Consumers' Reaction to Corporate ESG Performance:

Evidence from Store Visits

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Abstract

Using micro-level data on consumer shopping behavior, this paper investigates end-consumers' attitudes toward firms' ESG behavior, and as importantly, the ability of consumers to affect firms' policy concerning sustainability issues. We find that consumers care about firms' approach toward ESG, and consumers' behavior can impact firms' attitudes. Using ESG incidents as a proxy, we find that the reduction in store visits is more pronounced for ESG-conscious consumers, such as those living in democratic counties, and counties with a higher fraction of educated and younger residents. Online shopping interest data yields similar results. Using abnormally hot temperature as a shock to residents' awareness of sustainability issues, we show the effect is plausibly causal.

Keywords: ESG, Corporate Sustainability, Consumer Demand, Cash Flows, Big Data

JEL Classification: G14, G32, M14

1. Introduction

Environmental, social, and governance (ESG) issues are a topic of growing focus in the business world and academia alike. In particular, a lively debate is emerging about the role of corporations in adopting more sustainable ESG policies (Hart and Zingales, 2017; Bebchuk and Tallarita, 2020; Edmans, 2023). It is almost an article of faith that external pressures from various stakeholders can be applied to improve corporate ESG performance. These channels include divestment and engagement activities by shareholders (Dimson et al., 2015; Duchin, et al, 2022), regulations and taxes imposed by governments, the impact of the labour force, and pressure from consumers.[1] While there is growing evidence of the impacts of regulatory actions and taxes/subsidies (Bolton and Kacperczyk, 2021; Brown, Martinsson, and Thomann, 2022), the (limited) impact of investors (Dyck et al., 2019; Chen, Dong, and Lin, 2020; Berk and van Binsbergen, 2021; Heath et al., 2023), and some evidence on the association between labour retention and ESG policies (e.g. Krueger, Metzger, and Wu, 2021 and Cen, Qiu, and Wang, 2022), there is only scant systematic evidence on whether consumers are a possible group of influence. This paper takes an important step in this direction by examining end-consumers' attitude toward ESG, and how their attitudes eventually affect corporate ESG behavior.

Because consumers' attitudes toward ESG are unobservable, we exploit their reaction to ESG incidents as a proxy. Traditionally, studying the reaction of consumers to corporate ESG performance has posed several challenges. First, firm sales, as reported in financial statements in quarterly frequency, are coarse measures of consumer demand. For example, a firm can increase

[1] Several surveys indicate that consumers are willing to shun firms engaging in ESG incidents or pay higher prices for more sustainable products. For example, 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.

its sales by opening new stores while its same-store sales could decrease.[2] Furthermore, the aggregate nature of firm sales prevents researchers from studying the potential heterogeneity in consumers' response to the occurrence of ESG incidents. Second, ESG ratings are noisy, often inaccurate, and at times measure attributes not related to the main focus of sustainability. Third, making an attribution from consumer action to firm ESG performance has obvious identification challenges due to confounding non-ESG news and reverse causality.

To overcome these challenges, we use a novel data set tracking consumer store visits from SafeGraph, combined with news data on ESG incidents from RepRisk, thereby allowing us to elicit consumers' attitude toward ESG in a large sample. Baseline results show that consumers on average do care about corporate ESG behavior. Specifically, we show that consumer foot-traffic significantly decreases to firms' commerce locations in the month immediately following ESG incidents.[3] On average, a firm with one ESG incident in a month experience approximately a 1.2% decline in consumer foot-traffic to its stores relative to firms without any ESG incidents. The negative impact of ESG incidents on firms' consumer foot-traffic lasts for several months, and we do not observe any reversal in consumer store visits in the long run, indicating that the initial reduction in consumer store visits is permanent. Additional analyses suggest that firms' ESG incidents affect consumer foot-traffic by influencing the demand of consumers with a preference for corporate sustainability. We find consistent evidence that firms' ESG news influences consumers' online shopping interest, as measured by the shopping-related Google search volume of brand names. Importantly, we show that consumers' attitude toward ESG has a real impact:

[2] 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.

