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

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Abstract

Using granular barcode-level sales data from retail stores, we show that environmental and social ratings are positively related 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 own sales. Controlling for product-year-level heterogeneity, monthly product sales decline after negative firm news on environmental and social issues. Finally, immediately after major natural and environmental disasters, sales in counties located close to the disasters become more sensitive to environmental ratings. Our study provides direct evidence that environmental and social activities affect the revenues of the firm.

Keywords: Retail, ESG, Corporate Social Responsibility

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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). Despite a substantial number of articles on this issue, the mechanism through which E&S activities could affect corporate performance and value remains poorly understood. On the one hand, E&S efforts could affect firm value through 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, Pástor, Stambaugh, and Taylor 2022, Pedersen, Fitzgibbons, and Pomorski 2021). On the other hand, E&S activities 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 (e.g., Servaes and Tamayo 2013, Dai, Liang, and Ng 2021), and employee productivity could be affected by the employer's E&S practices (Edmans 2011). 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. 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).

In this paper, we shed further light on the cash flow channel, and in particular on how consumers in retail markets react to a firm's E&S activities. The advantage of our setting over prior work is that we have detailed barcode-level sales data on specific products sold at the level of US counties.

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. 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 quality from an E&S perspective, a quality that may be perceived through the E&S ratings of the brand owner. 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.

Using the Nielsen Retail Scanner Data over the period of 2008 to 2016, we find that a brand owner's E&S rating is 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 relative to its rival products sold in the same county. 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 for 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 or the corporate governance of the firm.

Next, we investigate different demographic characteristics that may explain local consumer responses to corporate E&S practices. Previous studies have shown that people with different demographic characteristics have different views on E&S issues (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 are differentially concerned about E&S issues. We find positive and significant point estimates for the interactions between E&S scores and both the share of Democratic voters and income. These findings are consistent with the role of consumers' political leaning and financial conditions in shaping their preferences to consume socially responsible products.

We also assess the importance of local product market competition in shaping firms' 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 local product market competition is influenced by a firm's relative E&S performance, then local product sales should be negatively related to the E&S rating of local rivals. This is indeed 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, it is unlikely that our results are spurious due to the lack of sufficient controls. However, we perform two sets of additional analyses that are even less subject to this criticism. 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 demand for the products 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$\times$year fixed effects, which further alleviates the concern of omitted variables.

Second, we exploit a series of major natural and environmental disasters as shocks to the salience of E&S concerns for local consumers. 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 responsiveness of consumption decisions to firm/product quality from the E&S perspective, 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 the environmental and community ratings. We also find that this effect dissipates with distance to the disaster counties.

This study contributes to the literature on ESG/CSR by providing direct evidence that E&S efforts affect consumer demand–the cash flow channel of ESG. Our hypothesis 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-month level allows for a more refined apples-to-apples comparison, thereby reducing the likelihood that the results are due to omitted variable bias. Moreover, there could be heterogeneity among consumers in terms of their exposure to E&S issues as well as their preferences to consume socially responsible products, but these within-consumer heterogeneities cannot be uncovered using firm-level data. Our study overcomes this challenge using retail data that is granular at both the product and geographical levels, monthly-frequency analyses of consumer responses to E&S news, and a series of natural and environmental disasters as a source of exogenous shocks to local consumers' awareness of E&S issues. 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 customers' heterogeneous preferences to consume socially responsible products.

While several articles have studied the discount rate channel by examining the relation between ESG and stock returns (e.g., Hong and Kacperczyk 2009) and discussing E&S investing from a shareholder's perspective (e.g., Riedl and Smeets 2017, Hartzmark and Sussman 2019, Pástor, Stambaugh, and Taylor 2021, 2022, Pedersen, Fitzgibbons, and Pomorski 2021)), there is relatively less evidence on the cash flow channel. A concurrent study by Derrien, Krüger, Landier, and Yao (2022) discusses the cash flow channel by examining the relation between negative E&S news and analysts' earnings forecasts. Our paper complements their work by examining the actual consumer demand in local retail markets and exploring the role of consumer heterogeneity, as opposed to the projected aggregate demand inferred from analyst forecasts.

