities and subsequent sales that we uncover cannot be explained by concerns regarding product quality.

Next, we examine the robustness of our findings to the construction of the E&S measure that we employ. Our main E&S measure is the one proposed by Albuquerque, Koskinen, and Zhang (2019), where total concerns are subtracted from total strengths and divided by the sum of the maximum number of strengths and concerns in a given year. The advantage of this metric is that its constituents evolve over time as specific areas of E&S performance become more important, and certain strengths or weaknesses become more relevant. Albuquerque, Koskinen, and Zhang (2019) also propose an alternative measure, where total strengths (concerns) are first divided by the maximum number of strengths (concerns) in a given year. The scaled concerns are then subtracted from the scaled strengths to obtain an E&S metric. The advantage of this alternative metric is that strengths and concerns receive the same weight, while the importance of various elements of E&S performance can still vary over time. In column (1) of Table 6, we show that our estimate of Equation (1) is robust to this alternative way of standardizing the E&S rating.

A second alternative measure is proposed by Servaes and Tamayo (2013). They first scale the reported strengths and weaknesses by the possible maximum individually for each of the five E&S items included in their measure (i.e. community, diversity, employees, environment, and human rights). They then sum up these scaled strengths and weaknesses, and, finally, they subtract the

sum of the scaled weaknesses from the sum of the scaled strengths. The advantage of this approach is that the five E&S items receive the same weight in each period. As illustrated in column (2) of Table 6, we continue to find a significant relation between lagged E&S performance and local sales using this alternative method of constructing the E&S metric.

Our next set of robustness tests focuses on the source of ESG data. The work of Berg, Koelbel, and Rigobon (2022) points out substantial divergences across ESG ratings from different providers, and it is, therefore, important to ensure that our results are not specific to the dataset being used. In column (3) of Table 6, we employ data from the Sustainalytics database, which has also been used in ESG research (e.g., Engle, Giglio, Kelly, Lee, and Stroebel 2020, Huynh and Xia 2021a, Serafeim and Yoon 2023). We compute the E&S metric as the equally-weighted average of the environmental and social pillar scores provided by Sustainalytics. While this database covers fewer firms, thereby reducing the number of observations by around 3.3 million, we continue to find a significant positive relation between a firm's E&S rating and its local product category sales using this alternative dataset.

In column (4), we employ data from the RepRisk database. As discussed previously, this dataset covers ESG incidents. To construct an E&S metric from these data, we count the number of E&S incidents in a given year and take its negative, such that a higher value represents "better" E&S performance. Our findings persist using this dataset as well.

Finally, in Table B2 in the Appendix, we also show that the positive correlation between firm E&S ratings and subsequent product sales remains statistically significant and similar in magnitude compared to our baseline specification if we include county×module×year fixed effects instead of county×year and module×year fixed effects (while also including firm×module×county fixed effects as before). We do not employ this tighter specification as the baseline specification because in a substantial number of counties, the focal firm is the only firm in our sample in a given year, and,

as a result, these observations get dropped from this alternative specification, thereby reducing the sample size.

In sum, our main finding that better E&S performance is associated with higher subsequent product sales at the county level is not sensitive to the way in which we deal with missing advertising and R&D expenses, to the inclusion of firms' corporate governance and product quality as controls, to the exact construction of the E&S variable, to the ESG database being used, and to different combinations of high-dimensional fixed effects.

3.3 Local demographic characteristics

In this section, we look into the county-level demographic characteristics that may explain the relation between firm E&S performance and local product sales. In particular, we examine whether consumers who vote for the Democratic Party, have higher incomes, or who are more educated are more likely to be concerned about E&S practices. If so, local markets with a higher share of such consumers would see a stronger correlation between E&S ratings and local sales. We test this hypothesis by including an interaction between the E&S scores and the corresponding demographic characteristics:

$$Log\_sales_{i,d,c,y} = \alpha + \beta_1 E\&S_{i,y-1} \times Demographics_{c,y-1} + \gamma_{i,c,d} + \lambda_{c,y} + \eta_{d,y} + \theta_{i,y} + \varepsilon_{i,d,c,y}. \quad (2)$$

As in Equation (1), we include firm×county×product module fixed effects ($\gamma_{i,c,d}$), county×year fixed effects ($\lambda_{c,y}$), and product module×year fixed effects ($\eta_{d,y}$) in Equation (2). Moreover, since our variable of interest here is an interaction between a firm characteristic and a county characteristic, we can also include firm×year fixed effects ($\theta_{i,y}$) in the models to account for the effect of unobservable time-varying firm characteristics on product sales. As a result, the standalone variables $E\&S$ and $Democrat/Income/Education$ are absorbed by the firm×year fixed effects and county×year fixed effects, respectively.

Table 7 presents the estimates of Equation (2). The coefficients in columns (1) through (3) represent interactions between E&S and each of the demographic characteristics individually, while they are all combined in column (4). Whereas all the coefficients of the individual interactions are positive, only the interaction with the proportion of Democratic voters in a county is significant when considered individually. However, when all interactions are included together in column (4), the coefficient estimates for both $E\&S \times Democrat$ and $E\&S \times Income$ are significantly positive. Thus, in counties with higher per capita income and with a higher proportion of Democratic voters, a company's product sales respond more to its perceived E&S performance. Based on the estimates in column (4), a one-standard-deviation increase in the proportion of Democratic voters (0.14) and per capita income (10.81) is related to a higher sensitivity of local sales to corporate E&S ratings by 8.5% and 5.9% relative to the baseline estimate (0.9196 in column 1 of Table 4). These results point to substantial heterogeneity in the effect of E&S efforts on subsequent sales and attest to the importance of controlling for local demographic characteristics when assessing the merits of E&S expenditures.

Importantly, other than showing the demographic heterogeneities in the consumer response to firm E&S practices, the evidence in Table 7 also significantly limits the scope of potential omitted variables, since we control for firm×year fixed effects, firm×county×product module fixed effects, county×year fixed effects, and product module×year fixed effects. For example, confounding factors at the location level, such as urban vs. rural differences, would be accounted for by the county×year fixed effects. For an unobserved firm characteristic to explain our results, this characteristic needs to have a stronger correlation with the firm's E&S score and local product sales in counties with more Democratic voters and higher household income. The most plausible interpretation of our results is that a firm with an improvement in E&S performance experiences an increase in sales in counties where more consumers care about the firm's E&S performance.

3.4 Corporate E&S ratings of local product market rivals

In this section, we examine how the perceived E&S performance of a firm's local rivals affects its local product sales. If consumers factor their social and environmental concerns into their purchasing decisions, firms will not only be competing on product price and quality but also on their perceived E&S performance. Thus, better E&S performance of the local product market rivals of a firm could have a negative externality on the demand for the firm's products. Furthermore, the top E&S performer in a local market may impose particularly strong peer pressure on local rivals by attracting demand from consumers with ESG preferences. If so, a firm's product sales in a county could be negatively affected by the average and the top E&S performance of local rival firms. To test this prediction, we re-estimate Equation (1) by replacing the E&S rating of the focal firm with the average or the top E&S rating of the rival firms that sell products in the same product module and the same county as the focal firm.

Table 8 reports the estimates of the peer effects analyses. The sample size drops to around 9 million observations for this test because observations without a rival firm that has a non-missing E&S rating are excluded from the sample. The estimates in columns (1) and (3) show that a firm's product sales are negatively related to the average E&S rating and the top E&S rating of the local rivals. In terms of the economic magnitude, a one-standard-deviation increase in the average E&S score of local rival firms (0.08) is related to a 5.8% decrease in the focal firm's dollar sales and a one-standard-deviation increase in the top E&S score of local rival firms (0.10) is related to a 12.3% decrease in the focal firm's dollar sales. Thus, local consumer demand for a firm's products is sensitive to the perceived E&S performance of local rivals, especially for the rival with the highest level of E&S activities.

