Consumers Reaction to Corporate ESG Performance: Evidence from Store Visits

Abstract

We investigate end consumers' reaction to corporate ESG performance. Using granular GPS data, we find that foot-traffic to firms' stores significantly decreases in the month following negative ESG incidents. Foot-traffic decreases more for stores located in democratic counties and counties with a larger fraction of highly educated and younger residents, consistent with ESG reputation influencing the demand of consumers with a preference for corporate sustainability. On the other hand, the effects are similar across stores selling durable and non-durable goods, suggesting that our results are unlikely to be driven by the information channel that a firm's ESG practices inform consumers about the quality of its products or longevity. Overall, our findings contribute to the "doing well by doing good" debate and suggest that a firm's ESG reputation can affect its financial performance and shareholder value through the consumer demand channel.

1. Introduction

The issue of whether and how ESG policies shape firm value and financial performance has gathered considerable interests from both industry and academia in recent years. To date, there are still no definitive conclusion on the relationship between a firm's ESG policies and shareholder value (Ferrell, Liang, and Renneboog, 2016; Lins, Servaes, and Tamayo, 2017; Bansal, Wu, and Yaron, 2022). The literature has proposed several channels by which a firm's ESG policies can affect its value. First, a firm's ESG profile may affect its exposure to environmental regulatory risks, which in turn affect expected returns of stocks or bonds issued by such firms (Bolton and Kacperczyk, 2021; Hsu et al., 2022). Second, a firm's ESG polices may affect investment decisions of institutional investors (Heath et al., 2021; Pastor, Stambaugh, and Taylor, 2021), whose aggregate demand shifts can influence a firm's cost of capital. However, at least so far, empirical research did not document a meaningful impact of ESG policies on firms' cost of capital (Berk and Binsbergen, 2021). Third, a firm's ESG reputation may affect its profitability and competitiveness by influencing the hiring and retention of employees (Edmans, 2011; Krueger et al., 2021). Last, and perhaps most importantly, a firm's ESG policies may affect its cash flows by influencing consumer demand for its products or services.[1] This conjecture is supported by survey evidence that consumers are willing to shun from firms engaging in bad ESG incidents or pay higher prices for more sustainable products.[2] Experimental studies from marketing literature also document that consumer behavior can be altered by ESG information (Sen and Bhattacharya,

[1] The consumer preference for ESG channel can also affect firm value through affecting its cost of capital, as predicted by theoretical models in Albuquerque et al. (2019) and Sauzet and Zerbib (2022).

[2] For example, a recent McKinsey report (Koller et al., 2019) argues that one way through which ESG creates value for shareholders is by driving consumer preference. Business wire (2021) reported that "one third of consumers are willing to pay a premium for sustainable products." A survey conducted by ING (2019) revealed that 61% of respondents said that they would be less likely to buy a product if the company was performing poorly on environmental practices.

2001). To date, however, there is limited evidence from the field on whether firms' ESG reputation indeed shape consumer behavior.

Studying the link between firms' ESG practices and consumer demand in large samples has traditionally posed several challenges. First, firm sales, typically reported in financial statements, are aggregated and coarse measure of consumer demand. For example, a firm can increase its sales by opening stores in new regions while its same-store sales growth could be negative.[3] Furthermore, the lack of granularity prevents researchers from studying the potential heterogeneity in consumers' response to the occurrence of ESG news. Second, a firm's ESG rating (or score) is typically persistent over time and may correlate with unobservable firm characteristics (e.g., corporate culture) that affect consumer behaviours. Therefore, it is difficult to cleanly attribute any change in consumer behaviour to a firm's ESG reputation.

Using a unique dataset tracking consumer store visits from SafeGraph and ESG news data from RepRisk, we are able to provide systematic and large-sample evidence to this important channel. Specifically, we show that foot-traffic significantly decreases to firms' commerce locations in the month immediately following negative ESG news (incidents).[4] Economically, a one-standard-deviation increase in the log number of ESG incidents on average leads to an approximately 1.1% decrease in monthly store visits. Additional tests suggest that the economic mechanism through which firms' ESG news affecting consumer foot-traffic is by influencing the demand of consumers with preference for corporate sustainability. We find similar results that

[3] The importance of store-level sales growth information is evident from earnings conference calls, where analysts often ask managers questions about same-store sales growth, suggesting that analysts view store-level sales growth containing incremental information about firm performance in addition to aggregated sales in accounting reports.

[4] We use two measures to capture consumer store visits. The first measure is the natural logarithm of the number of visits to a store in a month, and the second one is the natural logarithm of the number of visitors to a store in a month. The key independent variable of interest is the natural logarithm of one plus the number of negative ESG incidents for a firm in the previous month.

firms' ESG news influence consumers' online shopping behaviors, which are proxied by the shopping-related Google search volume index of brand names.

One important innovation of our study is to use granular data from SafeGraph that tracks the GPS coordinates of a large panel of consumers' cell phones across the U. S. The coverage of SafeGraph is comprehensive and highly granular. For example, Noh, So, and Zhu (2021) report that in February of 2020, the SafeGraph database contains records covering approximately 13% of the U.S. population. The SafeGraph database does not identify personal information about the consumer but does capture their precise intra-day location. SafeGraph matches these GPS records with commercial locations and provides the daily visits to stores. In verification tests, we find a strong positive correlation between store foot traffic aggregated to firm-quarter level and quarterly sales reported in Compustat. On average, a 1% increase in firm-level store visits is associated with a 0.43% increase in firm sales in the same quarter.

A key benefit of the granularity of the data is that it allows us to control for a host of high-dimensional fixed effects that help rule out many alternative explanations for our results. For example, the use of store fixed effects accounts for persistent difference in consumer foot-traffic due to difference in store location or brand name. Furthermore, we use industry*year-month and county*year-month fixed effects to mitigate concerns that our results are driven by industry-wide fluctuations in consumer demand or time-varying local economic conditions. Our results barely change even when we insert industry*county*year-month fixed effects, which account for potential heterogeneous impacts of local economic shocks on consumer demand for different sectors. The inclusion of industry*county*year-month fixed effects implies that consumer store visits decrease more in the month following negative ESG incidents, relative to visits to another store located in the same county and belonging to the same sector but is owned by a different firm with fewer ESG incidents. Thus, alternative explanations for our results would need to explain variation in consumer activity that concentrates after ESG incidents that is not explained by macroeconomic, local, and/or industry-specific economic shocks.

Another important difference with prior studies (Servaes and Tamayo, 2013) is that we use the realized ESG incidents from RepRisk as the main measure of firms' ESG profiles. This addresses an important concern associated with ESG ratings, which are typically persistent at firm level, and consumers may not be aware of ESG rating changes. Focusing on ESG news allows us to identify salient shocks to firms' ESG reputation that consumers likely pay attention to. Using data on realized ESG incidents also allows us to avoid the well-documented inconsistencies across different ESG rating providers (Berg, Koelbel, and Rigobon, 2022).

We propose and test two economic channels that can potentially explain why consumers store visits decrease after they learn about ESG incidents of the firm operating the store. First, as indicated by the survey evidence, consumers may have non-pecuniary preferences for corporate sustainability and are less willing to purchase goods from firms with poor ESG reputation (the "preference" channel). A second non-mutually exclusive explanation is that a firm's ESG profiles could inform consumers about the quality of its products or longevity (the "information" channel). Longevity matters for consumer purchase decision especially for firms selling durable goods, as consumers may forgo purchasing durable goods from firms that may be unable to provide complementary services after the purchase.

To test the "preference" channel, we exploit geographic variation in individual preferences for corporate sustainability. Our first proxy for sustainability preference is the residents' political leanings, measured by the share of the presidential vote in a county that went to Hilary Clinton in the 2016 election. Both anecdotal stories and empirical evidence suggest that Democrats, in contrast to Republicans, are more apt to support causes such as environmental and labor protection while opposing smoking, guns, and defense (Hong and Kostovetsky, 2012; Bernstein et al., 2022). Consistent with our conjecture, we find a stronger negative effect of ESG incidents on consumer foot-traffic to stores located in democratic counties compared to those in republican counties. Our second test exploits the heterogeneity in residents' average education and age. When we split our sample based on the percentage of adults with bachelor's degree and the percentage of adults older than 60 years, we find more pronounced effects in counties with a greater representation of educated and young residents. This is consistent with a common belief that younger and more educated residents care more about sustainability issues.

We also conduct several tests to assess the plausibility of the "information" channel. First, we control for earnings news in the baseline regression, which arguably provide more informative signals about firms' prospects and longevity than ESG news. Using standardized unexpected earnings (*SUE*) as a proxy for earnings news, we find that foot traffic to stores significantly increases (decreases) following the announcement of positive (negative) earnings news. This suggests that consumers may infer from earnings news about firms' prospects and longevity, which then affect their purchase decision. More importantly, however, our key result still holds with similar economic magnitude after controlling for earnings news and two monthly measures of firm fundamental changes including analyst earnings forecast revisions and short interests. Moreover, compared to ESG news, the impact of earnings news on consumer foot-traffic is weaker, both economically and statistically. Since it is unlikely that ESG incidents could provide more informative signals about firm longevity than earnings news, the results suggest that the negative consumer reaction to ESG incidents is unlikely to be fully explained by the "information" channel.

Second, we conduct a subsample test by splitting our sample into firms selling durable and non-durable goods. The idea is that if ESG reputation is informative about firms' longevity, the effect of ESG incidents on consumer store visits should be more pronounced for firms selling durable goods (e.g., furniture, automobiles).[5] Based on Fama-French 12 industry classifications, however, we find the impacts of ESG incidents on consumer foot traffic is larger for stores selling non-durable goods than those selling durable goods, although the difference is not statistically significant.

Third, we conduct cross-sectional analysis based on firms' past ESG performance. The idea is that if ESG news provide information to consumers about firm longevity, the effect we document should be stronger for firms with poorer ESG reputation to begin with. The reason is that if consumers associate poorer ESG performance with deteriorating firm fundamentals, they should worry more about the longevity of firms with poorer ESG profiles and consequently, their purchase decision should be more sensitive to new ESG incidents. We measure firms' prior ESG reputation using the occurrence of ESG incidents over the past twelve months. Contrary to the prediction of the "information" channel, the negative consumer response to ESG incidents is more pronounced for firms with better historical ESG reputation. One potential explanation is that consumers are likely to be surprised more by negative ESG incidents from firms with historically good ESG records, and hence adjust their purchasing behavior more dramatically. Collectively, these results suggest that our main finding of a negative consumer response to ESG incidents is unlikely to be explained by the "information" channel.