2 Data

2.1 Retail sales data

Our main source of data is Nielsen Retail Scanner Data, 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 U.S. drug store sales, 53% of the U.S. grocery store sales, and 32% of the U.S. 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.

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 information 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 (called modules), covering 2,641 counties. The final sample for the analysis using E&S news includes 97,598 unique products in 844 product categories produced by 171 firms. The sample period for our analysis is from 2008 to 2016 because data on E&S news start in 2007.

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, 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 E&S activities and 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.

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-occuring 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. We also exclude governance news from the analysis.

For each product-month observation, we aggregate the number of unique news stories from month -6 to month $m-4$, 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 wasting 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 define all variables in Appendix A.

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

3.1 Baseline analyses

As we mention in Section 2, Nielsen Retail Scanner Data consists of the weekly quantity and price data of individual products sold at the store level. 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 corporate E&S activities and 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 take the average unit price across all products in the same firm-module group. Using these data, we estimate the following regression:

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

$Log\_sales_{i,d,c,y}$ 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.

[Insert Table 4 around here]

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.

We repeat the estimation of Equation (1) by decomposing sales into unit sales and price per unit:

$$Log\_units_{i,d,c,y} = \alpha + \beta_1 E\&S_{i,y-1} + \delta' CONTROL_{i,y-1} + \gamma_{i,c,d} + \lambda_{c,y} + \eta_{d,y} + \varepsilon_{i,d,c,y}. \tag{2}$$

$$Log\_price_{i,d,c,y} = \alpha + \beta_1 E\&S_{i,y-1} + \delta' CONTROL_{i,y-1} + \gamma_{i,c,d} + \lambda_{c,y} + \eta_{d,y} + \varepsilon_{i,d,c,y}. \tag{3}$$

Columns (2) and (3) of Table 4 present the estimates of the above regressions. The estimates in column (2) show that the number of products sold is positively related to 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 rating, 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.

One concern 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 remains 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, similar to the magnitude of changes in dollar sales. None of the control variables are significant, except for lagged profitability, which is positively related to product sales levels.

Note that the number of observations declines by 26% in models (4) through (6). This is because advertising and R&D expenses are often missing in Compustat. In model (1) of Table 5, we show that our findings persist if we set missing R&D and advertising expenses equal to zero. In model (2), we show that our findings are unaffected if we scale R&D and advertising by sales instead of by assets, and in model (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 activities and firm sales, we also investigate whether measures of corporate governance affect 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. This governance index also ranges from -1 to +1. These results are displayed in model (1) of Table 6. 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 effect of E&S efforts on sales persists. Since several studies (e.g., Hartzell and Starks 2003, McCahery, Sautner, and Starks 2016, Chung and Zhang 2011) have pointed out that institutional ownership is associated with good governance, we use it as an alternative measure of corporate governance in model (2). 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.

Overall, our results indicate that firms with higher E&S activities experience higher sales, holding the product, 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 customer demand channel in explaining how E&S activities can potentially impact cash flows and firm value.

3.2 Local demographic characteristics

Next, we look into the county-level demographic characteristics that may explain the relation between firm E&S ratings and local market sales. In particular, we examine whether consumers who vote for the Democratic Party, have higher incomes, and 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 relationship 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:

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

$$Log\_sales_{i,d,c,y} = \alpha + \beta_1 E\&S_{i,y-1} \times Income_{c,y-1} + \gamma_{i,c,d} + \lambda_{c,y} + \eta_{d,y} + \theta_{i,y} + \varepsilon_{i,d,c,y}. \quad (5)$$

$$Log\_sales_{i,d,c,y} = \alpha + \beta_1 E\&S_{i,y-1} \times Education_{c,y-1} + \gamma_{i,c,d} + \lambda_{c,y} + \eta_{d,y} + \theta_{i,y} + \varepsilon_{i,d,c,y}. \quad (6)$$