Because a firm competes with different sets of rivals across markets, our measures of local rival average and top E&S ratings vary across counties within each firm-year. Therefore, we can include

firm×year fixed effects in the peer-effect models to limit the scope of omitted variables further and strengthen the identification. We report these estimates in columns (2) and (4) of Table 8. The estimates show that the negative effect of the average rival E&S performance on the focal firm's sales disappears. However, the effect of the top E&S performer on product sales remains statistically and economically significant after including firm×year fixed effects. This result further supports the notion that local competition in E&S activities affects consumer demand, and supports the work of Cao, Liang, and Zhan (2019) that peer effects are important in understanding the impact of E&S activities on firm value.

Note that the rival test is based on the US publicly listed firms in our sample with an E&S score. Privately held rivals, such as Mars, or foreign firms such as L'Oréal, Nestlé, or Unilever are therefore not included. In our sample, the median number of firms per county-module-year (including the focal firm) is 2, and the mean is 2.37. Thus, one should think about this rival test as a proxy for whether a firm is a leader or follower with respect to E&S activities for a given product category in a given county.

4 Negative E&S news and monthly product sales

In this section, we further explore the time-series dynamics of consumers' perception of a firm's E&S practices and the resultant changes in product sales. For this purpose, we turn to E&S news reported by RepRisk to identify changes in the public's perception of a firm's E&S practices on a monthly basis. Table B1 shows the list of topics for each news category. We count the number of negative E&S-related incidents per quarter and relate the occurrence of such incidents to the firm's sales level. The unit of observation is different in these tests compared to the previous analyses along three dimensions. First, given that we have the exact timing of the negative news events, we can study sales at the monthly level, rather than the yearly level. Second, we sum the sales of a firm's

products across counties as these tests do not exploit differences in demographics across counties. Third, in our prior tests, we aggregated all of a firm's sales of different products within a product module to improve computational efficiency. Now that we have collapsed sales across all counties, we can disaggregate sales at the individual product level. Thus, using the individual product-month level sales data, we estimate the following regression:

$$Log\_sales_{i,p,m} = \alpha + \beta_1 News_{m-6,m-4} + \beta_2 News_{m-3,m-1} + \beta_3 News_{m+1,m+3} + \eta_{p,y} + \gamma_{d,m} + \epsilon_{i,p,m}. \quad (3)$$

The dependent variable, $Log\_sales_{i,p,m}$, represents the natural logarithm of dollar sales of product p sold by firm i in month m. The independent variables of interest are the counts of negative E&S news stories for firm i from month $m-6$ to $m-4$, $m-3$ to $m-1$, and $m+1$ to $m+3$. This specification includes product module×year-month fixed effects ($\gamma_{d,m}$) and product×year fixed effects ($\eta_{p,y}$) to absorb monthly changes in the broad sales category and yearly changes in sales of the specific product by a given firm. Thus, our estimates capture within-year variation in product sales caused by negative E&S news. Hence, while there still could be changes in unobservable firm and product characteristics that may coincide with E&S news and affect retail sales, these coincidences also need to happen in the same month that the E&S news is revealed in order to confound our estimates.

If negative E&S news about a firm leads to reduced product sales, there should be a lead-lag relation between news stories and sales changes. In particular, we would expect a significant negative coefficient only on the lagged news counts, but not on the leading news count.

Column (1) of Table 9 presents the results. Since we have collapsed the data across local markets to get the total monthly sales of each product, we estimate the standard errors with two-way clustering at the firm and module levels. The coefficients on news counts from months $m-6$ to $m-4$ and from months $m-3$ to $m-1$ are negatively related to product sales in month m. By contrast, there is no significant correlation between product sales in month m and news about a

firm's E&S incidents from months $m+1$ to $m+3$. Thus, product sales decline after but not before the publication of negative E&S news. The lead-lag relationship between negative E&S news and subsequent sales declines within a product-year is consistent with a causal effect of E&S news on product sales. In terms of economic magnitude, an additional piece of negative firm E&S news in months $m-3$ to $m-1$ is related to a decline in product sales of about 1.0% in month m. Since the long-term effects of E&S news are absorbed by the product×year fixed effects, this estimate likely understates the actual impact of E&S news on product sales.

We also study which type of news catches the attention of the consumer. To that effect, in columns (2) to (4) of Table 9, we repeat the estimation of Equation (3) by separately counting different types of news based on the classification by RepRisk. The estimates show that product demand significantly declines after the publication of negative social and cross-cutting news, while environmental news is not significantly related to subsequent sales. The negative demand response to bad news on cross-cutting issues appears to be the strongest, which is not surprising given that such news items affect multiple elements of ESG.

5 Natural and environmental disasters and consumer response

In our final test of the relation between a firm's perceived E&S performance and subsequent sales, we study natural and environmental disasters. The salience of these events may enhance local consumer awareness of E&S issues and hence their sensitivity to the product brand owner's perceived E&S performance. At the same time, these events are likely exogenous to the firms' one-year lagged choice of E&S policies and consumer perception of product quality, allowing for a cleaner identification of the impact of E&S policies on product sales. Several recent articles on climate change also use natural disasters to measure individual awareness of climate change issues (e.g., Baldauf, Garlappi, and Yannelis 2020, Alok, Kumar, and Wermers 2020, Huynh and Xia 2021b). As we aim to measure

consumer awareness of E&S issues, we include environmental disasters directly created by human activities as well as natural disasters.

We obtain a list of severe natural and environmental disasters from 2008 to 2016 from the website of the Environmental Protection Agency ("Key Incidents and Milestones," see Table B4). The first environmental disaster recorded by the Environmental Protection Agency since the beginning of our retail sample is the Deepwater Horizon Oil Spill in April 2010, and the last environmental disaster is the Elk River Spill in January 2014.[2] To use the granularity of our data while keeping the computation time manageable, we aggregate a firm's retail sales data in a specific county and month to the department level, of which there are 10. We then estimate the following regression model:

$$Log\_sales_{i,k,c,m} = \alpha + \beta_1 E\&S_{i,y-1} \times Disaster_{c,m} + \gamma_{i,c,k} + \lambda_{c,m} + \eta_{k,m} + \theta_{i,m} + \varepsilon_{i,k,c,m}. \quad (4)$$

where k refers to the product department. The independent variable of interest is $E\&S_{i,y-1} \times Disaster_{c,m}$, where $E\&S_{i,y-1}$ is the E&S score for firm i in calendar year $y-1$, and $Disaster_{c,m}$ is a binary variable that equals one for all observations in county c and year-month m if an environmental disaster occurred within 500 miles from the county in the past 12 months. Thus, $Disaster_{c,m}$ is a treatment variable capturing local markets that have recently received a salient shock to E&S awareness. In the model, we include firm×department×county fixed effects ($\gamma_{i,c,k}$), firm×year-month fixed effects ($\theta_{i,m}$), department×year-month fixed effects ($\eta_{k,m}$), and county×year-month fixed effects ($\lambda_{c,m}$) to account for potential omitted variables along these dimensions. We exclude the county where the disaster occurred to prevent any direct effect of the disaster from driving the estimates. Thus, the treated group includes county-year-month observations that are exposed to the salience of the disasters but that are not directly impacted by them.