We conduct additional tests to exploit the interaction between ESG incidents of product market peers and store visits. First, we expect the negative consumer response to ESG incidents to be stronger when stores owned by product market peers are available in the same county. In such

[5] This prediction is supported by prior evidence that consumers, especially those who purchase durable goods, care about the long-term viability of firms, because they benefit from the continuing availability of service and maintenance (Hortaçsu et al., 2013).

case, consumers can more easily switch to peer stores to buy similar products without affecting their daily life. Using the Text-based Network Industry Classification to identify product market peers (Hoberg and Phillips, 2016), we find evidence consistent with this prediction. Subsample analysis reveals that the decrease in consumer store visits in response to ESG incidents is about 75% stronger for stores when peer stores are available in the same county, relative to those without peer stores. Second, we examine the spillover effect of peer firms' ESG incidents on consumer foot traffic to stores owned by the focal firm. The idea is that consumers may not only respond to ESG incidents of the focal firm, but also to ESG incidents of peer firms due to reputation spillover.[6] Consistent with this prediction, we find a significantly negative effect of peer firms' ESG incidents on consumer foot-traffic to the focal store.

Finally, we explore the implications of change in consumer store visits for firm value by examining whether store visits aggregated to firm level are associated with contemporaneous stock return. Using panel regressions with firm and year-month fixed effects, we find that firm-level store visits are indeed positively associated with its stock return. Economically, a one-standard-deviation increase in the natural log of firm-level store visits (visitors) is associated with 289 (222) bps of higher stock return in the same month. Recent studies (Glossner, 2021; Derrien et al., 2021) document that ESG incidents negatively predict future stock return and analysts forecasts of firm earnings and sales. These studies propose the cash flow channel as the underlying explanation for the return predictability of ESG incidents. Our finding complements these studies and highlights the mechanism through which ESG incidents affect firm cash flows is through influencing consumer demand.

[6] Using the 2015 Volkswagen (VW) emissions scandal as a natural experiment, Bachmann et al. (2019) document a large spillover effect from the scandal to the non-VW German auto manufacturers.

We conduct several robustness tests for our baseline results. First, the negative consumer response to firms' ESG incidents is robust when we exclude governance-related incidents or examine the impacts of environmental and social incidents separately. Second, we find similar results using alternative measures of firm ESG practices including the RepRisk index (*RRI*) from RepRisk and monthly ESG risk ratings provided by Sustainalytics. Third, we conduct an event study of changes in consumer foot-traffic in the weeks around ESG incidents, and find similar results. This helps rule out an alternative explanation for our results that firms experience ESG incidents may cut advertising expenditures, which then leads to a reduction in consumer activity. The consistent findings we obtain with the weekly store visits suggest that the result is unlikely driven by the advertising channel, as firms are unlikely to change advertising policies shortly after the occurrence of ESG incidents. We also address this concern by controlling for a firm's advertising expenditures (scaled by sales) in the baseline regressions and find similar results.

The rest of the paper proceeds as follows. Section 2 briefly reviews the related literature and highlights the contribution of our paper. Section 3 details the datasets used in this study and presents the summary statistics. Section 4 presents our main results regarding consumer responses to firms' ESG incidents. We also conduct cross-sectional heterogeneity tests to shed light on the economic mechanisms. We conduct supplementary tests in Section 5. Section 6 concludes the paper.

2. Related Literature and Contribution

Our paper primarily contributes to the ongoing debate on whether firms can do well by doing good. Empirical studies so far have documented mixed evidence regarding the relationship between a firm's ESG practices and its financial performance and shareholder value. However, it is often difficult to pin down the direction of causal relation from these studies. It remains possible that better ESG policies simply indicates a well-run firm, that is, a firm can afford to do good things if doing well. More importantly, little is known about the exact channels through which ESG policies influence firm value. A few exceptions propose that the cash flow channel could lead to a positive effect of sustainability practices on firm value. For example, Edmans (2011) document that employee satisfaction is beneficial for shareholder value. Servaes and Tamayo (2013) show that CSR activities are value enhancing for firm with more consumer awareness, as proxied by advertising expenses. Their explanation is similar to our paper that firms' CSR activities can create value by influencing consumer behavior.

Relative to their paper, we provide more direct evidence using more granular and refined measure of consumer demand, which allows us to pin down the direction of causation and to examine the heterogeneity in consumer response.[7] We also differentiate with their paper by using ESG news (instead of ESG ratings) as shocks to firms' ESG reputation. This is important because ESG ratings are slow-moving firm characteristics and Servaes and Tamayo (2013) show the importance of controlling for firm fixed effects when testing the relationship between ESG and firm performance. Focusing on another important stakeholder, i.e., employees, Krueger et al. (2021) provide evidence that firms with better ESG policies pay lower wages, implying that ESG policies can create value for shareholders through a reduction in wages. Using analyst earnings forecast to proxy for investor expectations about future firm fundamentals, Derrien et al. (2021) present evidence that analysts significantly downgrade earnings forecasts of firms experiencing ESG incidents. They also find the downward revisions of earnings forecasts reflect expectations of

[7] A few papers document that consumers do react to the ESG performance of financial institutions, in the forms of greater flows into mutual funds with higher sustainability ratings (Hartzmark and Sussman, 2019) and a decline in deposit growth following the release of negative bank social performance (Chen, Huang, and Wang, 2022).

lower future sales (rather than higher future costs), which is consistent with our evidence that negative shocks to a firm's ESG reputation led to lower consumer demand for its products.[8]

Our paper is also related to a growing literature examining whether important stakeholders can influence firms' ESG policies. Studies have documented that institutional investors and banks can positively influence firms' ESG policies, especially for investors and lenders who care about sustainability (Dyck et al., 2019; Chen, Dong, and Lin, 2020; Azar et al., 2021; Gantchev, Giannetti, and Li, 2022; Houston and Shan, 2022). Dai, Liang, and Ng (2020) and Schiller (2018) find that socially responsible corporate customers can infuse similar socially responsible business practices in their dependent suppliers. Closely related to our study, Bisetti, She, and Zaldokas (2022) document that U.S. importers cut trade relationships when their international suppliers face environmental and social (E&S) incidents. Our paper differs from these papers as we focus on the behavior of end-consumers rather than corporate customers. One implication of our study is that end-consumers may promote good ESG practices for firms directly selling to end-consumers and indirectly transmit ESG policies along the entire supply chain.

Our study also contributes to a growing literature that uses granular consumer-generated data as a leading indicator of firm sales and stock returns. For examples, recent studies use satellite image tracking the number of cars in retailer's parking lots, credit-card spending transaction and NielsenIQ scanner data to nowcast firms' revenue and earnings news (Froot et al., 2017; Zhu, 2019; Katona et al., 2022; Agarwal, Qian, and Zou, 2021; Dichev and Qian, 2022). Using similar geo-location data as ours, Jin, Stubben, and Ton (2022) find that customer loyalty explains variation in the revenues and earnings persistence. Noh, So, and Zhu (2021) show that foot-traffic to firms' commerce locations significantly increases in the days following their earnings announcements.

[8] Gloßner (2021) finds that ESG incidents (from RepRisk) negatively predict future stock returns, suggesting that stock market investors underreact to ESG news.

The geo-location data has also been used in studies examining the benefits and costs of lockdown policies during the recent COVID-19 outbreak (Painter and Qiu, 2021; Bizjak et al., 2022).[9] Our paper differs from these studies as we investigate end-consumers responses to firms' ESG practices, an increasingly important corporate objective.[10]

3. Data and Sample

In this section, we first detail the different datasets used in our study and report summary statistics. We then conduct validation test for the foot traffic data.

3.1 Data and Sample Selection

We obtain the store-level foot traffic data in the U.S. from the SafeGraph database. SafeGraph collects anonymized GPS data from users' mobile phone apps (i.e., weather or mapping apps etc.) for more than 6 million points-of-interests (POIs) with over 6,000 distinct brands. The database provides us with a unique way to observe consumers' foot-traffic at the store level.[11] The data have been used in prior studies in economics and finance (e.g., Painter, 2021; Gurun, Nickerson, and Solomon, 2022; Jin, Stubben, and Ton, 2022; Noh, So, and Zhu, 2022; Bizjak et al., 2022). However, to the best of our knowledge, ours is the first to use the data for research on the effects of corporate ESG reputation on consumer activity.

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[9] For example, Bizjak et al. (2022) show that firms with Republican-leaning CEOs experience an increase in store visits during COVID-19 lockdown periods, relative to firms with Democratic-leaning CEOs. Painter and Qiu (2021) find that residents in Republican counties are less likely to completely stay at home after a state-mandated stay-at-home order has been implemented relative to those in Democratic counties.

[10] Interestingly, several recent papers show that improving ESG policies may have detrimental effects on consumer demand. Painter (2021) finds that Walmart's 2019 statement on gun control led to a reduction in foot traffic in highly Republican counties. Gurun, Nickerson, and Solomon (2022) find that the provision of public goods by Starbucks crowd out consumer demand. Agarwal et al. (2020) show that customer responses to privacy leakage breaches are weak and short-lived, suggesting that consumers value the perceived benefit of convenience more than cost of privacy leakages.

[11] One caveat about the SafeGraph data is that we are unable to observe the intent to purchase the focal firms' products at stores owned by non-focal firms. For example, we do not capture visits to Walmart to buy PepsiCo products if PepsiCo has ESG incidents.

SafeGraph provides us the daily number of visits to a store, the number of unique visitors to a store, the name and industry affiliation[12] of the firm that owns the store, and the address of the store (including the latitude and longitude). For our purpose, we track monthly visits and unique visitors at the store level. The SafeGraph data is available starting from January 2018 and our sample ends in September 2020.

We obtain firms' ESG incidents from the RepRisk database, which screens over 80,000 media and stakeholder sources over 20 languages every day to look for negative incidents (news) related to ESG issues for both public and private firms. The ESG incidents are classified into 28 distinct issues. Environmental issues include news about climate change, pollution, waste issues, etc. Social issues include child labour, human rights abuses, etc. Governance issues include executive compensation issues, corruption, etc. One incident can be associated with multiple issues and therefore can belong to two or more E/S/G categories. Each incident is measured on a scale from one to three, which indicates the severity (harshness), reach (influence), and novelty (newness) of the incident. The data provider also provides a RepRisk index (RRI), which is constructed using proprietary algorithm (based on severity, reach, and novelty) to reflect the impact of ESG incidents. The RepRisk database has been used by a few recent studies that examine how various market participants react to negative shocks to firms' ESG reputation, including shareholders, employees, and equity analysts (Gantchev, Giannetti, and Li, 2022; Derrien et al., 2021; Bonelli et al., 2022).

