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

Finance Working Paper N° 926/2023

January 2026

Jean-Marie Meier
University of Texas at Dallas

Henri Servaes
London Business School, CEPR and ECGI

Jiaying Wei
Southwestern University of Finance & Economics

Steven Chong Xiao
University of Texas at Dallas

ECGI Working Paper Series in Finance

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Abstract

Using barcode-level retail sales data, we show that firms with higher environmental and social (E&S) ratings experience greater local sales. This effect increases with advertising intensity, while the adverse reaction to declining E&S ratings is amplified by negative media coverage. The results are stronger in counties with more Democrats and higher income. Rivals with higher E&S ratings negatively affect a firm's sales. Negative E&S news significantly reduces demand. Environmental disasters amplify nearby consumers' sensitivity to E&S ratings. Our findings identify consumer preferences as a key determinant of the E&S-sales relation, thereby providing a microfoundation for 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 Classifications: D12, G32, G50, M14

Jean-Marie Meier
Assistant Professor of Finance
University of Texas at Dallas
800 W. Campbell Road
Richardson, TX 75080, USA
e-mail: meier@utdallas.edu

Henri Servaes
Richard Brealey Professor of Corporate Governance
London Business School
Sussex Place, Regent's Park
London, NW1 4SA, United Kingdom
phone: +44 207 000 8268
e-mail: hservaes@london.edu

Jiaying Wei
Associate Professor
Southwestern University of Finance & Economics
No 55, Guanghuacun Street
Chengdu 610074, China
phone:
e-mail: weijy@swufe.edu.cn

Steven Chong Xiao*
Associate Professor of Finance
University of Texas at Dallas
800 West Campbell Road
Richardson, TX 75080-3021, USA
e-mail: steven.xiao@utdallas.edu

*Corresponding Author

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Jean-Marie Meier, Henri Servaes, Jiaying Wei, Steven Chong Xiao†

This draft: November 30, 2025
First draft: July 31, 2022

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†Meier: University of Texas at Dallas, and Fellow, Impact, Value, and Sustainable Business Initiative, Wharton School, University of Pennsylvania, meier@utdallas.edu; Servaes: London Business School, CEPR and ECGI, hservaes@london.edu; Wei: Institute of Financial Studies, Southwestern University of Finance and Economics, weijy@swufe.edu.cn; Xiao: University of Texas at Dallas, steven.xiao@utdallas.edu.

Conflict-of-Interest Disclosure Statement

Jean-Marie Meier
No conflict of interest to disclose.

Henri Servaes
No conflict of interest to disclose.

Jiaying Wei
No conflict of interest to disclose.

Steven Chong Xiao
No conflict of interest to disclose.

1 Introduction

Over the past two decades, Environmental, Social, and Governance (ESG) issues have garnered increasing attention from business leaders, academics, policymakers, and the general public. A popular viewpoint is that firms can "do well by doing good," i.e., corporate investments in Environmental and Social activities (E&S) can help firms achieve higher profits and maximize shareholder value. Despite numerous articles on this issue, Gillan et al. (2021) and Starks (2023) in her Presidential Address point out that the mechanisms through which E&S activities can affect corporate performance and value creation remain poorly understood. This contrasts with an extensive literature on the factors affecting capital expenditures, 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 et al., 2001; Hong and Kacperczyk, 2009; Krüger, 2015; Albuquerque et al., 2019; Bolton and Kacperczyk, 2021; Pástor et al., 2021, 2022; Pedersen et al., 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 et al., 2021; Christensen et al., 2023); 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 et al., 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 et al., 2017).[1] However, except for concurrent studies such as Christensen et al. (2023), no prior studies directly relate consumer choices to firm E&S investments. Instead, the focus of prior research has been on relating E&S efforts to measures of profitability and firm value, outcomes that can be affected by many factors in addition to consumer choice, such as cost structure, product mix, and geographic coverage.

In this paper, we examine how retail consumers react to a firm's E&S investments to de-

[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 et al., 2023), which would suggest that E&S activities and profits are negatively related.

termine whether consumer choices contribute to the cash flow channel of E&S. If consumers are concerned about the social and environmental externalities of their consumption decisions, these concerns should be reflected in their choice of products and services. As such, the demand for a product could be affected by its perceived quality from an E&S perspective. This argument follows the reasoning of McWilliams and Siegel (2001) and Albuquerque et al. (2019), which posits that consumers consider a firm's E&S activities as a product attribute, just like 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 believe 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 NielsenIQ 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 county level in the US. 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 data from 2008 to 2019 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 associated with a 10.6% increase in sales in the subsequent year for the average product 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 of potentially omitted variables. Nevertheless, our findings are robust to including various controls that could be correlated with sales and E&S activities, such as advertising, corporate governance, corporate culture, or the firm's product quality.

Next, we study how consumers become informed about the firms' E&S ratings and how they can link specific brands to firms. Consumers likely do not track these scores directly, given the complexity and variability of firm-level E&S ratings (Berg et al., 2022). Instead, we hypothesize that consumers become informed about a firm's E&S performance through advertising and through media coverage of significant E&S-related incidents. Consistent with this information-based mechanism, we find stronger consumer responses to E&S ratings for firms with higher advertising expenditures. Moreover, advertising predominantly amplifies consumer awareness of a firm's E&S strengths rather than concerns. Conversely, adverse consumer reactions to deterioration in E&S ratings are amplified by media coverage of negative E&S events, highlighting the role of the media in disseminating information about firms' shortcomings in E&S policies.

We also note that 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. Besides learning about a firm's E&S activities through advertising and media coverage, finding such information has also become easier over time, as consumers can browse the internet in-store on their smartphones and have various smartphone apps at their disposal that allow users to scan product barcodes and provide immediate information on the E&S performance of the manufacturers.

We also investigate demographic characteristics, such as political affiliation and economic conditions, that may explain local consumer responses to corporate E&S investments. Previous studies indicate that individuals with distinct demographic profiles respond differently to corporate social responsibility (CSR) activities (e.g., Di Giuli and Kostovetsky, 2014; Lins et al., 2017; Dyck et al., 2019). We find that the relation between a firm's E&S ratings and product sales is significantly stronger in counties with a higher proportion of Democratic Party voters and higher average incomes. These findings suggest that consumers' sustainability preferences are shaped by their political and economic circumstances, influencing their purchasing decisions in response to perceived CSR.

We next assess whether local product market competition affects consumers' responses to E&S policies, as consumers may choose among brands based on their social preferences. If consumers integrate social and environmental considerations into their purchasing decisions, firms may compete not only on traditional product attributes, such as price and quality, but also on perceived E&S performance (Cao et al., 2019). Consistent with this mechanism, local product sales for a firm are negatively correlated with the E&S performance of its rivals selling similar products in the same county. This negative externality is particularly pronounced when the highest-rated local competitor exhibits strong E&S performance.

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. However, we cannot entirely rule out that changes in firms' E&S policies could be correlated with changes in other unobservable firm characteristics that affect sales. To alleviate such concerns, we conduct two additional analyses where omitted variable bias or endogeneity concerns are less applicable. First, we examine the monthly lead-lag relation between precisely dated negative corporate E&S news and sales at the individual product level. This analysis aggregates sales across counties, exploits within-product-year variation, and incorporates stringent product×year and product category×year-month fixed effects, significantly limiting omitted variable bias from unobserved seasonal or persistent firm-level trends. We find robust evidence that negative E&S news significantly reduces consumer demand, with sales declines occurring after, but not before, news releases. We also show that these declines occur through reductions in the number of stores with positive sales of the product (extensive margin) and decreased sales per store (intensive margin).

Second, we exploit a series of major natural and environmental disasters as exogenous shocks to the salience of E&S issues for consumers in neighboring counties unaffected by the disasters. Holding fixed firms' prior-year E&S scores and product characteristics, increased consumer awareness triggered by nearby disasters may heighten consumer sensitivity to firms' perceived E&S performance. Utilizing a stacked difference-in-differences approach with extensive fixed effects, we find that consumer demand becomes significantly more responsive to firms' E&S ratings after nearby disasters. Demand responses also emerge in markets sharing common media coverage and in regions more socially connected to the disaster-affected areas, suggesting that both media exposure and interpersonal networks amplify the salience of E&S issues. Interestingly, the heightened consumer sensitivity driven by geographic proximity and media attention dissipates gradually over time, whereas consumer responses associated with social connections exhibit greater persistence.

Finally, we investigate whether financial markets recognize and price in the cash-flow effects of firms' E&S performance. We demonstrate that the stock market reaction around adverse news events significantly predicts subsequent product sales, but only when investors have had prior exposure to similar negative E&S news for the same firm.

This study contributes to the literature on ESG and CSR by demonstrating that ESG activities influence product sales, an essential component of firm cash flows and corporate value. Leveraging detailed barcode-level sales data at the firm–product category–county–year level, our setting allows for refined comparisons, minimizing concerns about omitted variable bias and enabling us to explore the socioeconomic determinants of consumers' heterogeneous preferences for socially and environmentally responsible firms. The local market details also enable us to examine how competitive dynamics shape the ESG-sales relation, and how plausibly exogenous variation in consumer awareness, caused by local salient events, affects this relation. Firm-level data, on the other hand, aggregate across diverse product lines and geographic markets, potentially masking the heterogeneous E&S exposure within firms.

In addition, firm-level outcomes such as sales and profitability embed endogenous managerial responses, including supply-side adjustments in product mix and market footprint. As a result, even with exogenous variation in E&S quality, firm-level estimates may still confound consumer reactions with strategic firm choices. Perhaps as a result of this aggregation, empirical evidence on the cash flow channel remains inconclusive. For example, Di Giuli and Kostovetsky (2014) document a negative or neutral relation between CSR and financial performance, whereas Gillan et al. (2010) and Servaes and Tamayo (2013) report a positive association between CSR and profits. Recent work by Derrien et al. (2025) also studies responses to negative news on RepRisk. While their focus is on analyst earnings forecasts, which decline substantially after negative news, they do find that these forecasts reflect expected sales reductions. In contrast, our approach isolates the consumer-demand effect from endogenous firm strategies more effectively. As such, we contribute to the "value versus values" discussion highlighted by Starks (2023) in her Presidential Address by demonstrating that ESG activities influence consumer product demand, and provide a microfoundation for the cash flow channel of ESG.

There are several concurrent studies examining related questions (Houston et al. (2024), Christensen et al. (2023), Cen et al. (2024), Duan et al. (2024), Dube et al. (2023), Hacamo (2023), Conway and Boxell (2024), Agarwal et al. (2023), Xiao et al. (2025)). We provide a detailed comparison of these studies with ours in Table 1. Many of these papers focus on how negative ESG incidents affect household-level purchasing decisions, using survey data and anticipated sales inferred from store visits. Their findings, consistent with our news-based tests, typically document a reduction in consumer demand following negative ESG events. Two studies that do not focus on negative ESG incidents are Cen et al. (2024) and Conway and Boxell (2024). Cen et al. (2024) find that consumer choices relate positively to workplace equality, a component of the overall E&S performance that we study. Conway and Boxell (2024) relate consumption decisions to social stances taken by corporations and find that consumers most aligned with these stances increase their consumption decisions after a company takes a stance.

The study closest to ours is Christensen et al. (2023), who examine consumer responses to negative corporate social irresponsibility (CSI) news using NielsenIQ Scanner and RepRisk data, but report that the vast majority of CSI revelations are not followed by changes in sales. In their sample, consumers only react to a small subset of severe negative events that are accompanied by abnormal media coverage (3% of the total). Two critical distinctions explain this divergence between our work and theirs. First, our analysis exclusively covers US-listed firms and encompasses all types of negative environmental and social events, whereas Christensen et al. (2023) include both public and private firms, from both the US and abroad, and focus solely on negative social incidents. The average firm in their sample is small, private, and headquartered outside the US. The negative events in our sample are disproportionately concentrated among large public firms, which likely enhances consumer awareness and responsiveness. Without the ability to link product and manufacturer, consumers are unable to react to negative news. Second, while Christensen et al. (2023) focus on negative news shocks to only the "S" element, our baseline analysis using E&S ratings captures broader perceptions of firm E&S performance, incorporating strengths and concerns. Moreover, we find that consumers respond more strongly to E&S strengths than concerns, especially when strengths are potentially promoted via advertising. This distinction highlights that our baseline results capture more general consumer responses, extending beyond mere reactions to bad news, and offer a broader perspective on how firms can build consumer goodwill through positive E&S actions. In addition, we exploit geographic variation in the E&S-sales relation. As detailed in Table 1, our study provides a more comprehensive and generalizable framework for understanding how corporate E&S practices influence consumer demand and firm value, uniquely integrating large-sample barcode-level sales data, positive and negative E&S signals, and environmental disasters as a quasi-natural experiment.

We recognize that NielsenIQ Scanner data primarily cover products of firms in the fast-moving consumer goods sector, and caution against generalizing these findings to the business-to-business (B2B) sector. However, we note that in a B2B setting studied by Dai et al. (2021), customers are found to exert a positive influence on their suppliers' E&S efforts, albeit these improvements are only beneficial to the customers themselves.

The marketing literature has also examined consumer responses to corporate sustainability and social responsibility activities.[2] These studies typically employ lab experiments, consumer surveys, or field studies to explore how consumers respond to specific CSR campaigns, cause-related marketing initiatives, charitable activities, and CSR-related corporate communications. Many of these papers document positive effects of CSR on consumer attitudes such as brand loyalty, trust, perceived fairness, and willingness to pay, while others highlight conditions under which CSR initiatives might negatively affect consumer perceptions or purchasing intent, especially if CSR motives are perceived as insincere, ambiguous, or unrelated to core business activities. However, these studies generally have narrower scopes, relying on experiments or surveys with limited external validity, or focus on specific CSR actions, such as charitable giving, limiting the generalizability of their findings. In contrast, our paper provides comprehensive evidence linking overall corporate E&S performance directly to actual consumer purchasing decisions across numerous products, firms, and local markets over multiple years. By leveraging detailed barcode-level sales data, extensive high-dimensional fixed effects, and quasi-exogenous shocks from natural disasters, we offer robust and generalizable evidence on consumer-driven market incentives for E&S investments, substantially broadening and complementing the findings from existing marketing research.

2 Data

2.1 Retail sales data

Our primary data source is the NielsenIQ Retail Scanner Database, which provides comprehensive information on the quantity and price of product sales at the retail store level at a

[2] For example, see Nickerson et al. (2022); Andrews et al. (2014); Jung et al. (2017); Ellen et al. (2006); Chernev and Blair (2015); Sen and Bhattacharya (2001); Yoon et al. (2006); Du et al. (2011); Brown and Dacin (1997); Lichtenstein et al. (2004); Schamp et al. (2023); Luo and Bhattacharya (2006); Miller and Sturdivant (1977).

weekly frequency.[3] There are approximately 30,000-35,000 participating grocery, drug, mass merchandiser, and other stores (varying by year) from about 90 retail chains that voluntarily contribute these sales data.

The coverage is very extensive. For example, in 2011, the NielsenIQ 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.[4] Each product is uniquely identified by a Universal Product Code (UPC), or barcode hereafter, with the first 6–9 digits representing the Global Company Prefix (GCP) that identifies the manufacturer, as assigned by GS1 US (the organization responsible for issuing barcodes).

Internet Appendix Tables A1 and A2 and Figure A1 illustrate the coverage of the NielsenIQ Scanner Database. NielsenIQ classifies around 6 million products into three nested layers of aggregation: 10 departments, 117 product groups, and 1,343 product categories (called modules).[5] Table A1 describes the ten departments and some of the product groups included in those departments. Table A2 provides some examples of product modules.[6]

The sample period for our analysis is from 2008 to 2019. We end the sample in 2019 to avoid confounding effects from the COVID-19 pandemic, which introduced major shifts in consumer behavior and store operations starting in 2020. To maintain consistency in store coverage across years, we further restrict the analysis to a balanced panel of 24,224 stores that report sales continuously throughout the sample period. This restriction ensures that our identification strategy, which relies on within-unit variation in product sales, is not confounded by changes in the composition of stores over time.[7]

[3]Among others, this dataset has been used in the finance literature by Fracassi et al. (2022) to study the impact of private equity on pricing, Baker et al. (2024) to study household working capital management, Granja and Moreira (2023) to study how disruptions in firms' credit access affect new product offerings, and Kepler et al. (2023) to study so-called stealth acquisitions, including their effects in product markets.

[4]We discuss the incentives of manufacturers and retailers to share data with NielsenIQ in Section *A.1* of the Internet Appendix

[5]The counts of departments, product groups, and product modules are based on the April 2022 vintage of NielsenIQ's product file.

[6]For example, one module is "Snacks – potato chips", which falls under the product group of "Snacks" and the product department of "Dry Grocery". The database differentiates this specific type of snack from other similar snacks, such as "Snacks – tortilla chips," which belong to a different product module under the same product group and department. As this example illustrates, the products we compare across firms are very similar.

[7]NielsenIQ's store coverage remains relatively constant over the period 2008-2017 before expanding substantially in 2018 and again in 2021. Maintaining a balanced panel ensures that our findings are not affected

We link the product owners with GCP codes to public firms from CRSP based on fuzzy name matching. We further merge the above data with other sources. These include financial statement information from Compustat, E&S news from the RepRisk database, and ESG ratings from the MSCI ESG Stats database.[8] The NielsenIQ Retail Scanner Database 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.

2.2 E&S data

We obtain firms' E&S scores from MSCI ESG Stats (formerly called KLD). This data set has the longest time series of any of the available ESG data sets and has been used extensively in academic research (see, e.g., Deng et al. (2013) and Lins et al. (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 et al., 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 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. However, we control for governance and product variables in some 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. We follow Albuquerque et al. (2019) in using a standardized score: we sum

by the location and product mix of the stores being added. Through 2017, our selected stores consistently account for approximately 80% of total NielsenIQ dollar sales across all stores.

[8] Additional sample filters and matching procedures are discussed in the Internet Appendix Section *A.2*.

the number of strengths across all five categories for each firm and year, subtract the total number of concerns for each firm-year, and divide this difference by the sum of the maximum number of strengths and maximum number of concerns. This measure ranges from -1 to 1. In our robustness tests, we discuss two alternative ways of standardizing the E&S ratings.

2.3 E&S news and rating measures

We obtain data on E&S-related news from 2007 to 2019 from the RepRisk database. RepRisk collects news from a wide range of sources and covers firm-specific ESG news worldwide in different languages. The 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 recurring issues and 2 for new issues. For our analysis, we use the novel news incidents (novelty score = 2) to identify consumers' response around these news releases. When multiple news stories about a firm are reported on the same day, we count them as one news incident because 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 E&S 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 A3 in the Internet Appendix shows the list of topics for each news category.

2.4 Sample description and summary statistics

The final sample for the analysis of the relation between sales and E&S ratings includes 196 firms with products in 939 product categories (modules), covering 2,244 counties. The final sample for the analysis using E&S news includes 73,013 unique products in 802 modules produced by 132 firms. Although our sample consists of a relatively small number of firms, they consistently represent 19% to 24% of all sales in the NielsenIQ dataset (see Table A4 in the Internet Appendix). The fraction that is not represented consists mainly of sales by private firms, foreign firms, or smaller publicly listed firms that do not have an E&S rating.

Table 2 presents the summary statistics of our main variables. A complete list of variable definitions is provided in the Appendix: Variable Definitions that follows the Conclusion. The control variables (but neither the dependent variable nor the E&S variables) are winsorized at the 1st and 99th percentiles. Panel A of Table 2 shows variables in the firm–product module–county–year level sample, which is used for the baseline analysis. Our baseline regression includes approximately 16.6 million observations. After adding the firm-level controls, we still have more than 12.6 million observations. The average E&S score is 0.08 with a standard deviation of 0.09. The median firm in our sample has total assets of \$17.85 billion, leverage of 0.29, Tobin's Q of 1.97, ROA of 15%, and its advertising and R&D expenditures amount to 5% and 1% of its total sales on Compustat.

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 monthly product sales. The average firm/product has 1.32 negative E&S incidents in months $m-3$ to $m-1$. Panel C presents the summary statistics of variables in the firm-department-county-month sample, which we use to examine the effect of environmental disasters on consumer behavior.

For additional information about our sample, we provide supplementary analyses and detailed discussions in the Internet Appendix. Specifically, we present time-series trends on firms' E&S performance, consumer purchases, and product assortment, and compare the industry composition and firm characteristics of our sample with those of other U.S. public firms. These analyses indicate that our sample mainly comprises large consumer-oriented firms, particularly in the fast-moving consumer goods sector.

3 Corporate E&S Ratings and Annual Product Sales in Local Markets

3.1 Baseline analyses

As described in Section 2, NielsenIQ Retail Scanner Data consist of weekly store-level quantity and price data of individual products. To balance the trade-off between data granularity and computational workload, we collapse the original data into various levels when testing different hypotheses.[9] In our baseline analyses, we investigate the relation between compa-

[9]In the Internet Appendix, we also show that our results are robust if we use the same level of aggregation across all tests.

nies' 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. 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-product module group. We then estimate the following regression model:

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

$ln(Sales_{i,d,c,y})$ 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 $y-1$. $CONTROL_{i,y-1}$ is a vector of lagged firm-level characteristics that may be correlated with a firm's E&S performance, including *ln(Assets)*, *Leverage*, *Q*, *ROA*, *Advertising*, and *R&D*.

Our data structure allows for a granular identification strategy. Unlike standard corporate finance panel research designs, which treat the firm as the unit of analysis and use firm and year fixed effects to obtain within-firm estimates, our data are at the firm–product module–county–year level. In this context, applying firm fixed effects would still allow cross-sectional variation within firms, i.e., across products and counties in a given year. Such variation can introduce noise that could offset or enhance the estimated effects of firm E&S performance on consumer demand. For example, firms may decide to expand geographically or across product lines, making within-firm estimates more difficult to interpret.

Instead, we treat the firm–product module–county combination as the unit, i.e., the equivalent of the firm component in a firm-year panel analysis. Therefore, we include firm×county×product module fixed effects ($\gamma_{i,c,d}$), which absorb all time-invariant heterogeneity within each product module-county-firm combination, such as local brand strength, consumer preferences, or retailer presence. We also include county×year fixed effects ($\lambda_{c,y}$) to control for local economic shocks or demand shifts, and product module×year fixed effects ($\eta_{d,y}$) to capture time-varying national trends in product categories. While this is our preferred specification, we show in Figure 1 that our main findings are robust to a wide range of alternative fixed effects structures.

We estimate Equation (1) using OLS and report standard errors clustered three ways: by firm, product module, and county. This conservative clustering explains why the t-statistics of our estimates do not appear to be artificially large despite the large number of observations at the firm-product module-county level. Model (1) of Table 3 presents the estimates from Equation (1) without including firm-level control variables. The coefficient on the lagged E&S score is positive and statistically significant, indicating that higher E&S performance is associated with increased local product sales in the subsequent year. The effect is also economically meaningful: a one standard deviation increase in the E&S score (0.09) corresponds to a 10.6% increase in local product sales in the following year ($e^{(1.1216\times 0.09)} - 1$). While this effect may appear large, it is important to note that the estimate reflects variation in E&S scores within each firm–product module–county unit over time. In contrast, the overall standard deviation includes both cross-sectional and time-series variation. Focusing solely on time-series variation, the within-firm standard deviation of the E&S score is approximately 0.05, implying that a one standard deviation increase in this dimension is associated with a 5.8% increase in subsequent product sales ($e^{(1.1216\times 0.05)} - 1$).