Table 10 reports the results. The estimates indicate that firm sales in a given county-department

[2]Two environmental disasters in 2016, Hurricane Matthew and the Columbia River Spill, are near the end of our sample period and are not included in the analysis because of a lack of sufficient post-event data.

group become more sensitive to the firm's E&S rating if a disaster occurs within 500 miles of the focal county. Specifically, within 12 months after the occurrence of an environmental disaster, a one-standard-deviation increase (0.09) in the E&S rating of a firm is related to an additional 0.6% increase in its product sales in the nearby markets. This is consistent with the idea that nearby environmental disasters enhance consumer awareness of E&S issues and, thus, the perceived quality of retail products from an E&S perspective.[3]

In columns (2) to (6), we separately examine the consumer responses to the five components of a firm's E&S performance. Consistent with the salience effect of nearby environmental and natural disasters on consumer awareness of the environmental externalities of their consumption, the retail sales' correlation with firms' environmental scores increases significantly for markets located near the disasters. Furthermore, there is a significant increase in the sensitivity of retail sales to firms' ratings in community engagement. This result likely reflects consumers' heightened attention to firm support for the local communities that would be impacted by disasters. By contrast, there is no change in the sensitivity of retail sales to the other components of a firm's E&S rating. Thus, environmental and natural disasters appear to have drawn consumer attention to firm attributes that are likely associated with the prevention of and recovery from environmental disasters.

Equation (4) considers all markets located more than 500 miles away from these environmental and natural disasters as the control group. To further examine the role of geographic distance in moderating the salience of environmental disasters, we consider the within-treated-group variation in the distance from environmental disasters. Specifically, we decompose $Disaster_{c,m}$ into five dummies that each capture an additional 100 miles distance from the disaster. If the salience of E&S concerns created by the disasters indeed decreases with geographic distance, we should expect the post-disaster enhancement in local sales sensitivity to firm E&S ratings to decrease with distance. Consistent with

[3]This result is robust to excluding the neighboring counties that might also have been affected by the incidents, with the coefficient (0.0773) and the t-statistic (2.55) close to the baseline estimate.

this conjecture, the estimates presented in Column (7) of Table 10 indeed show that the coefficients on the E&S×Disaster interactions become smaller for the treatment subgroups that are located further away from the disasters.

We also estimate a modified version of Equation (4) to better understand the time-series dynamics of consumer sensitivity to E&S performance from eight quarters before to eight quarters after the disasters. That is, we study the disaster effect on a quarterly basis over the two-year period around the disaster. Figure 2 presents the estimates of the dynamic version of Equation (4). The figure shows that for markets located within 500 miles of a natural or environmental disaster, the sensitivity of consumer demand to firm E&S ratings does not increase until the first quarter after the occurrence of the disaster. This pattern supports the parallel trend assumption for our empirical setting. Interestingly, the enhancement in the consumer sensitivity to E&S ratings for the treated markets is significant only up to the third quarter after the disasters and reverses afterward. Thus, natural and environmental disasters appear to only induce temporary consumer attention to firm E&S practices, suggesting that the effect of salient events on consumer awareness of E&S issues is transient.

6 Possible Supply Effects

Hitherto, we have interpreted the significant relation between a firm's E&S rating and subsequent sales to imply that consumers adjust their demand based on the firm's perceived E&S performance and based on negative news stories regarding their E&S activities. An alternative interpretation could be that our findings stem from supply effects whereby companies change the supply of products due to changes in their E&S profile.

Supply effects could stem from a variety of sources. One possible mechanism is that firms with more E&S strengths and fewer E&S concerns increase their supply because they enjoy a lower cost

of capital (Albuquerque, Koskinen, and Zhang 2019, Pedersen, Fitzgibbons, and Pomorski 2021, Pástor, Stambaugh, and Taylor 2021). Another is that employee productivity can be affected by the employer's E&S practices (Edmans 2011) or that high E&S firms can pay lower wages (Krüger, Metzger, and Wu 2023).

Several pieces of evidence speak more in favor of the demand rather than the supply interpretation, however. First, our finding that the response of consumers to a firm's E&S efforts depends on the demographics of the county where the products are sold is unlikely to be explained by the supply effects. Any increases in product supply should affect sales in all counties in the same proportion since the firms in our sample are large publicly listed firms that operate in the entire United States. While it is entirely possible that a firm with improving E&S performance chooses to increase supply more in counties that are more sensitive to the performance improvements, such differential supply-side adjustments are precisely supportive of the demand effect: firms supply more in counties where demand is higher or growing more rapidly.

Second, a similar argument applies to the result on natural and environmental disasters. There is no clear reason why firms with better E&S performance would increase their product supply differentially in counties close to disasters relative to counties further away, except if they anticipate differential changes in demand. Third, the supply argument is also unlikely to explain why a firm's sales depend on the E&S efforts of its rival firms; consumers switching their demand between substitutable products is a much more plausible explanation for this result.

In sum, the above arguments favor a demand-driven over a supply-driven interpretation of our findings that higher E&S ratings of a firm are associated with higher subsequent sales.

7 Conclusion

Using barcode-level sales data, we find that firms with better perceived E&S performance have higher subsequent local product sales. A one-standard-deviation increase in a brand owner's E&S rating, which proxies for the firm's perceived E&S performance, is related to a 9.2% increase in next-year sales for the firm's products relative to other very similar products sold in the same county. The positive effect of a firm's E&S performance on local product sales is stronger in markets with more Democratic voters and with a higher average income. A firm's local product sales are negatively affected by the higher E&S performance of its local product market rivals. Further analysis using monthly sales data reveals that revenues also declines after the publication of negative E&S news. Using a series of natural and environmental disasters as exogenous shocks to the salience of E&S concerns for local consumers, we find a significant increase in the sensitivity of local retail sales to firms' E&S performance after the disaster events for counties located closer to the events. The granularity of our data allows for the inclusion of a battery of high dimensional fixed effects in all our tests, reducing the likelihood that our findings are due to omitted variables.

Overall, by establishing a robust positive relation between firms' perceived E&S performance and product sales in local retail markets, our study suggests that consumer demand is indeed responsive to firms' E&S practices, making it possible for firms to "do well by doing good" through the cash flow channel. Of course, improvements in E&S do not come without cost. Examining whether the benefit of revenue increases outweighs the cost of E&S investments or whether firms can somehow enhance consumer demand without incurring the cost of E&S activities through greenwashing is a fruitful avenue for future research.

References

Albuquerque, R., Y. Koskinen, C. Zhang, 2019. Corporate social responsibility and firm risk: Theory and empirical evidence. Management Science 65(10), 4451–4469.

Alok, S., N. Kumar, R. Wermers, 2020. Do fund managers misestimate climatic disaster risk. Review of Financial Studies 33(3), 1146–1183.

Baldauf, M., L. Garlappi, C. Yannelis, 2020. Does climate change affect real estate prices? Only if you believe in it. Review of Financial Studies 33(3), 1256–1295.

Baron, D. P., 2007. Corporate social responsibility and social entrepreneurship. Journal of Economics & Management Strategy 16(3), 683–717.

Berg, F., J. F. Koelbel, R. Rigobon, 2022. Aggregate confusion: The divergence of ESG ratings. Review of Finance 26(6), 1315–1344.

Bolton, P., M. Kacperczyk, 2021. Do investors care about carbon risk?. Journal of Financial Economics 142(2), 517–549.

Cao, J., H. Liang, X. Zhan, 2019. Peer effects of corporate social responsibility. Management Science 65(12), 5487–5503.

Capgemini, 2020. How sustainability is fundamentally changing consumer preferences. Unpublished working paper. Capgemini Research Institute.

Cen, L., Y. Han, C. Liu, J. Wu, 2023. The rise of conscious consumers: The impact of corporate workplace equality on household spending. Working paper.