[3] 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 threatened with the loss of consumers subsequently improve their ESG performance. Thus, under the reasonable assumption that ESG incidents are not random, that is, they are more likely to occur in firms that care less about and devote fewer resources to sustainability, our findings suggest that consumer actions give firms incentives to devote more resources and invest more in making their operations more sustainable.

One novelty 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 consumers but does capture their precise intra-day location. SafeGraph matches these GPS records with commercial locations and provides the data on daily visits to stores. In validation tests, we find a strong positive association between 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. In addition, we find that a firm's store visits are positively associated with its stock return in the same month. This suggests that consumers' demand changes in response to ESG events, as captured by store visits, and is a key driver of shareholder value.

For two reasons we use the actual ESG incidents from RepRisk as the main measure of firms' ESG performance, an important departure from prior studies (Servaes and Tamayo, 2013). First, focusing on ESG news allows us to identify salient shocks to firms' ESG behavior that consumers likely pay attention to, unlike ESG ratings which are less salient and more persistent through time. Second, using data on ESG incidents also allows us to avoid the issue of ESG rating disagreement across different rating providers (Berg, Koelbel, and Rigobon, 2022).

Empirically, a key advantage of the granularity of the store visits data is that it allows us to control for a rich set of 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 by year-month and county by year-month fixed effects to absorb variation in store visits that are driven by industry trends or time-varying local economic conditions. Our results barely change even when we use industry by county by year-month fixed effects, which account for potential heterogeneous impacts of local economic shocks on consumer demand across different sectors. The results indicate 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 owned by a different firm with fewer ESG incidents. Thus, alternative explanations for our results would need to explain variation in consumer activity concentrated right after ESG incidents that is not explained by macroeconomic, local, and/or industry-specific economic shocks.

To further address the omitted variable issue arising from potential confounding firm characteristics and non-ESG news, we exploit a setting where consumers' concern about ESG issues increased for exogeneous reasons. Following Choi et al. (2020) and Di Giuli et al. (2022), we use abnormally high temperature as a shock to residents' concern about ESG issues. This setting allows us to conduct a within-incident analysis, as we can compare how consumers subject to high temperature shocks to consumers that are not, respond to the same ESG incident. We find that the effect of ESG incidents on consumer foot-traffic decline is more pronounced for those living in counties experiencing abnormally high temperature. Crucially, as we include firm by year-month fixed effects in this test, the results suggest that the impact of ESG incidents on consumer foot-traffic is plausibly causal and unlikely explained by omitted firm characteristics or non-ESG news.

Importantly, we examine whether the negative reaction to ESG incidents from end-consumers triggers any adjustments to the firm's future ESG performance. We find that firms facing the loss of consumers due to ESG incidents improve their ESG performance relative to those facing less pressure from consumers. The results provide direct evidence that consumers could promote better ESG practices for firms directly selling to end-consumers.

We can think of two possible explanations for consumers' negative reaction to ESG incidents. The first explanation is the preference channel. Simply put, consumers prefer firms with "good" ESG standing. The second possible explanation is that the 'bad ESG' behavior is a negative signal about the overall quality of firm conduct—and hence the decline in store visits and sales. We label this the information channel. To test the plausibility of these two channels, we exploit geographic variation in individual preference for corporate sustainability. The preference channel predicts variation in consumer response as a function of individual preference for corporate sustainability, while the information channel suggests a reaction that is independent of individual preference 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 spending (Hong and Kostovetsky, 2012; Di Giuli and Kostovetsky, 2014; Bernstein et al., 2022). Consistent with the preference channel, we find the negative reaction to ESG incidents is around 20% stronger for consumers living in Democratic counties compared to those in Republican counties.