To construct our sample, we begin with the universe of all firms in the SafeGraph database that are publicly listed on the U.S. stock exchanges (i.e., NYSE, NASAQ, and AMEX). Since the main identifier is the firm name, we manually merge the SafeGraph data with RepRisk by

[12] Our industry classification is based on the North American Industry Classification System (NAICS) code.

searching for the same firm name to obtain the ESG incidents data. We then merge with the Compustat and CRSP database to obtain firm financial variables and stock return data. After merging with these databases, our final sample contains 11,361,099 store-year-month observations with 266 unique publicly listed firms from January 2018 to September 2020. Our sample size is comparable to other studies using the SafeGraph data.[13]

In Figure 1, we plot the industry composition of our sample firms based on their two-digit NAICS codes. Unsurprisingly, most firms in our sample are from retail (48.5%), finance and insurance (24.1%), or accommodation/food services (16.2%) sectors. One of the advantages of the geo-location data on store visits is its broad coverage of stores. For instance, it covers several different granular categories within the retail industry (e.g., fashion, furniture, appliances, movie theatres, restaurants, coffee shops, and car dealerships). In addition, the brands of stores in our sample are easily recognized by the consumer as associated with the firm involved in ESG incidents.

Table 1 presents the summary statistics of our sample. The average (median) value of *Ln(visits*) is 5.187 (5.505), indicating that the average (median) number of monthly store visits is 179 (246). The average (median) number of monthly unique visitors is 118 (157). The total number of ESG incidents across all firm-years in our sample is 7,871 and 219 out of 266 firms have at least one ESG incidents during our sample period. The average value of *Ln(ESG incidents+1)* is 0.326, indicating that the average number of monthly ESG incidents for a firm is 0.39. The distribution of ESG incidents is highly positively skewed, as both the median and 75th percentile value of *Ln(ESG incidents+1)* is zero. Firms in our sample on average have cash holdings of 7.1%, market-

[13] For example, Noh, So, and Zhu (2021) identify 224 unique firms over the period from January 2017 through February 2020.

to-book ratio of 2.06, leverage ratio of 0.31, return-on-assets of 13.6%, and past-12 month return of 10.3%.

3.2 Do Store Visits Reflect Consumer Demand?

As the foot-traffic data we use captures only consumer interests (not actual transactions), we first validate whether consumer foot-traffic to stores is a reasonable proxy for firm sales. To conduct the validation test, we first aggregate the number of visits and visitors at store-month level to firm-quarter level. We then examine whether firm-level store visits (the growth of store visits) are positively associated with firms' quarterly sales (sales growth) in the same quarter.[14] Table 2 shows that the coefficients of *Ln(Firm visits), Ln(Firm visitors), Firm visits growth* and *Firm visitors growth* are all positive and highly significantly, suggesting that consumer store visits is a good proxy for firm sales and consumer demand. As we include firm-fixed effects in the regression, the coefficient estimate of *Ln(Firm visits)* in column (1) suggests that on average, a 1% increase in a firm's store visits nowcasts a 0.44% increase in its quarterly sales. The results are similar when we look at sales growth in columns (3) and (4). There is a strong positive correlation between growth in firm-level store visits (visitors) and sales growth in the same quarter. Overall, the results validate that consumer foot-traffic to stores captures consumer demand reasonably well.

4. Empirical Results

In this section, we first present the main results of the effects of ESG incidents on consumer store visits. We then conduct tests to shed light on the economic mechanisms underlying the main results.

[14] One caveat when we aggregate the number of unique visitors at monthly frequency to quarterly frequency is that the aggregation may not be accurate as a unique visitor could visit the same store more than once in a quarter.

4.1 Baseline results

We begin our analysis by examining whether consumer foot traffic to a store decrease in the month following negative ESG incidents of the firm operating the store. We estimate the following regression models using the monthly foot traffic to a store as the dependent variable of interest:

$$FootTraffic_{s,i,m} = \beta_0 + \beta_1 Ln(ESG\ incidents + 1)_{i,m-1} + \Sigma\beta_i Controls_{i,y-1} + \gamma' FEs + \varepsilon_{s,i,m} \quad (1)$$

where $FootTraffic_{s,i,m}$ is measured by $Ln(Visits)_{s,i,m}$ and $Ln(Visitors)_{s,i,m}$. $Ln(Visits)_{s,i,m}$ is the natural logarithm of the number of visits to store *s* of firm *i* in month *m*. $Ln(Visitors)_{s,i,m}$ is the natural logarithm of the number of unique visitors to store *s* of firm *i* in month *m*. $Ln(ESG\ incidents)_{i,m-1}$ is the natural logarithm of one plus the number of negative ESG incidents for firm *i* in month *m*-1. Following Bizjak et al. (2022), $Controls_{i,y-1}$ indicates a list of firm characteristics measured in year *y*-1 (prior to the occurrence of foot traffic), including a firm's cash holdings (*Cash*), its market-to-book ratio (*Market-to-book*), leverage ratio (*Leverage*), return-on-assets (*ROA*), the natural log of firm sales (*Ln(Sales)*), and past twelve-month cumulative stock return (*Return_12m*).

We include store fixed effects in all specifications to control for time-invariant store characteristics, such as the brand popularity and the location of the store, that may affect consumer demand.[15] We also insert the *County-Year-Month* and *Industry-Year-Month* fixed effects to control for the impact of time-varying local economic conditions and industry-level fluctuations in consumer demand, respectively. In our most stringent specification, we include *Industry-County-*

[15] For example, stores located in more convenient places should attract more consumer foot traffic than those located in distant areas.

Year-Month fixed effects to account for the heterogenous impacts of local economic conditions on consumer demand of products from different sectors.[16] The inclusion of *Industry-County-Year-Month* fixed effects implies that we are essentially comparing consumer foot-traffic to a store owned by a firm with more ESG incidents, relative to foot-traffic to another store located in the same county and belonging to the same sector, but is owned by a different firm with fewer ESG incidents. We report *t*-statistics based on robust standard errors clustered at the county by year-month level. The intercept term is omitted for brevity.

Table 3 presents the baseline results. Columns (1) - (4) (columns (5) - (8)) report the results of the effect of ESG incidents on the number of store visits (visitors). Across different empirical specifications, we find that the coefficients of *Ln(ESG incidents+1)* are negative and highly significant with similar coefficient estimates, suggesting that foot-traffic to firms' commerce locations significantly decreases in the month following ESG incidents. For example, the coefficient of *Ln(ESG incidents+1)* is -0.017 (*t*-stats = -30.377) when we include both *Store* and *Industry-County-Year-Month* fixed effects and a host of control variables. In terms of the economic magnitude, the coefficient estimates in columns (4) and (8) imply that a one-standard-deviation increase in *Ln(ESG incidents+1)* on average leads to an approximately 1.11% (=0.017*0.654*100%) decrease in both monthly store visits and visitors, respectively. As the inclusion of *Store* and *Industry-County-Year-Month* fixed effects represent our most stringent specification, we report all the remaining results with store-year-month level observations using this set of fixed effects.

[16] For example, Mian and Sufi (2014) show that decline in housing net worth in a county has a larger impact on non-tradable sectors compared to tradeable sectors.

4.2 Robustness tests

In the Online Appendix, we conduct robustness checks for the baseline results by using alternative measures of firm ESG policies and including additional firm-level controls. Firstly, we look at separately the impacts of environmental and social incidents on store visits to examine whether consumers respond differently to different dimensions of corporate sustainability. Panel A of Table IA.1 presents the results. Columns (1) - (2) (columns (4) - (5)) report the results using *Ln(E incidents+1)* and *Ln(S incidents+1)* as key variables of interest, respectively. We find the decrease in consumer store visits following negative environmental and social incidents are similarly significant, with slightly stronger consumer reaction to firms' environmental incidents. For example, column (1) reports that the coefficient of *Ln(E incidents+1)* is -0.022 (*t*-stats = -24.68), implying that a one-standard-deviation increase in *Ln(E incidents+1)* leads to an approximately 0.99% decrease in monthly store visits. By comparison, a one-standard-deviation increase in *Ln(S incidents+1)* leads to an approximately 0.84% decrease in monthly store visits. In columns (3) and (6), we find similar results when we exclude governance-related incidents from the construction of ESG incidents (*Ln(E&S incidents+1)*).

Secondly, we use the RepRisk Index (RRI) as an alternative measure of firm ESG reputation. The RRI ranges from 0 to 100 and is calculated based on proprietary algorithms, which incorporate the severity, the reach, and the novelty of the incident. According to RepRisk, an increase in RRI reflects new ESG incidents, while RRI decreases mechanically if there are no new ESG incidents over a certain period. We therefore construct a variable *RRI increase*, defined as the change of RRI between the current month and the prior month if the change is positive. We assign a value of zero to *RRI increase* if the monthly change of RRI is negative. We then run panel regressions of monthly store visits (and visitors) on *Ln(RRI increase+1)* and report the results in

Panel B of Table IA.1. We find negative and highly significant coefficients of *Ln(RRI increase+1)* for both *Ln(Visits)* and *Ln(Visitors)*, suggesting that our baseline finding is robust to using the RepRisk Index that takes into account the reach and severity of the incidents. We also use the monthly ESG risk ratings provided by Sustainalytics as an alternative measure of firm ESG policies and re-run the baseline regressions. Panel C of Table IA.1 shows that our main results are also robust to using this alternative measure of ESG reputation.

One alternative explanation for our main result is that the decrease in consumer store visits following firm ESG incidents could be driven by firms cutting advertising expenses. To rule out this possibility, we add a variable *Ad_Exp*, defined as advertising expenses scaled by sales, as an additional control in the baseline regression. We report the results in Table IA.2. Consistent with the intuition, the positive and significant coefficient of *Ad_Exp* suggests that firms attract more consumer store visits when they spend more on advertisement. More importantly, however, the coefficient of *Ln(ESG incidents +1)* remains similar after controlling for advertising expenditures, suggesting that our key finding of a negative effect of ESG incidents on consumer store visits is unlikely driven by changes in advertising expenses by firms experiencing negative ESG shocks.