As in Equations (1) to (3), 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 Equations (4) to (6). 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 Equations (4) to (6). The coefficients in models (1) through (3) represent interactions between E&S and each of the demographic characteristics individually, while they are all combined in model (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 model (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 the its E&S ratings. 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 rating by 8.5% and 5.9% relative to the baseline estimate (0.9196 in column 1 of Table 4). These results 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 indicates that omitted variables are unlikely to lead to the relation we observe. Such an omitted firm characteristic would not only have to explain the observed correlation between E&S ratings and local market sales but would also need to have a stronger effect on local sales in markets with more Democratic voters and households with higher incomes. This condition significantly limits the scope of potential omitted variables.

[Insert Table 7 around here]

3.3 Corporate E&S ratings of local product market rivals

In this section, we examine how the 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 ratings 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 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 E&S performance of local rivals, especially for the rivals with the highest levels 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 further limit the scope of omitted variables 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 performers on product sales remains statistically and economically significant after including firm×year fixed effects. This further support the notion that local competition in E&S activities affects consumer demand.

[Insert Table 8 around here]

3.4 Robustness tests

We conduct a variety of tests to ensure that our main findings are robust to the construction of our E&S variable and the use of alternative datasets for E&S ratings.

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. They 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. In model (1) of Table 9, we show that our estimate of Equation (1) is robust to this alternative way of standardizing the E&S rating.

A second alternative 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 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 all subcategories of the data receive the same weight. As illustrated in model (2) of Table 9, we continue to find a significant relation between lagged E&S efforts 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 model (3) of Table 9, we compute the E&S metric as the average of the environmental and social pillar scores provided by 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 2022). While the Sustainalytics database covers fewer firms, thereby reducing the number of observations by around 3.3 million, we continue to find a significant relation between E&S activities and local product category sales using this alternative dataset.

Finally, in model (4), we employ data from the RepRisk database. As discussed previously, this dataset covers ESG news. To construct an E&S measure, 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. A one-standard-deviation increase in firms' E&S performance in terms of the reduction of negative E&S news (10.06) is associated with an 11.7% increase in local product sales.

In sum, our main finding that better E&S performance is associated with subsequent increases in product sales at the county level is not sensitive to the exact construction of the E&S variable or the ESG dataset being used.

4 Negative E&S news and monthly product sales

Next, we further explore the time-series dynamics of consumer perception of a firm's E&S practices and the resultant changes in product sales. For this purpose, we turn to the E&S news reported by RepRisk to identify changes in the public perception of a firm's E&S practices on a quarterly basis. Table B1 shows the list of topics for each news category. Specifically, 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 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:

$$Log\_sales_{i,p,m} = \alpha + \beta_1 News_{m-6,m-4} + \beta_2 News_{m-3,m-1} + \beta_3 News_{m+1,m+3} + \eta_{p,y} + \gamma_{d,m} + \epsilon_{i,p,m}. \quad (7)$$

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 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×month fixed effects and product×year fixed effects 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 releases and sales changes in the time series. In particular, we would observe a significantly negative coefficient only on the lagged news counts, but not on the leading news count. 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.

[Insert Table 10 around here]

Model (1) of Table 10 presents the results. The coefficients on news counts from month $m-6$ to $m-4$ and from month $m-3$ 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 bad firm E&S

news from month $m+1$ to $m+3$. Thus, product sales decline after but not before the release of negative E&S news. The lead-lag relationship between negative E&S news and sales drops within product-years 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 is related to a decline in product sales of about 1.0% in the following month. 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 more the attention of the consumers. To that effect, in columns 2 to 4 of Table 10, we repeat the estimation of Equation (7) by separately counting different types of the news based on the classification by RepRisk. The estimates show that product demand significantly declines after the release of 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 Nearby natural and environmental disasters and consumer response