Cheng, H., H. Hong, K. Shue, 2023. Do managers do good with other people's money. Review of Corporate Finance Studies 12(3), 443—-487.

Christensen, H., E. De George, A. Joffre, D. Macciocchi, 2023. Consumer and analyst responses to corporate social irresponsibility. Working paper.

Chung, K. H., H. Zhang, 2011. Corporate governance and institutional ownership. Journal of Financial and Quantitative Analysis 46(1), 247–273.

Dai, R., H. Liang, L. Ng, 2021. Socially responsible corporate customers. Journal of Financial Economics 142(2), 598–626.

Deng, X., J.-k. Kang, B. S. Low, 2013. Corporate social responsibility and stakeholder value maximization: Evidence from mergers. Journal of Financial Economics 110(1), 87–109.

Derrien, F., P. Krüger, A. Landier, T. Yao, 2023. ESG news, future cash flows, and firm value. Working paper.

Di Giuli, A., L. Kostovetsky, 2014. Are red or blue companies more likely to go green? Politics and corporate social responsibility. Journal of Financial Economics 111(1), 158–180.

Duan, T., F. W. Li, R. Michaely, 2023. Consumers' reaction to corporate ESG performance: Evidence from store visits. Working paper.

Dube, S., H. S. G. Lee, D. Wang, 2023. Do consumers vote with their feet in response to negative ESG news? Evidence from consumer foot traffic to retail locations. Working paper.

Dyck, A., K. V. Lins, L. Roth, H. F. Wagner, 2019. Do institutional investors drive corporate social responsibility? International evidence. Journal of Financial Economics 131(3), 693–714.

Edmans, A., 2011. Does the stock market fully value intangibles? Employee satisfaction and equity prices. Journal of Financial Economics 101(3), 621–640.

Engle, R. F., S. Giglio, B. Kelly, H. Lee, J. Stroebel, 2020. Hedging climate change news. Review of Financial Studies 33(3), 1184–1216.

Fich, E. M., J. Harford, A. L. Tran, 2015. Motivated monitors: The importance of institutional investors' portfolio weights. Journal of Financial Economics 118(1), 21–48.

Gillan, S., J. C. Hartzell, A. Koch, L. T. Starks, 2010. Firms' environmental, social and governance (ESG) choices, performance and managerial motivation. Working paper.

Gillan, S. L., A. Koch, L. T. Starks, 2021. Firms and social responsibility: A review of ESG and CSR research in corporate finance. Journal of Corporate Finance 66, 101889.

Hartzell, J. C., L. T. Starks, 2003. Institutional investors and executive compensation. Journal of Finance 58(6), 2351–2374.

Heinkel, R., A. Kraus, J. Zechner, 2001. The effect of green investment on corporate behavior. Journal of Financial and Quantitative Analysis 36(4), 431–449.

Hong, H., M. Kacperczyk, 2009. The price of sin: The effects of social norms on markets. Journal of Financial Economics 93(1), 15–36.

Houston, J. F., C. Lin, H. Shan, M. Shen, 2023. How does ESG shape consumption?. Working paper.

Huynh, T. D., Y. Xia, 2021a. Climate change news risk and corporate bond returns. Journal of Financial and Quantitative Analysis 56(6), 1985–2009.

——— , 2021b. Panic selling when disaster strikes: Evidence in the bond and stock markets. Management Science 69(12), 7448–7467.

Koh, P.-S., D. M. Reeb, 2015. Missing R&D. Journal of Accounting and Economics 60(1), 73–94.

Krüger, P., 2015. Corporate goodness and shareholder wealth. Journal of Financial Economics 115(2), 304–329.

Krüger, P., D. Metzger, J. Wu, 2023. The sustainability wage gap. Working paper.

Lins, K. V., H. Servaes, A. Tamayo, 2017. Social capital, trust, and firm performance: The value of corporate social responsibility during the financial crisis. Journal of Finance 72(4), 1785–1824.

Masulis, R. W., S. W. Reza, 2015. Agency problems of corporate philanthropy. Review of Financial Studies 28(2), 592–636.

McCahery, J. A., Z. Sautner, L. T. Starks, 2016. Behind the scenes: The corporate governance preferences of institutional investors. Journal of Finance 71(6), 2905–2932.

Pástor, L., R. F. Stambaugh, L. A. Taylor, 2021. Sustainable investing in equilibrium. Journal of Financial Economics 142(2), 550–571.

——— , 2022. Dissecting green returns. Journal of Financial Economics 146(2), 403–424.

Pedersen, L. H., S. Fitzgibbons, L. Pomorski, 2021. Responsible investing: The ESG-efficient frontier. Journal of Financial Economics 142(2), 572–597.

Riedl, A., P. Smeets, 2017. Why do investors hold socially responsible mutual funds?. Journal of Finance 72(6), 2505–2550.

Schiller, C., 2018. Global supply-chain networks and corporate social responsibility. Working paper.

Serafeim, G., A. Yoon, 2023. Stock price reactions to ESG news: The role of ESG ratings and disagreement. Review of Accounting Studies 28(3), 1500–1530.

Servaes, H., A. Tamayo, 2013. The impact of corporate social responsibility on firm value: The role of customer awareness. Management Science 59(5), 1045–1061.

Starks, L. T., 2023. Presidential address: Sustainable finance and ESG issues—Value versus values. Journal of Finance 78(4), 1837–1872.

Xiao, Z., X. Zheng, Y. Zheng, 2023. The economic and financial impact of negative environmental and social practices: Evidence from consumer store visits. Working paper.

Figure 1: Layers of Nielsen Scanner Data

This figure presents the nested structure of the layers of Nielsen Scanner Data. Nielsen Scanner Data are divided first into ten departments. 124 product groups are nested within the departments. The groups are further divided into 1,404 product modules. Lastly, product is the most granular level that distinguishes one unique product from another. Each product is identified with one Universal Product Code (UPC).

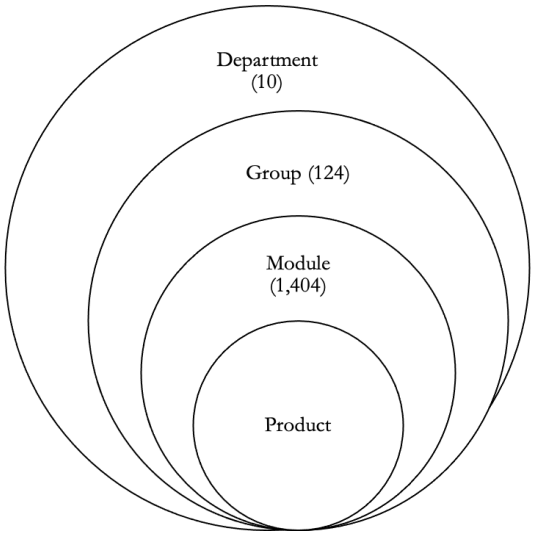

Figure 2: Product sales around nearby natural and environmental disasters

This figure presents the estimates of a dynamic version of Equation (4) using firm-product department-county-month level panel data. We replace the post-disaster dummy in Equation (4) with event-time dummies that indicate firm-product department-county-month observations from eight quarters before to eight quarters after the occurrence of an environmental disaster within 500 miles. The dependent variable is the natural logarithm of dollar sales. The horizontal axis refers to quarters around an environmental disaster. Each node denotes the point estimate for the interaction between $E\&S$ ratings and the corresponding event-time dummy. The cap spikes are the 95% confidence intervals. We include firm×product department×county fixed effects, firm×year-month fixed effects, product department×year-month fixed effects, and county×year-month fixed effects to account for potential omitted variables along these dimensions. We exclude counties where the disasters occurred to prevent the direct effect of the disasters from driving the estimates.