In a similar fashion, our second and third tests of these competing explanations exploits the heterogeneity in residents' education level and age, respectively. Survey evidence suggests that younger and more educated individuals exhibit a stronger concern for environmental and social issues (Giglio et al., 2023). As in the previous test, the preference channel suggests that variation in consumer foot-traffic is a function of age and education, while the information channel does not. When we split the sample based on the percentage of adults in a county with bachelor's degrees and the percentage of adults older than 60 years, we find more pronounced effects in counties with a greater proportion of educated and young residents. This is consistent with the notion that younger and more educated consumers care more about sustainability issues.

We conduct further tests to exploit the cross-sectional variation in consumers' reaction to ESG news. First, we expect the negative consumer response to ESG incidents to be stronger when peer stores owned by competing firms are available in the same county. In such cases, consumers can more easily switch to peer stores to buy similar products without affecting their daily life. Using the Text-based Network Industry Classifications to identify product market peers (Hoberg and Phillips, 2016), we find evidence consistent with this prediction. Subsample analysis reveals that the negative consumer response to ESG incidents is about 75% stronger for stores with peer stores available in the same county, relative to those without peer stores.

Second, consumers reaction to ESG incidents likely depend on their prior view of firms' ESG reputation. The reason is that ESG incidents from firms with good historical ESG standing are more surprising and possibly contain more information than incidents from 'repeated offenders'; and hence consumers may adjust their shopping behavior more dramatically the greater the surprise is. Consistent with our conjecture, we find the negative consumer reaction (reduced store visits) to ESG incidents is stronger when the occurrence of ESG incidents is less expected. Economically, the decline in store visits is three times stronger in the subsample of firms without any ESG incidents in the past 12 months, relative to those firms with ESG incidents in the past.

We conduct several robustness tests for our main findings. First, the negative consumer response to firms' ESG incidents holds when we examine the impacts of environmental, social, and governance incidents separately. The effect is stronger for environmental and social incidents and weaker for governance-related incidents. The latter results further suggest that environmental and social preferences rather than information about the firm's quality drive the results. Second, using the severity score of ESG incidents from RepRisk, we find consumers react more negatively to more severe ESG incidents. Third, we find similar results with alternative measures of firm ESG performance, including the RepRisk index (*RRI*) and monthly ESG risk ratings provided by Sustainalytics. Fourth, we find the main results persist when we control for several proxies of non-ESG news and advertising expenditures (scaled by sales) at the firm level. Finally, the key finding holds when we remove product-related incidents and drop the sample period after the outbreak of COVID-19 in U. S.

This study contributes to the literature along several dimensions. First, our paper contributes to the growing literature examining the influences of various stakeholder groups on firms' ESG practices, including institutional investors (Dyck et al., 2019; Azar et al., 2021; Gantchev et al., 2022; Heath et al., 2023), banks (Houston and Shan, 2022), and governments (Brown et al. 2022). We show that consumers are potentially an important group of stakeholders that not only care about ESG issues but also help improve corporate ESG practices. While previous studies have looked at the role of *corporate customers* in promoting sustainable practices in their dependent suppliers (Dai, Liang, and Ng, 2021; Schiller, 2018; Bisetti, She, and Zaldokas, 2022), our paper differs by focusing on the role of *end-consumers*. We show that consumers can promote better ESG practices for firms directly selling to end-consumers, which may facilitate the transmission of sustainable ESG policies along the entire supply chain.