In our final test of the relation between a firm's E&S activities and subsequent sales, we study natural and environmental disasters. The salience of these events may enhance local consumers' 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 consumers' perception of product quality, allowing for an identification of the impact of E&S policies on product sales. Several recent articles on climate change 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 consumers' 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 B2). The first environmental disaster recorded by the EPA since the beginning of our retail sample is the Deepwater Horizon Oil Spill in April 2010. 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:

$$Log\_sales_{i,k,c,m} = \alpha + \beta_1 E\&S_{i,y-1} \times Disaster_{c,m} + \gamma_{i,c,k} + \lambda_{c,m} + \eta_{k,m} + \theta_{i,m} + \varepsilon_{i,k,c,m}. \quad (8)$$

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 of 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 11 reports the results. The estimates indicate that firm sales in a given county-department group become more sensitive to the firm's E&S ratings if a disaster occurred within 500 miles of the focal county. This is consistent with the idea that nearby environmental disasters enhance consumers' awareness of E&S issues and thus the quality of retail products from an E&S perspective.

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 response to firms' environmental scores significantly increase for markets located near the disasters. Furthermore, there is also 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 consumers' attention to firm contributions to the prevention of and recovery from environmental disasters.

Equation (8) considers all markets located more than 500 miles away from these environmental 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 be decreasing with distance. Consistent with this conjecture, the estimates presented in Column (7) of Table 11 indeed show that the coefficient magnitude is smaller for the treatment subgroups that are located further away from the disasters.

We also estimate a modified version of Equation (8) to better examine the time-series dynamics of consumer sensitivity to E&S ratings from eight quarters before to eight quarters after the disasters.

[Insert Figure 2 around here]

Figure 2 presents the estimates of the dynamic version of Equation (8). 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 Conclusion

Using barcode-level retail store data that record weekly store-level sales, we find that higher E&S ratings positively affect subsequent local product sales. The positive effect of E&S ratings on local product sales is stronger in markets with more Democratic voters and with a higher average income. Further analysis using monthly sales data reveals that revenue also declines after the release 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 firm 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, reducing the likelihood that our findings are due to omitted variables. Overall, by establishing a significant positive relation between E&S activities and product sales in local retail markets, our study indicates that the cash flow channel is important in understanding how E&S creates firm value.

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Figure 1: Layers of Nielsen Scanner Data

This figure presents the nested structure of the layers of Nielsen Scanner Data. Nielsen Scanner Data is 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 distinguished one unique product from another. Each product is identified with one Universal Product Code (UPC).

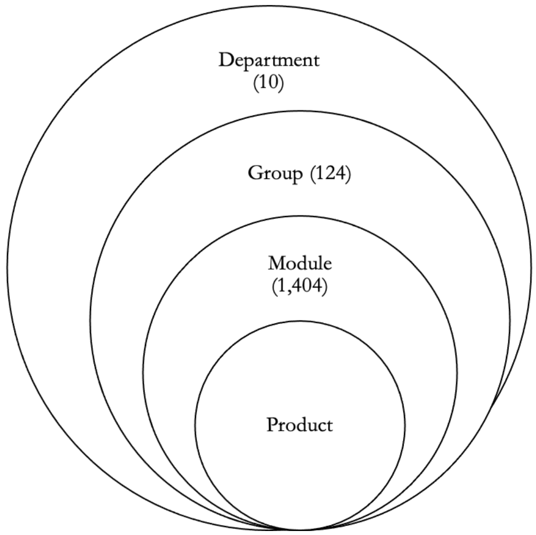

Figure 2: Product sales around nearby environmental disasters

This figure presents the estimates of a dynamic version of Equation (8) using firm-product department-county-month level panel data. Specifically, we replace the post-disaster dummy in equation (8) 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.