4.3 The long-term effects of ESG incidents on store visits

Our baseline results show a reduction in consumer store visits in the month immediately following negative ESG incidents. It is intriguing to examine whether the decrease of foot traffic following ESG incidents is a temporary phenomenon or lasts for longer periods. To that end, we cumulate the monthly store visits (visitors) over the first to the third month and over the fourth to the sixth month following ESG incidents, respectively. We then regress the cumulative number of store visits (visitors) over these two horizons on *Ln(ESG incidents+1)* and report the results in

Table 4. The results show that the negative impact of ESG incidents on firms' consumer foot traffic last for three months, and the effect becomes smaller and statistically insignificant after 3 months following ESG incidents. As we do not observe any reversal in consumer store visits in the longer horizon, it suggests that the initial reduction in consumer store visits seems to be permanent and is thus detrimental to shareholder value.

4.4 Event study of changes in store visits in the weeks around ESG incidents

To further mitigate concerns about confounding events or news, we conduct an event study of changes in consumer store visits in the weeks following negative ESG news. To rule out delayed consumer reactions to past ESG incidents, for each new ESG incident event, we require the firm to have no ESG incidents in the prior 24 weeks. We restrict our sample to a short window of [-12, +12] calendar weeks around the occurrence of ESG incidents. We estimate the following regression at store-week level with 5,814,864 store-week observations:

$$Ln(Visits + 1)_{s,i,w} = \beta_0 + \beta_1 Post_{i,w} + \Sigma\beta_i Controls_{i,y-1} + \gamma' FEs + \varepsilon_{s,i,w}$$

where $Ln(Visits + 1)_{s,i,w}$ is the natural logarithm of the number of visits to a store *s* of firm *i* on week *w*. $Post_{i,w}$ is an indicator variable equal to one if the week *w* of firm *i* is after the occurrence of ESG incidents, and zero otherwise. We insert *Store* and *County-Week* and *Industry-Week* fixed effects (or *Industry-County-Week* fixed effects) for the regressions.

Table 5 reports the results. We find that the coefficients of *Post* are negative and highly significant across different specifications, suggesting that consumer foot-traffic decreases significantly in the weeks following negative ESG incidents compared to the weeks before. For example, column (4) shows that the coefficient of *Post* is -0.012 (*t*-stats = -12.212) when we include both *Store* and *Industry-County-Year-Month* fixed effects and a list of control variables.

In terms of the economic magnitude, the coefficient estimate indicates that weekly consumer store visits decrease by 1.2% within the 12 weeks after the occurrence of ESG incidents. The consistent results we obtain using the higher frequency weekly store visit measure suggest that our key finding is unlikely driven by confounding firm events.

4.5 Economic Channels

We test two economic channels that can potentially explain our finding of a negative effect of firms' ESG incidents on consumer store visits. First, as shown by the survey evidence, consumers may have non-pecuniary preferences for corporate sustainability and are less willing to purchase products from firms with poor ESG reputation (the "preference" channel). A second non-mutually exclusive channel is that a firm's ESG policies could inform consumers about the quality of its products or longevity (the "information" channel). In this subsection, we conduct a host of cross-sectional analyses to examine the relative importance of these two channels.

4.5.1 Non-pecuniary Preferences for ESG

To test the first channel, we exploit geographic variation in personal preferences for corporate sustainability. Our prediction is that the negative consumer responses to firm ESG incidents should be more pronounced for those with stronger ESG preference. Our first proxy for consumers' ESG preference is the political leanings of residents, as measured by the share of the presidential vote in a county that went to Hilary Clinton in the 2016 presidential election. Ample evidence suggests that Democrats, in contrast to Republicans, are more apt to support causes such as environmental and labor protection while opposing smoking, guns and defense.[17] We partition our sample of stores into two groups, democratic and republican, based on whether a store is in a county where the fraction of voting for Hilary Clinton is above or below sample median. We then conduct subsample test for the effect of ESG incidents on consumer store visits and report the results in Panel A of Table 6.

Consistent with the "preference" channel, we find a larger decrease in consumer foot-traffic in response to ESG incidents for stores located in democratic counties. For example, column (1) ((2)) shows that the coefficient of *Ln(E incidents+1)* is -0.018 (-0.015) in democratic (republican) counties. The *F*-statistics testing the difference in the coefficients of *Ln(ESG incidents+1)* in two subsamples indicate that the difference is statistically significant for both the number of store visits (p-value = 0.034) and visitors (p-value = 0.003).

Our second and third proxy for consumer ESG preference are the education level and age of a county's residents. These are motivated by a popular perspective in neoclassical economics that sustainability issues are "luxury goods" that are likely to be of concern only to those whose more basic needs for food, housing, and survival are adequately met (Baumol and Oates, 1993). In addition, the younger generation is usually believed to have a stronger preference for sustainability than the older generation do.[18] To test these predictions, we use the percentage of adults with bachelor's degree (2015-2019 average) and the percentage of adults older than 60 years (2018-2020) at county level to measure the average education and age of store visitors,

[17] For example, Hong and Kostovetsky (2012) find that mutual fund managers who make campaign donations to Democrats hold less of their portfolios (relative to non-donors or Republican donors) in companies that are deemed socially irresponsible. There are also recent news reporting that the ESG investing approach is under Republican attacks (Bloomberg, 2022).

[18] For example, the 2022 Survey of Investors, Retirement Savings, and ESG reports that around two-thirds (65 percent) of young investors are very concerned about environmental and social issues such as carbon emissions, renewable energy sourcing, workplace diversity, and workplace conditions, compared with only 30 percent of older investors (58 years and old).

respectively.[19] We divide our sample into two groups based on whether the store is located in a county with above-average education level or the fraction of old population in each state-year. We then conduct subsample test for the effect of ESG incidents on store visits and report the results in Panels B and C of Table 6, respectively. Consistent with our prediction, we find a stronger decrease of store visits in response to ESG incidents in counties with a greater fraction of highly educated and younger residents. For example, Panel B shows that the coefficient of *Ln(ESG incidents+1)* is -0.018 (-0.014) for the subsample of stores located in counties with above (below) average education level. The *F*-statistics testing the difference in the coefficients of *Ln(ESG incidents+1)* in two subsamples are statistically significant (p-value lower than 0.01). Panel C reports similar results based on the fraction of old people in a county.

Collectively, these cross-sectional heterogeneity tests support the "preference" channel that the negative consumers response to ESG incidents is more pronounced when consumers are more likely to exhibit a strong preference for sustainability.

4.5.2 ESG Incidents Signaling Firm Longevity

Alternatively, ESG news could affect consumer demand by informing consumers about the quality of a firm's products or its longevity. To examine this "information" channel, we include additional control for earnings news in the baseline regression. Earnings news arguably provide more informative signals about firms' future prospect than ESG news. As a result, the effect of ESG incidents on store visits should become weaker once we control for earnings news under the "information" channel. We use earnings surprise to capture earnings news and denote it as *SUE*.

[19] The data on county-level education is obtained from 2015-19 American Community Survey 5-year average county-level estimates. The data on population age is obtained from 2018-2020 Annual County Resident Population by Age, Sex, Race, and Hispanic Origin from U.S. Census Bureau, Population Division.

In addition, Noh, So, and Zhu (2021) find that consumers store visits increase in the days following firms' earnings announcements, potentially due to earnings announcements drawing consumers' attention to the announcing firms. We thus add a variable *EAM* in the baseline regression, which is a dummy variable equals to one if the prior month is an earnings announcement month, and zero otherwise. We also include two additional measures to capture changes in firm fundamentals, including revisions in analyst consensus forecast of earnings-per-share (*FREV*) and short interest ratio (*short ratio*).[20]

Table 7 shows that the coefficients of *SUE* are around 0.017 (*t*-stats = 17.149), consistent with the findings of Noh, So, and Zhu (2021) that earnings news may shape consumer demand by informing them about firms' fundamentals or longevity. In addition, the coefficient of *FREV* is significantly positive, while the coefficient of *short ratio* is significantly negative, consistent with the information content of analyst earnings forecast revisions and short interests. Importantly, our main result still holds with similar economic magnitude after controlling for earnings news and other proxies of firm fundamental changes. Moreover, compared to the impact of ESG news, the impact of earnings news is weaker, both economically and statistically. For example, the coefficient estimate of *SUE* in column (1) suggests that a one-standard-deviation decrease in *SUE* leads to an approximately 0.46% (=0.271*0.017*100%) decrease in monthly store visits, which is less than half of the economic effect of ESG incidents on store visits. Since it is unlikely that ESG news could provide more informative signals about firm fundamentals than earnings news, the results suggest that the negative consumers response to ESG incidents is unlikely to be fully explained by the "information" channel.

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[20] Both analyst earnings forecast revisions and short interest ratio are commonly used measures of changes in firm fundamental performance. See for example, Dechow et al. (2001), Easton and Monahan (2005), and Da and Warachka (2009). Compared to accounting-based measures of firm fundamentals which are only available at quarterly frequency, these two measures are available at monthly frequency.

Second, we conduct a subsample test based on whether the store mainly sells durable or non-durable goods. If consumers infer firms' longevity from ESG incidents, their purchase decisions should be more sensitive to ESG news of firms selling durable goods (e.g., furniture, automobiles). This prediction is motivated by prior studies documenting that consumers, especially those who purchase durable goods, care about the long-term viability of firms, because they benefit from the continuing availability of service and maintenance (Hortaçsu et al., 2013). To test this prediction, we divide our sample into two groups of firms selling durable and non-durable goods, based on Fama and French 12 industry classifications.[21] Table 8 shows that the negative impacts of ESG incidents on consumer foot traffic is larger for stores selling non-durable goods than those selling durable goods, although the difference between the two subsamples is not statistically significant according to the *F*-test. For example, the coefficient estimates in columns (1) and (2) imply that a one-standard-deviation increase in *Ln(ESG incidents+1)* on average leads to an approximately 1.2% (0.9%) decrease in consumer foot traffic to stores selling non-durable (durable) goods.