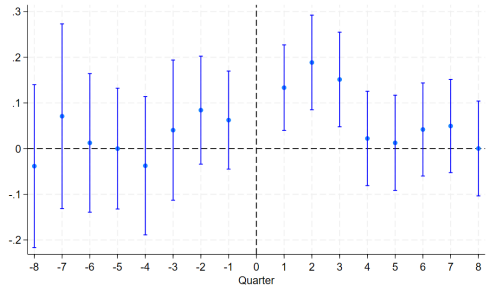

Table 1: List of Department Codes in Nielsen Retail Scanner Data

The following table shows the list of department codes and the number of product groups under each department.

Code	Description	Product Groups
0	Health and Beauty Aids	21 (e.g., baby care, cosmetics, cough and cold remedies, deodorant)
1	Dry Grocery	41 (e.g., baby food, baking mixes, candy, cereal, coffee, condiments, crackers)
2	Frozen Foods	12 (e.g., ice cream, frozen pizza, frozen vegetables)
3	Dairy	12 (e.g., cheese, eggs, yogurt)
4	Deli	1
5	Packaged Meat	1
6	Fresh Produce	1
7	Non-Food Grocery	12 (e.g., detergent, diapers, fresheners/deodorizers, household cleaners)
8	Alcohol	4 (beer, wine, liquor, coolers)
9	General Merchandise	19 (e.g., batteries/flashlights, candles, computer/electronic, cookware)

Table 2: Examples of Product Modules in Nielsen Retail Scanner Data

The table shows the product modules in the "Snacks" group (group code 1,507) of the "Dry Grocery" department (department code 1).

Module Code	Module Name
1,184	DIP - MIXES
1,185	DIP - CANNED
1,270	SNACKS - PORK RINDS
1,271	SNACKS - MEAT
1,318	SNACKS - PUFFED CHEESE
1,323	SNACKS - POTATO CHIPS
1,324	SNACKS - POTATO STICKS
1,325	SNACKS - CORN CHIPS
1,326	SNACKS - TORTILLA CHIPS
1,327	SNACKS - REMAINING
1,328	POPCORN - POPPED
1,329	POPCORN - UNPOPPED
1,330	SNACKS - PRETZEL
1,332	SNACKS - CARAMEL CORN
1,333	SNACKS - VARIETY PACKS
1,341	CRACKERS - SANDWICH & SNACK PACKS
1,422	TRAIL MIXES
1,452	SNACKS - HEALTH BARS & STICKS

Table 3: Summary Statistics

This table presents the summary statistics of variables. Panel A presents variables in the firm-module-county-year level sample. *Log_sales* is the natural logarithm of dollar sales. *Log_units* is the natural logarithm of units of sales. *Log_price* is the natural logarithm of price per unit. *E&S* is a standardized E&S rating following Albuquerque, Koskinen, and Zhang (2019). *Log_assets* is the natural logarithm of total assets in millions of dollars. *Leverage* is the sum of long-term debt and debt in current liabilities divided by total assets. *Q* is the sum of total assets and the difference between the market value and book value of total common equity, divided by total assets. *ROA*, *Advertising* and *R&D* are all scaled by lagged assets. *Governance* is the number of governance strengths minus governance concerns, standardized by the sum of the maximum number of strengths plus the maximum number of concerns among all firms in a given year. *Inst. Ownership* is the number of shares held by institutional investors divided by the total number of shares outstanding. *Product* is the number of product strengths minus product concerns, standardized by the sum of the maximum number of strengths plus the maximum number of concerns among all firms in a given year. *Democrat* is the proportion of Democratic voters in the most recent presidential election in a county. *Education* is the proportion of the population holding a college or higher degree in the county in a given year. *Income* is the average income per capita in the county in a given year. *E&S*2, *STDKLD*, *Sustainalytics*, and *RepRisk* are alternative measures of firms E&S performance. *E&S (rival average)* and *E&S (rival top)* are the average and maximum *E&S* of rival firms that sell the same-module products in the same county as the focal firms. Panel B presents variables in the product-month level sample. *News* is the number of negative E&S incidents for a firm over a period. For instance, $News_{m-3,m-1}$ is the number of negative E&S incidents from month $m-3$ to month $m-1$. Panel C presents variables in the firm-department-county-month level sample. *Disaster* is a binary variable that equals one for observations in a county if an environmental disaster occurred within 500 miles of the county in the past 12 months. A detailed description of these variables is in Appendix A.

Panel A: Sample at the firm-module-county-year level

	N	Mean	S.D.	P25	P50	P75
Log_sales	14,947,562	6.81	2.58	5.00	6.73	8.55
Log_units	14,947,562	5.56	2.58	3.64	5.43	7.33
Log_price	14,947,562	1.33	0.83	0.82	1.21	1.79
E&S	14,947,562	0.08	0.10	0.02	0.07	0.14
Log_assets	11,077,044	9.61	1.61	8.35	9.78	11.13
Leverage	11,077,044	0.31	0.13	0.23	0.29	0.39
Q	11,077,044	2.13	0.89	1.56	1.95	2.45
ROA	11,077,044	0.17	0.07	0.12	0.16	0.21
Advertising	11,077,044	0.05	0.04	0.02	0.03	0.07
R&D	11,077,044	0.02	0.02	0.01	0.01	0.02
Governance	11,077,044	0.01	0.09	0.00	0.00	0.00
Inst. Ownership	11,077,042	0.68	0.19	0.61	0.70	0.77
Product	11,077,044	0.00	0.11	-0.06	0.00	0.07
Democrat	14,943,629	0.43	0.14	0.33	0.42	0.52
Education	11,157,608	0.14	0.06	0.10	0.13	0.18
Income	14,748,306	38.02	10.81	31.30	35.93	41.99
E&S2	14,947,562	0.13	0.17	0.00	0.10	0.23
STDKLD	14,947,562	0.51	0.83	0.00	0.33	0.98
Sustainalytics	7,782,734	64.19	8.88	59.71	65.75	71.29
RepRisk	9,367,873	-9.17	10.06	-15.00	-6.00	-2.00
E&S (rival average)	9,170,161	0.08	0.08	0.03	0.07	0.12
E&S (rival top)	9,170,161	0.12	0.10	0.04	0.11	0.18

Panel B: Sample at the product-month level

	N	Mean	S.D.	P25	P50	P75
Log_sales	3,856,028	7.72	3.78	4.67	8.23	10.86
$\text{News}_{m-6,m-4}$ (All)	3,856,028	0.88	1.58	0.00	0.00	1.00
$\text{News}_{m-3,m-1}$ (All)	3,856,028	0.90	1.61	0.00	0.00	1.00
$\text{News}_{m+1,m+3}$ (All)	3,856,028	0.93	1.63	0.00	0.00	1.00
$\text{News}_{m-6,m-4}$ (Environmental)	3,856,028	0.41	0.89	0.00	0.00	0.00
$\text{News}_{m-3,m-1}$ (Environmental)	3,856,028	0.42	0.91	0.00	0.00	0.00
$\text{News}_{m+1,m+3}$ (Environmental)	3,856,028	0.43	0.92	0.00	0.00	1.00
$\text{News}_{m-6,m-4}$ (Social)	3,856,028	0.51	1.09	0.00	0.00	1.00
$\text{News}_{m-3,m-1}$ (Social)	3,856,028	0.52	1.10	0.00	0.00	1.00
$\text{News}_{m+1,m+3}$ (Social)	3,856,028	0.53	1.11	0.00	0.00	1.00
$\text{News}_{m-6,m-4}$ (Cross-cutting)	3,856,028	0.67	1.27	0.00	0.00	1.00
$\text{News}_{m-3,m-1}$ (Cross-cutting)	3,856,028	0.70	1.30	0.00	0.00	1.00
$\text{News}_{m+1,m+3}$ (Cross-cutting)	3,856,028	0.72	1.32	0.00	0.00	1.00