Second, our paper is related to the large literature examining the impacts of ESG policies on firms' operating performance. Empirical evidence so far is inconclusive (Gillan, Koch, and Starks, 2021). Importantly, we still do not know much about the channels through which a firm's ESG policies influence its operating performance. A few papers propose that a firm's sustainability practices can affect its operating performance by influencing the behaviours of important stakeholders, such as consumers (Servaes and Tamayo, 2013) and employees (Krueger et al., 2021). For example, Servaes and Tamayo (2013) show that CSR activities are value-enhancing for firms with more consumer awareness, as proxied by advertising expenses. Compared to Servaes and Tamayo (2013), our paper innovates along several dimensions. Firstly, we use more granular and high-frequency measures of consumer activities to show that consumer demand is indeed one important channel through which a firm's ESG practices may affect its operating performance. Secondly, we use temperature shocks as a natural experiment to establish the causal impacts of ESG performance on consumers and rule out confounding effects from non-ESG news. Thirdly, we exploit geographic variations in individual preference of sustainability to shed light on the channels underlying consumer reaction to ESG incidents.

Like ours, several concurrent papers document similar findings that consumers react negatively to ESG incidents. Our paper differs in several important dimensions, including the measurement of consumer behavior, the identification strategy, and the research focus. First, Cen et al. (2022), Houston et al. (2022), Meier et al. (2023), and Christensen et al. (2023) use Nielsen retail scanner data to measure consumer purchases from supermarkets and grocery stores. The foot-traffic data we use from SafeGraph captures a much broader sample of B2C firms including finance and accommodation/food services. We also show that consumers' attitude toward ESG manifests in their online shopping activities. While Dube, Lee, and Wang (2023) and Xiao, Zheng, and Zheng (2023) also use foot-traffic data from SafeGraph to measure consumer behaviours, they focus more on the differential reaction across consumers with different ESG consciousness. Furthermore, we provide plausibly causal evidence of the effect of ESG news on consumer activities by using abnormally hot temperatures as a shock to consumers' concern for ESG issues. Last but not least, ours is the only paper directly testing whether consumers' attitude toward ESG pressures firms to improve their ESG performance.

The rest of the paper proceeds as follows. Section 2 details the data used in this study, presents the summary statistics, and validates store visits as a reasonable proxy for consumer demand. Section 3 presents our main results regarding consumer responses to firms' ESG incidents. We also conduct cross-sectional heterogeneity tests to shed light on the underlying channels. We conduct robustness tests and rule out alternative explanations in Section 4. Section 5 concludes the paper.

2. Data and Sample

In this section, we first detail the data used in our study and report summary statistics. We then validate that the foot-traffic data is a reasonable measure of consumer demand.

2.1 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-interest (POIs) with over 6,000 distinct brands. The database provides us with a unique way to observe consumers' foot-traffic at the store level.[4] The data have been used in prior studies in economics and finance (e.g., Painter, 2021; Gurun, Nickerson, and Solomon, 2023; Jin, Stubben, and Ton, 2022; Noh, So, and Zhu, 2022; Bizjak et al., 2022).

SafeGraph provides us the daily number of visits to a store, the number of unique visitors to a store, the name and industry affiliation[5] 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, and others. Social issues include child labor, human rights abuses, and others. Governance issues include executive compensation issues, tax evasion, and corruption, and others. One incident can be associated with multiple issues and therefore can belong to two or more ESG 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. RepRisk also provides a RepRisk index (RRI), which is constructed using proprietary algorithms (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

[4] 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.
[5] Our industry classification is based on the North American Industry Classification System (NAICS).

examine how various market participants, including shareholders, employees, and equity analysts (Gantchev, Giannetti, and Li, 2022; Derrien et al., 2021; Bonelli et al., 2022), react to negative shocks to firms' ESG reputations.

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 searching for the same firm name to obtain the ESG incidents data. We merge that with the Compustat and CRSP database to obtain firm accounting and stock return variables. 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.[6]

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 dataset 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

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

of firm-months with ESG incidents in our sample is 2,116 and 219 out of 266 firms have at least one ESG incident during our sample period. Within the ESG incidents sample, the fraction of incidents are 59.3%, 93.7% and 51.5%, respectively.[7] 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-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%.