The tightness of the fixed effects in model (1) of Table 3 is highlighted by the number of fixed effects estimated. In this model with 16,616,170 observations, we estimate 2,421,827 firm×county×product module fixed effects, 26,710 county×year fixed effects, and 9,443 product module×year fixed effects. These fixed effects greatly limit the scope of potentially omitted variables.

We repeat the estimation of Equation (1) by decomposing sales into unit sales and price per unit. Models (2) and (3) of Table 3 present the estimates of the regressions with the dependent variables $ln(Units_{i,d,c,y})$ and $ln(Price_{i,d,c,y})$. The estimates in model (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 10.8% in the following year ($e^{(1.1368\times 0.09)} - 1$), similar to the magnitude of changes in dollar sales from model (1). Thus, when a firm has 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 model (3) do not show a significant relation between the average product unit price and the E&S rating. Hence, better E&S performance appears to increase revenues primarily through greater demand at a given price, rather than through higher prices.[10]

[10]Note, however, that the total units and average price of products sold in these specifications are calculated by aggregating over multiple barcode-level products within a given module. For example, if a firm sells a

One issue with the models reported in models (1) through (3) is that E&S activities measured at the firm level may be correlated with other time-varying firm-level variables. 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 a series of control variables: size, leverage, Q, profitability (ROA), advertising intensity and R&D intensity. Our inferences remain unchanged, as reported in models (4) to (6). The coefficients on the E&S variable decline only slightly in magnitude and remain statistically and economically significant in models (4) and (5). For example, based on the estimates in model (4), a one-standard-deviation increase in the E&S score (0.05, based on time-series variation) is associated with a 5.5% rise in dollar sales in the following year ($e^{(1.0662 \times 0.05)}$). For comparison, a one-standard-deviation increase (based on time-series variation) in ROA and advertising intensity yields increases in sales of 3.0% and 4.4%, respectively. These comparisons highlight that the economic magnitude of the E&S effect is comparable to other first-order firm characteristics that are significantly related to product sales.

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 consumer preferences in explaining how E&S investments can affect sales, cash flows, and firm value.

To shed further light on the nature of the consumer's response to corporate E&S performance, we explore whether the effect varies systematically across different aspects of E&S and different product categories. In Internet Appendix Table A6, we re-estimate our baseline specification using each of the five individual E&S rating categories provided by MSCI ESG Stats: Community, Diversity, Employee Relations, Environment, and Human Rights. The results show that consumer demand responds positively to multiple facets of a firm's social and environmental practices. Coefficients are positive in four out of five categories

single can of soda for $1 and a six-pack of the same soda for $6 in a county, the calculated total sales quantity is 2 and the average price is $3.5. As a result, variations in *ln(Units)* and *ln(Price)* may reflect changes in the product mix rather than true shifts in demand or pricing. This aggregation limits the interpretability of the coefficients in the price regressions and introduces potential noise unrelated to the consumer response. Therefore, we treat the price regression results with caution and view the specifications using *ln(Sales)* as the dependent variable as the preferred approach for assessing the impact of E&S performance on consumer demand. In Section *6.1*, we return to the question of pricing and provide additional analyses using product-level data that is more appropriate for identifying price effects.

and statistically significant in three: Diversity, Employee Relations, and Human Rights.

We next examine heterogeneity across product types using subsample regressions by product department, as reported in Internet Appendix Table A7. Departments correspond to the coarsest and most stable level of product classification in the NielsenIQ dataset. Across the ten departments analyzed, the estimated coefficient on the E&S score is positive in eight and statistically significant in five. The largest and most precisely estimated effects appear in Health and Beauty, General Merchandise, and Frozen Foods—categories that tend to feature products with relatively higher unit prices. While the price variation across departments is limited due to the nature of fast-moving consumer goods in our dataset, the results suggest that consumers may be more responsive to E&S practices in categories where the purchasing decision involves greater deliberation or where brand perception is more salient. These results are discussed in more detail in Section *C.1* of the Internet Appendix.

Together, these analyses confirm that consumer responses to firm E&S performance are both broad-based and substantively grounded.

3.2 Robustness tests

In this section, we conduct various tests to assess the robustness of the positive relation between firm E&S ratings and local product sales.

E&S-sales relation at the firm-year level Our baseline empirical design operates at a highly disaggregated level, where we relate sales outcomes to firm-level E&S ratings using data at the firm–product module–county–year level. This approach allows us to exploit within-firm variation across products and geographic markets. In this subsection, we verify whether the positive relation between E&S ratings and sales also holds when the data are aggregated to the firm-year level.

Table 4 presents the estimates of Equation (1) at the firm-year level using total dollar sales aggregated across all product modules and counties in our sample. The positive relation between E&S and sales persists. Across specifications, the coefficient on *E&S* is positive and statistically significant in three of the four models. In particular, the coefficient on *E&S* is significantly positive in models (2) and (4), where we additionally control for the natural logarithm of the number of product modules ($\ln(\#Modules)$) and counties ($\ln(\#Counties)$)

in which the firm operates. These variables capture the extensive margin of firm activity: sales can increase either because of higher demand within an existing product module–county pair (the intensive margin) or because firms expand into new products or geographic markets (the extensive margin). The strongly positive coefficients on both variables confirm that broader product and geographic scopes are associated with higher firm-level sales. In the models that include the other firm-level control variables as well (models (3) and (4)), the coefficient on *E&S* is statistically significant only if $\ln(\#Modules)$ and $\ln(\#Counties)$ are included, indicating the importance of accounting for the extensive margin.

However, product and market expansion are themselves firm choices that may respond endogenously to E&S performance. Moreover, there is naturally a lot of heterogeneity in county size and the size of each product market. As a result, even after including the number of products and markets, it remains challenging to separate consumer demand responses from managerial decisions in the firm-level regressions.

In terms of magnitude, the estimated E&S coefficients at the firm-year level are somewhat larger than those in the baseline disaggregated regressions. In model (4), which includes all firm and extensive-margin controls, the coefficient on E&S is 1.65, significant at the 10% level, compared with 1.07 in model (4) of Table 3. Part of this difference reflects the distribution of E&S in the two samples: the standard deviation of firm-level E&S is 0.078, slightly smaller than the 0.088 standard deviation in the disaggregated data. Adjusting for this lower dispersion reduces the apparent gap in magnitude implied by the two coefficients. A second, and likely more substantive, reason is the difference in implicit weighting. The firm-level specification weights each firm-year equally, whereas the disaggregated regressions implicitly up-weight large, diversified firms that contribute many product module–county observations. If such firms operate in product categories or regions with weaker E&S sensitivity, this weighting would attenuate the estimate in the disaggregated regressions.

To explore these differences further, Internet Appendix Table A9 examines how product and market heterogeneities affect the firm-level E&S–to-sales sensitivity. Panel A augments the firm-year regressions by interacting *E&S* with ln(#Modules) and ln(#Counties). Both interaction terms are significantly negative, indicating that firms operating across a broader range of products or markets exhibit lower average E&S-to-sales sensitivity. Since diversified firms carry greater implicit weight in the baseline (disaggregated) specification, their average

E&S-sales sensitivity would lead to a smaller magnitude of the baseline estimates.[11]

Alternative measures of E&S Internet Appendix Table A11 employs three alternative approaches to measuring E&S. First, we show that our results hold using tercile- and quintile-based categorical variables of $E\&S$.

Second, we explore alternative ways of standardizing the E&S rating. Specifically, we adopt Albuquerque et al. (2019)'s alternative standardization of E&S ($E\&S2$), which normalizes strengths and concerns separately by their respective category maxima before differencing. We also apply the method of Servaes and Tamayo (2013) ($STDKLD$), which first standardizes strengths and concerns for each of the five E&S dimensions individually before aggregating them. Both alternatives yield positive and significant estimates.

Third, Berg et al. (2022) document a divergence across the ESG ratings of different providers. We note, however, that these ratings are generally positively correlated, which suggests that they capture firm E&S performance noisily.[12] Nevertheless, to ensure that our findings are robust when using different ESG data sources, we next replace the MSCI ESG Stats database with alternative data sources. We first use the Sustainalytics database, which has also been used in ESG research (e.g., Engle et al., 2020; Huynh and Xia, 2021a). The estimate indicates that a one-standard-deviation increase (8.34) in the Sustainalytics E&S score corresponds to an 11.4% increase ($e^{0.0129\times 8.34}-1$) in local product sales, which is very similar to the magnitude in the baseline model. We then use RepRisk E&S news data by taking the negative annual count of reported E&S-related incidents. Despite differences across databases in rating methodology and coverage, our results remain consistent: better E&S performance is robustly associated with higher local product sales.

Alternative fixed-effects specifications To assess the robustness of our findings to alternative fixed-effects specifications, we systematically re-estimate our baseline model using

[11] In Section B of the Internet Appendix, we study the relation between geographic and product module expansion and E&S-to-sales sensitivity by examining the product-level and county-level E&S-to-sales sensitivities in our sample. When firms decide to expand, they do so into product modules and counties that are less sensitive to E&S performance compared to the counties and modules in which they already operate. As a result, the E&S-to-sales sensitivity at the firm level is directly affected by these expansion decisions.

[12] According to Berg et al. (2022), on the E-dimension, the correlations range from 0.23 to 0.7, while on the S-dimension, they range from 0.21 to 0.68. Thus, the divergence in E&S ratings does not appear to be worse than the divergence in analyst earnings forecasts, price targets, or buy/sell recommendations.

a wide array of fixed-effects combinations. Figure 1 presents the estimated coefficients on the E&S score, along with 90% confidence intervals, across 19 different specifications, where the black boxes indicate that a given fixed effect is included. The first model replicates our baseline estimate from model (4) of Table 3 and serves as a benchmark. Subsequent models incrementally vary the inclusion of various fixed effects, ranging from specifications with no fixed effects (model (2)) to the most saturated specification with two sets of three-way fixed effects (model (19)). As Figure 1 shows, our core findings remain robust across a broad range of fixed effects specifications.

First-difference specification Table 5 presents first-difference regressions at the firm–product module–county–year level. By differencing, we eliminate all time-invariant heterogeneity at the unit level and thus drop the firm×product module×county fixed effects from the model. Model (1) confirms the baseline relation: changes in E&S ratings are positively associated with changes in product sales.[13] Model (2) categorizes E&S changes into annual quintiles, using indicators for quintile 1 (significant downgrades), quintile 2 (moderate downgrades), quintile 4 (moderate upgrades), and quintile 5 (large upgrades), with the middle quintile as the omitted category. The results show that product sales respond significantly to both ends of the E&S rating change distribution: a firm–product module–county–year observation in the top quintile of E&S rating changes experiences a roughly 7.0 percentage point increase ($e^{0.0673} - 1$) in product sales growth compared to the median group (the omitted category). Conversely, a firm in the bottom quintile of E&S rating changes sees about a 3.6 percentage point decline ($e^{-0.0368} - 1$) in product sales growth relative to the median. [14]This evidence indicates that consumer demand responds most strongly to large and salient changes in E&S performance, both upward and downward.[15] We have also estimated this first-difference specification at the firm-year level, and present the estimates in the Internet Appendix Section B.

[13]In terms of economic significance, increasing the change in the E&S rating by one standard deviation (0.065) corresponds to a change in sales growth of approximately 4 percentage points (0.6187 × 0.065).

[14]The difference in $\Delta E\&S$ between the mean of Quintile 1 and the mean of Quintile 5 is 0.0974. Multiplying this by the continuous coefficient in model (1) (0.6187) yields an implied change of approximately 6 percentage points in $\Delta\ln(\text{Sales})$, which is similar in magnitude to the difference observed in the quintile specification.

[15]The variation in E&S ratings is not limited to a few firms experiencing a lot of changes. More than 40% of the firms in our sample have at least one major downgrade (defined as being in the bottom quintile of annual E&S changes) over the period 2008-2019, and more than 30% have at least one major upgrade.

Corporate governance In this section, we examine whether our results are confounded by corporate governance. This serves as a placebo test: if our findings capture genuine consumer reactions to E&S performance, governance should have no effect on sales. We incorporate two governance measures in Table 6. In model (1), we include a governance index constructed using MSCI ESG Stats governance strengths and concerns and applying the same scaling methodology as for our E&S measure. The effect of E&S ratings remains robust and significant, while the effect of governance is insignificant. In model (2), we follow prior studies (e.g., Hartzell and Starks, 2003; McCahery et al., 2016) and use institutional ownership from Thomson Reuters as a proxy for governance quality. Institutional ownership is unrelated to sales, and the E&S coefficient remains virtually unchanged.[16]

Controlling for price and quantity Our baseline analyses examine product sales separately in terms of both quantity and price, treating each as a dependent variable in different specifications. However, one might be concerned that the positive relation between firms' E&S ratings and product sales quantities could be influenced by product pricing, or vice versa. To address this possibility, in Table A12 of the Internet Appendix, we conduct a robustness test by explicitly controlling for price when analyzing product quantities sold and controlling for quantity when analyzing unit prices. The results show that after controlling for prices, the relation between E&S scores and sales quantity remains significantly positive. By contrast, the relation between E&S scores and unit price remains insignificant after controlling for units sold.[17]

Product quality To address concerns that differences in product quality may confound our findings, we add three measures related to product quality to our model: (i) the lagged standardized product quality score from MSCI ESG Stats; (ii) lagged product recalls from the U.S. Food and Drug Administration (FDA), which oversees food-related safety incidents; and (iii) lagged product recalls from the Consumer Product Safety Commission (CPSC),

[16]We acknowledge that governance can also act as a noisy proxy for underlying firm quality. Firms with stronger governance are often better managed, and higher-quality firms may naturally achieve stronger sales performance regardless of their E&S ratings. Our findings are not consistent with this interpretation.

[17]The coefficient on E&S in model (4) of Table 3 is unchanged if we additionally control for *ln(Price)* (coefficient of 1.065, t-statistic of 2.88).

which covers a wide range of consumer goods.[18] In an additional test, we limit the sample to product modules classified as "minimally processed" (e.g., fresh meat, milk, eggs, and produce), where consumers are better able to judge product quality directly via sensory cues like appearance or freshness compared to more processed products such as deodorant. For this test, we manually code all product modules.

As shown in Internet Appendix Table A13, Panel A, the E&S coefficient remains robust across all specifications, providing additional reassurance that the E&S-sales relation is not spuriously driven by product quality. The point estimate is the largest in the minimally processed subsample, consistent with stronger effects when consumers can directly assess product quality through sensory cues. Among the quality controls, FDA food recalls are significantly and negatively associated with sales, suggesting that consumers respond to major product safety incidents. In Panel B, we report the effect of E&S on price after controlling for product quality. The point estimates for E&S are insignificant in all models, as is the case in the baseline specifications when using *ln(Price)* as the dependent variable. However, product quality scores are positively related to price, suggesting that the MSCI ESG Stats measure captures an economically relevant aspect of product quality.

Other robustness tests For brevity, we discuss other robustness tests in detail in the Internet Appendix. Section *C.2* examines time-series variation in the effect of E&S on sales. Section *C.3* shows that our results persist when controlling for proxies of corporate culture. Section *C.4* shows that the results are robust to alternative definitions of advertising and R&D. Section *C.5* shows that our results are robust when controlling for different proxies of firm size. Tables A17 to A19 show that our results are robust when using an unbalanced store sample, when extending the baseline analyses to 2020 (the latest year to which our sample can be extended due to the availability of the MSCI ESG Stats database), and when we do both.

[18] The FDA recalls fall into three categories: food, drug, and (medical) devices. We restrict our analysis to food-related recalls, as only this category is relevant for our barcode-level data.

4 How Consumers Link Firms to E&S Ratings

A natural question that arises from our analyses is how consumers become informed about firms' environmental and social (E&S) practices. Given the complexity, variability, and potential noise inherent in E&S ratings, it seems unlikely that consumers directly monitor and respond to specific rating scores. Indeed, we do not argue that consumers precisely track firm-level E&S ratings; instead, ratings serve as proxies for consumers' general perceptions of a firm's overall E&S performance. This leads us to examine how consumers form these general perceptions. We propose two channels: firm advertising and media coverage.

We begin by investigating the role of advertising in Table 7. In model (1), we show that adding the *Advertising* × *E&S* interaction to our baseline specification yields a positive and significant coefficient, indicating that consumers' sensitivity to E&S increases with firm advertising. Advertising may also affect consumer awareness of positive and negative E&S attributes differently. If consumers care about a firm's E&S record, companies may advertise their E&S credentials while seeking to obscure any E&S concerns. In model (2), we decompose the E&S score into strengths and concerns (with concerns measured as a positive number). The estimates indicate that consumer demand responds positively and significantly to E&S strengths, but not to concerns. Model (3) further reveals that advertising plays a vital role in explaining this result: the effect of E&S strengths on consumer demand increases with advertising intensity, whereas the corresponding interaction for concerns is statistically insignificant. These results support the notion that firms can strategically use advertising to highlight their E&S achievements while downplaying their shortcomings.

Next, we study the role of the media in shaping customer awareness. To do so, we analyze consumer responses to changes in firms' E&S ratings. Table 8 presents first-difference regressions estimated at the firm–product module–county–year level. In model (1), we first decompose changes in E&S ratings into positive and negative components, both expressed in absolute values. As such, we expect a positive coefficient for improvements in E&S ratings and a negative coefficient for deteriorations. The results align with these expectations in sign, but only the coefficient on positive changes is statistically significant. This asymmetric response mirrors earlier findings in Table 7, where we document that consumers are more responsive to E&S strengths than to concerns. Model (2) of Table 8 incorporates media coverage as a potential channel for consumer awareness. We interact E&S changes with changes in E&S-related negative news stories reported by RepRisk ($\Delta News$). The results show that increased negative media coverage significantly strengthens the negative response to E&S downgrades, while it has no significant effect on E&S improvements.

The above results suggest an information-based mechanism through which consumers form perceptions of firms' E&S performance. Although consumers may not track detailed E&S ratings directly, the increase in consumer awareness through advertising increases the likelihood that they become aware of positive E&S actions. Conversely, consumer awareness of negative E&S issues is predominantly driven by negative media coverage. Thus, advertising and media jointly shape consumer perceptions and purchasing decisions regarding firms' environmental and social practices.

We do not claim that all consumer awareness goes through the advertising and media channels, and that these channels are powerful enough to inform all consumers about a firm's E&S activities. Neither do we claim that all consumers have to care about a firm's E&S record. Even if only a minority of consumers seek out information on firms' E&S performance, their purchase decisions alone can generate the effects we document. The awareness of these consumers can be enhanced through advertising and negative news stories, but there are also other ways of finding out about a firm's E&S record. For example, there are now several smartphone Apps available that have been around for more than a decade (e.g., Buycott), that allow consumers to use a product's barcode or name to receive information on its manufacturer's E&S activities.[19]

5 Moderating Factors

5.1 Local demographic characteristics

In this section, we study county-level demographics that may affect the strength of the relation between firm E&S performance and local product sales. We examine whether consumers who vote for the Democratic Party, have higher incomes, or are more educated place greater weight on firms' E&S practices when making purchase decisions. If so, markets with a higher share of such consumers should see a stronger correlation between E&S ratings and local sales. We test this hypothesis by including an interaction between the E&S score and

[19] As an example, Internet Appendix Figures A5 and A6 show screenshots of an app and a specific product.

the corresponding demographic characteristics in the following model:

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

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 is an interaction between a firm characteristic and a county characteristic, we can also include firm×year fixed effects ($\theta_{i,y}$) to account for the effect of unobservable time-varying firm characteristics on product sales. As a result, the standalone variables $E\&S$, $Democrat/Income/Education$, and the control variables are absorbed.

Table 9 reports the results. In models (1) through (3), we examine each demographic variable individually, while model (4) includes all interactions jointly. The interaction between E&S ratings and the share of Democratic Party voters is positive and significant, both in isolation and when controlling for the other demographic variables. In the full model (model (4)), we also find a significant coefficient on the interaction between E&S and per capita income, suggesting that both political orientation and economic status shape consumers' responsiveness to firm E&S efforts. Based on the estimates in model (4), a one-standard-deviation increase in the proportion of Democratic Party voters (0.14) and in income ($17,390) is associated with increases in E&S-to-sales sensitivity of 7.0% and 8.0%, respectively, relative to the baseline effect of 1.1216 (Table 3, model (1)).[20]

Importantly, by including an extensive set of fixed effects, this analysis substantially limits the scope for alternative explanations. For example, local confounding factors such as urbanization, cost of living, or retail infrastructure are absorbed by county×year fixed effects, while firm×year fixed effects capture firm-level confounding factors such as firm productivity. Given our evidence, a potential omitted firm characteristic would need to be both correlated with E&S ratings and have a differential effect on sales across counties with varying demographic profiles. The most plausible interpretation, therefore, is that consumers' intrinsic preferences for purchasing products from socially and environmentally

[20]The lack of significance of the E&S income interaction when it is included by itself in model (2) is due to an omitted variable problem. Within counties over time, there is a negative relation between income and the average Democratic Party vote. Thus, when the income interaction is included alone in model (2) of Table 9, it also partly captures the political leaning effect in the opposite direction, turning the overall effect insignificant.

responsible firms shape the relation between firm E&S practices and local product demand.

5.2 Competition: E&S ratings of local product market rivals

We next examine how firms compete on E&S performance within local product markets. If consumers factor social and environmental concerns into their purchasing decisions, then firms will compete not only on price and quality but also on their perceived E&S performance. Better E&S performance among a firm's local product market rivals may thus exert a negative externality on its sales. In particular, the strongest E&S performer in a local market may impose especially intense peer pressure by attracting ESG-conscious consumers.

To test this mechanism, we re-estimate Equation (1) by replacing the focal firm's E&S rating with either the average or the top E&S rating of its local rivals, defined as other firms selling products in the same product module and county. Table 10 presents the results. Models (1) through (4) include the E&S score for the average rival, while models (5) through (8) use the E&S score of the top local rival. Models (1) and (5) show that both the average and top E&S performance of local rivals are negatively associated with the focal firm's product sales. The effects are economically meaningful: a one-standard-deviation increase in the average rival E&S score (0.07) corresponds to a 7.6% decrease in sales ($e^{-1.1233\times0.07}-1$), while a one-standard-deviation increase in the top rival's E&S score (0.09) corresponds to a 12.3% decrease ($e^{-1.4501\times0.09}-1$). These patterns are consistent with consumers reallocating demand toward firms with superior perceived E&S standing within local markets.

To ensure that differences in other observable rival characteristics do not confound these effects, models (2), (4), (6), and (8) include average rival firm-level controls. These controls have little impact on the rival E&S coefficient. Models (3), (4), (7), and (8) include firm×year fixed effects, which allow us to compare a given firm's performance across different markets within the same year. This approach further alleviates concerns about firm-level confounding variables. In these models, the adverse effect of average rival E&S ratings becomes statistically insignificant (model (3)). In contrast, the effect of the top rival E&S score remains both statistically and economically significant (model (7)). This suggests that consumers are particularly responsive to standout E&S leaders in a given product market and location. Models (4) and (8) include both the rival firm-level controls and firm×year fixed effects. The coefficient on the top rival E&S score remains negative and significant at the 10% level, confirming that the peer effects persist after accounting for a wide range of rival firm attributes.[21]

6 Identification

As pointed out above, a concern with our findings is that consumers are not responding to changes in firms' E&S policies, but instead to concurrent changes in other firm characteristics correlated with E&S performance. The robustness tests discussed in Section *3.2* account for many of these potential characteristics. In addition, any omitted firm characteristic would not only need to be positively correlated with E&S scores and local product sales, but since we include firm×year fixed effects in both the demographic and rival analyses, it must also explain within-firm variation across counties and competitive contexts.