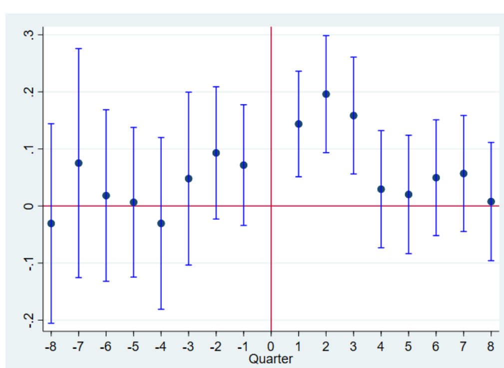

Table 1: List of Department Codes in Nielsen Retail Scanner Data

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 at the firm-module-county-year level. *Log_sales* is the natural logarithm of dollar sales. *Log_units* is the natural logarithm of unit 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. *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 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. *Democrat* is the proportion of Democratic voters. *Education* is the proportion of the population holding a college and above degree. *Income* is the average income per capita in the county that year. *E&S(rivalaverage)* and *E&S(rivaltop)* are the average and maximum *E&S* of rival firms that sell the same-module products in the same county as the focal firms. *E&S2*, *STDKLD*, *Sustainalytics*, and *RepRisk* are alternative measures of firms' E&S performance. A detailed description of these variables is in Appendix A.

	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
Democrat	14,943,629	0.43	0.14	0.33	0.42	0.52
Income	14,748,306	38.02	10.81	31.30	35.93	41.99
Education	11,157,608	0.14	0.06	0.10	0.13	0.18
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

Table 4: E&S Ratings and Local Product Sales

This table presents the estimates of Equations (1) to (3) at the firm-module-county-year level. The dependent variable is the natural logarithm of dollar sales, the natural logarithm of unit 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 the parentheses are estimated based on three-way clustered standard errors at the firm, module, and county levels. *, ** and *** indicate significance better than 10%, 5%, and 1% respectively.

Dependent Variable:	Log_sales (1)	Log_units (2)	Log_price (3)	Log_sales (4)	Log_units (5)	Log_price (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)
ln(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 - 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 the 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 the parentheses are estimated based on three-way clustered standard errors at the firm, module, and county levels. *, ** and *** indicate significance better 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)
ln(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 6: E&S Ratings and Local Product Sales - Governance & Institutional Ownership

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. In Model (1) we use a corporate governance rating, while in Model (2) we use institutional ownership. 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 the parentheses are estimated based on three-way clustered standard errors at the firm, module, and county levels. *, ** and *** indicate significance better than 10%, 5%, and 1% respectively.

Dependent Variable:	Log_sales	
	(1)	(2)
E&S	0.7365**	0.9017***
	(2.09)	(2.67)
ln(Assets)	0.0065	-0.0343
	(0.04)	(-0.21)
Leverage	-0.1317	-0.2181
	(-0.36)	(-0.55)
Q	0.0547	0.0421
	(0.68)	(0.52)
ROA	1.7057**	1.8883**
	(2.25)	(2.41)
Advertising	-2.1521	-2.6094
	(-1.33)	(-1.59)
R&D	4.0642	3.3700
	(1.17)	(0.98)
Governance	0.5084**	
	(2.08)	
Inst. Ownership		-0.2383
		(-1.46)
Firm × Module × County FE	Yes	Yes
County × Year FE	Yes	Yes
Module × Year FE	Yes	Yes
Adjusted R^2	0.917	0.917
Observations	11,077,044	11,077,042

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

This table presents the estimates of Equations (4) to (6) 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 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 the parentheses are estimated based on three-way clustered standard errors at the firm, module, and county levels. *, ** and *** indicate significance better 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 the parentheses are estimated based on three-way clustered standard errors at the firm, module, and county levels. *, ** and *** indicate significance better 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 Ratings and Local Product Sales - Alternative Specifications.