Third, we exploit the difference in firms' historical ESG reputation. Our prediction is that if a firm's ESG incidents inform consumers about its longevity, the effect we document should be stronger for firms with poorer ESG reputation to begin with. The reason is that new ESG incidents should drive firms with poorer fundamentals closer to bankruptcy than for firms with strong fundamentals. Consequently, consumers should worry more about the longevity of firms with poorer historical ESG reputation and respond more strongly to new ESG incidents of such firms. We measure firms' historical ESG reputation using the occurrence of ESG incidents over the past 12 months. We then conduct a subsample test based on whether a firm has any negative ESG

[21] Specifically, we categorize all firms in the "Consumer Durables" industry in the Fama-French 12 industry groups as firms selling durable goods and the remaining firms as the "Other" group.

incidents in the past 12 months and report the results in Table 9. Contrary to the "information" channel, we find the decrease in consumer store visits in response to ESG incidents is much stronger for firms with better historical ESG reputation to begin with. For example, column (1) ((2)) shows the coefficient of *Ln(ESG incidents+1)* is -0.073 (-0.018) in the sample of firms without (with) any ESG incidents in the past 12 months. The *F*-statistics indicate that the differences in the coefficients of *Ln (ESG incidents)* between the two subsamples are statistically significant for both the number of visits (p-value =0.000) and visitors (p-value =0.000). One explanation could be that consumers are likely more surprised by negative ESG incidents from firms with good ESG reputation, and hence change their purchase behavior more dramatically.

Viewed as a whole, these results are inconsistent with the "information" channel that a firm's ESG reputation affects consumer activities by informing consumers about its product quality or longevity, although we cannot fully rule out this alternative channel.

5. Supplementary Analyses

In this section, we conduct several supplementary tests to explore (1) the cross-sectional heterogeneity based on consumers' costs of switching to peer stores; (2) any spillover effects of peer firms' ESG incidents on foot traffic to focal firms' stores; (3) the implication of store visits for stock return; (4) the impact of ESG incidents on consumers' online shopping interest.

5.1 Availability of Product Market Peers

Our first supplementary test explores the heterogeneity in consumer responses to ESG incidents based on the availability of peer stores selling similar products in the same area. Intuitively, the negative consumers response to ESG incidents should be stronger when consumers can more easily switch to peer stores in the same county for purchase. To test this idea, we separately examine the effect of ESG incidents on consumer store visits for subsamples partitioned by the availability of peer stores in the same county-year. Following the literature, we use the Text-based Network Industry Classification (TNIC) to identify product market peers, as developed by Hoberg and Phillips (2016).

Table 10 reports the results. Consistent with our conjecture, the decrease in consumer store visits following negative ESG incidents is indeed larger when there are peer stores operating in the same county in the same year. For example, column (1) ((2)) shows the coefficient of *Ln(ESG incidents+1)* is -0.014 (-0.008) for the subsample of stores with (without) peer stores operating in the same area. The *F*-statistics indicates that the difference in the coefficients of *Ln (ESG incidents)* between the two subsamples is statistically significant for both the number of visits and visitors.

5.2 Spillover Effects of Peer Firms' ESG Incidents

Next, we examine any spillover effects of peer firms' ESG incidents on consumer foot traffic to stores owned by the focal firm. It is possible that consumers not only react to ESG news of the focal firm, but also to ESG incidents of peer firms due to reputational spillover. To test this conjecture, we estimate the following regression model:

$$FootTraffic_{s,i,m} = \beta_0 + \beta_1 Ln(Peer\ ESG\ incidents + 1)_{i,m-1} + \beta_2 Ln(ESG\ incidents + 1)_{i,m-1} + \Sigma\beta_i Controls_{i,y-1} + \gamma' FEs + \varepsilon_{s,i,m} \quad (2)$$

where $Ln(Peer\ ESG\ incidents + 1)_{i,m-1}$ is the natural log of one plus the average number of ESG incidents of peer firms in month *m-1*. Other variables are the same as in the model (1).

Table 11 reports the results. We find that the coefficients of *Ln(Peer ESG incidents+1)* are negative and statistically significant, suggesting that consumers significantly reduce visits to stores owned by a focal firm when its peers have negative ESG incidents. The negative spillover effect may be due to categorical thinking at industry level by consumers regarding ESG reputation.

5.3 Implication for Stock Return

Third, we examine the implication of consumer store visits for shareholder value by testing the relationship between firm store visits and its stock return. We run the following panel regression with observations at stock-year-month level:

$$RET_{i,y,m} = \beta_0 + \beta_1 FootTraffic_{i,y,m} + \Sigma\beta_i Controls_{i,y-1} + \gamma' FEs + \varepsilon_{i,y,m} \quad (3)$$

where $RET_{i,y,m}$ is monthly stock return of firm i in month m of year y. $FootTraffic_{i,y,m}$, measured by *Ln(Firm visits)* and *Ln(Firm visitors)*, is the monthly store visits aggregated to firm level for firm *i* in month *m* of year *y*. All control variables are observed at the end of year *y-1*. We include firm fixed effects and year-month fixed effects in the model. We report the *t*-statistics based on standard errors clustered at firm level.

Table 12 reports the results. We find the coefficients of *Ln(Firm visits)* and *Ln(Firm visitors)* are both significantly positive, implying that consumer store visit is positively correlated with shareholder value. In terms of the economic significance, a one-standard-deviation increase in the log of monthly store visits (visitors) at firm level is associated with 289 (222) bps of higher stock return in the same month. This result, when combined with our main finding that ESG incidents negatively affect consumer store visits, suggests that a firm's ESG policies can affect its shareholder value through the consumer demand channel.

5.3 ESG incidents and online consumer interest

Our final supplementary test examines whether shocks to a firm's ESG reputation also influence consumers' online shopping interest for its products. Specifically, we use the shopping-related search volume index (SVI) of brand names from Google Trends to proxy for online customer interest. This sample enables us to examine whether our main results generalize to consumer online shopping activities, which has become an important part of consumer purchases.

Google Trends is a service provided by Google Inc. that tracks online search frequencies of user-specified terms. Since its initiation in 2004, Google Trends data have been applied in various fields of academic research. For example, existing studies in finance (e.g., Da, Engelberg, and Gao, 2011) use Google SVI of the stock ticker of a firm to capture retail investor attention. Marketing studies also use Google searches to measure prepurchase information acquisition by consumers (e.g., Hu, Du, and Damangir, 2014). Following Hu, Du, and Damangir (2014) and Sun (2017), we take additional procedures to obtain a more precise measure of consumer interest. First, we focus on the SVI of brand names so that the search activities are more likely conducted by consumers. Second, we adopt the advanced functions of Google Trends by selecting the "shopping" category to isolate consumer interest from other types of online interest.

Table 13 reports the effect of ESG incidents on online consumer interest. We select the same set of firms as in our main analysis, and the sample period runs from February 2007 to September 2020. The dependent variable in the regression is *SVI_adjusted*, defined as the Google SVI of the brand names of a company in month *t* minus its average SVI in the past three months. The independent variable of interest is *Ln(ESG incidents+1)* measured in month *t*-1. The unit of observation is at brand-year-month level, and we control for the same set of variables as in the baseline model (1). In columns (1) and (2), we include *Brand* and *Year-Month* fixed effects, and in columns (3) and (4), we include *Brand* and *Industry-Year-Month* fixed effects. The inclusion of *Brand* fixed effects allows us to isolate the within-brand variation in online consumer interest. The inclusion of *Industry-Year-Month* fixed effects accounts for any time-varying, industry-specific factors (e.g., launch of e-commerce business) that may shape online consumer behavior. Across all specifications, we find that the coefficients of *Ln(ESG incidents+1)* are negative and significant. In terms of the economic magnitude, the coefficient estimate in column (4) implies that a one-standard-deviation increase in *Ln(ESG incidents+1)* on average leads to an approximately 0.12 decrease in *SVI_adjusted*, which represents about 1% of the standard deviation of *SVI_adjusted*. Overall, our main finding of a negative effect of ESG incidents on consumer demand extend to firms' e-commerce businesses.

6. Conclusion

In this paper, we investigate end consumers' reaction to firms' ESG performance. Using granular GPS data, we find that foot-traffic to firms' commerce locations significantly decreases in the month following negative ESG incidents. The results are robust after controlling for earnings news and with alternative measures of ESG performance. Using demographic information, we find that the decreases in consumer foot-traffic are more pronounced in areas with a greater percentage of more educated individuals and for consumers living in democratic counties. Consumer reactions are also stronger for firms with better historical ESG reputation and for stores selling non-durable goods. Collectively, our findings contribute to the "doing well by doing good" debate and suggest that a firm's ESG polices can affect its financial performance and value through the consumer demand channel.

Appendix A Variable definitions and data sources

Variables	Definition	Source
Footprint variables		
Ln(Visits)	The natural logarithm of the number of visits to a store in month t	SafeGraph
Ln(Visitors)	The natural logarithm of the number of unique visitors to a store in month t	SafeGraph
Ln(Visits)_Month 1 to 3	The natural logarithm of the cumulative number of visits to a store from month t+1 to t+3	SafeGraph
Ln(Visits)_Month 4 to 6	The natural logarithm of the cumulative number of visits to a store from month t+4 to t+6	SafeGraph
Ln(Visitors)_Month 1 to 3	The natural logarithm of the cumulative number of unique visitors to a store from month t+1 to t+3	SafeGraph
Ln(Visitors)_Month 4 to 6	The natural logarithm of the cumulative number of unique visitors to a store from month t+4 to t+6	SafeGraph
Ln(Firm visits)	The natural logarithm of the aggregate number of visits to all stores owned by a firm in month t (or quarter t)	SafeGraph
Ln(Firm visitors)	The natural logarithm of the aggregate number of visitors to all stores owned by a firm in month t (or quarter t)	SafeGraph
Firm visits growth	The quarterly percentage change of the aggregate number of visits to stores that are operated by a firm	SafeGraph
Firm visitors growth	The quarterly percentage change of the aggregate number of visitors to stores that are operated by a firm	SafeGraph
SVI_adjusted	The adjusted Google searching volume index (SVI) of the brand name of a company in the shopping category. The adjusted SVI is the difference between the monthly SVI and average SVI in the past three months.	Google Trends
ESG incidents variables		
Ln(ESG incidents+1)	The natural logarithm of one plus the number of negative ESG incidents in a firm-month	RepRisk
Ln(E incidents+1)	The natural logarithm of one plus the number of negative environmental incidents in a firm-month	RepRisk
Ln(S incidents+1)	The natural logarithm of one plus the number of negative social incidents in a firm-month	RepRisk
Ln(E&S incidents+1)	The natural logarithm of one plus the number of negative environmental and social incidents in a firm-month	RepRisk
Ln(RRI increase+1)	The natural logarithm of one plus the increase of RepRisk index (RRI) in a firm-month. The increase of RRI is defined as the positive change of RRI between the current month and	RepRisk