2.2 Do Store Visits Reflect Consumer Demand?

As the foot-traffic data we use capture only consumer interests (not actual transactions), we first validate whether consumer foot-traffic to stores is a reasonable proxy for firm sales. Specifically, we examine whether firm-level store visits (the growth of store visits) are positively associated with firms' quarterly sales (sales growth) in the same quarter by running the following regression.[8]

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

where $Ln(Sales)_{i,y,q}$ is the quarterly sales of firm *i* in quarter q of year y. $FootTraffic_{i,y,q}$, measured by *Ln(Firm visits)* and *Ln(Firm visitors)*, is the monthly store visits aggregated to firm level for firm *i* in quarter q of year y. $Controls_{i,y-1}$ indicates a set of firm characteristics observed at the end of year *y-1*, 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

[7] Note that an ESG incident may correspond to multiple E/S/G issues, so the fraction does not add up to one.
[8] One caveat about aggregating 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.

(*Ln(Sales)*), and past twelve-month cumulative stock return (*Return_12m*). We include firm fixed effects and year-quarter fixed effects in the model and cluster standard errors at the firm level.

Columns (1) and (2) of Table 2 show that the coefficients of *Ln(Firm visits)* and *Ln(Firm visitors)* are all positive and highly significant, 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 quarterly 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.

Given that consumer demand is a key driver of firm value, we also test whether there is a significant relationship between store visits and a firm's contemporaneous stock return. We run the following panel regression with observations at stock-year-month level:

$$RET_{i,y,m} = \beta_0 + \beta_1 FootTraffic_{i,y,m} + \Sigma\beta_i Controls_{i,y-1} + \gamma' FEs + \varepsilon_{i,y,m} \quad (2)$$

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*.

Columns (5) and (6) of Table 2 report 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 associated with firm value. In terms of the economic effect, 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. Overall, the results validate that consumer foot-traffic to stores captures consumer demand reasonably well.

3. Empirical Results

In this section, we first present the main analyses of the effects of ESG incidents on consumer store visits. We then show the effects are plausibly causal by using hot temperature shocks as identification. We further conduct cross-sectional heterogeneity tests to shed light on the channels underlying the main results. Finally, we examine whether consumers' reaction triggers any adjustments on the firm's future ESG performance.

3.1 Baseline Results

We begin our analysis by examining how consumer foot-traffic to a store changes in the month following negative ESG incidents on the part of the firm owning the store. We estimate the following regression models using the monthly foot-traffic to a store as the dependent variable of interest:

$$FootTraffic_{s,i,m} = \beta_0 + \beta_1 Ln(ESG\ incidents + 1)_{i,m-1} + \Sigma\beta_i Controls_{i,y-1} + \gamma' FEs + \varepsilon_{s,i,m} \qquad (3)$$

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.[9] 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-Year-Month* fixed effects to account for the heterogenous impacts of local economic conditions on consumer demand for products from different sectors.[10] 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 with foot-traffic to another store located in the same county and belonging to the same sector but 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 firm with one ESG incident in a month experiences approximately a 1.2% (=0.017*0.693*100%) decline in consumer foot-

[9] For example, stores located in more convenient places should attract more consumer foot-traffic than those located in distant areas.
[10] 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.

traffic to its stores relative to firms without any ESG incident. As the inclusion of *Store* and *Industry-County-Year-Month* fixed effects represents more stringent specification, we report all the remaining results with store-year-month level observations using this set of fixed effects.

Not all ESG incidents are of equal importance to consumers. A direct implication of our story is that consumers should react more negatively to more severe ESG incidents. To test this prediction, we separate ESG incidents into high severity and low severity groups using the RepRisk severity score. We then replace *Ln(ESG incidents+1)* with two variables, *High severity Ln(ESG incidents+1)* and *Low severity Ln(ESG incidents+1)*, and re-run the baseline regressions. Table IA.1 in the Internet Appendix shows that both the coefficients of *High severity Ln(ESG incidents+1)* and *Low severity Ln(ESG incidents+1)* are negative and highly significant. Importantly, the coefficient estimate of *High severity Ln(ESG incidents+1)* is much larger than the coefficient of *Low severity Ln(ESG incidents+1)* for both the number of visits and unique visitors. The finding suggests that consumers pay attention to the content of ESG news and boycott more of those firms with more severe ESG incidents.