To further address any potential residual concerns, we introduce two additional analyses in this section. First, we exploit within-year variation arising from consumer exposure to negative E&S news, which rules out explanations involving any slow-moving firm or product characteristics. Second, we leverage a quasi-exogenous shock to consumer E&S awareness driven by nearby natural and environmental disasters, which are orthogonal to both time-varying and persistent firm and product characteristics. Finally, we also explain why potential supply effects cannot account for our results.

6.1 Negative E&S news and monthly product sales

In this section, we examine the time-series dynamics of consumers' perceptions of a firm's E&S practices and the resulting changes in product sales. We draw on negative E&S news reported by RepRisk to track changes in the public's perception of a firm's E&S practices on a monthly basis. We count the number of negative E&S-related incidents over rolling three-month windows and relate the occurrence of such incidents to the firm's sales level.

[21] Our tests include only publicly listed U.S. firms; private and foreign competitors are excluded. The rival analysis is limited to county–product module combinations with at least one rival firm in addition to the focal firm. With firm × year fixed effects, identification also requires variation in rival identity within each focal firm–year group across counties. These restrictions explain the smaller sample size in Table 10 relative to Table 9. The median (mean) number of firms per county–module–year is 3 (4), including the focal firm. Thus, these tests capture competitive dynamics among a relatively small number of visible rivals in each market.

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 a firm's product sales across counties, as these tests do not exploit geographic differences. 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.[22] Thus, we estimate the following regression using the individual product-month level sales data:

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

The dependent variable, $ln(Sales_{i,p,m})$, represents the natural logarithm of dollar sales of product p sold by firm i in month m. The key explanatory variables are the counts of negative E&S news stories for firm i in the three quarters surrounding month m: from $m-6$ to $m-4$, $m-3$ to $m-1$, and $m+1$ to $m+3$. This specification includes product module×year-month fixed effects ($\gamma_{d,m}$), which control for shocks to broad product categories over time, and product×year fixed effects ($\eta_{p,y}$), which control for all product-level changes occurring at annual or slower frequencies, such as shifts in product features, pricing, availability, or firm strategy. These fixed effects are deliberately stringent: by removing product-year means from the data, they substantially reduce the risk of omitted variable bias from unobserved seasonal or firm-level trends, ensuring that only short-run monthly deviations around news events contribute to identification. However, this comes at the cost of excluding any persistent effects of E&S news that extend beyond the calendar year in which they occur. As a result, our estimates capture only short-run variation in consumer demand around E&S news events, relative to the product's average performance in that year. They should be interpreted as conservative lower bounds of the full effect. For a non-E&S event to confound our estimates, it must coincide precisely with month-specific shocks not already captured by these fixed effects. Since we have aggregated the data across local markets to obtain the total monthly

[22] Maintaining county-level sales, as in our baseline analysis, introduces substantial noise due to the proliferation of low-value monthly sales observations in small counties. Moreover, the product–month aggregation enables us to separately examine the intensive and extensive margins of consumer response—an analysis that would not be feasible if we preserve the geographic granularity. Nevertheless, we confirm in Table A20 in the Internet Appendix that our findings on negative E&S news remain robust when using the same cross-sectional aggregation (i.e., firm-product module-county-month level) as in our baseline analyses, with the only difference being the yearly vs. monthly dimension.

sales of each product, we estimate the standard errors using two-way clustering at the firm and product levels.

Model (1) of Table 11 presents the results for total product dollar sales. 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 relation between negative E&S news and subsequent sales reductions 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 1.1% in month m.

Next, we explore whether the decline in revenue occurs along the intensive or extensive margins. In model (2) of Table 11, the dependent variable is the natural logarithm of the number of stores with non-zero sales for each product. The estimates reveal that negative E&S news also reduces store coverage: the coefficient on $News_{m-3,m-1}$ is -0.0093, implying a 0.9% decline per negative news item in the number of stores selling the product following the news. Model (3) examines the intensive margin by using the natural logarithm of dollar sales per store as the dependent variable. The coefficient on $News_{m-3,m-1}$ is -0.0018, corresponding to a 0.18% decline in sales per store for each negative news item. Thus, negative E&S news affects firm revenue through both intensive and extensive margins.[23]

In Table A22 in the Internet Appendix, we re-estimate Equation (3) but replace the dependent variable with $ln(Units)$ in Panel A and $ln(Price)$ in Panel B. When we use monthly unit sales as the dependent variable, the coefficient for $News_{m-3,m-1}$ is significantly negative, while that for $News_{m+1,m+3}$ is not. These estimates are similar to those in model (1) of Table 11, suggesting that product sales volume tends to decline after the release of negative E&S news, rather than before. By contrast, when we use $ln(Price)$ as the dependent variable in model (1) of Panel B, the coefficients for both $News_{m-3,m-1}$ and $News_{m+1,m+3}$ are significantly positive at the 10% level. Products sold by firms experiencing negative E&S

[23] To study which type of news is most relevant to consumers, we repeat the estimation of Equation (3) of Table 11 in Table A21 of the Internet Appendix, but count different types of news separately based on the classification by RepRisk (Environmental, Social, Cross-Cutting). Demand significantly declines after both negative Environmental and Social types of news.

news tend to be priced about 0.9% higher prior to the news release and remain at a similar price level afterward. Thus, there is no evidence to suggest that firms reduce their prices after negative news releases to counterbalance declining sales volumes.

To further investigate the effect of negative E&S news on sales, we also conduct an event study with matched controls. Our prior investigation examines sales in a given month as a function of news events over the prior (and subsequent) periods. The event-study design focuses on negative news events in a given month and their effect on future sales. For each firm-product combination with at least one negative E&S news event in a given month m (the treated products), we find a control firm-product combination with no negative news in month m and in the previous six months (with replacement). We select the control product from the same product module that experiences the pre-event growth rate in sales (i.e, $ln(sale_{m-1}) - ln(sale_{m-6})$) closest to the treated product. If the closest distance in growth rates exceeds 10%, the treated-control pairs are excluded from this analysis. The resulting sample comprises 1,277 news events that feature at least one negative news story in a given month, covering 24,770 firm-product combinations.

For the 13-month window starting six months before the event, we then estimate a stacked difference-in-differences (DID) regression, stacking all treated and control firm-product combinations. Table 12 shows the results. We find a 10.15% ($e^{-0.1070}$-1) decline in sales after negative news events. While this decline is mostly due to a 9.49% decline in unit sales, we also find a significant 0.7% price decline. This test also allows us to separate out the news events deemed severe by RepRisk. As Table 12 shows, the effect for severe events relative to other negative news events is insignificant.

Figure 2 presents a dynamic version of the stacked DID model, based on the main specification where all levels of severity are combined. The graph shows no pre-treatment difference in sales between treated and control products until the month of the news event, attesting to the quality of the matching. Following the news release, treated products exhibit a significant decline in sales over the entire six-month period relative to control products.[24]

[24]The estimated effect from the stacked DID analysis appears considerably larger than that from the baseline panel regression reported in Table 11, but these two results cannot be compared directly for three reasons. First, the 1.1% sales drop we document in Model (1) of Table 11 reflects the marginal effect of each additional negative E&S news story in the preceding three months, while the estimate in Table 12 compares firms *with* news stories to firms *without* news stories in a given month and the preceding six months. Second, our specification in Table 11 includes product ×year fixed effects, which absorb all persistent changes

Taken together, these analyses indicate that consumers respond to negative news stories by substantially reducing their purchases of the products of affected manufacturers.

6.2 Natural and environmental disasters and consumer response

In this section, 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' historical E&S policy choices and consumer perception of product quality, allowing for a cleaner identification of the impact of E&S performance on product sales moderated by consumer awareness.[25] Because we aim to measure consumer awareness of E&S issues more broadly, we include both natural disasters and environmental disasters directly caused by human activities.

We obtain a list of severe natural and environmental disasters from 2009 to 2018 from the Environmental Protection Agency (see Table A23 in the Internet Appendix).[26] To capture the effect of these events on local consumer behavior, we construct a stacked difference-in-differences (DID) design across events. The stacked DID framework accommodates variation in event timing and allows us to avoid biases associated with two-way fixed effects estimators when treatment effects are heterogeneous and time-varying (Roth et al. 2023). In our context, the impact of disasters on consumer sensitivity to E&S performance may be short-lived and fade over time, making the stacked design ideal for estimating such dynamic, staggered effects. Moreover, because disasters occur at different times and locations, some counties may simultaneously serve as treated units in one event and controls in another; the stacked approach isolates each event's effect cleanly while preserving consistent identification.

For each disaster, we collect sales data from counties within 1,000 miles of the disaster's location over a 37-month window centered around the event (i.e., 18 months before and

in product sales within a calendar year. As a result, any longer-term effects of negative E&S news are not captured, making the baseline estimates intentionally conservative. Third, because of the stringent matching requirement, this sample contains 1,277 news event months, compared to the baseline sample, which contains 3,069 incidents across 2,020 firm-months.

[25]Prior studies on climate change also use natural disasters to measure individual awareness of climate change issues (e.g., Baldauf et al. 2020, Alok et al. 2020, Huynh and Xia 2021b).

[26]We exclude disaster events near the beginning and the end of our sample period to allow for sufficient pre- and post-event data.

18 months after).[27] To exploit the granularity of our data while keeping the computation manageable, we aggregate a firm's sales data in a specific county and month to the product department level (10 in total). We then estimate the following regression model:

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

where e refers to event, i to firm, k to the product department, c to the county, and m to the month. The independent variable of interest is $E\&S_{i,y-1} \times Disaster_{e,m} \times Proximity_{e,c}$, where $E\&S_{i,y-1}$ is the E&S score for firm i in calendar year $y-1$, $Disaster_{e,m}$ is an indicator equal to one for observations within event e during the 6 months after the event, including the event month. $Proximity_{e,c}$ is the geographic proximity to the disaster location, proxied by the negative log of distance, which we use as the treatment variable. Thus, the coefficient on the triple interaction measures how the effect of a firm's prior E&S score on product sales varies with the proximity to a disaster after it occurs.[28]

In the models, we include event×firm×product department×county fixed effects ($\gamma_{e,i,c,k}$), event× firm×year-month fixed effects ($\theta_{e,i,m}$), event×product department×year-month fixed effects ($\eta_{e,k,m}$), and event×county×year-month fixed effects ($\lambda_{e,c,m}$) to account for potential omitted variables along these dimensions within each event. 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 firm-product department-county-month observations that are exposed to the salience of the disasters but that are not directly impacted by them. Standard errors are double-clustered at the firm and county levels.[29]

[27]To ensure sufficient observations in both the pre- and post-disaster periods, we require each firm-department-county group to have at least 27 months (9 quarters) of non-missing data.

[28]These models estimated at the product department level contain 43,373,020 observations. Using data at the finer firm–product module–county–month level, as in the baseline analysis, increases the sample size to nearly 200 million. This significantly raises the computational burden, especially for dynamic DID estimation, and introduces substantial noise in the data, as many observations at this finer level contain very low sales values. Nonetheless, Table A24 in the Internet Appendix shows that our main findings remain robust under this alternative specification.

[29]As discussed by Wing et al. (2024), clustering standard errors at the treatment-unit level (firm–product department–county in our context) adequately accounts for correlation within treated units and repeated observations across events. However, in our main stacked DID regressions, we adopt an even more conservative approach of clustering at a coarser level (firm and county) to align with the clustering used throughout our previous analyses. This coarser clustering generally produces larger standard errors, making it more difficult to detect statistically significant treatment effects. Conversely, in the dynamic DID specification,

Table 13 reports the results. Model (1) shows that sales respond more strongly to firms' E&S ratings in the post-disaster period in geographically closer areas. In model (2), we discretize geographic proximity into four distance bands: within 0–200, 200–400, 400–600, and 600–800 miles from the disaster site, with the 800-1000-mile band as the omitted group. We then interact these indicators with *E&S* and the disaster indicator. The estimates show that the positive post-disaster response to E&S performance is the strongest within the closest distance band and diminishes with distance. This spatial attenuation further supports the interpretation that these events raise E&S salience among nearby consumers.[30]

We also examine the parallel-trend assumption and the time-series dynamics of consumer sensitivity to E&S performance by estimating a dynamic version of Equation (4). Specifically, we replace the *Disaster* indicator with event-quarter indicators in the triple interaction term to estimate the treatment effect on a quarterly basis over the 37-month period around the disaster. Figure 3 presents the estimates. It shows that for markets located closer to 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. Interestingly, this enhanced sensitivity is significant only up to the second quarter after the disaster and reverses afterward. Thus, the impact of these disasters on consumer awareness is short-lived.

To better understand the time-series dynamics of this result and the economic channels through which environmental disasters influence nearby consumer demand for products from high-E&S firms, we explore two plausible mechanisms: media exposure and social connections. Disasters often trigger intense local media coverage, especially within the same state or Designated Market Area (DMA). DMAs are markets covered by the same television channels. Consumers located in the same state or DMA are likely to receive similar news content. This coverage can temporarily increase awareness and concern for environmental and social issues, thereby elevating the salience of firms' E&S practices. However, as media attention fades, this awareness could quickly subside. In parallel, disasters could also increase awareness through personal networks: consumers may learn about a disaster and its consequences

which we discuss subsequently, our goal is to rigorously test for parallel trends by carefully evaluating the significance of pre-event trends. Here, clustering at the finer treatment-unit level, as recommended by Wing et al. (2024), is more conservative because it generates smaller standard errors, thus making it harder to confirm the absence of significant pre-trends.

[30]Section D of the Internet Appendix expands the analyses of Table 13 using the five E&S category scores individually.

via communication with friends and family residing in the affected areas. Such interpersonal diffusion of concerns may persist longer, as socially connected individuals continue discussing the recovery process and its implications.

To test these two mechanisms, we re-estimate the dynamic difference-in-differences specification using two alternative treatment proxies. In the first specification, we define treatment exposure based on whether the consumer market lies within the same state or DMA as the disaster event. The results, shown in Panel A of Figure 4, reveal a clear post-disaster increase in the sensitivity of product sales to firm E&S ratings beginning in the first quarter after the event. This increase, however, attenuates rapidly by the fourth quarter, consistent with the notion that media-driven salience is short-lived.

In the second specification, we define treatment exposure using the natural logarithm of the Social Connectedness Index (SCI) between the local markets and the disaster-affected counties. This index is developed by Bailey et al. (2018) based on the Facebook friendship network, and captures the intensity of interpersonal ties between regions. The results in Panel B of Figure 4 show a similar rise in E&S sensitivity following the disaster, but the effect is more persistent, extending several quarters beyond the event. This temporal pattern supports the view that socially connected consumers remain engaged with the implications of disasters over a longer horizon, likely due to ongoing conversations and updates from their networks. The two figures indicate that both media coverage and social networks play a role in driving the short-run rise in E&S-to-sales sensitivity, but this effect decays faster in the media channel than through social ties.

6.3 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 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 various sources. One possible mechanism is that firms with more E&S strengths and fewer E&S concerns increase their supply because of a lower cost of capital (Albuquerque et al., 2019; Pedersen et al., 2021; Pástor et al., 2021). Another possible mechanism 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 et al., 2023).

Several pieces of evidence speak more in favor of the demand interpretation, however. First, our finding that consumers' responses to a firm's E&S efforts depend on the demographics of the county where the products are sold is unlikely to be explained by the supply effects. While a firm with improving E&S performance may choose to increase supply more in counties that are more sensitive to these performance enhancements, 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, with regard to the tests on natural and environmental disasters, supply-side factors could explain why firms might reallocate inventory from disaster-stricken areas to nearby markets, increasing product availability and sales in those locations. However, while such supply-side shifts may plausibly affect the overall *level* of sales or prices, they are unlikely to explain the observed increase in the *correlation* between E&S ratings and consumer purchases. Specifically, we find that following nearby disasters, consumers become more likely to buy from firms with higher E&S ratings and less likely to buy from those with lower ratings. This pattern is more consistent with a change in consumer preferences driven by heightened awareness of E&S issues following salient environmental events.

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 more plausible explanation for this result.

Fourth, the within-year sales response to negative ESG news is also more likely to be driven by reduced consumer demand than by reduced supply by the firm, as it is unlikely that negative ESG news would affect the short-term within-year supply of a firm's products.

Fifth, retailers and manufacturers generally hold substantial inventories. Table A26 in the Internet Appendix reports inventory days for selected firms: roughly one to four months for retailers and one to three months for manufacturers. For supply disruptions to arise, retailers and manufacturers must deplete their inventories. Thus, such disruptions should appear in the data with a lag, yet we find that the effect of negative news and disasters occurs within a month.

The above arguments favor a demand- over a supply-driven interpretation of our findings.

7 Does the Stock Market Price in the Cash Flow Effect of E&S?

Our results thus far suggest that firm E&S performance can influence consumer demand and, therefore, impact future cash flows. To investigate whether this cash-flow effect is priced, we examine the short-term stock market reaction to negative E&S news events and their predictive power for subsequent consumer demand.[31] We calculate the cumulative abnormal (market-adjusted) returns (CARs) around negative E&S news using a three-day window from one day before to one day after each news event. We sum these CARs across all E&S news events occurring within a given month and use these monthly aggregates from months $m-1$, $m-2$, and $m-3$ to predict product sales in month m.

Table A27 in the Internet Appendix reports the results. For the full sample, we do not find a significant negative relation between product sales and CARs around E&S news occurring in the prior three months, suggesting that investors either do not expect subsequent sales to decline as a result of the event or do not believe that these declines will affect the value of the firm. However, if we condition the sample on instances where firms also had negative E&S news in the prior months, we find that CARs around news events now significantly predict future sales. These findings imply that investors learn from past exposures and can more accurately anticipate the sales consequences of negative E&S news if such events had occurred previously. For a more detailed discussion of these results and additional evidence, see Section E in the Internet Appendix.

8 Conclusion

Using barcode-level sales data, we document that firms with better E&S performance experience significantly higher subsequent local product sales. The granularity of our data permits extensive use of high-dimensional fixed effects, thereby reducing concerns about omitted variables. A one-standard-deviation increase in a brand owner's E&S rating is associated with a 10.6% increase in next-year sales relative to similar products sold within the same county. Consumers respond more strongly to a firm's E&S performance when it is more advertising intensive and receives more negative media coverage, suggesting that advertising and media

[31] For recent work studying the stock price reaction associated with negative E&S news, see Gantchev et al. (2022), Akey et al. (2024), and Derrien et al. (2025).

coverage are channels through which consumers can become informed about a firm's E&S activities. Consumer responses also vary significantly by demographic groups: consumers from more Democratic Party leaning counties and counties with higher average income have stronger E&S preferences. Moreover, we document meaningful competitive effects, as local product sales decline when rivals in the same county achieve superior E&S ratings.

We use two sets of tests to further tighten the identification of our results. First, we find that monthly sales decline following negative E&S news, and the stock market reaction to such news predicts future sales. Second, leveraging quasi-exogenous shocks from natural and environmental disasters, we observe heightened consumer sensitivity to firms' E&S ratings after such shocks in counties near disaster-stricken counties, counties within the same media market, and counties with more social connections to the disaster-stricken counties.

There are various reasons why consumers could have E&S preferences: (a) personal values and ethics; (b) avoidance of guilt and negative impact; (c) social pressure; (d) concern about long-term sustainability and future generations. Although our setting does not allow us to disentangle these underlying motives, the finding that the impact of E&S ratings on subsequent sales strengthens in counties close to disaster-stricken counties suggests that concern about long-term sustainability is an important contributing factor.

Do companies actually profit from increased sales associated with higher E&S ratings, or do they spend the additional revenue primarily on (potentially superficial) marketing or better product features? We provide robust evidence that increased sales explain at least part of the cash flow channel of E&S. However, our data do not allow us to measure the associated costs and resulting profits. Evaluating the profitability implications of increased sustainability remains a crucial avenue for future research.

Regarding policy implications, our findings imply that consumer preferences can play a significant role in steering firms toward sustainability, even without stringent regulatory mandates. The concern with such "top-down" regulatory mandates is that they impose costly requirements on firms and consumers, many of whom may not actually care about E&S. However, if a segment of consumers actively prefers products from high-E&S companies, this "bottom up" approach can encourage E&S investment without additional regulation. When other consumers, who may not care about sustainability per se, notice that E&S activities are good for business, they may become more supportive of such activities themselves.

Our study also provides evidence of the beneficial informational role of media coverage in curbing potential greenwashing, implying that media scrutiny can serve as a disciplinary force for firms. Regulation could then focus on reducing the cost of E&S investments, such as by streamlining permitting processes, rather than imposing rigid compliance requirements.[32]

Appendix: Variable Definitions

This appendix provides the variable definitions for variables employed in the paper. For variables only employed in the Internet Appendix, the variable definitions are in Appendix F of the Internet Appendix. The variable definitions are provided in alphabetical order, with the exception that the ln() part of a variable name is ignored. The control variables (but neither the dependent variable nor the E&S variables) are winsorized at the 1% and 99% level.

- *Advertising*: Advertising expenditures divided by concurrent sales. Internet Appendix Table A15 illustrates alternative ways of measuring firms' advertising intensity.
- *ln(Assets)*: The natural logarithm of total assets in millions of dollars.
- *ln(#Counties)*: The natural logarithm of the number of counties for which the firm has positive sales of any product.
- *Democrat*: The proportion of Democratic Party voters in the most recent presidential election for a county-year.
- *Disaster*: A binary variable that is one for observations in a county if an environmental or natural disaster occurred within 1,000 miles of the county in the past 6 months.
- *Education*: The percentage of the population with a college education or above in a county-year.
- *E&S*: Following Albuquerque et al. (2019), we sum the number of strengths across all five categories for each firm-year, subtract the total number of concerns for each firm-year, and divide this difference by the sum of the maximum number strengths and maximum number of concerns. This measure ranges from -1 to 1. The measure covers five categories: employee relations, community, environment, diversity, and human rights.

[32] An example of fast permitting is that in 2023 and 2024 Texas, a state that is often deemed to be unfriendly toward renewable energy, built more renewable energy than the rest of the US combined.

- $\Delta E\&S$: The first difference of the $E\&S$ rating.
- $I[\Delta E\&S \in \textit{Quintile } i]$: An indicator variable set equal to 1 if $\Delta E\&S$ falls in quintile i of the annual cross-section of firms (Quintile 1 most negative, Quintile 5 most positive; Quintile 3 omitted in regressions), and zero otherwise.
- *E&S Concerns*: The concerns component of the *E&S* variable.
- *E&S Strengths*: The strengths component of the *E&S* variable.
- *E&S (rival average)*: The average of the E&S scores of the firm's local (within county) peer firms that sell products in the same product module.
- *E&S (rival top)*: The maximum of the E&S scores of the firm's local (within county) peer firms that sell products in the same product module.
- *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 in a given year.
- $I[Common\_Media\_Coverage]$: An indicator variable if a county and the disaster county are in the same state or in the same designated market area (DMA; a definition of common media markets by NielsenIQ).
- *Income*: The average income per capita (in thousands of dollars) in a county-year.
- *Inst. Ownership*: The number of shares held by institutional investors divided by the total number of shares outstanding.
- *Leverage*: (Long-term debt + debt in current liabilities) / total assets.
- *ln(#Modules)*: The natural logarithm of the number of product modules in which the firm has positive sales.
- $\Delta News$: The first difference of the *News* variable, which captures the change in the number of E&S-related news items from RepRisk.
- *ln(Number_of_Stores)*: The natural logarithm of the number of stores with non-zero sales at the product-month-level.
- *ln(Price)*: The natural logarithm of price per unit.
- *Proximity*: *Distance* is the distance between the disaster county and the focal county in miles. *Proximity* is the negative natural logarithm of *Distance*. We also decompose *Distance* into four dummy variables that indicate post-event markets within 0-200 miles, 200-400 miles, 400-600 miles, and 600-800 miles, with the base group being those more than 800 miles away from the disaster location. See, for example, $I[\text{Distance}\in$

$(0mi, 200mi]$.