	the month before. Negative and zero change of PRI is coded as zero	
Post	An indicator variable equal to one if the store-week is after the negative ESG events, and zero if the store-week is before the negative ESG events.	
Ln(Peer ESG incidents+1)	The natural logarithm of one plus peer firms' ESG incidents. Peer firms' ESG incidents is defined as the average number of ESG incidents of product market peers that operate at least one store in the same county as the focal firm's store. Following the literature, we use the Text-based Network Industry Classification (TNIC) approach to identify peer firms, as developed by Hoberg and Phillips (2016)	RepRisk, Hoberg and Phillips (2016)
Firm level variables		
Cash	Compustat item CH / Compustat item AT	Compustat
Market-to-book	[Compustat item AT + (Compustat item CSHO ∗ Compustat item PRCC_F) - Compustat item CEQ] / Compustat item AT	Compustat
Leverage	(Compustat item DLTT + Compustat item DLC) / Compustat item AT	Compustat
ROA	Compustat item EBITDA / Compustat item AT	Compustat
Ln(Sales)	The natural logarithm of Compustat item SALE	Compustat
Sales growth	The growth of Compustat item SALE	Compustat
Return_12m	The twelve-month cumulative return from month t-12 to t-1	Compustat
Ad_Exp	Compustat item XAD/Compustat item SALE. Missing value of XAD is set to zero.	Compustat
SUE	The earnings surprise in the prior month, where earnings surprise is unexpected earnings scaled by stock price.	Compustat
EAM	An indicator variable equal to one if quarterly earnings is announced in the prior month, and zero otherwise	Compustat
FREV	The analyst forecast revision scaled by stock price in the prior month.	I/B/E/S
Short ratio	The shorting volume ratio, which is defined as shorting volume scaled by shares outstanding in the prior month.	FINRA
Stock return	Monthly stock returns	CRSP
Other variables		
Democratic (republic) counties	The subsample that stores located in counties that share of the presidential vote that went to Hilary Clinton in the 2016 election is higher (lower) than the sample median.	MIT Election Lab

High (low) education	The subsample that stores located in counties that the percentage of adults with bachelor's degree (including adults completing some college or associate degree) is higher (lower) than the sample median, based on 2015-2019 average estimates of American Community Survey	U.S. Census Bureau
Young (Old)	The subsample that store located in counties that the percentage of adults older than 60 year-old is higher (lower) than the state-year median, based on 2018-2020 Annual County Resident Population Estimates by Age, Sex Race, and Hispanic Origin.	U.S. Census Bureau
High (low) ESG	The subsample of firms without (with) the negative ESG incidents in the prior twelve months.	RepRisk
With (without) peers	The subsample of stores that have (do not have) product market peers' stores operating in the same county. Following the literature, we use the Text-based Network Industry Classification (TNIC) approach to identify peer firms, as developed by Hoberg and Phillips (2016).	Hoberg and Phillips (2016)
Durable (non-durable) goods	The subsample of firms selling durable (non-durable) goods, based on SIC code and Fama-French 12 industry groups.	Fama and French 12 industry classifications

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Figure 1 Industry composition
The pie chart below shows the industry composition of our sample firms disaggregated at the 2-digit NAICS code level.

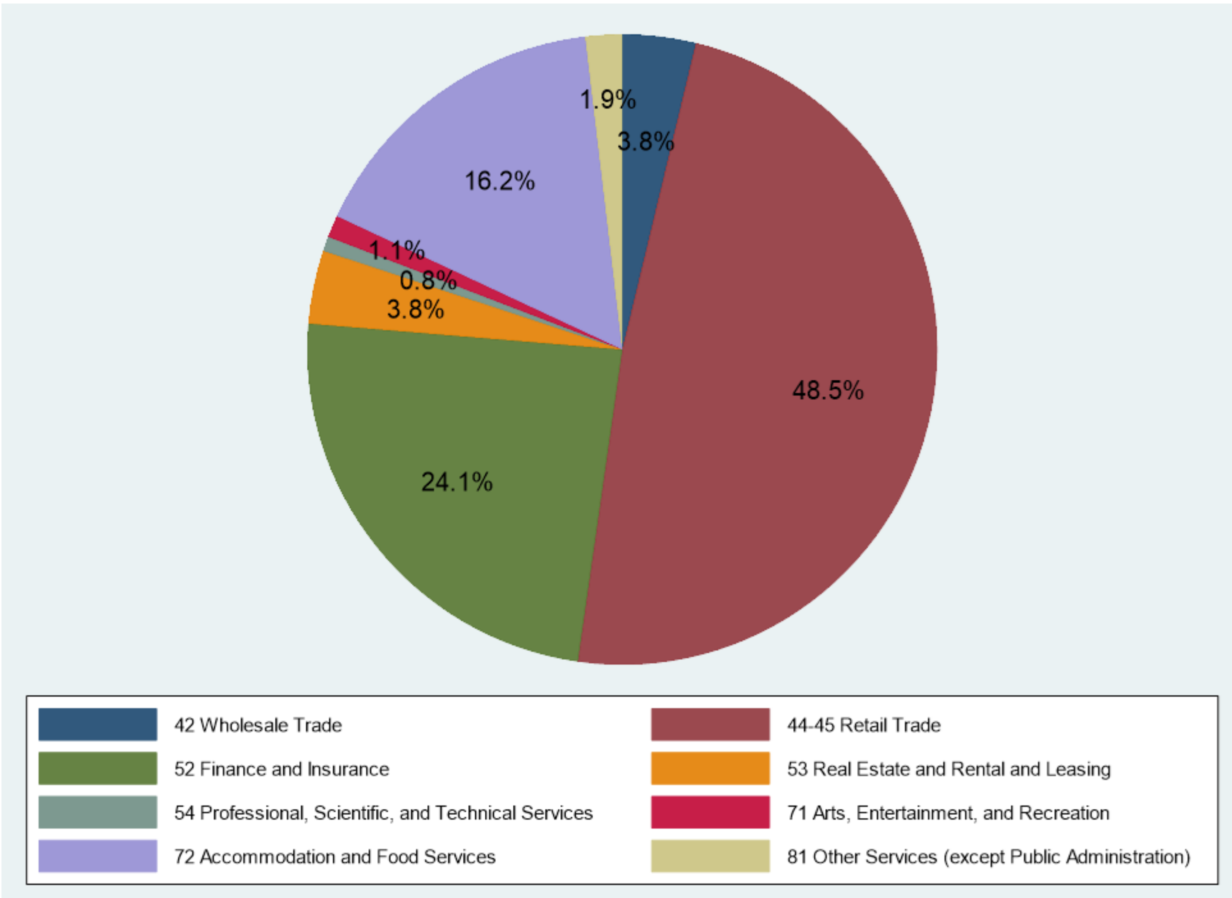

Table 1 Summary statistics

The table reports the mean, median, standard deviation, 25th and 75th percentile of main variables. See Appendix A for variable definitions. The consumer foot traffic variables are observed at store-year-month level. ESG incidents are reported at firm-year-month level. Firm-level characteristics are at firm-year level. The sample period is from January 2018 to September 2020.

Variable	N	Mean	Median	SD	p25	p75
Foot traffic variables						
Ln(Visits)	11,361,099	5.187	5.505	1.633	4.466	6.232
Ln(Visitors)	11,361,099	4.771	5.056	1.580	4.007	5.820
Ln(Visits)_Month 1 to 3	11,157,184	6.414	6.662	1.476	5.700	7.358
Ln(Visits)_ Month 4 to 6	11,091,021	6.459	6.690	1.447	5.753	7.380
Ln(Visitors)_ Month 1 to 3	11,157,184	5.987	6.211	1.444	5.247	6.947
Ln(Visitors)_ Month 4 to 6	11,091,021	6.029	6.236	1.418	5.293	6.970
ESG incidents						
Ln(ESG incidents+1)	8,314	0.326	0.000	0.654	0.000	0.693
ESG incidents	8,314	0.947	0.000	2.727	0.000	1.000
Ln(E incidents+1)	8,314	0.168	0.000	0.451	0.000	0.000
Ln(S incidents+1)	8,314	0.290	0.000	0.598	0.000	0.000
Ln(E&S incidents+1)	8,314	0.315	0.000	0.638	0.000	0.000
Ln(RRI increase+1)	8,314	0.269	0.000	0.703	0.000	0.000
Ln(Peer ESG incidents+1)	7,689	0.418	0.167	0.562	0.000	0.693
Firm-level characteristics						
Cash	769	0.071	0.037	0.090	0.014	0.096
Market-to-book	769	2.058	1.439	1.702	1.068	2.387
Leverage	769	0.313	0.221	0.361	0.093	0.417
ROA	769	0.136	0.122	0.107	0.043	0.188
Ln(Sales)	769	8.370	8.210	1.756	7.109	9.369
Return_12m	769	0.103	0.077	0.369	-0.132	0.287
Ad_Exp	769	0.022	0.014	0.032	0.002	0.029
SUE	2,617	-0.017	0.001	0.271	-0.005	0.005
FREV	6,885	-0.006	0.000	0.105	-0.000	0.000
Short ratio	8,299	0.070	0.037	0.086	0.015	0.097
Other variables						
SVI_adjusted	75,908	-0.067	0.000	11.452	-5.667	4.667

Table 2 Firm-level store visits and firm-level sales

This table reports panel regression of quarterly firm-level sales and sales growth on quarterly firm-level store visits. The dependent variables are *Ln(Sales)* and *Sales growth* in quarter q. The independent variable of interest is *Ln(Firm visits), Ln(Firm visitors), Firm visits growth,* and *Firm visitors growth* in quarter q. The unit of observation is at firm-year-quarter level. See Appendix A for variable definitions. Numbers in parentheses are t-statistics based on standard errors clustered at firm level. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively.