Panel C: Sample at the firm-department-county-month level

	N	Mean	S.D.	P25	P50	P75
Log_sales	11,435,971	6.19	2.67	4.20	6.13	8.07
E&S	11,435,971	0.06	0.09	0.00	0.04	0.11
Disaster	11,435,971	0.28	0.45	0.00	0.00	1.00

Table 4: E&S Ratings and Local Product Sales

This table presents the estimates of Equation (1) at the firm-module-county-year level. The dependent variable is the natural logarithm of dollar sales, the natural logarithm of units of sales, and the natural logarithm of price per unit in columns (1) to (3), respectively. The independent variable of interest is *E&S*. In columns (4) to (6), we also control for firm characteristics including *Log_assets*, *Leverage*, *Q*, *ROA*, *Advertising*, and *R&D*. Detailed definitions of the variables are in Appendix A. We include firm×county×module fixed effects, county×year fixed effects, and module×year fixed effects in the regressions. The *t*-statistics in parentheses are estimated based on three-way clustered standard errors at the firm, module, and county levels. *, ** and *** indicate significance higher than 10%, 5%, and 1%, respectively.

Dependent Variable:	Log_sales	Log_units	Log_price	Log_sales	Log_units	Log_price
	(1)	(2)	(3)	(4)	(5)	(6)
E&S	0.9196***	0.9104***	0.0094	0.8577**	0.8984**	-0.0203
	(2.78)	(2.68)	(0.14)	(2.46)	(2.59)	(-0.22)
Log_assets				-0.0076	-0.0079	-0.0054
				(-0.05)	(-0.05)	(-0.23)
Leverage				-0.1409	-0.0750	-0.0867
				(-0.38)	(-0.20)	(-1.19)
Q				0.0509	0.0367	0.0086
				(0.64)	(0.49)	(0.62)
ROA				1.7435**	1.5182**	0.2217
				(2.32)	(2.07)	(1.32)
Advertising				-2.5043	-2.4388	-0.2456
				(-1.57)	(-1.52)	(-0.85)
R&D				3.5766	2.8272	0.6053
				(1.02)	(0.87)	(1.04)
Firm × Module × County FE	Yes	Yes	Yes	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Module × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.905	0.916	0.929	0.917	0.926	0.937
Observations	14,947,562	14,947,562	14,947,562	11,077,044	11,077,044	11,077,044

Table 5: E&S Ratings and Local Product Sales - Governance, Institutional Ownership, and Product Quality

This table presents the estimates of Equation (1) at the firm-module-county-year level. The dependent variable is the natural logarithm of dollar sales. The independent variable of interest is *E&S*. We also control for firm characteristics including *Log_assets*, *Leverage*, *Q*, *ROA*, *Advertising*, and *R&D*, plus a proxy for corporate governance or product quality. In column (1) we use the standardized corporate governance rating; in column (2) we use institutional ownership; in column (3) we use the standardized product rating. Detailed definitions of the variables are in Appendix A. We include firm×county×module fixed effects, county×year fixed effects, and module×year fixed effects in the regressions. The *t*-statistics in parentheses are estimated based on three-way clustered standard errors at the firm, module, and county levels. *, ** and *** indicate significance higher than 10%, 5%, and 1%, respectively.

Dependent Variable:	Log_sales		
	(1)	(2)	(3)
E&S	0.7365**	0.9017***	0.8116**
	(2.09)	(2.67)	(2.57)
Log_assets	0.0065	-0.0343	0.0066
	(0.04)	(-0.21)	(0.04)
Leverage	-0.1317	-0.2181	-0.1311
	(-0.36)	(-0.55)	(-0.36)
Q	0.0547	0.0421	0.0558
	(0.68)	(0.52)	(0.70)
ROA	1.7057**	1.8883**	1.7005**
	(2.25)	(2.41)	(2.22)
Advertising	-2.1521	-2.6094	-2.6485*
	(-1.33)	(-1.59)	(-1.69)
R&D	4.0642	3.3700	3.5446
	(1.17)	(0.98)	(1.02)
Governance	0.5084**		
	(2.08)		
Inst. Ownership		-0.2383	
		(-1.46)	
Product			-0.2365
			(-0.77)
Firm × Module × County FE	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes
Module × Year FE	Yes	Yes	Yes
Adjusted R^2	0.917	0.917	0.917
Observations	11,077,044	11,077,042	11,077,044

Table 6: E&S Ratings and Local Product Sales - Alternative E&S Measures

This table presents robustness tests for the estimates of Equation (1) at the firm-module-county-year level using alternative E&S measures. The dependent variable is the natural logarithm of dollar sales. The independent variables of interest are alternative measures of the E&S rating. In column (1), we use $E\&S2$, developed by Albuquerque, Koskinen, and Zhang (2019). In column (2), we use $STDKLD$, following Servaes and Tamayo (2013). In columns (3) and (4) we use alternative E&S performance measures based on the Sustainalytics and RepRisk databases, respectively. The E&S measure based on Sustainalytics is computed as the equally-weighted average of the environmental and social pillar scores. The E&S measure based on RepRisk is computed by taking the negative value of the number of a firm's E&S-related incidents in the previous year. We also control for the following firm characteristics *Log_assets*, *Leverage*, *Q*, *ROA*, *Advertising*, and *R&D*. Detailed definitions of the variables are in Appendix A. We include firm×county×module fixed effects, county×year fixed effects, and module×year fixed effects in the regressions. The *t*-statistics in parentheses are estimated based on three-way clustered standard errors at the firm, module, and county levels. *, ** and *** indicate significance higher than 10%, 5%, and 1%, respectively.

Dependent Variable:	Log_sales			
Data:	MSCI ESG STATS		Sustainalytics	RepRisk
Measure:	$E\&S2$	$STDKLD$		
	(1)	(2)	(3)	(4)
E&S	0.4448**	0.0953***	0.0242**	0.0116***
	(2.39)	(2.68)	(2.24)	(2.87)
Firm Controls	Yes	Yes	Yes	Yes
Firm × Module × County FE	Yes	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes
Module × Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.917	0.917	0.926	0.924
Observations	11,077,044	11,077,044	7,782,734	9,367,873

Table 7: Local Market Demographics, E&S Ratings, and Product Sales

This table presents the estimates of Equation (2) at the firm-module-county-year level. The dependent variable is the natural logarithm of dollar sales. The independent variables of interest are the interactions between the E&S rating and county-level demographic characteristics. County characteristics include the proportion of Democratic voters, income per capita, and the proportion of the population with a college degree or above. Columns (1) to (3) include the interaction of each county characteristic with our E&S measure, and column (4) includes all three interactions. Detailed definitions of the variables are in Appendix A. We include firm×county×module fixed effects, county×year fixed effects, module×year fixed effects, and firm×year fixed effects in the regressions. The t-statistics in parentheses are estimated based on three-way clustered standard errors at the firm, module, and county levels. *, ** and *** indicate significance higher than 10%, 5%, and 1%, respectively.