- *Q*: (Total assets - book value of common equity - deferred taxes + market value of common equity) / Total assets.
- *R&D*: R&D expenditures divided by concurrent sales. Internet Appendix Table A15 illustrates alternative ways of measuring firms' R&D intensity.
- *ROA*: EBITDA divided by lagged assets.
- *ln(Sales)*: The natural logarithm of dollar sales.
- *ln(Sales_per_Store)*: The natural logarithm of dollar sales per store. First, the average sales per store are computed (for all stores with non-zero sales). Then the natural logarithm of this average is taken (all calculations are at the product-month-level).
- *ln(Social Connectedness Index)*: The natural logarithm of the Social Connectedness Index between a county and the disaster county. The Social Connectedness Index is from Bailey et al. (2018). Social connections are based on Facebook data.
- *ln(Units)*: The natural logarithm of number of units sold.

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Figure 1: Alternative Fixed Effects for Baseline Specification

This figure re-estimates the baseline specification of model (4) of Table 3, which is reported as the first model of this figure, with different sets of fixed effects. The dependent variable is the natural logarithm of dollar sales of a given firm in a product module-county-year. The independent variable of interest is *E&S*. We control for *ln(Assets)*, *Leverage*, *Q*, *ROA*, *Advertising*, and *R&D*. Detailed definitions of the variables are in the Appendix. We plot the 90% confidence intervals for the point estimates based on three-way clustered standard errors at the firm, product module, and county levels. The grid below the coefficient plot summarizes the set of controls and fixed effects included in each specification. Each column represents one regression model (numbered 1–19). A dark square indicates that the corresponding control or fixed effect labeled on the left is included in that specification, while a light square indicates that it is not.

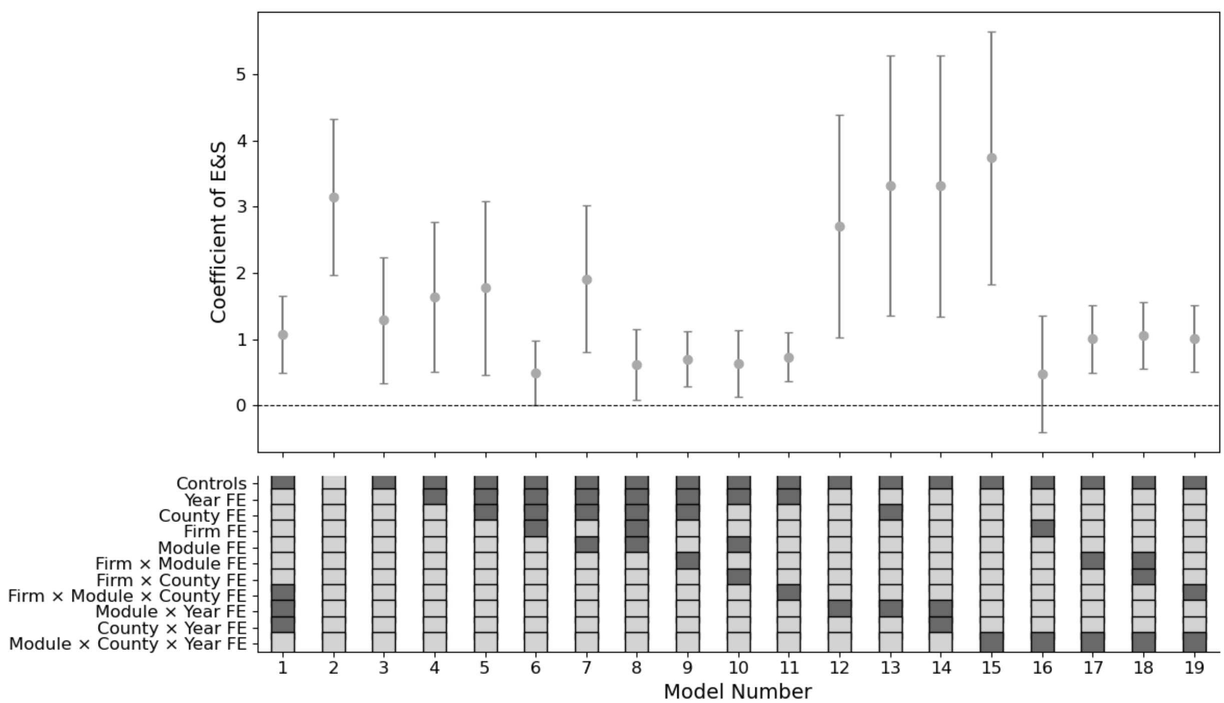


Figure 2: Product Sales Around Negative E&S News

This table presents the estimates of a stacked DID Model using product-level sales data from six months before to six months after negative E&S news events. Each treated product is matched to a control product from the same product module that has no negative E&S news prior to the event month and exhibits the pre-event trend in sales volume closest to the treated product. If the difference in the sales trends exceeds 10%, the matched treated-control pair is removed. The horizontal axis refers to months around the E&S news event. Each node illustrates the point estimate for the interaction between the treatment indicator and corresponding event-month indicators. The dashed lines represent 95% confidence intervals.

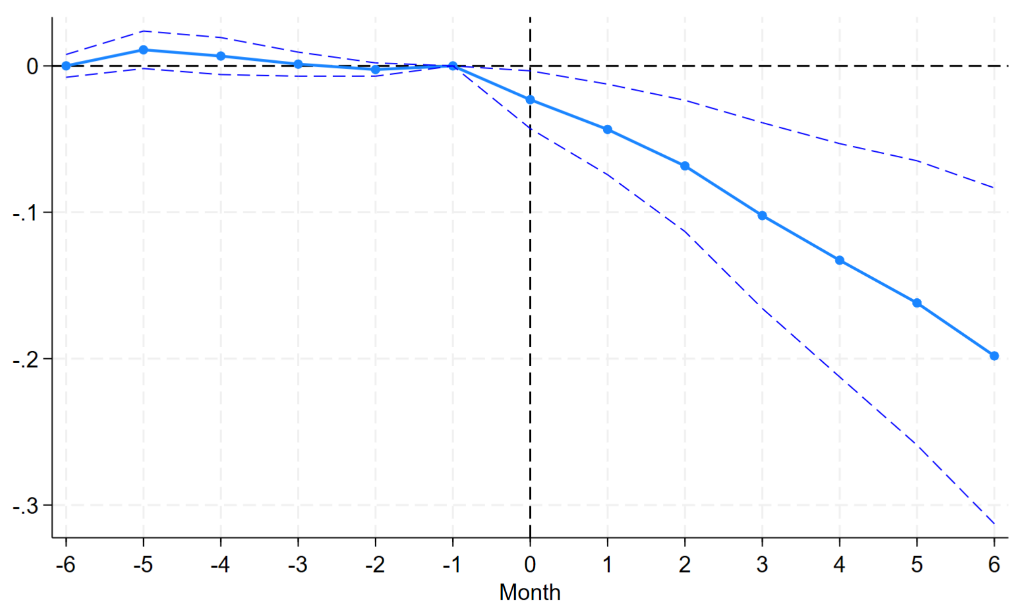


Figure 3: Product Sales Around Nearby Natural and Environmental Disasters

This figure presents the estimates of a dynamic version of Equation (4) using firm-product department-county-month level sales data, where the *Disaster* indicator is replaced with event-quarter indicators in the triple interaction term of Equation (4) to estimate the treatment effect on a quarterly basis over the event window around the disasters. The dependent variable is the natural logarithm of dollar sales. The horizontal axis refers to quarters around a disaster event. Each node denotes the point estimate for the interaction between the *E&S* rating, geographic proximity to the disaster proxied by negative log distance, and the corresponding event-quarter indicator. The dashed lines represent 95% confidence intervals.

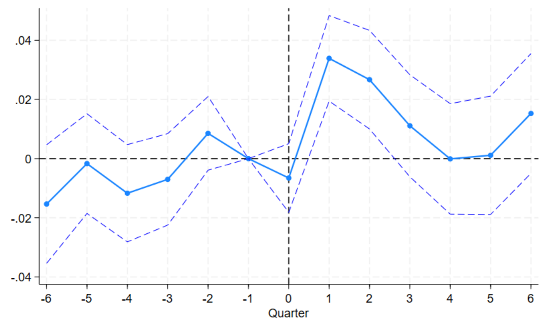
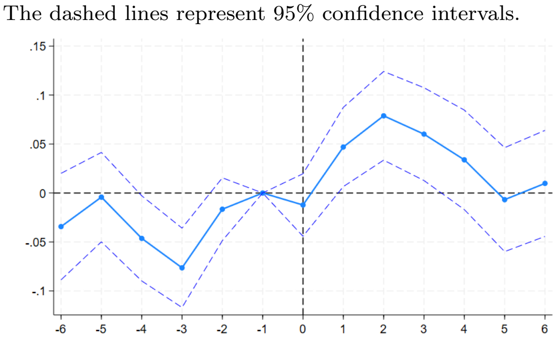
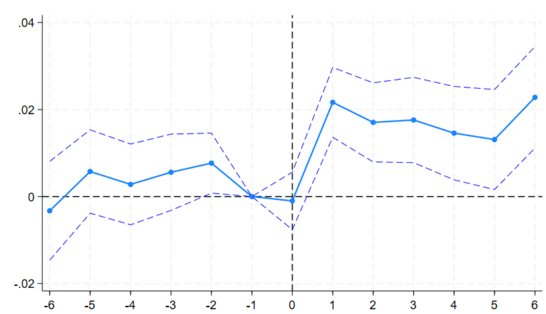


Figure 4: Product Sales Around Nearby Natural and Environmental Disasters — Common Media Coverage and Social Connections

This figure presents the estimates of a dynamic version of Equation (4) using firm-product department-county-month level sales data, where the *Disaster* indicator is replaced with event-quarter indicators in the triple interaction term of Equation (4) to estimate the treatment effect on a quarterly basis over the event window around the disasters. The dependent variable is the natural logarithm of dollar sales. In Panel A the treatment variable is a common-media-coverage indicator that equals one if the consumer market is in the same state or DMA (Designated Market Area) as the disaster county. In Panel B the treatment variable is the log of the Social Connectedness Index (SCI) between a given county and the disaster county. Each node shows the coefficient estimate on the interaction between the *E&S* rating, the treatment variable, and the event-quarter indicator. The dashed lines represent 95% confidence intervals.



Panel A: Common Media Coverage



Panel B: Social Connectedness Index (SCI)

Table 1: Comparison with Recent Papers on the Cash-Flow Channel of ESG

This table compares our study with recent papers on the cash flow channel of ESG/E&S. The table is coded based on the versions of the papers available on SSRN as of October 3, 2025. The column for *Main Dep. Variable* contains the data source for the main dependent variable. Product Granularity refers to the use of product-level variation in the tests. Geographic Granularity refers to the use of county-level variation in the tests. The column for *Quasi-Natural Experiment* excludes those using ESG incidents/news. The column for *Finance Outcomes* excludes firm sales/consumer purchases as outcome variables. Robustness implies it is used in a robustness test, but not as the main variable. G stands for the Governance in ESG; S stands for Social in ESG.

Paper	Main Dep. Variable	Actual Sales	Product Granularity	Geographic Granularity	E&S Rating (Main)	E&S Rating (Robustness)	E&S Incidents	E&S Strengths & Concerns	Quasi-Natural Experiment	Finance Outcomes
Our paper	Barcode Sales	✓	✓	✓	MSCI ESG Stats	Sustainalytics, RepRisk	✓	✓	✓	✓
Agarwal et al. (2023)	Chinese Credit Card	✓			Sino-Securities Index (incl. G)	ESG from Hexun.com			✓	✓
Cen et al. (2024)	Survey	Self-Reported			Workplace Equality	MSCI Diversity			✓	✓
Christensen et al. (2023)	Barcode Sales	✓	✓				S			Analyst Forecasts
Conway and Boxell (2024)	US Credit Card	✓		✓	S Alignment					✓
Duan et al. (2024)	Store Visits	Robustness		✓		Sustainalytics, RepRisk	✓ (incl. G)		✓	✓
Dube et al. (2023)	Store Visits	Robustness					✓ (incl. G)			
Hacamo (2023)	Store Visits			✓			Racial Prejudice			
Houston et al. (2024)	Survey	Self-Reported	✓				✓ (incl. G)		✓	
Xiao et al. (2025)	Store Visits	Robustness		✓			✓			✓

Table 2: Summary Statistics

Panel A presents variables in the firm–product module–county–year level sample. Panel B presents variables in the product-month level sample. Panel C presents variables in the event-firm–department–county–month level sample. A detailed description of these variables is in the Appendix.

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

	N	Mean	S.D.	P25	P50	P75
ln(Sales)	16,616,170	6.83	2.54	5.07	6.76	8.55
ln(Units)	16,616,170	5.52	2.60	3.66	5.44	7.31
ln(Price)	16,616,170	1.37	0.83	0.86	1.25	1.83
E&S	16,616,170	0.08	0.09	0.02	0.08	0.13
ln(Assets)	12,564,537	9.70	1.55	8.42	9.79	11.11
Leverage	12,564,537	0.32	0.14	0.24	0.29	0.42
Q	12,564,537	2.23	0.98	1.56	1.97	2.56
ROA	12,564,537	0.17	0.07	0.12	0.15	0.21
Advertising	12,564,537	0.06	0.04	0.02	0.05	0.09
R&D	12,564,537	0.02	0.02	0.01	0.01	0.02
Governance	12,564,537	-0.00	0.09	0.00	0.00	0.00
Inst. Ownership	12,564,537	0.69	0.18	0.61	0.70	0.77
Democrat	16,139,160	0.41	0.14	0.31	0.41	0.51
Income	16,527,560	65.21	17.39	53.73	61.42	72.12
Education	16,527,560	14.87	6.04	10.20	13.70	18.60

Panel B: Sample at the product-month level

	N	Mean	S.D.	P25	P50	P75
ln(Sales)	3,011,688	8.01	3.72	5.06	8.69	11.09
ln(Number_of_Stores)	3,011,688	5.11	2.93	2.64	5.36	7.65
ln(Sales_per_Store)	3,011,688	2.91	1.40	2.08	2.87	3.69
$\text{News}_{m-3,m-1}$ (All)	3,011,688	1.32	1.82	0.00	1.00	2.00

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

	N	Mean	S.D.	P25	P50	P75
ln(Sales)	43,373,020	6.65	2.48	4.85	6.59	8.37
E&S	43,373,020	0.07	0.09	0.00	0.06	0.12
Proximity	43,373,020	-6.25	0.61	-6.69	-6.42	-5.99
$I[Common\_Media\_Coverage]$	43,373,020	0.06	0.23	0.00	0.00	0.00
ln(Social Connectedness Index)	43,373,020	7.82	1.13	7.10	7.63	8.30

Table 3: E&S Ratings and Local Product Sales

This table presents estimates of Equation (1), which is estimated at the firm–product module–county–year level. The dependent variables are the natural logarithm of dollar sales, the natural logarithm of unit sales, and the natural logarithm of price per unit. The independent variable of interest is *E&S*. In models (4) to (6), we control for the following firm characteristics: *ln(Assets)*, *Leverage*, *Q*, *ROA*, *Advertising*, and *R&D*. Detailed definitions of the variables are in the Appendix. The t-statistics in parentheses are estimated based on three-way clustered standard errors at the firm, product module, and county levels. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	ln(Sales) (1)	ln(Units) (2)	ln(Price) (3)	ln(Sales) (4)	ln(Units) (5)	ln(Price) (6)
E&S	1.1216***	1.1368***	0.0223	1.0662***	1.1354***	0.0014
	(3.54)	(3.32)	(0.36)	(3.01)	(2.94)	(0.01)
ln(Assets)				0.0788	0.1094	-0.0330**
				(0.71)	(0.96)	(-2.26)
Leverage				-0.1799	-0.2054	0.0092
				(-0.51)	(-0.59)	(0.17)
Q				-0.0111	-0.0191	0.0022
				(-0.17)	(-0.31)	(0.21)
ROA				1.4947**	1.1670*	0.2731**
				(2.49)	(1.96)	(2.48)
Advertising				6.2761***	5.4637***	0.4868
				(2.83)	(2.64)	(1.14)
R&D				2.2611	-1.2319	2.9267*
				(0.44)	(-0.27)	(1.74)
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	0.904	0.915	0.931	0.915	0.923	0.937
Observations	16,616,170	16,616,170	16,616,170	12,564,537	12,564,537	12,564,537

Table 4: E&S Ratings and Local Product Sales — Firm-Level Evidence

This table presents regression models of firm sales as a function of E&S and control variables using firm-year level data. The dependent variable is the natural logarithm of dollar sales aggregated across product modules and counties in a given year. The independent variable of interest is *E&S*. We control for the following firm characteristics: *ln(Assets)*, *Leverage*, *Q*, *ROA*, *Advertising*, and *R&D*. We also control for ln(#Modules) and ln(#Counties), defined as the log number of distinct product modules and counties with positive sales within a firm-year. Detailed definitions of the variables are in the Appendix. The *t*-statistics in parentheses are estimated based on standard errors clustered at the firm level. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:		*ln(Sales)*		
	(1)	(2)	(3)	(4)
E&S	4.4039**	1.7621**	2.9613	1.6508*
	(2.57)	(2.16)	(1.54)	(1.91)
ln(# Modules)		0.5363***		0.7472***
		(3.66)		(4.59)
ln(# Counties)		1.5385***		1.5724***
		(19.67)		(15.93)
Control Variables	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.897	0.971	0.924	0.980
Observations	1,576	1,576	765	765

Table 5: E&S Ratings and Local Product Sales — First Difference Regressions

This table presents estimates of Equation (1) using a first-difference specification at the firm–product module–county–year level. The dependent variable is the first difference in the natural logarithm of dollar sales. The main independent variable is the lagged first difference in the *E&S* rating. Model (1) uses the continuous first-differenced measure; model (2) replaces it with quintile indicators constructed within each calendar year: Quintile 1 represents the most negative changes, Quintile 5 represents the most positive changes, and Quintile 3 is the middle quintile omitted as the base group. The control variables *ln(Assets)*, *Leverage*, *Q*, *ROA*, *Advertising*, and *R&D*, are also first-differenced. Detailed definitions of the variables are in the Appendix. *t*-statistics, reported in parentheses, are based on three-way clustered standard errors at the firm, product module, and county levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	Δln(Sales)	
	(1)	(2)
$\Delta E\&S$	0.6187**	
	(2.49)	
$I[\Delta E\&S \in$ Quintile 1]		-0.0368*
		(-1.66)
$I[\Delta E\&S \in$ Quintile 2]		0.0040
		(0.08)
$I[\Delta E\&S \in$ Quintile 4]		0.0081
		(0.16)
$I[\Delta E\&S \in$ Quintile 5]		0.0673**
		(2.14)
Control Variables (First-differenced)	Yes	Yes
County × Year FE	Yes	Yes
Module × Year FE	Yes	Yes
Adjusted R^2	0.243	0.243
Observations	10,625,136	10,625,136

Table 6: E&S Ratings and Local Product Sales — Governance and Institutional Ownership

This table presents estimates of Equation (1), which is estimated at the firm–product module–county–year level, with the inclusion of controls for corporate governance. The dependent variable is the natural logarithm of dollar sales. The independent variable of interest is *E&S*. We also control for the following firm characteristics: *ln(Assets)*, *Leverage*, *Q*, *ROA*, *Advertising*, and *R&D*. In model (1), the governance control is the standardized corporate governance rating using MSCI ESG Stats, applying the same scaling methodology as for our E&S measure. In model (2), the governance control is institutional ownership. Detailed definitions of the variables are in the Appendix. The t-statistics in parentheses are estimated based on three-way clustered standard errors at the firm, product module, and county levels. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	ln(Sales)	
	(1)	(2)
E&S	1.0184***	1.0899***
	(3.16)	(3.15)
Governance	0.1617	
	(0.85)	
Inst. Ownership		-0.1480
		(-1.39)
Control Variables	Yes	Yes
Firm × Module × County FE	Yes	Yes
County × Year FE	Yes	Yes
Module × Year FE	Yes	Yes
Adjusted R^2	0.915	0.915
Observations	12,564,537	12,564,537

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

This table presents estimates of Equation (1), which is estimated at the firm–product module–county–year level, with additional interactions between Advertising and E&S and splits of E&S into strengths and concerns. The dependent variable is the natural logarithm of dollar sales. The independent variables of interest are the E&S rating, its strength and concern components, and their interactions with *Advertising*. We control for the following firm characteristics: *ln(Assets)*, *Leverage*, *Q*, *ROA*, and *R&D*. Detailed definitions of the variables are in the Appendix. The t-statistics in parentheses are estimated based on three-way clustered standard errors at the firm, product module, and county levels. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:		ln(Sales)	
	(1)	(2)	(3)
E&S	-0.0342		
	(-0.07)		
Advertising	5.3824**	6.2700***	5.1915**
	(2.29)	(2.80)	(2.25)
E&S × Advertising	14.7479**		
	(2.17)		
E&S Strengths		1.0880***	-0.0907
		(2.81)	(-0.20)
E&S Concerns		-0.8766	-0.6213
		(-1.37)	(-0.46)
E&S Strengths × Advertising			15.0320**
			(2.28)
E&S Concerns × Advertising			-0.6870
			(-0.03)
Control Variables	Yes	Yes	Yes
Firm × Module × County FE	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes
Module × Year FE	Yes	Yes	Yes
Adjusted R^2	0.915	0.915	0.915
Observations	12,564,537	12,564,537	12,564,537

Table 8: Changes in E&S Ratings, E&S News Coverage, and Local Product Sales

This table presents estimates of Equation (1) using a first-difference specification at the firm-product module-county-year level. The dependent variable is the first difference in the natural logarithm of dollar sales. We decompose the absolute change in $E\&S$ into positive and negative components, and interact them with ΔNews, the change in the number of E&S-related news items from RepRisk. Both $\Delta E\&S$ and ΔNews are computed at the firm-product module-county level. The control variables *ln(Assets)*, *Leverage*, *Q*, *ROA*, *Advertising*, and *R&D*, are also first-differenced. Detailed definitions of the variables are in the Appendix. The t-statistics, reported in parentheses, are based on three-way clustered standard errors at the firm, product module, and county levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	Δln(Sales)	
	(1)	(2)
$\|\Delta E\&S\|$ (*positive*)	1.0701**	0.9414*
	(2.42)	(1.96)
$\|\Delta E\&S\|$ (*negative*)	-0.1265	0.1125
	(-0.37)	(0.28)
$\|\Delta E\&S\|$ (*positive*) $\times$ $\Delta News$		-0.2399
		(-1.58)
$\|\Delta E\&S\|$ (*negative*) $\times$ $\Delta News$		-0.3345**
		(-2.25)
$\Delta News$		0.0068
		(1.22)
Control Variables (First-differenced)	Yes	Yes
County × Year FE	Yes	Yes
Module × Year FE	Yes	Yes
Adjusted R^2	0.243	0.264
Observations	10,625,136	9,124,045