Variables	Ln(Sales)		Sales growth	
	(1)	(2)	(3)	(4)
Ln(Firm visits)	0.435***			
	(7.146)			
Ln(Firm visitors)		0.487***		
		(8.551)		
Firm visits growth			0.420***	
			(10.857)	
Firm visitors growth				0.440***
				(12.323)
Cash	-0.171	-0.146	-0.061	-0.047
	(-1.017)	(-0.857)	(-0.426)	(-0.327)
Market-to-book	0.024	0.022	0.021	0.020
	(0.841)	(0.777)	(1.581)	(1.580)
Leverage	-0.052	-0.049	0.163**	0.160**
	(-0.442)	(-0.429)	(2.074)	(2.061)
ROA	-0.044	-0.003	-0.122	-0.143
	(-0.107)	(-0.008)	(-0.463)	(-0.565)
Return_12m	0.110***	0.105***	0.035***	0.031**
	(5.601)	(5.327)	(2.797)	(2.564)
Firm FEs	YES	YES	YES	YES
Year-Quarter FEs	YES	YES	YES	YES
Adjusted R^2	0.988	0.989	0.366	0.384
Observations	2,668	2,668	2,399	2,399

Table 3 ESG incidents and store visits

This table reports the effect of ESG incidents on consumer store visits. The sample period runs from January 2018 to September 2020. The dependent variables are *Ln(Visits)* and *Ln(Visitors)* in month m. The independent variable of interest is *Ln(ESG incidents+1)* in month m-1. The unit of observation is at store-year-month level. See Appendix A for variable definitions. Numbers in parentheses are *t*-statistics based on standard errors clustered at county-year-month level. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively.

Variables	Ln(Visits)				Ln(Visitors)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(ESG incidents+1)	-0.019***	-0.020***	-0.016***	-0.017***	-0.018***	-0.019***	-0.016***	-0.017***
	(-33.934)	(-35.515)	(-28.844)	(-30.377)	(-34.757)	(-36.098)	(-29.742)	(-31.027)
Cash			0.132***	0.129***			0.134***	0.128***
			(20.780)	(19.772)			(22.485)	(20.649)
Market-to-book			0.039***	0.038***			0.036***	0.035***
			(47.709)	(47.180)			(46.412)	(45.774)
Leverage			0.039***	0.044***			0.056***	0.060***
			(14.679)	(16.571)			(22.396)	(24.036)
ROA			-0.249***	-0.235***			-0.196***	-0.183***
			(-28.515)	(-26.695)			(-23.172)	(-21.352)
Ln(Sales)			0.075***	0.067***			0.050***	0.042***
			(31.363)	(27.681)			(21.687)	(18.305)
Return_12m			0.087***	0.088***			0.090***	0.090***
			(35.201)	(34.440)			(35.939)	(35.230)
Store FEs	YES	YES	YES	YES	YES	YES	YES	YES
County-YM FEs	YES	NO	YES	NO	YES	NO	YES	NO
Industry-YM FEs	YES	NO	YES	NO	YES	NO	YES	NO
Industry-County-YM FEs	NO	YES	NO	YES	NO	YES	NO	YES
Adjusted R^2	0.933	0.933	0.933	0.933	0.941	0.941	0.942	0.942
Observations	11,361,099	11,361,099	11,361,099	11,361,099	11,361,099	11,361,099	11,361,099	11,361,099

Table 4 The long-run effect of ESG incidents on store visits

This table reports the long-run effect of ESG incidents on consumer store visits. The dependent variables in columns (1) to (4) are *Ln(Visits) over Month 1 to 3*, *Ln(Visits) over Month 4 to 6*, *Ln(Visitors) over Month 1 to 3*, and *Ln(Visitors) over Month 4 to 6*, respectively. The independent variable of interest is *Ln(ESG incidents+1)* in month m-1. The unit of observation is at store-year-month level. See Appendix A for variable definitions. Numbers in parentheses are *t*-statistics based on standard errors clustered at county-year-month level. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively.

Variables	Ln(Visits) over Month 1 to 3	Ln(Visits) over Month 4 to 6	Ln(Visitors) over Month 1 to 3	Ln(Visitors) over Month 4 to 6
	(1)	(2)	(3)	(4)
Ln(ESG incidents+1)	-0.006***	-0.001	-0.006***	-0.001
	(-13.667)	(-1.124)	(-14.010)	(-1.069)
Controls	YES	YES	YES	YES
Store FEs	YES	YES	YES	YES
Industry-County-YM FEs	YES	YES	YES	YES
Adjusted R^2	0.950	0.947	0.957	0.954
Observations	11,157,184	11,091,021	11,157,184	11,091,021

Table 5 Event study of changes in store visits in the weeks around ESG incidents

This table reports the changes in store visits in the weeks around ESG incidents. We focus on the sample of store-weeks in the [-12, +12] calendar-week window around the negative ESG incidents. The dependent variable is *Ln(Visit)* in week *w*. The independent variable is *Post*, which is an indicator variable equal to one if the week is after the occurrence of negative ESG news, and zero otherwise. The unit of observation is at store-year-week level. See Appendix A for variable definitions. Numbers in parentheses are *t*-statistics based on standard errors clustered at county-year-week level. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively.

Variables	Ln(Visits)			
	(1)	(2)	(3)	(4)
Post	-0.018***	-0.015***	-0.013***	-0.012***
	(-20.329)	(-15.426)	(-14.897)	(-12.212)
Controls	NO	NO	YES	YES
Store FEs	YES	YES	YES	YES
County-Week FEs	YES	NO	YES	NO
Industry-Week FEs	YES	NO	YES	NO
Industry-County-Week FEs	NO	YES	NO	YES
Adjusted R^2	0.917	0.919	0.917	0.920
Observations	5,814,864	5,814,864	5,814,864	5,814,864

Table 6 Subsample tests conditional on county demographics

Panel A of this table reports the effect of ESG incidents on consumer store visits conditional on the political leanings at county-level, which we obtain from the county-level share of the presidential vote that went to Hilary Clinton in the 2016 election. Panel B reports the subsample results conditional on the average education in a county. Panel C reports the subsample results conditional on the percentage of population older than 60 years in a county. The dependent variables are *Ln(Visits)* and *Ln(Visitors)* in month m. The independent variable of interest is *Ln(ESG incidents+1)* in month m-1. The last row presents p-values from the F-test for differences in the coefficient on *Ln(ESG incidents+1)* between the two subsamples. The unit of observation is at store-year-month level. See Appendix A for variable definitions. Numbers in parentheses are *t*-statistics based on standard errors clustered at county-year-month level. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively.

Panel A: ESG incidents and store visits conditional on county-level political leaning

Variables	Ln(Visits)		Ln(Visitors)	
	Democratic counties	Republican counties	Democratic counties	Republican counties
	(1)	(2)	(3)	(4)
Ln(ESG incidents+1)	-0.018***	-0.015***	-0.017***	-0.014***
	(-27.574)	(-14.566)	(-28.301)	(-14.410)
Controls	YES	YES	YES	YES
Store FEs	YES	YES	YES	YES
Industry-County-YM FEs	YES	YES	YES	YES
Adjusted R^2	0.934	0.930	0.942	0.941
Observations	9,531,725	1,802,710	9,531,725	1,802,710
F test for Ln(ESG incidents+1)	0.034		0.003	

Panel B: ESG incidents and store visits conditional on visitor education

Variables	Ln(Visits)		Ln(Visitors)	
	High education	Low education	High education	Low education
	(1)	(2)	(3)	(4)
Ln(ESG incidents+1)	-0.018***	-0.014***	-0.017***	-0.013***
	(-27.858)	(-14.373)	(-28.521)	(-14.592)
Controls	YES	YES	YES	YES
Store FEs	YES	YES	YES	YES
Industry-County-YM FEs	YES	YES	YES	YES
Adjusted R^2	0.934	0.928	0.942	0.940
Observations	9,554,227	1,806,095	9,554,227	1,806,095
F test for Ln(ESG incidents+1)	0.003		0.001	

Panel C: ESG incidents and store visits conditional on visitor age

Variables	Ln(Visits)		Ln(Visitors)	
	Young	Old	Young	Old
	(1)	(2)	(3)	(4)
Ln(ESG incidents+1)	-0.017***	-0.015***	-0.017***	-0.014***
	(-26.765)	(-14.741)	(-27.479)	(-14.580)
Controls	YES	YES	YES	YES
Store FEs	YES	YES	YES	YES
Industry-County-YM FEs	YES	YES	YES	YES
Adjusted R2	0.934	0.931	0.942	0.940
Observations	9,110,855	2,231,158	9,110,855	2,231,158
F test for Ln(ESG incidents+1)	0.083		0.019	

Table 7 Controlling for changes in firm fundamentals

This table reports the effect of ESG incidents on consumer store visits, controlling for change in firm fundamentals. The dependent variables are *Ln(Visits)* and *Ln(Visitors)* in month m. The independent variable of interest is *Ln(ESG incidents+1)* in month m-1. *SUE* is the earnings surprise in month m-1, where earnings surprise is the change in quarterly EPS from four quarters ago scaled by stock price one month before earnings announcements. *EAM* is an indicator variable equal to one if quarterly earnings is announced in the month m-1, and zero otherwise. *FREV* is the revision in analyst consensus forecast of EPS scaled by stock price in the month m-1. *Short ratio* is defined as monthly short interests scaled by shares outstanding in month m-1. The unit of observation is at store-year-month level. See Appendix A for variable definitions. Numbers in parentheses are *t*-statistics based on standard errors clustered at county-year-month level. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively.

Variables	Ln(Visits) (1)	Ln(Visitors) (2)
Ln(ESG incidents+1)	-0.016***	-0.016***
	(-22.898)	(-23.165)
Cash	0.190***	0.197***
	(27.479)	(29.986)
Market-to-book	0.036***	0.034***
	(44.871)	(45.242)
Leverage	0.049***	0.063***
	(16.380)	(22.647)
ROA	-0.316***	-0.287***
	(-34.369)	(-32.386)
Ln(Sales)	0.082***	0.064***
	(25.079)	(20.174)
Return_12m	0.063***	0.064***
	(32.379)	(33.304)
SUE	0.017***	0.018***
	(17.149)	(18.781)
EAM	0.000	-0.000
	(0.106)	(-0.417)
FREV	0.261***	0.266***
	(25.145)	(25.257)
Short ratio	-0.441***	-0.445***
	(-62.959)	(-64.630)
Store FEs	YES	YES
Industry-County-YM FEs	YES	YES
Adjusted R^2	0.938	0.946
Observations	9,414,594	9,414,594

Table 8 Subsample tests conditional on firms selling durable or non-durable goods

This table reports the effect of ESG incidents on consumer store visits conditional on whether the firm sells durable or non-durable goods. We classify the subsample of firms selling durable and non-durable goods based on Fama and French 12 industry classifications. The last row presents p-values from the F-test for differences in the coefficient on *Ln(ESG incidents+1)* between the two subsamples. The unit of observation is at store-year-month level. See Appendix A for variable definitions. Numbers in parentheses are *t*-statistics based on standard errors clustered at county-year-month level. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively.