This table presents the robustness tests for 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 the standardized measures of E&S rating. In column (1), we use the alternative measure, $E\&S2$, developed by Albuquerque, Koskinen, and Zhang (2019). In column (2), we use the alternative standardized E&S rating, $STDKLD$, following Servaes and Tamayo (2013). In columns (3) and (4) we use alternative firm E&S performance measures provided by Sustainalytics and RepRisk. The E&S performance based on Sustainalytics is measured by taking the equal-weighted average of the environmental and social pillar scores. The E&S performance based on RepRisk is measured by taking the negative value of the number of a firm's E&S-related incidents in the previous year. 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 the parentheses are estimated based on three-way clustered standard errors at the firm, module, and county levels. *, ** and *** indicate significance better 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 × 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 10: E&S News and Monthly Product Sales

This table presents the estimates of Model (7) using the 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. Product fixed effects are nested within firm fixed effects. Hence, controlling for product×year fixed effects is more stringent and we do not need to further control for firm fixed effects. Detailed definitions of the variables are in Appendix A. The t-statistics in the parentheses are estimated based on two-way clustered standard errors at the firm and module levels. *, ** and *** indicate significance better than 10%, 5%, and 1% respectively.

Dependent Variable:	Log_sales_m			
News Type:	All	Environmental	Social	Cross-cutting
	(1)	(2)	(3)	(4)
$\text{News}_{m-6,m-4}$	-0.0123**	-0.0007	0.0002	-0.0168***
	(-2.36)	(-0.12)	(0.04)	(-3.00)
$\text{News}_{m-3,m-1}$	-0.0099**	-0.0037	-0.0122**	-0.0088*
	(-2.51)	(-0.59)	(-2.15)	(-1.71)
$\text{News}_{m+1,m+3}$	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 11: Product Sales Around Natural and Environmental Disasters

This table presents the estimates of Equation (8) 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 from 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 the parentheses are estimated based on two-way clustered standard errors at the firm and county levels. *, ** and *** indicate significance better 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	0.0719**	0.2046**	0.4454*	0.1020	0.1371	-0.3329	
	(2.21)	(2.13)	(1.92)	(1.51)	(1.38)	(-0.52)	
E&S × Disaster$_{(0mi,100mi]}$							0.0966**
							(2.10)
E&S × Disaster$_{(100mi,200mi]}$							0.0768**
							(2.13)
E&S × Disaster$_{(200mi,300mi]}$							0.0748*
							(1.90)
E&S × Disaster$_{(300mi,400mi]}$							0.0561
							(1.14)
E&S × Disaster$_{(400mi,500mi]}$							0.0626
							(1.63)
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	11,429,572	11,429,572	11,429,572	11,429,572	11,429,572	11,429,572	11,429,572

Appendix

A Variable Definitions

- *Log_sales*: The natural logarithm of dollar sales.
- *Log_units*: The natural logarithm of units of sales.
- *Log_price*: The natural logarithm of price per unit.
- *E&S*: A standardized E&S rating used in the main analysis (following Albuquerque, Koskinen, and Zhang 2019) that covers five categories including employee relations, community, environment, social, 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.
- *Log_assets*: The natural logarithm of total assets.
- *Leverage*: The sum of long-term debt and debt in current liabilities divided by total assets.
- *Q*: The sum of total assets and the difference between the market value and book value of total common equity, divided by total assets.
- *ROA*: EBITDA divided by lagged assets.
- *Advertising*: Advertising expenditure divided by lagged assets.
- *R&D*: R&D expenditure divided by lagged assets.
- *Governance*: The number of governance strengths minus 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*: The number of shares held by institutional investors divided by the total number of shares outstanding.

- *E&S2*: An alternative standardized E&S rating following Albuquerque, Koskinen, and Zhang (2019) that covers five categories including employee relations, community, environment, social, 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 strength minus the standardized concern.

- *STDKLD*: An alternative standardized E&S rating following Servaes and Tamayo (2013) that covers five categories including employee relations, community, environment, social, 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 equal-weighted average of the environmental and social pillar scores.

- *RepRisk*: The negative value of the number of a firm's E&S-related incidents in the previous year.

- *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.

- *Income*: The average income per capita in a county-year.

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: 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 (8) in Section 5. Source for the disasters: EPA. 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, MI	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
Hurricane Matthew	2016.10	Onslow, NC	16.5 bn	603 died
Columbia River Spill	2016.6	Wasco, OR	170 mio	None