Table 9: Local Market Demographics, E&S Ratings, and Local Product Sales

This table presents the estimates of Equation (2), which is estimated at the firm-product 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 Party voters, income per capita, and the percentage of the population with a college degree or above. Models (1) to (3) include the interaction of each county characteristic with our E&S measure, and model (4) includes all three interactions. Detailed definitions of the variables are in the Appendix. The *t*-statistics in parentheses are estimated based on three-way clustered standard errors at the firm, product module, and county levels. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	ln(Sales)			
	(1)	(2)	(3)	(4)
E&S × Democrat	0.5726***			0.5641***
	(3.01)			(3.45)
E&S × Income		0.0037		0.0051**
		(1.28)		(2.54)
E&S × Education			0.0065	-0.0086
			(0.72)	(-0.99)
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	0.910	0.910	0.910	0.910
Observations	16,139,160	16,527,560	16,527,560	16,139,160

Table 10: E&S Ratings of Local Product Market Rivals

This table presents regressions estimated at the firm-product module-county-year level, where the dependent variable is the natural logarithm of dollar sales. The independent variables of interest are the average and the maximum *E&S* ratings of local peer firms that sell products in the same product module and in the same county. In the even columns, we include the following characteristics for the average rival firm: *ln(Assets)*, *Leverage*, *Q*, *ROA*, *Advertising*, and *R&D*. Detailed definitions of the variables are in the Appendix. The t-statistics in parentheses are estimated based on three-way clustered standard errors at the firm, product module, and county levels. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	ln(Sales)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
E&S (rival average)	-1.1233**	-1.0973***	-0.2663	0.1226				
	(-2.48)	(-2.66)	(-0.68)	(0.38)				
E&S (rival top)					-1.4501***	-1.3453***	-1.0223***	-0.6884*
					(-3.86)	(-3.19)	(-2.92)	(-1.77)
Average Rival Firm Controls	No	Yes	No	Yes	No	Yes	No	Yes
Firm × Module × County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm × Year FE	No	No	Yes	Yes	No	No	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Module × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.893	0.900	0.901	0.906	0.893	0.900	0.901	0.906
Observations	9,965,389	6,545,945	9,965,311	6,545,925	9,965,389	6,545,945	9,965,311	6,545,925

Table 11: E&S News and Monthly Product Sales

This table presents the estimates of Equation (3) using product-month-level data. The dependent variable in model (1) is the natural logarithm of dollar sales of a given product in month m. The dependent variable in model (2) is the natural logarithm of the number of stores with non-zero sales of the product. The dependent variable in model (3) is the natural logarithm of product dollar sales per store. The independent variables are the number of negative news stories on RepRisk from month $m-6$ to month $m-4$, from month $m-3$ to month $m-1$, and from month $m+1$ to month $m+3$. All types of news except governance are included. Firm fixed effects are subsumed by product fixed effects. Detailed definitions of the variables are in the Appendix. The t-statistics in parentheses are estimated based on two-way clustered standard errors at the firm and product module levels. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	ln(Sales)$_m$ (1)	ln(Number_of_Stores)$_m$ (2)	ln(Sales_per_Store)$_m$ (3)
News$_{m-6,m-4}$	-0.0074**	-0.0058*	-0.0015
	(-2.07)	(-1.89)	(-1.42)
News$_{m-3,m-1}$	-0.0111***	-0.0093***	-0.0018*
	(-2.96)	(-2.78)	(-1.82)
News$_{m+1,m+3}$	0.0012	0.0006	0.0005
	(0.45)	(0.31)	(0.59)
Module × Year-month FE	Yes	Yes	Yes
Product × Year FE	Yes	Yes	Yes
Adjusted R^2	0.937	0.946	0.903
Observations	3,011,688	3,011,688	3,011,688

Table 12: E&S News and Monthly Product Sales — Event-study Approach

This table presents the estimates of a stacked DID Model using monthly product-level sales data from six months before to six months after negative E&S news events. Treated firm-products are products from firms that receive at least one negative news story in a given month. Control firm-products are products from firms that do not receive a negative news story during a given month and the prior six months, that are part of the same product module, and have sales growth in the previous six months closest to the treated firm-products. If there are no control firm-products with a sales trend within 10% of the treated firm-product, the treated firm-product is removed. Control firm-products are chosen with replacement. *Treated* is an indicator variable that equals one for the treated products. *Post* is an indicator variable that equals one for the post-news months. *Severe* is an indicator variable that equals one for the most severe news based on the severity score provided by RepRisk. All news events that occur in the same month are considered as one cohort. Firm fixed effects are subsumed by the product fixed effects. Detailed definitions of the variables are in the Appendix. The *t*-statistics in parentheses are estimated based on two-way clustered standard errors at the firm and module levels. *, ** and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	ln(Sales) (1)	ln(Units) (2)	ln(Price) (3)	ln(Sales) (4)	ln(Units) (5)	ln(Price) (6)
Treated × Post	-0.1070***	-0.0997***	-0.0067***	-0.1057***	-0.0983***	-0.0069***
	(-3.13)	(-3.11)	(-2.67)	(-3.14)	(-3.11)	(-2.80)
Treated × Post × Severe				-0.0289	-0.0323	0.0036
				(-0.66)	(-0.74)	(0.87)
Cohort × Product FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort × Module × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.963	0.965	0.983	0.963	0.965	0.983
Observations	5,023,330	5,023,330	5,023,330	5,023,330	5,023,330	5,023,330

Table 13: Product Sales Around Natural and Environmental Disasters

This table presents the estimates of a stacked DID model (Equation (4)) using product sales data aggregated to the firm-product department-county-month level. For each disaster event, we include observations located within 1000 miles of its location (excluding the disaster county) and keep a 37-month window (i.e., 18 months before, 18 months after) around the event. We then stack the relevant observations for all the events for estimation. The dependent variable is the logarithm of dollar sales. In model (1), the independent variable is the triple interaction term $E\&S \times Disaster \times Proximity$. *Disaster* is a binary variable that equals one for observations in each event if an environmental disaster occurs in the past 6 months. *Distance* is the distance between the disaster county and the focal county in miles. *Proximity* is geographic proximity computed as the negative of the natural logarithm of *Distance*. In model (2), we decompose *Distance* into four binary variables based on various intervals. Detailed definitions of the variables are in the Appendix. The t-statistics in parentheses are estimated based on two-way clustered standard errors at the firm and county levels. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	ln(Sales)	
	(1)	(2)
E&S × Disaster × Proximity	0.0309*	
	(1.87)	
E&S × Disaster × I[Distance$\in$ (0mi, 200mi]]		0.0802**
		(2.23)
E&S × Disaster × I[Distance$\in$ (200mi, 400mi]]		0.0340
		(1.32)
E&S × Disaster × I[Distance$\in$ (400mi, 600mi]]		0.0122
		(0.56)
E&S × Disaster × I[Distance$\in$ (600mi, 800mi]]		0.0200
		(1.08)
Event × Firm × Department × County FE	Yes	Yes
Event × Department × Year-month FE	Yes	Yes
Event × Firm × Year-month FE	Yes	Yes
Event × County × Year-month FE	Yes	Yes
Adjusted R^2	0.969	0.969
Observations	43,373,020	43,373,020

Internet Appendix for "Do Consumers Care About ESG? Evidence from Barcode-Level Sales Data"

A Additional Details on the Data

A.1 Incentives of manufacturers and retailers to share data with NielsenIQ

Retailers and manufacturers both have strong incentives to share data with NielsenIQ.

- Manufacturers benefit from data sharing with NielsenIQ by gaining:
  - Retail-end visibility and market share: Manufacturers see actual retail sales and shares by category, brand, package, channel, and time, rather than only their shipments and wholesale prices.
  - Promotion and pricing effectiveness: Point of Sale (POS) data facilitates promotion response analysis and marketing mix modeling.
- Retailers benefit from data sharing with NielsenIQ by gaining:
  - Category management and benchmarking: Retailers benchmark categories and brands against the broader market, they optimize assortment and shelf space, and calibrate pricing and promotions.
  - Negotiation with suppliers: Third-party market reads help retailers and manufacturers negotiate trade terms using common, audited facts on category growth and share.
- Why do both parties use a third party like NielsenIQ rather than bilateral data exchange?
  - While retailers and manufacturers can share data directly, such bilateral arrangements often lack standardization and are susceptible to conflicts of interest. For example, retailers may have incentives to overstate the effectiveness of their promotions or selectively report sales data. Moreover, manufacturers and retailers are unlikely to trust their competitors to provide valid or complete data. NielsenIQ plays a neutral intermediary role, standardizing, auditing, and aggregating data across the retail landscape. This enables reliable market share measurement and facilitates multi-party decision-making.

- Beyond data aggregation, NielsenIQ also offers analytical services, including demand forecasting, promotion response modeling, and pricing optimization, that depend critically on harmonized, cross-retailer data. These services would not be possible through fragmented bilateral sharing alone.

A.2 Name matching

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. 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 obtain company prefix (GCP) and company name mappings from a 2014 snapshot of an open-source dataset originally hosted under the Product Open Data (POD) project, the predecessor to barcode.io. `https://github.com/EventideSystems/brocade_sources`. Although the original POD website is no longer actively maintained and has evolved into `barcode.io`, the 2014 snapshot provides a historical mapping between products and brand owners that aligns with our 2008–2019 sample period. This approach offers a more accurate historical link than the current GS1 registry (the organization responsible for issuing barcodes), which reflects only the current ownership information and may not accurately capture past firm–product links due to mergers and acquisitions during our sample period.

A.3 Time series plots

Panel A of Figure A2 shows the evolution of the average lagged E&S score, which ranges between -1 and 1.

Panels B through E of Figure A2 display time trends in key product-market outcomes: dollar sales (*ln(Sales)*), number of unique products offered (*ln(Products)*), number of units sold (*ln(Units)*), and average unit price (*ln(Price)*). Outside of the 2008-2009 financial crisis and its aftermath, the consumer demand patterns are relatively stable.

A.4 Industry distribution and distribution of firm characteristics for sample firms, sample-industry firms, and the Compustat universe

To understand how our sample firms compare to the Compustat universe, we examine the distributions of industry classifications in Figure A3. Our sample is heavily concentrated in consumer-related industries. For example, firms in the Food Products sector constitute over 20% of our sample, compared to just 2% of all Compustat firms. Machinery and Business Equipment (e.g., HP for printer ink cartridges and Sandisk for memory cards) and Drugs, Soap, Perfumes & Tobacco are also substantially overrepresented. Similarly, industries like Textiles & Apparel, and Consumer Durables (e.g., Nike and Crocs) are more prevalent in our sample. In contrast, industries such as Finance, Mining and Minerals, Oil and Petroleum Products, and Utilities are underrepresented. Our baseline specification (Model (4) of Table 3) also holds if we exclude all firms with a Fama-French 17 industry classification of "retail". This exclusion reduces the sample size by only 0.52% while the coefficient for E&S is 1.1104 instead of 1.0662 (t-statistic is 3.08 instead of 3.01 in the baseline).

Table A5 compares the distributions of firm characteristics across three groups: our sample firms, firms in the same 4-digit SIC industries as our sample firms ("Sample-industry Firms"), and the broader Compustat universe. Our sample firms are substantially larger than both comparison groups. Sample-industry firms exhibit median values of *Leverage* between our sample firms (highest leverage) and the broader universe (lowest leverage). Our sample firms have slightly lower median valuation (*Tobin's Q*) than sample-industry firms, and notably higher median valuation than all Compustat firms. Profitability (*ROA*) is markedly higher among our sample firms, with most observations above zero and fewer extreme losses compared to both comparison groups. In terms of intangible investments, sample-industry firms' spending on *Advertising* falls between our sample firms (highest spending) and the broader universe (lowest spending). In contrast, our sample firms' investment in *R&D* is consistently lower than that of both groups.

The industry composition and the firm characteristics of the sample firms suggest that our sample consists mainly of large consumer-related firms (B2C firms), in particular in so-called fast-moving consumer goods (FMCG). Thus, generalizing our results to different contexts, particularly B2B industries, should be done cautiously.

B Product and market scope, and E&S-to-sales sensitivity at the firm-year level

Table A9 investigates how the number of product modules and markets in which the firm operates affects the firm-level E&S–to-sales sensitivity. To do so, we re-estimate our base-case model in Panel A of Table A9, but include interactions between E&S and the number of product modules (model (1)) and counties (model (2)). Both interaction terms are significantly negative, indicating that firms operating across more products and markets exhibit lower E&S-to-sales sensitivity, on average. Because firms that are diversified across product modules and/or counties carry greater weight in the disaggregated specification, this finding partially explains why our baseline estimate reported in Table 3 is smaller in magnitude than the firm-level estimate reported in Table 4.

Panel B of Table A9 provides further supporting evidence for this interpretation. Based on Table A7, we divide all products into two groups: high E&S-sensitivity products and low E&S-sensitivity products (product departments with a significant E&S effect at the 5% level are deemed to be E&S-sensitive). We then compute the fraction of each firm's sales that falls into the high E&S-sensitivity category. In model (1) of Panel B, we estimate a regression model where the dependent variable is the fraction of a firm's product modules in E&S-sensitive departments. The main explanatory variable is the natural logarithm of the number of product modules in which the firm operates. We find weak evidence that firms with more modules have a lower share of sales in E&S-sensitive departments (coefficient=–0.0329, t=–1.10). Note that the department-level E&S-sensitivity itself is inherently a noisy estimate, which may explain the lack of statistical significance. Nevertheless, this result suggests that firms selling products in more modules do so in modules that are less E&S-sensitive. In model (2) of Panel B, the dependent variable is the average share of Democratic voters across all counties in which the firm sells products. The main explanatory variable is the natural logarithm of the number of counties in which the firm operates. We find a strong negative relation between the two (coefficient=–0.0239, t=–5.78), suggesting that firms operating in more counties tend to have a lower average Democratic vote share. This pattern is consistent with a common growth dynamic in retail industries: firms often begin in more urban, densely populated counties (which, in recent years, have had higher Democratic vote shares) and expand into more rural counties (which have had lower

Democratic vote shares). These findings are consistent with the idea that a firm's aggregate exposure to E&S ratings depends on how its sales are distributed across product types and consumer segments.

Firm-year first-difference specification Table A10 presents first-difference regressions at the firm–year level. One concern with such a specification is that changes in consumer demand are combined with endogenous changes in product mix and market coverage, as each observation is now benchmarked against the previous year's product and market portfolio. If firms expand into product categories or geographies with lower E&S sensitivity over time (as illustrated in Table A9), the specification in first differences will mechanically attenuate the measured E&S sales relation, even if consumers continue to reward E&S improvements within a given product and market. In models (1) and (2) of Table A10, the coefficient on E&S is positive but statistically insignificant across specifications. In models (3) and (4), when we include the interaction between changes in E&S performance and changes in the average Democratic Party vote share across the counties in which a firm operates, this interaction is positive in both models, and statistically significant in model (3). Since changes in average Democratic vote capture shifts in the E&S sensitivity of a firm's market footprint, this result indicates that expansion into less Democratic counties dampens the aggregate E&S elasticity. These results suggest that estimating first-difference models at the firm level may conflate the impact of E&S changes on sales with changes in the E&S sensitivities of the products and markets into which the firm expands.

C Additional Robustness Tests

C.1 Product department subsamples

We examine heterogeneity across product types using subsample regressions by product department, as reported in Table A7. Departments correspond to the coarsest and most stable level of product classification in the NielsenIQ dataset. Across the ten departments analyzed, the estimated coefficient on the E&S score is positive in eight and statistically significant in five. The largest and most precisely estimated effects appear in Health and Beauty, General Merchandise, and Frozen Foods—categories that tend to feature products with relatively higher unit prices. For instance, the average price per unit in Health and Beauty is $8.39, and in General Merchandise it is \$13.60, compared to \$2.77 in Dry Grocery. While the price variation across departments is limited due to the nature of fast-moving consumer goods in our dataset, the results suggest that consumers may be more responsive to E&S practices in categories where the purchasing decision involves greater deliberation or where brand perception is more salient. The two departments showing negative coefficients—Fresh Produce and Alcohol—are also the smallest in sample size, and neither estimate is statistically significant. These results appear to be driven more by sampling noise than by meaningful economic differences.

In the above test, we use a simplified specification which drops the product module $\times$ year fixed effects and module-level clustering. This allows for greater degrees of freedom in department subsamples with few product modules. For robustness, we also re-estimate the department-level regressions using the baseline specification, which includes product module $\times$ year fixed effects and three-way clustering (Table A8). The results remain qualitatively consistent with Table A7.

C.2 Time-series variation in the effect of E&S

Here we explore whether the relation between E&S performance and product sales holds on an annual basis and whether there is a time-series pattern in the magnitude of the effect. To do so, we estimate a modified version of the baseline regression by interacting the lagged E&S score with year dummies, allowing the coefficient to vary by year. Since this specification requires sufficient within-year variation in E&S performance, we drop the firm$\times$product module$\times$county fixed effects to retain both cross-sectional and time-series variation. As a result, the estimated coefficients tend to be larger than in the baseline model, which relies entirely on within-unit variation. This specification corresponds to Model (14) in Figure 1, where we similarly omit unit fixed effects while keeping county$\times$year and product module$\times$year fixed effects.

Figure A4 presents the resulting year-by-year estimates with 90% confidence intervals. The effect of E&S performance on product sales is persistently positive and statistically significant throughout the sample period, reinforcing the robustness of our main results. Moreover, the magnitude of the coefficients becomes noticeably larger in recent years, suggesting that consumer demand has grown increasingly responsive to firm E&S performance over time. This pattern is consistent with rising public awareness and greater attention to environmental and social issues in the marketplace.

C.3 Corporate culture

Prior research attests to the importance of corporate culture in driving value and performance (Guiso et al. (2006); Graham et al. (2022)). To ensure that our E&S measure is not proxying for culture, we employ the five corporate culture proxies established by Li et al. (2021), which measure whether a firm's culture is more or less oriented towards 1) innovation, 2) integrity, 3) quality, 4) respect, and 5) teamwork. We construct these five proxies following the framework described in their paper (Internet Appendix Section F contains a more detailed definition of these variables). In Table A14, we report results controlling for each of these five proxies individually. The coefficient estimates for E&S are very similar to our baseline estimates, while the culture measures are generally insignificant.

C.4 Alternative definitions of advertising and R&D

The number of observations in models (4)–(6) of Table 3 declines by 24% due to missing values for advertising and R&D expenses in Compustat. While one common approach is to impute zeros for missing values, we avoid this in our main analyses because the firms in our sample are large, publicly listed, and consumer-facing, making it unlikely that they spend nothing on advertising. Moreover, prior research shows that some firms with missing R&D do innovate (Koh and Reeb, 2015). Nevertheless, in Table A15, we show that our results remain robust when we follow this imputation strategy (model (1)), when we scale advertising and R&D by assets instead of sales (model (2)), and when we combine both adjustments (model (3)).

C.5 Alternative proxies for firm size

In our main specification, we control for firm size using total assets. To ensure that our results are not sensitive to the specific size proxy used, we re-estimate our baseline model using alternative firm size measures, including total sales from Compustat, market value of assets, and market value of equity. As shown in Table A16, the estimated effect of E&S ratings on product sales remains positive and statistically significant across all specifications.

D Additional Evidence on the Consumer Response to Natural and Environmental Disasters

In Table A25, we show the results of the tests on natural and environmental disasters when we break the E&S measure down into its five subcomponents. For completeness, model (1) shows the overall result as reported in Table 13, while models (2) through (6), show the subcomponents. Panel A contains the results for the continuous measure of proximity. The effects are particularly pronounced for the community component of E&S, suggesting that disasters draw attention to firms' engagement with and support for local communities. Environmental, employee relations, and diversity scores also display a positive, though weaker, association.

In Panel B of Table A25, we discretize geographic proximity into four distance bands, within 0–200, 200–400, 400–600, and 600–800 miles from the disaster site, with the 800-1000-mile band as the omitted group. We then interact these indicators with *E&S* and the disaster indicator. The estimates show that the positive response to E&S performance is the strongest within the closest distance band and is statistically significant for the overall E&S rating, the environmental rating, and the community rating, and diminishes as the distance from the disaster increases. This spatial attenuation further supports the interpretation that these events raise E&S salience among nearby consumers.

E Does the Stock Market Price in the Cash Flow Effect of E&S?

In this section, we provide more details on the analysis of the relation between the stock price reaction associated with negative E&S news and subsequent consumer demand.

We calculate the cumulative abnormal (market-adjusted) returns (CARs) around negative E&S news using a three-day window from one day before to one day after each news event. We sum these CARs across all E&S news events occurring within a given month and use these monthly aggregates from months $m-1$, $m-2$, and $m-3$ to predict product sales in month m. For firm-month observations without any E&S news in a month, we assign a CAR value of zero. We estimate the following regression model:

$$ln(Sales_{i,p,m}) = \alpha + \beta \cdot CAR_{m-k} + \eta_p + \gamma_m + \epsilon_{i,p,m}, \tag{5}$$

where $ln(Sales_{i,p,m})$ is the natural logarithm of dollar sales of product p sold by firm i in month m; CAR_{m-k} denotes the market-adjusted cumulative abnormal returns over all three 3-day window $[-1, 1]$ surrounding negative E&S news in a given month $m-k$ (with $k = 1, 2, 3$); η_p and γ_m are product and year–month fixed effects. The coefficient β captures the extent to which investors' immediate reactions to E&S news predict subsequent consumer demand for the firm's products.

Table A27 reports the results. In models (1) through (3), we regress monthly product sales on CARs around E&S news occurring in the prior three months for the full sample. While the coefficients are positive, they are not statistically significant, suggesting that investors either do not expect subsequent sales to decline as a result of the event or do not believe that these declines will affect the value of the firm. However, this result may obscure differences between initial news exposures and situations in which investors already have prior information from similar events.

To test whether investors learn from previous E&S news events, we re-estimate the previous regression in models (4) to (6), conditioning the sample on instances where firms had E&S news in the prior months. Remarkably, we find that CARs around news events now significantly predict future sales. For example, the coefficient in model (4) indicates that higher CARs around negative E&S news in a given month strongly predict higher sales in the next month for those firms that also had negative E&S news in the prior month (month $m-2$). These findings imply that investors learn from past exposures and can more accurately anticipate the sales consequences of negative E&S news when such news also occurred in the recent past.

To rule out the possibility that the above relation is spurious, we present a placebo test in Table A28 using CARs measured in the three-day window before the actual news events (days -4 to -2). These placebo CARs show no predictive power, confirming that the significant results in Table A27 genuinely reflect information embedded in market reactions to negative E&S news.

These findings yield two novel insights. First, it provides direct evidence that the stock market does price in the consumer demand effects of E&S incidents, a mechanism that has largely remained untested in the literature. Second, it shows that investors' ability to recognize and incorporate the cash flow consequences of E&S events improves with experience, highlighting a learning channel through which market efficiency with respect to E&S issues may evolve.

F Variable Definitions for Internet Appendix

This appendix provides the variable definitions for the variables used in the Internet Appendix. For variable definitions of variables used in the body of the paper, see the Appendix. The variable definitions are provided in alphabetical order, with the exception that the ln() part of a variable name is ignored. The control variables (but neither the dependent variable nor the E&S variables) are winsorized at the 1% and 99% level.