Variables	Ln(Visits)		Ln(Visitors)	
	Durable goods	Non-Durable goods	Durable goods	Non-Durable goods
	(1)	(2)	(3)	(4)
Ln(ESG incidents+1)	-0.013***	-0.018***	-0.014***	-0.017***
	(-3.931)	(-30.496)	(-4.811)	(-31.466)
Controls	YES	YES	YES	YES
Store FEs	YES	YES	YES	YES
Industry-County-YM FEs	YES	YES	YES	YES
Adjusted R^2	0.900	0.934	0.905	0.942
Observations	216,085	11,145,014	216,085	11,145,014
F test for Ln(ESG incidents+1)	0.145		0.270	

Table 9 Subsample tests conditional on firms' historical ESG reputation

This table repeats the effect of ESG incidents on consumer store visits conditional on firms' past ESG performance. We classify firms as high ESG performance if a firm does not have any negative ESG news in the past twelve months, and as low ESG performance if a firm has at least one negative ESG news. The last row presents p-values from the F-test for differences in the coefficient on *Ln(ESG incidents+1)* between the two subsamples. The unit of observation is at store-year-month level. See Appendix A for variable definitions. Numbers in parentheses are *t*-statistics based on standard errors clustered at county-year-month level. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively.

Variables	Ln(Visits)		Ln(Visitors)	
	High ESG Performance	Low ESG Performance	High ESG Performance	Low ESG Performance
	(1)	(2)	(3)	(4)
Ln(ESG incidents+1)	-0.073***	-0.018***	-0.079***	-0.019***
	(-16.107)	(-18.400)	(-17.674)	(-19.675)
Controls	YES	YES	YES	YES
Store FEs	YES	YES	YES	YES
Industry-County-YM FEs	YES	YES	YES	YES
Adjusted R^2	0.927	0.937	0.937	0.943
Observations	5,920,919	5,440,180	5,920,919	5,440,180
F test for Ln(ESG incidents+1)	0.000		0.000	

Table 10 Subsample tests conditional on the availability of product market peers

This table reports the effect of ESG incidents on consumer store visits for subsamples conditional on the availability of product market peers in the same county. Following the literature, we use the Text-based Network Industry Classification (TNIC) approach to identify peer firms, as developed by Hoberg and Phillips (2016). The last row presents p-values from the F-test for differences in the coefficient on *Ln(ESG incidents+1)* between the two subsamples. The unit of observation is at store-year-month level. See Appendix A for variable definitions. Numbers in parentheses are *t*-statistics based on standard errors clustered at county-year-month level. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively.

Variables	Ln(Visits)		Ln(Visitors)	
	Peer stores available	No peer stores	Peer stores available	No peer stores
	(1)	(2)	(3)	(4)
Ln(ESG incidents+1)	-0.014***	-0.008***	-0.013***	-0.007***
	(-21.053)	(-7.081)	(-21.142)	(-7.107)
Controls	YES	YES	YES	YES
Store FEs	YES	YES	YES	YES
Industry-County-YM FEs	YES	YES	YES	YES
Adjusted R^2	0.933	0.942	0.939	0.954
Observations	8,103,796	2,472,056	8,103,796	2,472,056
F test for Ln(ESG incidents+1)	0.000		0.000	

Table 11 The spillover effects of peer firms' ESG incidents on store visits

The table reports the spillover effect of peer firms' ESG incidents on consumer visits to focal store. The sample period runs from January 2018 to September 2020. The dependent variables are *Ln(Visits)* and *Ln(Visitors)* in month m. The independent variable is *Ln(Peer ESG incidents)* and *Ln(ESG incidents+1)* in month m-1. The unit of observation is at store-year-month level. See Appendix A for variable definitions. Numbers in parentheses are *t*-statistics based on standard errors clustered at county-year-month level. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively.

Variables	Ln(Visits)	Ln(Visitors)
	(1)	(2)
Ln(Peer ESG incidents+1)	-0.018***	-0.020***
	(-18.949)	(-22.057)
Ln(ESG incidents+1)	-0.015***	-0.014***
	(-26.459)	(-26.219)
Controls	YES	YES
Store FEs	YES	YES
Industry-County-YM FEs	YES	YES
Adjusted R^2	0.933	0.942
Observations	10,575,852	10,575,852

Table 12 Firm-level store visits and stock return

This table reports regression of contemporaneous stock return on monthly firm-level store visits. The dependent variables are *Stock return* in month m. The independent variable is *Ln(Firm visits)* and *Ln(Firm visitors)* in month m. The unit of observation is at firm-year-month level. See Appendix A for variable definitions. Numbers in parentheses are *t*-statistics based on standard errors clustered at firm level. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively.

Variables	Stock return	
	(1)	(2)
Ln(Firm visits)	0.012**	
	(2.296)	
Ln(Firm visitors)		0.009*
		(1.722)
Cash	0.046	0.045
	(0.737)	(0.726)
Market-to-book	-0.014***	-0.014***
	(-3.326)	(-3.344)
Leverage	0.086**	0.087**
	(2.002)	(2.012)
ROA	0.030	0.029
	(0.384)	(0.372)
Ln(Sales)	-0.013	-0.013
	(-0.507)	(-0.508)
Return_12m	-0.048***	-0.047***
	(-6.841)	(-6.806)
Firm FEs	YES	YES
Year-Month FEs	YES	YES
Adjusted R^2	0.365	0.365
Observations	8,298	8,298

Table 13 ESG incidents and online consumer interest

This table reports the effect of ESG incidents on online consumer interest, as measured by Google search volume index of the brand names of a company. The sample period runs from February 2007 to September 2020. The dependent variables are *SVI_adjusted* in month m, measured as the Google searching volume index (SVI) of the brand name of a company in the "shopping" category minus its average SVI in the past three months. The independent variable of interest is *Ln(ESG incidents+1)* in month m-1. The unit of observation is at brand-year-month level. See Appendix A for variable definitions. Numbers in parentheses are *t*-statistics based on standard errors clustered at brand level. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively.

Variables	SVI_adjusted			
	(1)	(2)	(3)	(4)
Ln(ESG incidents+1)	-0.257***	-0.262***	-0.176*	-0.180*
	(-2.767)	(-2.809)	(-1.803)	(-1.835)
Controls	NO	YES	NO	YES
Brands FEs	YES	YES	YES	YES
YM FEs	YES	YES	NO	NO
Industry-YM FEs	NO	NO	YES	YES
Adjusted R2	0.070	0.070	0.107	0.107
Observations	75,908	75,908	75,908	75,908

Internet Appendix to "Consumers Reaction to Corporate ESG Performance: Evidence from Store Visits"

Table IA.1 Alternative measures of firm ESG performance

This table reports the effects of alternative measures of firm ESG performance on consumer store visits. Panel A reports the regression of monthly store visits on firms' environmental incidents, social incidents, and E&S incidents separately. Panel B reports the regression of monthly store visits on *Ln(RRI increase+1)* in month m-1. In Panel C, we use firm ESG scores from Sustainalytics (*Ln(ESG_Sustainlytics)*) as a proxy for ESG performance. The sample period for Panel A and B runs from January 2018 to September 2020, while in Panel C the sample runs from January 2018 to December 2019. The unit of observation is at store-year-month level. See Appendix A for variable definitions. Numbers in parentheses are *t*-statistics based on standard errors clustered at county-year-month level. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively.

Panel A: Using environmental and social incidents separately

Variables	Ln(Visits)			Ln(Visitors)		
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(E incidents+1)	-0.022***			-0.022***		
	(-24.678)			(-24.653)		
Ln(S incidents+1)		-0.014***			-0.014***	
		(-25.236)			(-25.455)	
Ln(E&S incidents+1)			-0.018***			-0.018***
			(-31.949)			(-32.311)
Controls	YES	YES	YES	YES	YES	YES
Store FEs	YES	YES	YES	YES	YES	YES
Industry-County-YM FEs	YES	YES	YES	YES	YES	YES
Adjusted R^2	0.933	0.933	0.933	0.942	0.942	0.942
Observations	11,361,099	11,361,099	11,361,099	11,361,099	11,361,099	11,361,099

Panel B: Using increase in RepRisk Index as a proxy for ESG performance

Variables	Ln(Visits)	Ln(Visitors)
	(1)	(2)
Ln(RRI increase+1)	-0.008***	-0.008***
	(-27.603)	(-28.976)
Controls	YES	YES
Store FEs	YES	YES
Industry-County-YM FEs	YES	YES
Adjusted R^2	0.933	0.942
Observations	11,361,099	11,361,099

Panel C: Using firm ESG scores from Sustainalytics as a proxy for ESG performance

Variables	Ln(Visits)		Ln(Visitors)	
	(1)	(2)	(3)	(4)
Ln(ESG_Sustainalytics)	-0.107***	-0.034***	-0.027***	-0.004
	(-13.387)	(-3.997)	(-3.727)	(-0.493)
Controls	NO	YES	NO	YES
Store FEs	YES	YES	YES	YES
Industry-County-YM FEs	YES	YES	YES	YES
Adjusted R^2	0.959	0.959	0.966	0.966
Observations	6,287,509	6,287,509	6,287,509	6,287,509

Table IA.2 Controlling for advertising expenses

This table reports robustness test from regression of monthly store visits on *Ln(ESG incidents +1)* in month m-1 after controlling for advertising expenses scaled by sales (*Ad_Exp*). The unit of observation is at store-year-month level. See Appendix A for variable definitions. Numbers in parentheses are *t*-statistics based on standard errors clustered at county-year-month level. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively.

Variables	Ln(Visits) (1)	Ln(Visitors) (2)
Ln(ESG incidents+1)	-0.016***	-0.016***
	(-28.635)	(-29.126)
Cash	0.179***	0.180***
	(27.965)	(29.843)
Market-to-book	0.039***	0.037***
	(49.217)	(47.925)
Leverage	0.066***	0.083***
	(24.469)	(32.925)
ROA	-0.264***	-0.213***
	(-29.446)	(-24.306)
Ln(Sales)	0.012***	-0.015***
	(5.329)	(-6.804)
Return_12m	0.086***	0.089***
	(34.293)	(35.087)
Ad_Exp	0.580***	0.606***
	(59.622)	(64.096)
Store FEs	YES	YES
Industry-County-YM FEs	YES	YES
Adjusted R^2	0.933	0.942
Observations	11231243	11231243