Dependent Variable:	Log_sales			
	(1)	(2)	(3)	(4)
E&S × Democrat	0.5519**			0.5556**
	(2.40)			(2.59)
E&S × Income		0.0048		0.0050**
		(1.49)		(2.11)
E&S × Education			1.0183	-0.0012
			(1.06)	(-0.00)
Firm × Module × County FE	Yes	Yes	Yes	Yes
Firm × Year FE	Yes	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes
Module × Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.911	0.911	0.919	0.919
Observations	14,943,629	14,748,306	11,157,608	11,013,616

Table 8: E&S Ratings of Local Product Market Rivals

This table presents the estimates of regressions at the firm-module-county-year level. The dependent variable is the natural logarithm of dollar sales. The independent variables of interest are the average and the maximum $E\&S$ of local peer firms that sell same-module products in the same county. Detailed definitions of the variables are in Appendix A. In columns (1) and (3), we include firm×county×module fixed effects, county×year fixed effects, module×year fixed effects in the regressions. In columns (2) and (4), we further include firm×year fixed effects. The t-statistics in parentheses are estimated based on three-way clustered standard errors at the firm, module, and county levels. *, ** and *** indicate significance higher than 10%, 5%, and 1%, respectively.

Dependent Variable:	Log_sales			
	(1)	(2)	(3)	(4)
E&S (rival average)	-0.7258*	0.0459		
	(-1.85)	(0.13)		
E&S (rival top)			-1.2295***	-0.7517**
			(-3.50)	(-2.59)
Firm × Module × County FE	Yes	Yes	Yes	Yes
Firm × Year FE	No	Yes	No	Yes
County × Year FE	Yes	Yes	Yes	Yes
Module × Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.897	0.905	0.897	0.905
Observations	9,170,161	9,170,098	9,170,161	9,170,098

Table 9: E&S News and Monthly Product Sales

This table presents the estimates of Equation (3) using product-month-level data. The dependent variable is the natural logarithm of dollar sales in month m. The independent variables are the number of negative incidents from month $m-6$ to month $m-4$, from month $m-3$ to month $m-1$, and from month $m+1$ to month $m+3$. Column (1) includes all types (excluding governance) of news. Columns (2), (3), and (4) include environmental, social, and cross-cutting news, respectively. We include module×year-month fixed effects and product×year fixed effects in the regressions. Each observation of the dependent variable in the regression is the logarithm of total monthly dollar sales of one unique product. Firm fixed effects are subsumed by product fixed effects. Detailed definitions of the variables are in Appendix A. The t-statistics in parentheses are estimated based on two-way clustered standard errors at the firm and module levels. *, ** and *** indicate significance higher than 10%, 5%, and 1%, respectively.

Dependent Variable:	Log_sales$_m$			
News Type:	All	Environmental	Social	Cross-cutting
	(1)	(2)	(3)	(4)
News$_{m-6,m-4}$	-0.0123**	-0.0007	0.0002	-0.0168***
	(-2.36)	(-0.12)	(0.04)	(-3.00)
News$_{m-3,m-1}$	-0.0099**	-0.0037	-0.0122**	-0.0088*
	(-2.51)	(-0.59)	(-2.15)	(-1.71)
News$_{m+1,m+3}$	0.0016	-0.0042	-0.0076	0.0000
	(0.39)	(-0.98)	(-1.54)	(0.00)
Module × Year-month FE	Yes	Yes	Yes	Yes
Product × Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.941	0.941	0.941	0.941
Observations	3,856,028	3,856,028	3,856,028	3,856,028

Table 10: Product Sales Around Natural and Environmental Disasters

This table presents the estimates of Equation (4) using the firm-department-county-month level panel data. The dependent variable is the natural logarithm of dollar sales. The independent variable is the interaction between *E&S* and *Disaster*. In columns (1) to (6), *Disaster* is a binary variable that equals one for observations in a county if an environmental disaster occurred within 500 miles of the county in the past 12 months. In columns (2) to (6), we replace the overall *E&S* rating with the five category ratings. In column (7), we decompose *Disaster* into five dummy variables that indicate post-event markets within 0-100 miles, 100-200 miles, 200-300 miles, 300-400 miles, and 400-500 miles of the disasters. We include firm×department×county fixed effects, firm×year-month fixed effects, department×year-month fixed effects, and county×year-month fixed effects to account for potential omitted variables along these dimensions. We exclude counties where the disasters occurred to prevent the direct effect of the disasters from driving the estimates. Detailed definitions of the variables are in Appendix A. The *t*-statistics in parentheses are estimated based on two-way clustered standard errors at the firm and county levels. *, ** and *** indicate significance higher than 10%, 5%, and 1%, respectively.

Dependent Variable:	Log_sales						
E&S Category:	All	Environment	Community	Diversity	Employee Relation	Human Right	All
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
E&S × Disaster	0.0710**	0.2035**	0.4464*	0.1017	0.1309	-0.3240	
	(2.18)	(2.12)	(1.92)	(1.51)	(1.31)	(-0.51)	
E&S × Disaster$_{(0mi,100mi]}$							0.0977**
							(2.12)
E&S × Disaster$_{(100mi,200mi]}$							0.0773**
							(2.12)
E&S × Disaster$_{(200mi,300mi]}$							0.0730*
							(1.85)
E&S × Disaster$_{(300mi,400mi]}$							0.0534
							(1.08)
E&S × Disaster$_{(400mi,500mi]}$							0.0617
							(1.60)
Firm × Department × County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Department × Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm × Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County × Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.949	0.949	0.949	0.949	0.949	0.949	0.949
Observations	11,435,971	11,435,971	11,435,971	11,435,971	11,435,971	11,435,971	11,435,971

Appendix

A Variable Definitions

The variable definitions are provided in alphabetical order.

- *Advertising*: Advertising expenditure divided by lagged assets. Table B3 discusses alternative ways of measuring firms' advertising intensity.
- *Democrat*: The proportion of Democratic voters in the most recent presidential election for a county-year.
- *Education*: The proportion of the population with a college education or above in a county-year.
- *E&S*: A standardized E&S rating used in the main analysis (following Albuquerque, Koskinen, and Zhang 2019) that covers five categories: employee relations, community, environment, diversity, and human rights. It first sums up the number of strengths (concerns) across all categories for each firm and year. It then standardizes both the number of strengths and concerns by the maximum number of strengths plus the maximum number of concerns among all firms in the year. $E\&S$ is then computed as the standardized number of strengths minus the standardized number of concerns.
- *E&S2*: An alternative standardized E&S rating following Albuquerque, Koskinen, and Zhang (2019) that covers five categories: employee relations, community, environment, diversity, and human rights. It first sums up the number of strengths (concerns) across all categories for each firm and year. It then standardizes the number of strengths (concerns) by the maximum number of strengths (concerns) among all firms in the year. $E\&S2$ is then computed as the standardized strengths minus the standardized concerns.
- *Governance*: The number of governance strengths minus governance concerns, standardized by the sum of the maximum number of strengths plus the maximum number of concerns among all firms in a given year.
- *Income*: The average income per capita in a county-year.

- *Inst. Ownership*: The number of shares held by institutional investors divided by the total number of shares outstanding.
- *Leverage*: The sum of long-term debt and debt in current liabilities divided by total assets.
- *Log_assets*: The natural logarithm of total assets in millions of dollars.
- *Log_price*: The natural logarithm of price per unit.
- *Log_sales*: The natural logarithm of dollar sales.
- *Log_units*: The natural logarithm of units of sales.
- *Product*: The number of product strengths minus product concerns, standardized by the sum of the maximum number of strengths plus the maximum number of concerns among all firms in a given year.
- *Q*: The sum of total assets and the difference between the market value and book value of total common equity, divided by total assets.
- *R&D*: R&D expenditures divided by lagged assets. Table B3 discusses alternative ways of measuring firms' R&D intensity.
- *RepRisk*: The negative value of the number of a firm's E&S-related incidents in the previous year.
- *ROA*: EBITDA divided by lagged assets.
- *STDKLD*: An alternative standardized E&S rating following Servaes and Tamayo (2013) that covers five categories including employee relations, community, environment, diversity, and human rights. First, the number of strengths (concerns) of each category is standardized by the maximum number of strengths (concerns) among all firms in the category and year. Second, we sum up the standardized strengths (concerns) across all five categories. Finally, $STDKLD$ is computed as the sum of the standardized strengths minus the sum of the standardized concerns.
- *Sustainalytics*: The equally-weighted average of the environmental and social pillar scores.