- *Average Democrat*: The average Democratic Party vote share in proportion across all country-product module combinations in which a firm operates in a given year.
- *CAR[-1,1]*: The cumulative abnormal returns (market-adjusted) around negative E&S news using a three-day window from one day before to one day after each news event. We sum these CARs across all E&S news events occurring within a given month. For firm-month observations without any E&S news, we assign a CAR value of zero.
- *CAR[-4,-2]*: The placebo cumulative abnormal returns (market-adjusted) using the three-day window (day -4 to day -2) before E&S news. We sum these CARs across all E&S news events occurring within a given month. For firm-month observations without any E&S news, we assign a CAR value of zero.
- *ln(Compustat Sales)*: The natural logarithm of the Compustat sales in millions of dollars for a given firm in a given year.
- *CPSC Recalls*: The number of recalls by the Consumer Product Safety Commission (CPSC) for a given firm in a given year.
- *E&S2*: An alternative standardized E&S rating following Albuquerque et al. (2019) that covers five categories: employee relations, community, environment, diversity, and human rights. We first sum up the number of strengths (concerns) across all categories for each firm and year. We then standardize the number of strengths (concerns) by the maximum possible number of strengths (concerns) in the year. $E\&S2$ is computed as standardized strengths minus standardized concerns.
- *FDA Food Recalls*: The number of recalls by the Food and Drug Administration (FDA) for a given firm in a given year.
- *Innovation*: The innovation culture proxy, which is one of five corporate culture mea-

sures developed by Li et al. (2021). The five measures are derived from textual analysis of quarterly earnings call transcripts from the Capital IQ database. Specifically, the Q&A sections of earnings calls are processed using tokenization, lemmatization, named entity recognition (NER), and stop-word removal. Cultural scores for innovation, integrity, quality, respect, and teamwork are computed using a weighted term-frequency inverse document-frequency (tf-idf) approach. Annual firm-level culture scores are calculated by taking averages of these quarterly measures.

- *Integrity*: The integrity culture proxy , which is one of five corporate culture measures developed by Li et al. (2021). For more details on the construction of the measure, see *Innovation*.
- *Inventory Days*: 365 divided by *Inventory Turnover*.
- *Inventory Turnover*: Cost of goods sold divided by inventory.
- *ln(Market Value Assets)*: The natural logarithm of the market value of the firm's assets in millions of dollars. The market value of assets is defined as the book value of assets, plus the market value of equity, minus the book value of equity, minus deferred taxes.
- *ln(Market Value Equity)*: The natural logarithm of the market value of equity in millions of dollars.
- *Minimally Processed*: A sample that is restricted to those product modules whose items are minimally processed based on a manual coding of all product modules in the NielsenIQ data. Examples include eggs, milk, steak, bacon (but not sausages), and fresh cut flowers.
- *Product Quality*: 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.
- *Quality*: The quality culture proxy, which is one of five corporate culture measures developed by Li et al. (2021). For more details on the construction of the measure, see *Innovation*.
- *Respect*: The respect culture proxy, which is one five corporate culture measures developed by Li et al. (2021). For more details on the construction of the measure, see *Innovation*.
- *RepRisk*: The negative value of the number of E&S-related incidents of a given firm in a given year.

- *% Sensitive Department*: The proportion of E&S-sensitive departments across all county-product module combinations in a given year (i.e., departments with $E\&S$ sensitivity significantly positive at the 5% level or more in Table A7).
- *STDKLD*: An alternative standardized E&S rating following Servaes and Tamayo (2013) that covers five categories: employee relations, community, environment, diversity, and human rights. First, the number of strengths (concerns) of each category is standardized by the maximum possible number of strengths (concerns) in that 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.
- *Teamwork*: The teamwork culture proxy, which is one of five corporate culture measures developed by Li et al. (2021). See *Innovation* for more details on the construction.

References Appendix

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G Additional Figures and Tables

Figure A1: Layers of NielsenIQ Scanner Data

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

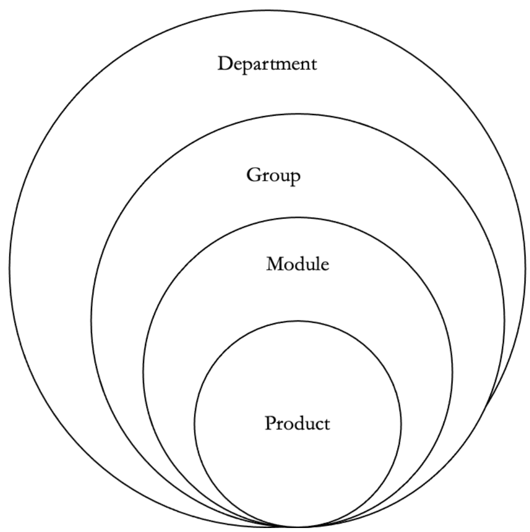
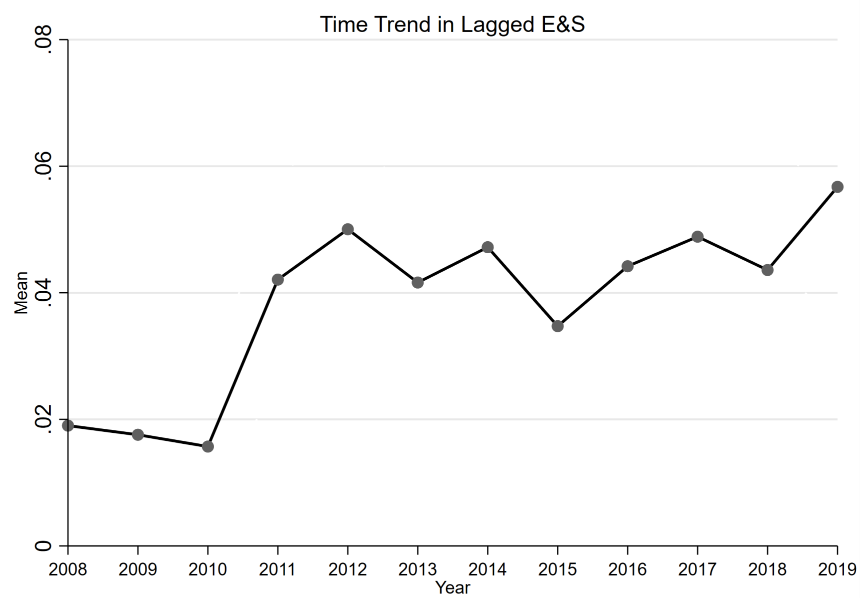
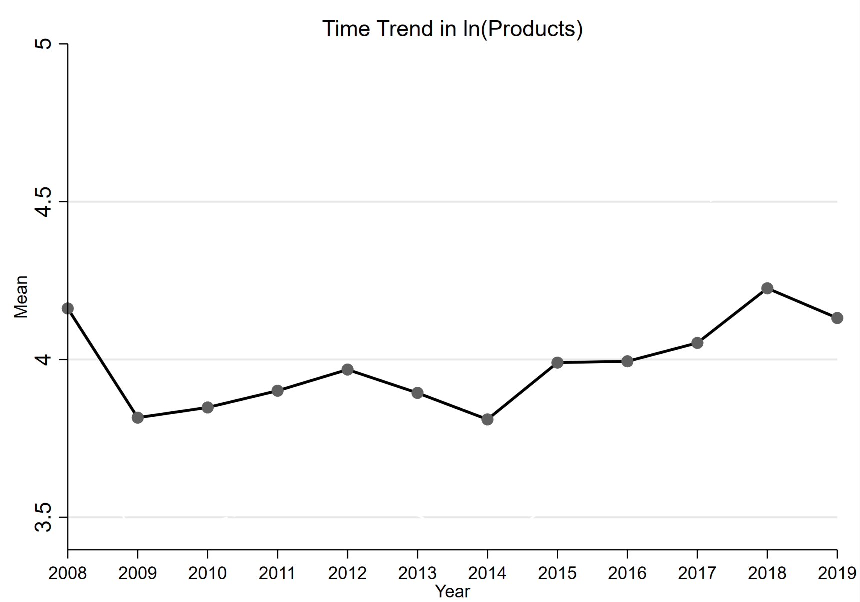


Figure A2: Time Trends in E&S Score, Sales, and Product Characteristics

This figure plots the time-series trends in firm-level E&S scores and product-market outcomes across our sample. We first collapse our data to the firm–year level by summing the dollar sales and unit sales, counting the unique number of products, and taking the average of product prices across modules and counties. We then collapse the firm-year level data further to the year level by calculating the cross-sectional mean for each variable.

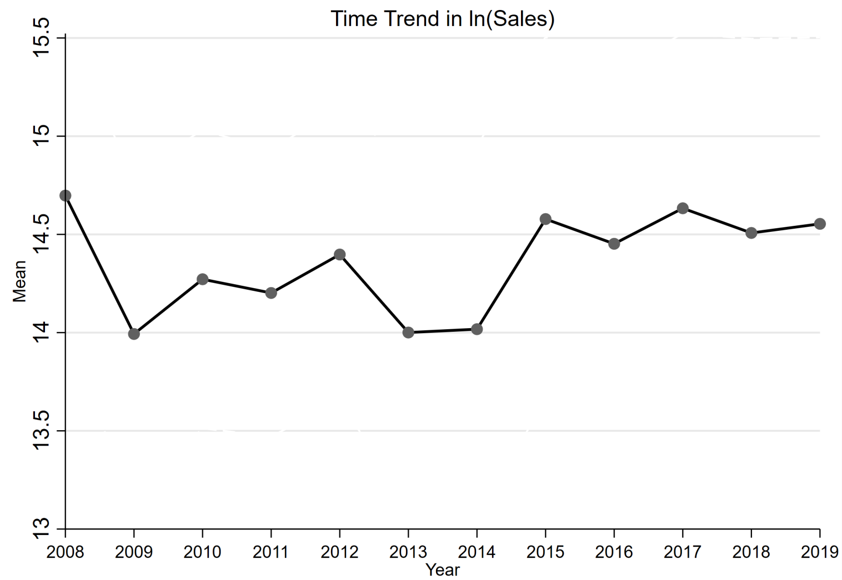


Panel A: Lagged E&S Score

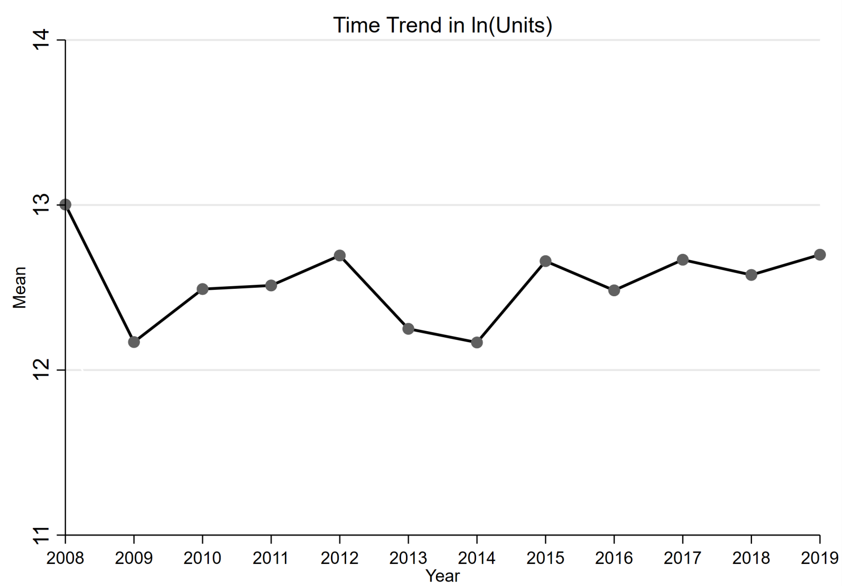


Panel B: ln(Number Products)

Figure A2: Time Trends in E&S Score, Sales, and Product Characteristics (Continued)

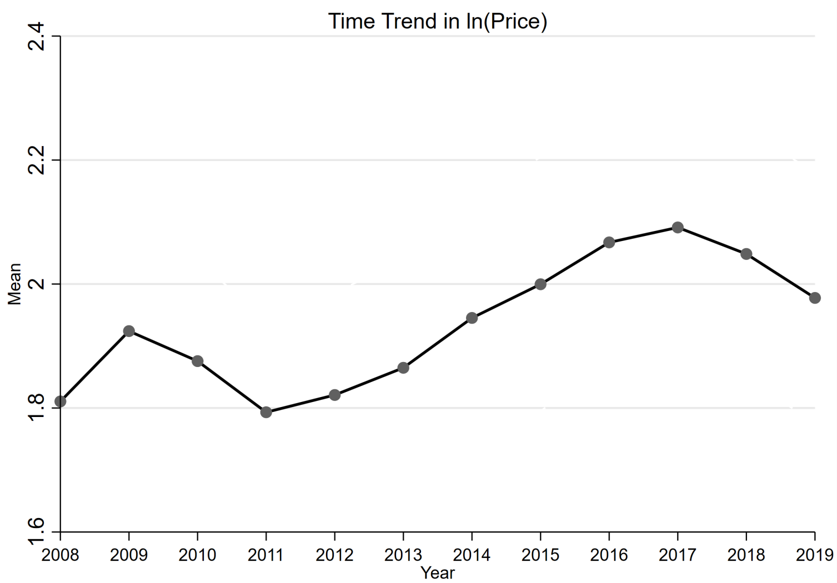


Panel C: ln(Sales)



Panel D: ln(Units)

Figure A2: Time Trends in E&S Score, Sales, and Product Characteristics (Continued)



Panel E: ln(Price)

Figure A3: Industry Distribution of Sample Firms

This figure compares the industry distribution of our sample firms in the baseline analysis with the universe of Compustat firms. Industries are classified using the Fama-French 17-industry classification. The vertical axis plots the percentage of firms in each industry. The black bars represent the distribution of sample firms, and the light gray bars represent the distribution of all Compustat firms. The industry categories are shown along the horizontal axis.

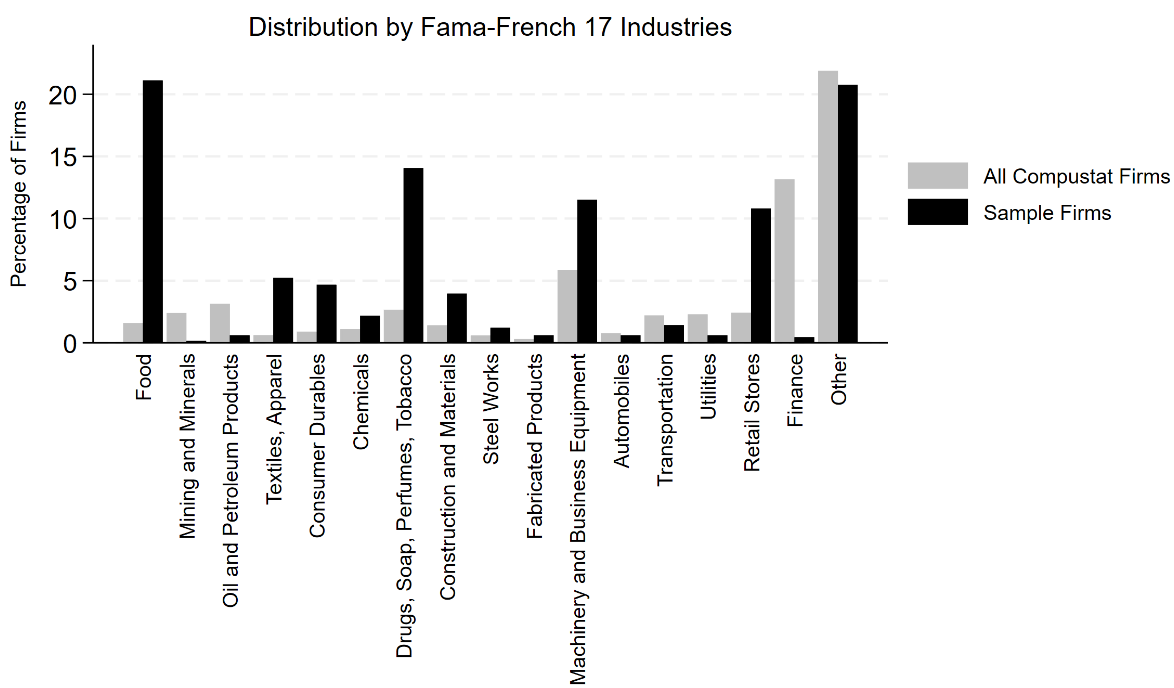


Figure A4: E&S Ratings and Local Product Sales — Time-Series Variation

This figure presents the year-by-year estimates of the relation between firms' lagged E&S scores and local product sales. These estimates are obtained from a modified version of the baseline regression model (Equation (1)) estimated at the firm–product module–county–year level. Specifically, we interact the lagged E&S score with year indicators corresponding to the year of the product sales, so that the coefficient for a given year y captures the association between the E&S score in year $y-1$ and product sales in year y. To accommodate this year-by-year specification, we drop the firm×product module×county fixed effects, which allows us to preserve the cross-sectional variation in the E&S score. We control for the following firm characteristics: *ln(Assets)*, *Leverage*, *Q*, *ROA*, *Advertising*, and *R&D*, and include county×year fixed effects, and product module×year fixed effects. Detailed definitions of the variables are in the Appendix and in Internet Appendix Section F. We plot the 90% confidence intervals for the point estimates based on three-way clustered standard errors at the firm, module, and county levels.

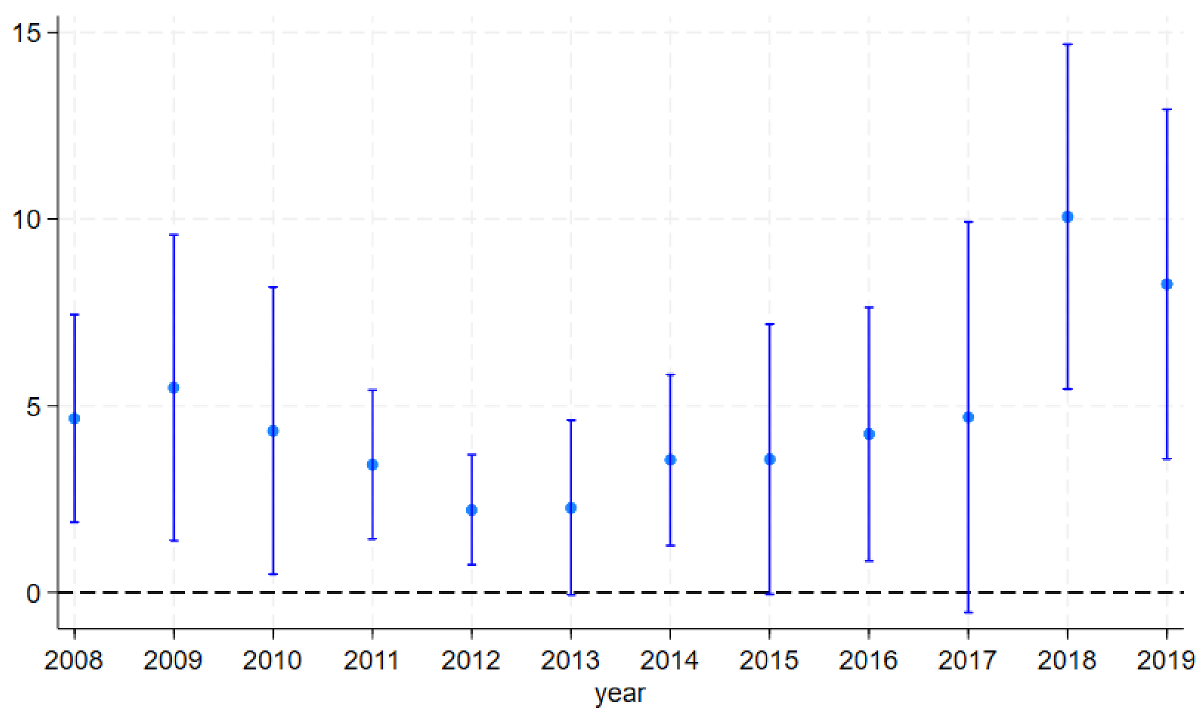


Figure A5: Smartphone App for E&S: Example 1

This screenshot from the app "Buycott" illustrates one of the many toothpastes for sale in the US under the "Crest" brand. It shows that this particular product and brand belong to the parent company Procter & Gamble.

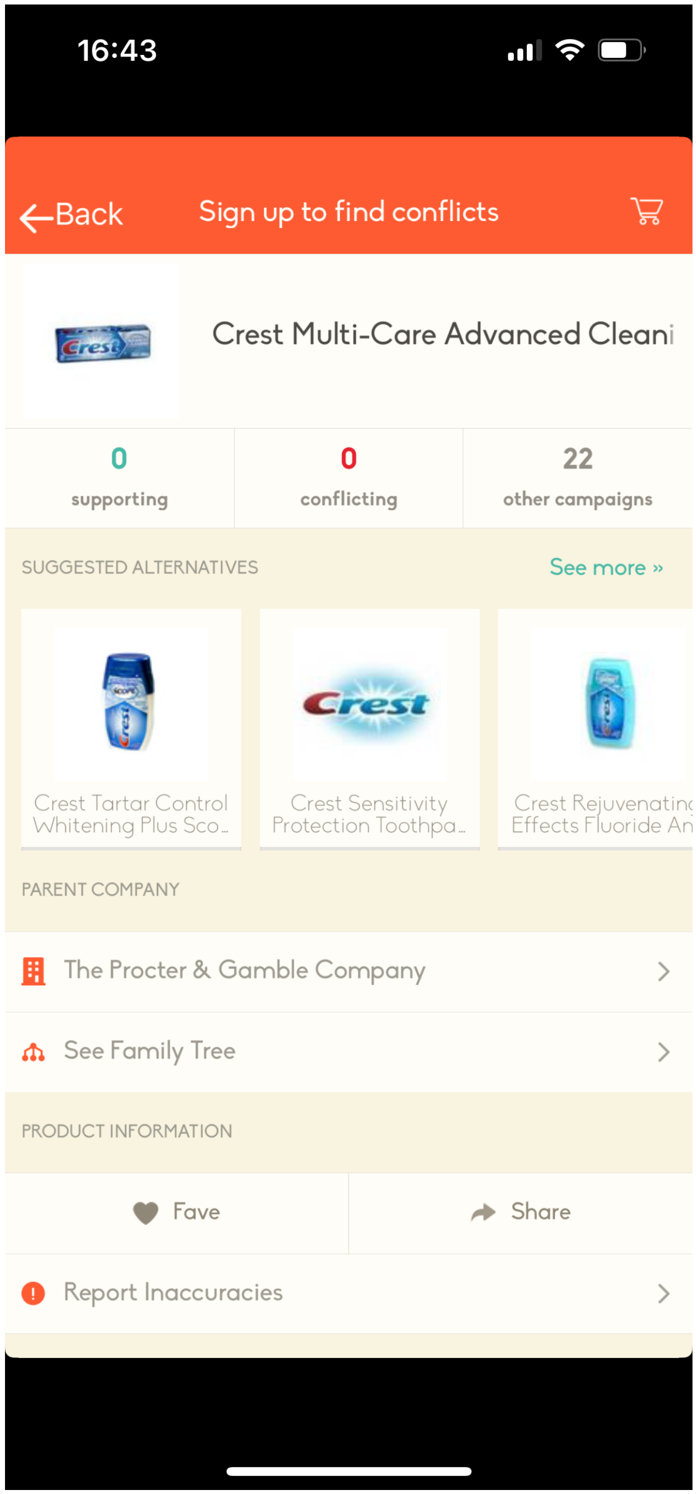


Figure A6: Smartphone App for E&S: Example 2

Clicking on “22 other campaigns” in Figure A5, shows a list of E&S issues related to the “Crest” brand and its parent company. This information can then be used on the spot to decide whether to purchase the specific product or not.

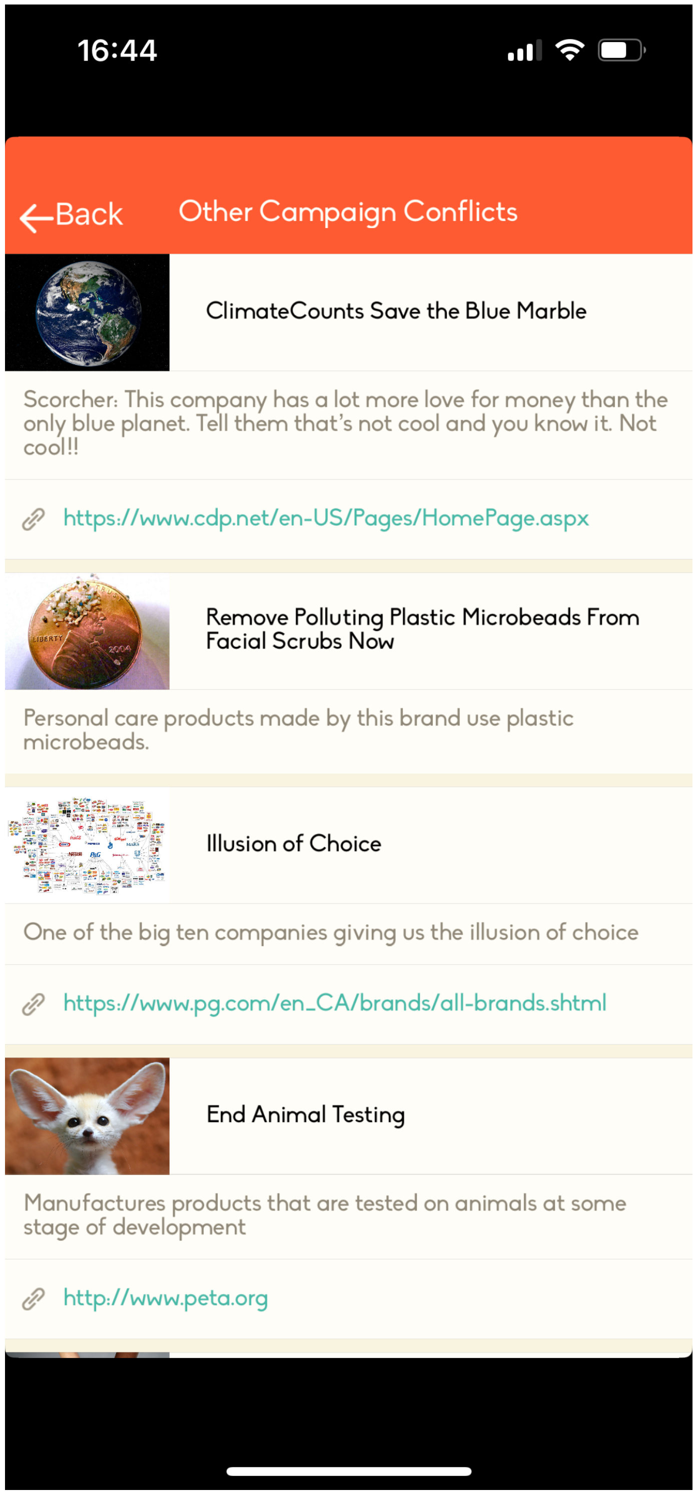


Table A1: List of Departments in NielsenIQ Retail Scanner Data

The following table lists all departments and some example product groups associated with each department.

Department	Example Product Groups
Health and Beauty Aids	Baby care, cosmetics, cough and cold remedies, deodorant
Dry Grocery	Baby food, baking mixes, candy, cereal, coffee, condiments
Frozen Foods	Ice cream, frozen pizza, frozen vegetables
Dairy	Cheese, eggs, yogurt
Deli	Product group identical to department - no further nesting
Packaged Meat	Packaged meats-deli, fresh meat
Fresh Produce	Product group identical to department - no further nesting
Non-Food Grocery	Detergent, diapers, fresheners/deodorizers, household cleaners
Alcohol	Beer, wine, liquor
General Merchandise	Batteries/flashlights, candles, computer/electronic, cookware

Table A2: Examples of Product Modules in NielsenIQ Retail Scanner Data

The table shows the product modules in the “Snacks” group of the “Dry Grocery” department.

Module Name
Dip - Mixes
Dip - Canned
Snacks - Pork Rinds
Snacks - Meat
Snacks - Puffed Cheese
Snacks - Potato Chips
Snacks - Potato Sticks
Snacks - Corn Chips
Snacks - Tortilla Chips
Snacks - Remaining
Popcorn - Popped
Popcorn - Unpopped
Snacks - Pretzel
Snacks - Caramel Corn
Snacks - Variety Packs
Crackers - Sandwich & Snack Packs
Trail Mixes
Snacks - Health Bars & Sticks

Table A3: 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 A4: Aggregate Sales for Sample Stores and Firms

This table shows annual aggregate sales figures from the NielsenIQ dataset between 2008 and 2019. Column (2) shows total dollar sales (in billions) from the 24,224 stores that report sales data continuously throughout the sample period. Column (3) presents the total dollar sales attributable to our sample firms within those stores. Column (4) shows the proportion of total store sales accounted for by the sample firms.

Year	Total Sales from Sample NielsenIQ Stores ($bn)	Sales Attributed to Sample Firms ($bn)	Share of Total Sales from Sample Firms
2008	168	40	24%
2009	171	40	24%
2010	173	42	24%
2011	182	42	23%
2012	183	42	23%
2013	186	38	20%
2014	189	41	22%
2015	194	42	22%
2016	202	43	21%
2017	197	40	20%
2018	199	44	22%
2019	199	37	19%

Table A5: Comparison of Distributions of Control Variables

This figure compares the distributions of key firm characteristics across three groups: our sample firms, firms within the same 4-digit SIC industries not covered by NielsenIQ data, and the broader Compustat universe.

	p10	p20	p30	p40	p50	p60	p70	p80	p90
ln(Assets)									
All Compustat Firms	1.616	3.141	4.180	5.113	5.917	6.639	7.379	8.197	9.353
Sample-industry Firms	1.068	2.747	3.751	4.573	5.333	6.080	6.949	7.925	9.210
Sample Firms	5.724	6.551	7.165	7.650	8.146	8.604	9.208	9.833	10.724
Leverage									
All Compustat Firms	0.000	0.000	0.033	0.095	0.167	0.246	0.333	0.446	0.645
Sample-industry Firms	0.000	0.000	0.013	0.092	0.175	0.252	0.332	0.438	0.686
Sample Firms	0.002	0.088	0.152	0.203	0.245	0.287	0.341	0.403	0.503
Q									
Compustat Firms	0.823	0.970	1.033	1.153	1.343	1.608	2.045	2.900	5.590
Sample-industry Firms	0.883	1.049	1.230	1.449	1.731	2.180	2.895	4.285	8.980
Sample Firms	1.023	1.174	1.326	1.474	1.693	1.938	2.209	2.623	3.400
ROA									
All Compustat Firms	-0.595	-0.137	-0.010	0.022	0.057	0.089	0.119	0.157	0.220
Sample-industry Firms	-1.048	-0.406	-0.110	0.013	0.070	0.099	0.129	0.168	0.233
Sample Firms	0.057	0.089	0.109	0.126	0.143	0.165	0.185	0.213	0.268
Advertising									
All Compustat Firms	0.001	0.003	0.006	0.009	0.012	0.017	0.024	0.038	0.075
Sample-industry Firm	0.001	0.003	0.006	0.010	0.015	0.024	0.036	0.060	0.127
Sample Firms	0.003	0.006	0.009	0.015	0.022	0.031	0.045	0.061	0.098
R&D									
All Compustat Firms	0.000	0.000	0.006	0.018	0.040	0.081	0.142	0.236	0.978
Sample-industry Firms	0.000	0.009	0.025	0.057	0.097	0.152	0.226	0.544	3.206
Sample Firms	0.000	0.001	0.005	0.011	0.015	0.021	0.031	0.060	0.134

Table A6: E&S Ratings and Local Product Sales — Rating Categories

This table presents the estimates of Equation (1) using firm-product module-county-year level data. The dependent variable is the natural logarithm of dollar sales. The independent variable of interest is *E&S* subdivided into its five components: Community, Diversity, Employee Relations, Environment, and Human Rights. We control for the following firm characteristics: *ln(Assets)*, *Leverage*, *Q*, *ROA*, *Advertising*, and *R&D*. Detailed definitions of the variables are in the Appendix and in Internet Appendix Section F. The t-statistics in parentheses are estimated based on three-way clustered standard errors at the firm, module, and county levels. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	*ln(Sales)*				
Category:	Community	Diversity	Employee Relation	Environment	Human Rights
	(1)	(2)	(3)	(4)	(5)
E&S	2.3816	2.4670***	1.8977***	-1.2710	9.1402**
	(1.50)	(3.19)	(3.19)	(-1.54)	(2.57)
Control Variables	Yes	Yes	Yes	Yes	Yes
Firm × Module × County FE	Yes	Yes	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes	Yes
Module × Year FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.915	0.915	0.915	0.915	0.915
Observations	12,564,537	12,564,537	12,564,537	12,564,537	12,564,537

Table A7: E&S Ratings and Local Product Sales — Product Departments

This table presents the estimates of Equation (1) using firm-product module-county-year level data for the 10 product departments. The dependent variable is the natural logarithm of dollar sales. The independent variable of interest is *E&S*. We control for the following firm characteristics: *ln(Assets)*, *Leverage*, *Q*, *ROA*, *Advertising*, and *R&D*. Detailed definitions of the variables are in the Appendix and in Internet Appendix Section F. We also report the average unit price in each department. The *t*-statistics in parentheses are estimated based on two-way clustered standard errors at the firm and county levels. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	*ln(Sales)*									
Department:	Health and Beauty	Dry Grocery	Frozen Foods	Dairy	Deli	Packaged Meat	Fresh Produce	Non-Food Grocery	Alcohol	General Merchandise
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
E&S	1.3275***	0.4926**	0.8337**	1.1265	1.2969	1.2926	-5.2873	0.9621*	-5.5033	1.7656***
	(5.64)	(2.40)	(2.47)	(0.95)	(0.85)	(0.89)	(-0.75)	(1.96)	(-1.24)	(3.73)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm × Module × County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.885	0.871	0.852	0.897	0.840	0.837	0.705	0.924	0.933	0.845
Observations	2,205,859	5,435,592	627,152	595,346	95,200	121,434	9,274	1,922,017	24,597	1,269,844
Average unit price in $	8.39	2.77	3.61	3.34	6.31	4.80	7.70	4.90	13.36	13.60

Table A8: E&S Ratings and Local Product Sales — Product Departments with Baseline Specification

This table presents the estimates of Equation (1) using firm-product module-county-year level data for the 10 product departments. The dependent variable is the natural logarithm of dollar sales. The independent variable of interest is *E&S*. We control for the following firm characteristics: *ln(Assets)*, *Leverage*, *Q*, *ROA*, *Advertising*, and *R&D*. Detailed definitions of the variables are in the Appendix and in Internet Appendix Section F. The t-statistics in parentheses are estimated based on three-way clustered standard errors at the firm, module, and county levels. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	*ln(Sales)*									
Department:	Health and Beauty	Dry Grocery	Frozen Foods	Dairy	Deli	Packaged Meat	Fresh Produce	Non-Food Grocery	Alcohol	General Merchandise
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
E&S	1.6139**	0.6317	1.5669**	3.0533	-0.4824	3.7708*	5.7259	1.3946**	6.5838	1.4497
	(2.04)	(1.31)	(2.16)	(1.14)	(-0.10)	(2.53)	(1.07)	(2.40)	(0.59)	(1.22)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm × Module × County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Module × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.934	0.901	0.896	0.919	0.878	0.860	0.750	0.944	0.949	0.904
Observations	2,205,788	5,435,509	627,141	595,343	95,193	121,434	9,268	1,921,980	24,592	1,269,814

Table A9: Product and Market Heterogeneity, and E&S-to-Sales Sensitivity at the Firm-year Level

In Panel A, the dependent variable is the firm-year level log dollar sales aggregated across product types and counties. Model (1) includes the interaction between *E&S* and the number of product modules with positive sales in a firm-year (ln(#Modules)) and model (2) the interaction between *E&S* and the number of counties with positive sales in a firm-year (ln(#Counties)). In Panel B, model (1), the dependent variable is *% Sensitive Department*, the proportion of E&S-sensitive departments across all county-product module combinations in a given year (i.e., departments with *E&S* sensitivity significantly positive at the 5% level or more in Table A7). In model (2), the dependent variable is *Average Democrat*, the average Democratic Party vote share in proportion across all country-product module combinations in which a firm operates in a given year. In all regressions, we control for *ln(Assets)*, *Leverage*, *Q*, *ROA*, *Advertising*, and *R&D*. Detailed definitions of the variables are in the Appendix and in the Internet Appendix Section F. The t-statistics based on standard errors clustered at the firm level are in parentheses. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A

Dependent Variable:	*ln(Sales)*	
	(1)	(2)
E&S	6.6869*	7.1447**
	(1.67)	(2.43)
E&S × ln(# Modules)	-1.7277*	
	(-1.74)	
E&S × ln(# Counties)		-0.7865*
		(-1.96)
ln(# Modules)	1.8763***	
	(5.88)	
ln(# Counties)		1.6467***
		(17.74)
Control Variables	Yes	Yes
Year FE	Yes	Yes
Firm FE	Yes	Yes
Adjusted R^2	0.932	0.979
Observations	765	765

Table A9 (continued)

Panel B

Dependent Variable:	*% Sensitive Department*	*Average Democrat*
	(1)	(2)
ln(# Modules)	-0.0329	
	(-1.10)	
ln(# Counties)		-0.0239***
		(-5.78)
ln(Assets)	-0.0025	-0.0036
	(-0.14)	(-0.67)
Leverage	-0.1031	-0.0124
	(-1.06)	(-0.59)
Q	-0.0029	0.0029
	(-0.27)	(0.76)
ROA	-0.1363	-0.0063
	(-1.09)	(-0.13)
Advertising	-0.7219*	-0.0834
	(-1.73)	(-0.79)
R&D	-1.3656**	-0.0694
	(-2.04)	(-0.45)
Year FE	Yes	Yes
Firm FE	Yes	Yes
Adjusted R^2	0.871	0.781
Observations	765	763

Table A10: E&S Ratings and Local Product Sales — Firm-level First-Difference Regressions

This table presents the baseline results using a first-difference specification with firm–year level data. The dependent variable is the first difference in the natural logarithm of dollar sales. All independent variables are first differenced as denoted by Δ. ln(#Modules) and ln(#Counties) are the log number of distinct product modules (counties) with positive sales within a firm-year. *Average Democrat* is the average Democratic Party vote share across all county-module combinations in which the firm operates. The control variables *ln(Assets)*, *Leverage*, *Q*, *ROA*, *Advertising*, and *R&D*, are also first-differenced. *t*-statistics, reported in parentheses, are based on standard errors clustered at the firm level. Detailed definitions of the variables are in the Appendix and in Internet Appendix Section F. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	ΔIn(Sales)			
	(1)	(2)	(3)	(4)
$\Delta E\&S$	0.4654	0.1683	0.4442	0.2218
	(1.04)	(0.34)	(1.04)	(0.47)
$\Delta E\&S$ × ΔAverage Democrat			54.2748**	35.1465
			(2.12)	(1.48)
ΔAverage Democrat			1.5512*	1.4900
			(1.75)	(1.14)
$\Delta ln(\#Modules)$	0.2681**	0.3018*	0.2579*	0.3058*
	(1.99)	(1.71)	(1.93)	(1.69)
$\Delta ln(\#Counties)$	1.4962***	1.5434***	1.5390***	1.5941***
	(18.78)	(13.47)	(17.30)	(12.49)
Control Variables (First-differenced)	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.688	0.719	0.689	0.722
Observations	1,317	627	1,313	625

Table A11: E&S Ratings and Local Product Sales — Alternative E&S Measures

This table presents robustness tests for the estimates of Equation (1) using firm-product module-county-year level data and 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 models (1) and (2), we use the annual quintiles and terciles of $E\&S$. In model (3), we use $E\&S2$, developed by Albuquerque et al. (2019). In model (4), we use $STDKLD$, following Servaes and Tamayo (2013). In models (5) and (6), 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 reported E&S-related incidents in the previous year for a given firm. We also control for the following firm characteristics: *ln(Assets)*, *Leverage*, *Q*, *ROA*, *Advertising*, and *R&D*. Detailed definitions of the variables are in the Appendix and in Internet Appendix Section F. The t-statistics in parentheses are estimated based on three-way clustered standard errors at the firm, module, and county levels. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	ln(Sales)					
Data:	MSCI ESG STATS				Sustainalytics	RepRisk
Measure:	Quintile	Tercile	$E\&S2$	$STDKLD$		
	(1)	(2)	(3)	(4)	(5)	(6)
E&S	0.0405*	0.0532*	0.5885**	0.0970***	0.0129*	0.0110***
	(1.92)	(1.86)	(3.16)	(2.79)	(1.98)	(3.34)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
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	0.915	0.915	0.915	0.915	0.924	0.921
Observations	12,564,537	12,564,537	12,564,537	12,564,537	9,634,174	11,230,471

Table A12: E&S Ratings and Local Product Sales — Price and Quantity Controls

This table presents the estimates of Equation (1) using firm-product module-county-year level data. The models employ units sold or unit price as the dependent variable, while using the other as a control variable. The independent variable of interest is *E&S*. We also control for the following firm characteristics: *ln(Assets)*, *Leverage*, *Q*, *ROA*, *Advertising*, and *R&D*. Detailed definitions of the variables are in the Appendix and in Internet Appendix Section F. The t-statistics in parentheses are estimated based on three-way clustered standard errors at the firm, module, and county levels. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	ln(Units) (1)	ln(Price) (2)
E&S	1.1353***	-0.0076
	(2.92)	(-0.08)
ln(Price)	0.1055***	
	(2.69)	
ln(Units)		0.0079**
		(2.38)
Controls Variables	Yes	Yes
Firm × Module × County FE	Yes	Yes
County × Year FE	Yes	Yes
Module × Year FE	Yes	Yes
Adjusted R^2	0.923	0.938
Observations	12,564,537	12,564,537

Table A13: E&S Ratings and Local Product Sales — Product Quality

This table presents the estimates of Equation (1) using firm-product module-county-year level data, and incorporating controls for product quality. In Panel A (B), the dependent variable is the natural logarithm of dollar sales (unit price). The independent variable of interest is *E&S*. We also control for the following firm characteristics: *ln(Assets)*, *Leverage*, *Q*, *ROA*, *Advertising*, and *R&D*. In addition, we use four different approaches to control for product quality. In model (1), we use the standardized product rating from MSCI ESG Stats. In model (2), we use the number of food-related recalls by the Food and Drug Administration (FDA) in the prior year. In model (3), we use the number of recalls by the Consumer Product Safety Commission in the prior year. In model (4), we restrict the sample to those product modules that contain minimally processed products. Detailed definitions of the variables are in the Appendix and in Internet Appendix Section F. The *t*-statistics in parentheses are estimated based on three-way clustered standard errors at the firm, module, and county levels. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: ln(Sales)

Dependent Variable:	ln(Sales)			
	(1)	(2)	(3)	(4)
E&S	1.0106***	0.9895***	1.0559***	2.4237*
	(3.05)	(2.90)	(2.88)	(1.99)
Product Quality	-0.2123			
	(-0.84)			
FDA Food Recalls		-0.0131**		
		(-2.09)		
CPSC Recalls			-0.0177	
			(-0.25)	
Sample	Baseline	Baseline	Baseline	Minimally Processed
Control Variables	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	0.915	0.915	0.915	0.911
Observations	12,564,537	12,564,537	12,564,537	428,775

Panel B: ln(Price)

Dependent Variable:	ln(Price)			
	(1)	(2)	(3)	(4)
E&S	0.0170	-0.0047	-0.0111	0.1914
	(0.19)	(-0.05)	(-0.12)	(0.88)
Product Quality	0.0599**			
	(2.34)			
FDA Food Recalls		-0.0010		
		(-0.91)		
CPSC Recalls			-0.0215	
			(-1.17)	
Sample	Baseline	Baseline	Baseline	Minimally Processed
Control Variables	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	0.938	0.937	0.938	0.864
Observations	12,564,537	12,564,537	12,564,537	428,775

Table A14: E&S Ratings and Local Product Sales — Corporate Culture

This table presents the estimates of Equation (1) using firm-product module-county-year data, and incorporating controls for corporate culture. The dependent variable is the natural logarithm of dollar sales. The independent variable of interest is *E&S*. We also control for the following firm characteristics: *ln(Assets)*, *Leverage*, *Q*, *ROA*, *Advertising*, and *R&D*. In addition, we control for proxies of corporate culture established by Li et al. (2021). The five proxies of corporate culture capture 1) innovation culture, 2) integrity culture, 3) quality culture, 4) respect culture, and 5) teamwork culture. Detailed definitions of the variables are in the Appendix and in Internet Appendix Section F. In model (1), we report the baseline specification of model (4) of Table 3, except that the sample is restricted to firms for which we have data on corporate culture. The *t*-statistics in parentheses are estimated based on three-way clustered standard errors at the firm, module, and county levels. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	ln(Sales)					
	(1)	(2)	(3)	(4)	(5)	(6)
E&S	1.2111***	1.2582***	1.1935**	1.2032***	1.2008**	1.2040***
	(2.65)	(2.80)	(2.59)	(2.65)	(2.62)	(2.65)
Innovation		-0.0204				
		(-1.55)				
Integrity			-0.0864*			
			(-1.84)			
Quality				-0.0432		
				(-1.33)		
Respect					-0.0335	
					(-0.84)	
Teamwork						-0.0063
						(-0.20)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
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	0.923	0.923	0.923	0.923	0.923	0.923
Observations	9,745,976	9,745,976	9,745,976	9,745,976	9,745,976	9,745,976

Table A15: E&S Ratings and Local Product Sales — Alternative Definitions of Advertising and R&D

This table shows that the estimates of Equation (1) using firm-module-county-year level data 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 control for the following firm characteristics *ln(Assets)*, *Leverage*, *Q*, *ROA*, *Advertising*, and *R&D*. In models (1) and (3), we replace missing values of advertising and R&D expenditures with zeros. In models (2) and (3), we standardize advertising and R&D expenditures by lagged assets instead of concurrent sales. Detailed definitions of the variables are in the Appendix and in Internet Appendix Section F. The t-statistics in parentheses are estimated based on three-way clustered standard errors at the firm, module, and county levels. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:		ln(Sales)	
Fill in zeros for Advertising and R&D:	Yes	No	Yes
Standardizing Advertising and R&D by:	Sales	Assets	Assets
	(1)	(2)	(3)
E&S	0.9374***	1.1227***	1.0619***
	(3.22)	(3.20)	(3.68)
Advertising (Sales, Zeros)	5.2741***		
	(3.05)		
R&D (Sales, Zeros)	-1.0561		
	(-0.34)		
Advertising (Assets)		0.3927	
		(0.26)	
R&D (Assets)		7.3191	
		(1.53)	
Advertising (Assets, Zeros)			0.2938
			(0.28)
R&D (Assets, Zeros)			3.6410
			(0.62)
Control Variables	Yes	Yes	Yes
Firm × Module × County FE	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes
Module × Year FE	Yes	Yes	Yes
Adjusted R^2	0.906	0.915	0.906
Observations	16,244,861	12,564,537	16,244,861