- *E&S (rival average)*: The average $E\&S$ of local peer firms that sell same-module products in the same county.

- *E&S (rival top)*: The maximum $E\&S$ of local peer firms that sell same-module products in the same county.

- *News*: The number of negative E&S incidents for a firm over a given period. For instance, $News_{m-3,m-1}$ in Table 9 is the number of negative E&S incidents from month $m-3$ to month $m-1$.

- *Disaster*: A binary variable that equals one for observations in a county if an environmental disaster occurred within 500 miles of the county in the past 12 months. In column (7) of Table 10, we also decompose *Disaster* into five dummy variables ($Disaster_{(0mi,100mi]}$, $Disaster_{(100mi,200mi]}$, $Disaster_{(200mi,300mi]}$, $Disaster_{(300mi,400mi]}$, $Disaster_{(400mi,500mi]}$) that indicate post-event markets within 0-100 miles, 100-200 miles, 200-300 miles, 300-400 miles, and 400-500 miles of the disasters.

B Additional Tables

Table B1: News Classification in RepRisk

The following table illustrates the classification of news in RepRisk.

News topic	Classification
Global pollution (including climate change and GHG emissions)	Environmental
Impacts on ecosystems/landscapes	Environmental
Local pollution	Environmental
Overuse and wasting of resources	Environmental
Waste issues	Environmental
Animal mistreatment	Environmental
Other environmental issues	Environmental
Child labor	Social
Discrimination in employment	Social
Forced labor	Social
Freedom of association and collective bargaining	Social
Human rights abuses and corporate complicity	Social
Impacts on communities	Social
Local participation issues	Social
Occupational health and safety issues	Social
Poor employment conditions	Social
Social discrimination	Social
Other social issues	Social
Controversial products and services	Cross-cutting Issues
Products (health and environmental issues)	Cross-cutting Issues
Supply chain issues	Cross-cutting Issues
Violation of national legislation	Cross-cutting Issues
Violation of international standards	Cross-cutting Issues

Table B2: Alternative Fixed Effects for Baseline Specification

This table re-estimates the baseline specification of Table 4 with a different set of fixed effects. The dependent variable is the natural logarithm of dollar sales, the natural logarithm of units of sales, and the natural logarithm of price per unit in columns (1) to (3), respectively. The independent variable of interest is *E&S*. In columns (4) to (6), we also control for firm characteristics including *Log_assets*, *Leverage*, *Q*, *ROA*, *Advertising*, and *R&D*. Detailed definitions of the variables are in Appendix A. We include firm×county×module fixed effects and County × Module × Year fixed effects in the regressions. The *t*-statistics in parentheses are estimated based on three-way clustered standard errors at the firm, module, and county levels. *, ** and *** indicate significance higher than 10%, 5%, and 1%, respectively.

Dependent Variable:	Log_sales	Log_units	Log_price	Log_sales	Log_units	Log_price
	(1)	(2)	(3)	(4)	(5)	(6)
E&S	0.8876***	0.8941***	-0.0051	0.8817***	0.9405***	-0.0363
	(2.94)	(2.86)	(-0.08)	(2.91)	(3.20)	(-0.43)
ln(Assets)				-0.0521	-0.0535	-0.0073
				(-0.33)	(-0.35)	(-0.33)
Leverage				-0.1252	-0.0775	-0.0672
				(-0.35)	(-0.22)	(-0.96)
Q				0.0575	0.0411	0.0103
				(0.78)	(0.58)	(0.75)
ROA				1.7707**	1.5591**	0.2197
				(2.41)	(2.13)	(1.34)
Advertising				-2.2226	-2.2182	-0.1749
				(-1.37)	(-1.37)	(-0.57)
R&D				2.9789	2.3008	0.4800
				(0.91)	(0.75)	(0.87)
Firm × Module × County FE	Yes	Yes	Yes	Yes	Yes	Yes
County × Module × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.860	0.878	0.903	0.861	0.876	0.906
Observations	8,852,187	8,852,187	8,852,187	5,371,080	5,371,080	5,371,080

Table B3: E&S Ratings and Local Product Sales - Alternative Definitions of Advertising and R&D

This table shows that the estimates of Equation (1) at the firm-module-county-year level are robust to alternative ways of measuring firm advertising and R&D activities. The dependent variable is the natural logarithm of dollar sales. The independent variable of interest is *E&S*. We also control for firm characteristics including *Log_assets*, *Leverage*, *Q*, *ROA*, *Advertising*, and *R&D*. In columns (1) and (3), we replace missing values of advertising and R&D expenditures with zeros. In columns (2) and (3), we standardize advertising and R&D expenditures by concurrent sales instead of lagged assets. Detailed definitions of the variables are in Appendix A. We include firm×county×module fixed effects, county×year fixed effects, and module×year fixed effects in the regressions. The *t*-statistics in parentheses are estimated based on three-way clustered standard errors at the firm, module, and county levels. *, ** and *** indicate significance higher than 10%, 5%, and 1%, respectively.

Dependent Variable:		Log_sales	
Fill in zeros for Advertising and R&D:	Yes	No	Yes
Standardizing Advertising and R&D by:	Assets	Sales	Sales
	(1)	(2)	(3)
E&S	0.8994***	0.8425**	0.8153**
	(2.73)	(2.40)	(2.49)
Log_assets	0.0524	-0.0073	0.0627
	(0.42)	(-0.04)	(0.51)
Leverage	0.4067	-0.0972	0.3769
	(1.31)	(-0.25)	(1.18)
Q	0.0257	0.0514	0.0371
	(0.44)	(0.61)	(0.62)
ROA	0.4832	1.2792**	0.2073
	(0.83)	(2.06)	(0.38)
Advertising	-1.1541	0.3563	3.6242*
	(-0.95)	(0.13)	(1.93)
R&D	4.2067	4.1180	-0.3101
	(1.11)	(0.66)	(-0.07)
Firm × Module × County FE	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes
Module × Year FE	Yes	Yes	Yes
Adjusted R^2	0.907	0.917	0.907
Observations	14,558,568	11,077,044	14,558,568

Table B4: List of Severe Environmental Disasters

The following table shows the list of severe environmental disasters from 2008 to 2016 used in the estimation of Equation (4) in Section 5. Source for the disasters: Environmental Protection Agency. Source for the damages and casualties numbers: Wikipedia.

Event	Year-month	Affected County	Damages	Casualties
Deepwater Horizon Oil Spill	2010.4	Plaquemines Parish, LA	17.2 bn	11 died
Kalamazoo River Oil Spill	2010.7	Hillsdale, MI	1.21 bn	None
Joplin Tornado	2011.5	Jasper, MO	3.64 bn	158 died
Silvertip Pipeline Spill	2011.7	Yellowstone, MT	135 mio	None
Hurricane Isaac	2012.8	Plaquemines Parish, LA	3.11 bn	34 died
Superstorm Sandy	2012.10	Ocean, NJ	68.7 bn	233 died
West Fertilizer Explosion and Fire	2013.4	Mclennan, TX	Over 200 homes damaged	15 died
2013 Colorado Floods	2013.9	Boulder, CO	1 bn	9 died
Elk River Spill	2014.1	Kanawha, WV	300,000 residents affected	None