Table A16: E&S Ratings and Local Product Sales — Alternative Firm Size Proxies

This table presents estimates of Equation (1) using firm-module-county-year level data, and controlling for alternative measures of firm size. The dependent variable is the natural logarithm of dollar sales. The independent variable of interest is *E&S*. We control for different measures of firm size including *ln(Compustat Sales)* (models (1) and (2)), *ln(Market Value Assets)* (models (3) and (4)), *ln(Market Value Equity)* (models (5) and (6)). In models (1), (3), and (5), we also control for *ln(Assets)*. We further control for the following firm characteristics: *Leverage*, *Q*, *ROA*, *Advertising*, and *R&D*. Detailed definitions of the variables are in the Appendix and in Internet Appendix Section F. The t-statistics in parentheses are estimated based on three-way clustered standard errors at the firm, module, and county levels. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	ln(Sales)					
	(1)	(2)	(3)	(4)	(5)	(6)
E&S	0.8163**	0.8785**	1.1063***	1.0719***	1.0971***	1.0694***
	(2.52)	(2.56)	(3.13)	(2.97)	(3.06)	(2.95)
ln(Compustat Sales)	0.4952***	0.2257**				
	(3.44)	(2.24)				
ln(Market Value Assets)			0.2146	0.0933		
			(0.87)	(0.93)		
ln(Market Value Equity)					0.1565	0.1046
					(1.13)	(1.21)
ln(Assets)	-0.2895*		-0.1351		-0.0706	
	(-1.90)		(-0.49)		(-0.40)	
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
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	0.915	0.915	0.915	0.915	0.915	0.915
Observations	12,564,537	12,564,537	12,564,537	12,564,537	12,564,537	12,564,537

Table A17: E&S Ratings and Local Product Sales — Unbalanced Store Panel

This table presents estimates of Equation (1) using firm-product module-county-year level data using the full (unbalanced) store panel of the NielsenIQ Retail Scanner Database. The sample spans the years 2008 to 2019. For details on the sample construction, see Section *2.1*. The dependent variables are the natural logarithm of dollar sales, the natural logarithm of unit sales, and the natural logarithm of price per unit. The independent variable of interest is *E&S*. In models (4) to (6), we control for the following firm characteristics: *ln(Assets)*, *Leverage*, *Q*, *ROA*, *Advertising*, and *R&D*. Detailed definitions of the variables are in the Appendix and in Internet Appendix Section F. The t-statistics in parentheses are estimated based on three-way clustered standard errors at the firm, module, and county levels. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	ln(Sales) (1)	ln(Units) (2)	ln(Price) (3)	ln(Sales) (4)	ln(Units) (5)	ln(Price) (6)
E&S	1.1240***	1.1097***	0.0394	1.0710***	1.0952***	0.0282
	(3.36)	(3.16)	(0.61)	(2.94)	(3.00)	(0.32)
Control Variables	No	No	No	Yes	Yes	Yes
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	0.895	0.907	0.929	0.905	0.914	0.936
Observations	19,777,702	19,777,702	19,777,702	14,891,123	14,891,123	14,891,123

Table A18: E&S Ratings and Local Product Sales — Sample Extension to 2020

This table presents estimates of Equation (1) using firm-product module-county-year level data with the sample is extended to 2020. For details on the sample construction, see Section *2.1*. The dependent variables are the natural logarithm of dollar sales, the natural logarithm of unit sales, and the natural logarithm of price per unit. The independent variable of interest is *E&S*. In models (4) to (6), we control for the following firm characteristics: *ln(Assets)*, *Leverage*, *Q*, *ROA*, *Advertising*, and *R&D*. Detailed definitions of the variables are in the Appendix and in Internet Appendix Section F. The t-statistics in parentheses are estimated based on three-way clustered standard errors at the firm, module, and county levels. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	ln(Sales)	ln(Units)	ln(Price)	ln(Sales)	ln(Units)	ln(Price)
	(1)	(2)	(3)	(4)	(5)	(6)
E&S	1.1603***	1.1794***	0.0157	1.1336***	1.2111***	-0.0059
	(3.25)	(3.05)	(0.23)	(2.79)	(2.79)	(-0.06)
Control Variables	No	No	No	Yes	Yes	Yes
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	0.903	0.914	0.933	0.914	0.922	0.940
Observations	17,678,915	17,678,915	17,678,918	13,425,961	13,425,961	13,425,962

Table A19: E&S Ratings and Local Product Sales — Unbalanced Store Panel and Sample Extension to 2020

This table presents estimates of Equation (1) using firm-product module-county-year level data and the full (unbalanced) store panel of the NielsenIQ Retail Scanner Database, with the sample extended up to 2020. For details on the sample construction, see Section *2.1*. The dependent variables are the natural logarithm of dollar sales, the natural logarithm of unit sales, and the natural logarithm of price per unit. The independent variable of interest is *E&S*. In models (4) to (6), we control for the following firm characteristics: *ln(Assets)*, *Leverage*, *Q*, *ROA*, *Advertising*, and *R&D*. Detailed definitions of the variables are in the Appendix and in Internet Appendix Section F. The t-statistics in parentheses are estimated based on three-way clustered standard errors at the firm, module, and county levels. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	ln(Sales)	ln(Units)	ln(Price)	ln(Sales)	ln(Units)	ln(Price)
	(1)	(2)	(3)	(4)	(5)	(6)
E&S	1.1750***	1.1635***	0.0369	1.1481***	1.1674***	0.0389
	(3.09)	(2.90)	(0.53)	(2.79)	(2.82)	(0.43)
Control Variables	No	No	No	Yes	Yes	Yes
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	0.893	0.905	0.930	0.903	0.912	0.936
Observations	21,070,857	21,070,857	21,070,859	15,948,682	15,948,682	15,948,682

Table A20: E&S News and Product Sales — Robustness Using Firm-Product Module-County-level Sales

This table presents the estimates of Equation (3) using firm-product module-county-month-level data. The dependent variable is the natural logarithm of dollar sales in month m. The independent variables are the number of negative news stories from month $m-6$ to month $m-4$, from month $m-3$ to month $m-1$, and from month $m+1$ to month $m+3$. Model (1) includes all types of news (excluding governance). Models (2), (3), and (4) include environmental, social, and cross-cutting news, respectively. Detailed definitions of the variables are in the Appendix and in Internet Appendix Section F. The t-statistics in parentheses are estimated based on three-way clustered standard errors at the firm, module, and county levels. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	$\ln(\text{Sales})_m$			
News Type:	All (1)	Environmental (2)	Social (3)	Cross-cutting (4)
$\text{News}_{m-6,m-4}$	-0.0006	-0.0036	-0.0004	-0.0014
	(-0.27)	(-1.51)	(-0.14)	(-0.48)
$\text{News}_{m-3,m-1}$	-0.0039*	-0.0087***	-0.0050*	-0.0020
	(-1.88)	(-3.15)	(-1.74)	(-0.82)
$\text{News}_{m+1,m+3}$	-0.0021	-0.0018	-0.0025	-0.0024
	(-1.01)	(-0.68)	(-1.10)	(-1.10)
Firm × Module × County × Year FE	Yes	Yes	Yes	Yes
County × Year-month FE	Yes	Yes	Yes	Yes
Module × Year-month FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.954	0.954	0.954	0.954
Observations	152,091,852	152,091,852	152,091,852	152,091,852

Table A21: E&S News and Monthly Product Sales — Split by News Type

This table presents the estimates of Equation (3) using product-month-level data. In Panels A, B, and C, the dependent variable is the natural logarithm of dollar sales of a given product in month m, the natural logarithm of the number of stores with non-zero sales of the product, and the natural logarithm of product dollar sales per store, respectively. The independent variables are the number of negative news stories from month $m-6$ to month $m-4$, from month $m-3$ to month $m-1$, and from month $m+1$ to month $m+3$. Model (1) includes all types of news (excluding governance). Models (2), (3), and (4) include environmental, social, and cross-cutting news, respectively. Firm fixed effects are subsumed by product fixed effects. Detailed definitions of the variables are in the Appendix and in Internet Appendix Section F. The t-statistics in parentheses are estimated based on two-way clustered standard errors at the firm and product module levels. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: ln(Sales)$_m$

News Type:	All (1)	Environmental (2)	Social (3)	Cross-cutting (4)
News$_{m-6,m-4}$	-0.0074**	-0.0034	-0.0041	-0.0099**
	(-2.07)	(-0.63)	(-0.87)	(-2.33)
News$_{m-3,m-1}$	-0.0111***	-0.0107**	-0.0165**	-0.0070**
	(-2.96)	(-2.01)	(-2.25)	(-2.03)
News$_{m+1,m+3}$	0.0012	-0.0028	-0.0049	0.0003
	(0.45)	(-0.69)	(-1.07)	(0.10)
Module × Year-month FE	Yes	Yes	Yes	Yes
Product × Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.937	0.937	0.937	0.937
Observations	3,011,688	3,011,688	3,011,688	3,011,688

Panel B: ln(Number_of_Stores)$_m$

News Type:	All (1)	Environmental (2)	Social (3)	Cross-cutting (4)
News$_{m-6,m-4}$	-0.0058*	-0.0017	-0.0030	-0.0082**
	(-1.89)	(-0.40)	(-0.76)	(-2.31)
News$_{m-3,m-1}$	-0.0093***	-0.0072*	-0.0127**	-0.0070**
	(-2.78)	(-1.74)	(-1.99)	(-2.30)
News$_{m+1,m+3}$	0.0006	-0.0029	-0.0048	-0.0003
	(0.31)	(-0.93)	(-1.31)	(-0.13)
Module × Year-month FE	Yes	Yes	Yes	Yes
Product × Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.946	0.946	0.946	0.946
Observations	3,011,688	3,011,688	3,011,688	3,011,688

Panel C: ln(Sales_per_Store)$_m$

News Type:	All (1)	Environmental (2)	Social (3)	Cross-cutting (4)
News$_{m-6,m-4}$	-0.0015	-0.0017	-0.0011	-0.0017
	(-1.42)	(-1.02)	(-0.87)	(-1.17)
News$_{m-3,m-1}$	-0.0018*	-0.0035*	-0.0038**	0.0000
	(-1.82)	(-1.69)	(-2.37)	(0.00)
News$_{m+1,m+3}$	0.0005	0.0001	-0.0001	0.0006
	(0.59)	(0.11)	(-0.06)	(0.61)
Module × Year-month FE	Yes	Yes	Yes	Yes
Product × Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.903	0.903	0.903	0.903
Observations	3,011,688	3,011,688	3,011,688	3,011,688

Table A22: E&S News and Monthly Product Sales — Price and Quantity

This table presents the estimates of Equation (3) using product-month-level data. In Panels A and B the dependent variable is the natural logarithm of units sold and the natural logarithm of price per unit of a given product, respectively. The independent variables are the number of negative news stories from month $m-6$ to month $m-4$, from month $m-3$ to month $m-1$, and from month $m+1$ to month $m+3$. Model (1) includes all types of news (excluding governance). Models (2), (3), and (4) include environmental, social, and cross-cutting news, respectively. Firm fixed effects are subsumed by product fixed effects. Detailed definitions of the variables are in the Appendix and in Internet Appendix Section F. The t-statistics in parentheses are estimated based on two-way clustered standard errors at the firm and product module levels. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: ln(Units)$_m$

News Type:	All	Environmental	Social	Cross-cutting
	(1)	(2)	(3)	(4)
News$_{m-6,m-4}$	-0.0074**	-0.0022	-0.0036	-0.0098**
	(-2.19)	(-0.41)	(-0.74)	(-2.42)
News$_{m-3,m-1}$	-0.0123***	-0.0113**	-0.0177**	-0.0087**
	(-3.41)	(-2.10)	(-2.55)	(-2.53)
News$_{m+1,m+3}$	0.0001	-0.0031	-0.0059	-0.0009
	(0.05)	(-0.78)	(-1.27)	(-0.31)
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	3,011,688	3,011,688	3,011,688	3,011,688

Panel B: ln(Price)$_m$

News Type:	All	Environmental	Social	Cross-cutting
	(1)	(2)	(3)	(4)
News$_{m-6,m-4}$	0.0000	-0.0009	-0.0003	-0.0000
	(0.02)	(-1.48)	(-0.41)	(-0.06)
News$_{m-3,m-1}$	0.0010*	0.0005	0.0009	0.0017***
	(1.79)	(0.66)	(1.14)	(2.75)
News$_{m+1,m+3}$	0.0009*	0.0004	0.0010	0.0011*
	(1.81)	(0.64)	(1.45)	(1.66)
Module × Year-month FE	Yes	Yes	Yes	Yes
Product × Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.916	0.916	0.916	0.916
Observations	3,011,688	3,011,688	3,011,688	3,011,688

Table A23: List of Severe Natural and Environmental Disasters

The following table shows the list of severe natural and environmental disasters from 2009 to 2018 used in the estimation of Equation (4) in Section *6.2*. Source for the disasters: Environmental Protection Agency (https://www.epa.gov/emergency-response/key-incidents-and-milestones, link last checked: Nov 7, 2025).

Event	Year-month	Affected County
Deepwater Horizon Oil Spill	2010.4	Plaquemines, LA
Kalamazoo River Oil Spill	2010.7	Kalamazoo, MI
Joplin Tornado	2011.5	Jasper, MO
Silvertip Pipeline Spill	2011.7	Yellowstone, MT
Hurricane Isaac	2012.8	Plaquemines, LA
Superstorm Sandy	2012.10	Ocean, NJ
West Fertilizer Explosion and Fire	2013.4	Mclennan, TX
2013 Colorado Floods	2013.9	Boulder, CO
Elk River Spill	2014.1	Kanawha, WV
Columbia River Spill	2016.6	Wasco, OR
Hurricane Matthew	2016.10	Duval, FL
Hurricane Harvey	2017.8	Harris, TX
2017 California Wildfire	2017.10	Sonoma, CA
Iowa Train Derailment	2018.6	Lyon, IA

Table A24: Product Sales Around Natural and Environmental Disasters — Robustness Using Firm-Product Module-County-level Sales

This table presents the estimates of a stacked DID model (Equation (4)) using product sales data aggregated to the firm-product module-county-month level. For each disaster event, we include observations located within 1000 miles of its location (excluding the disaster county) and keep a 37-month window (i.e., 18 months before, 18 months after) around the event. We then stack the relevant observations for all the events for estimation. The dependent variable is the natural logarithm of dollar sales. In model (1), the independent variable is the triple interaction term $E\&S \times Disaster \times Proximity$. *Disaster* is a binary variable that equals one for observations in each event if an environmental disaster occurs in the past 6 months. *Distance* is the distance between the disaster county and the focal county in miles. *Proximity* is geographic proximity computed as the negative of the natural logarithm of *Distance*. In model (2), we decompose *Distance* into four binary variables based on distance. Detailed definitions of the variables are in the Appendix and in Internet Appendix Section F. The t-statistics in parentheses are estimated based on three-way clustered standard errors at the firm, product module, and county levels. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	ln(Sales)	
	(1)	(2)
E&S × Disaster × Proximity	0.0171**	
	(2.22)	
E&S × Disaster × $I[\text{Distance} \in (0\text{mi}, 200\text{mi}]]$		0.0391**
		(2.30)
E&S × Disaster × $I[\text{Distance} \in (200\text{mi}, 400\text{mi}]]$		0.0157
		(1.37)
E&S × Disaster × $I[\text{Distance} \in (400\text{mi}, 600\text{mi}]]$		0.0138
		(1.00)
E&S × Disaster × $I[\text{Distance} \in (600\text{mi}, 800\text{mi}]]$		0.0081
		(0.85)
Event × Firm × Module × County FE	Yes	Yes
Event × Module × Year-month FE	Yes	Yes
Event × Firm × Year-month FE	Yes	Yes
Event × County × Year-month FE	Yes	Yes
Adjusted R^2	0.965	0.965
Observations	192,635,653	192,635,653

Table A25: Product Sales Around Natural and Environmental Disasters — Additional Results

This table presents the estimates of a stacked DID model (Equation (4)) using product sales data aggregated to the firm-product department-county-month level. For each disaster event, we include observations located within 1000 miles of its location (excluding the disaster county) and keep a 37-month window (i.e., 18 months before, 18 months after) around the event. We then stack the relevant observations for all the events for estimation. The dependent variable is the logarithm of dollar sales. In Panel A, the independent variable is the triple interaction term *E&S* × *Disaster* × *Proximity*. *Disaster* is a binary variable that equals one for observations in each event if an environmental disaster occurs in the past 6 months. *Distance* is the distance between the disaster county and the focal county in miles. *Proximity* is geographic proximity proxied by the negative natural logarithm of *Distance*. In models (2) to (6), we replace the overall *E&S* rating with the five category ratings. In Panel B, we decompose *Distance* into four binary variables based on distance. Detailed definitions of the variables are in the Appendix and in Internet Appendix Section F. The t-statistics in parentheses are estimated based on two-way clustered standard errors at the firm and county levels. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A

Dependent Variable:	ln(Sales)					
E&S Category:	All (1)	Environment (2)	Community (3)	Diversity (4)	Employee (5)	Human Rights (6)
E&S × Disaster × Proximity	0.0309*	0.0609	0.2217***	0.0637	0.0237	-0.1502
	(1.87)	(1.30)	(2.63)	(1.55)	(0.69)	(-0.88)
Event × Firm × Department × County FE	Yes	Yes	Yes	Yes	Yes	Yes
Event × Department × Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Event × Firm × Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Event × County × Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.969	0.969	0.969	0.969	0.969	0.969
Observations	43,373,020	43,373,020	43,373,020	43,373,020	43,373,020	43,373,020

Panel B

Dependent Variable:	ln(Sales)					
E&S Category:	All (1)	Environment (2)	Community (3)	Diversity (4)	Employee (5)	Human Rights (6)
E&S × Disaster × I[Distance$\in (0mi, 200mi]$]	0.0802**	0.1744*	0.5392***	0.1403	0.0864	-0.2462
	(2.23)	(1.77)	(2.85)	(1.60)	(1.14)	(-0.69)
E&S × Disaster × I[Distance$\in (200mi, 400mi]$]	0.0340	0.0377	0.2272*	0.0987	0.0094	-0.0863
	(1.32)	(0.57)	(1.85)	(1.43)	(0.19)	(-0.17)
E&S × Disaster × I[Distance$\in (400mi, 600mi]$]	0.0122	0.0003	0.0487	0.0362	0.0161	0.1028
	(0.56)	(0.00)	(0.39)	(0.71)	(0.39)	(0.20)
E&S × Disaster × I[Distance$\in (600mi, 800mi]$]	0.0200	0.0337	0.0797	0.0283	0.0421	0.1436
	(1.08)	(0.51)	(0.92)	(0.78)	(1.03)	(0.41)
Event × Firm × Department × County FE	Yes	Yes	Yes	Yes	Yes	Yes
Event × Department × Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Event × Firm × Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Event × County × Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.969	0.969	0.969	0.969	0.969	0.969
Observations	43,373,020	43,373,020	43,373,020	43,373,020	43,373,020	43,373,020

Table A26: Inventory Days for Retailers and Manufacturers

We compute the number of inventory days for retailers and manufacturers using financial statement data for 2008 to 2019, and then average the number of inventory days for each firm. Inventory turnover is computed as the cost of goods sold divided by inventory. Inventory days is 365 divided by inventory turnover. Some of the inventories of the manufacturers are not finished products, however, but production inputs. The manufacturers are from our sample. Our data sharing agreement with NielsenIQ does not allow us to investigate the identity of the retailers in our sample. Therefore we include the industry average of inventory days by retail store type for some publicly-listed retailers that are representative of different retail channel types.

Panel A: Retailers

Retail store types	Inventory Days
Large Merchandisers and Supermarkets	41
Other Grocery Retailers	39
Drugstores	43
Convenience Stores (including Gas Stations)	28
Discount Stores	74
Department Stores	104
Office Supply Stores	56
Pet Products	105
Book Stores	101

Panel B: Manufacturers

Company	Inventory Days
Campbell Soup	64
Church & Dwight	52
Clorox	46
Coca Cola	69
Colgate-Palmolive	70
General Mills	53
Hershey	64
Kimberly-Clark	59
McCormick & Company	95
Mondelez International	60
PepsiCo	40
Proctor & Gamble	60
Tyson Foods	32

Table A27: Stock Market Reaction to E&S News and Monthly Product Sales

This table presents estimates of Equation (5) using product-month-level data. The dependent variable is the natural logarithm of dollar sales of a given product in month m. $CAR[-1,1]_{m-1}$, $CAR[-1,1]_{m-2}$, and $CAR[-1,1]_{m-3}$ are the three-day market-adjusted cumulative abnormal returns (CAR) from one day before to one day after each negative E&S news event from RepRisk (excluding governance), summed across all news events in months $m-1$, $m-2$, and $m-3$, respectively. Detailed definitions of the variables are in the Appendix and in Internet Appendix Section F. The t-statistics in parentheses are estimated based on two-way clustered standard errors at the firm and product module levels. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	$\ln(\text{Sales})_m$					
Sample:	Full sample			Conditional on having E&S news in month:		
				$m-2$	$m-3$	$m-4$
	(1)	(2)	(3)	(4)	(5)	(6)
$CAR[-1,1]_{m-1}$	0.5656			3.2300***		
	(0.71)			(3.04)		
$CAR[-1,1]_{m-2}$		0.2572			2.6827***	
		(0.43)			(3.06)	
$CAR[-1,1]_{m-3}$			0.7184			3.3177***
			(1.24)			(3.39)
Product FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.711	0.718	0.725	0.686	0.693	0.701
Observations	3,578,672	3,502,525	3,427,467	1,134,030	1,104,148	1,081,547

Table A28: Stock Market Reaction to E&S News and Monthly Product Sales — Placebo Test

This table presents the estimates of Equation (5) using product-month-level data. The dependent variable is the natural logarithm of dollar sales of a given product in month m. $CAR[-4,-2]_{m-1}$, $CAR[-4,-2]_{m-2}$, and $CAR[-4,-2]_{m-3}$ are the three-day market-adjusted cumulative abnormal returns (CAR) for the placebo time window (day -4 to day -2) before negative E&S news events from RepRisk (excluding governance), summed across all news events in months $m-1$, $m-2$, and $m-3$, respectively. Detailed definitions of the variables are in the Appendix and in Internet Appendix Section F. The t-statistics in parentheses are estimated based on two-way clustered standard errors at the firm and product module levels. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	$\ln(\text{Sales})_m$					
Sample:	Full sample			Conditional on having E&S news in month:		
				$m-2$	$m-3$	$m-4$
	(1)	(2)	(3)	(4)	(5)	(6)
$CAR[-4,-2]_{m-1}$	0.8293			-1.2158		
	(0.91)			(-1.00)		
$CAR[-4,-2]_{m-2}$		0.9169			-0.5446	
		(0.95)			(-0.55)	
$CAR[-4,-2]_{m-3}$			1.4966			0.2921
			(1.55)			(0.34)
Product FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.711	0.718	0.725	0.686	0.693	0.701
Observations	3,578,672	3,502,525	3,427,467	1,134,030	1,104,148	1,081,547

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