3.2 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 fourth month and over the fifth to the ninth month following ESG incidents, respectively. We then regress the cumulative number of store visits (visitors) over these two horizons on *Ln(ESG incidents+1).* Table 4 shows that the negative impact of ESG incidents on firms' consumer foot-traffic last for four months, and the effect becomes smaller and less significant after four months following ESG incidents. As we do not observe any reversal in consumer store visits in the longer horizon, this suggests that the initial reduction in consumer store visits is permanent and thus detrimental to firm value.

3.3 Identification Using Hot Temperature Shocks

To address the omitted variable concern that the effect of ESG incidents may be confounded by non-ESG news or events, we exploit a setting where consumers' awareness of ESG issues increased for exogenous reasons. Following Choi et al. (2020) and Di Giuli et al. (2022), we use abnormally high temperatures as a shock to residents' awareness of ESG issues. This setting allows us to conduct a within-incident analysis, as we can compare how consumers living in counties with and without abnormally high temperature respond to the same ESG incidents.

To implement the test, we regress the consumer store visits in month *m* on the interaction between ESG incidents (in month *m*-1) and an indicator of abnormally high temperature for a county (in month *m*-2). Specifically, the *high temperature shock* is a dummy variable that equals one if the abnormal temperature of the county (location of the store) belongs to the top quintile of all counties in the month, and zero otherwise. We follow Di Giuli et al. (2022) to measure abnormal temperature.

Columns (1) and (3) of Table 5 report the results with the baseline specification of fixed effects. The interaction term between *high temperature shock* and *Ln (ESG incidents +1)* is negative and significant, suggesting that consumers who have just experienced abnormally high temperature respond more negatively to firms' ESG incidents. In columns (2) and (4), we further add firm by year-month fixed effects, which allows us to absorb both observed and unobserved firm characteristics and news. The coefficient of the interaction term is still negative and highly significant. Overall, the elevated consumer responses to ESG incidents following abnormally high temperature suggest that the effect we document is unlikely driven by confounding non-ESG news or unobserved firm characteristics.

3.4 Testing the Channels

In this subsection, we test two plausible channels underlying consumers' negative responses to ESG incidents. Our first explanation is motivated by the survey evidence, which states that consumers have a preference for corporate sustainability and are less willing to purchase products from firms with poorer ESG reputation (the "preference" channel). The second possible channel is that consumers may consider firm ESG performance as informative about the overall quality of firm conduct and hence adjust their purchasing behavior in response to ESG news (the "information" channel).

To distinguish these two (non-mutually exclusive) channels, we exploit geographic variation in individual preferences for corporate sustainability. The preference channel predicts that the negative consumer responses to ESG incidents should be more pronounced for consumers exhibiting stronger sustainability preference, while the information channel suggests a reaction that is independent of individuals' ESG preference. Our first proxy for 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. Existing evidence suggests that Democrats, in contrast to Republicans, are more apt to support causes such as environmental and labor protection and oppose smoking, gun ownership, and defense spending.[11] We partition our sample

[11] 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. Di Giuli and Kostovetsky (2014) find that firms headquartered in Democratic states are

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 analysis 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 proxies of ESG preference are the education level and age of a county's residents. These variables 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 does.[12] To test these predictions, we use the percentage of adults with bachelor's degrees (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, respectively.[13] We divide our sample into two groups based on whether the store is located in a

associated with higher CSR scores. Bloomberg reports that the ESG investing approach is under Republican attack (Bloomberg, 2022).

[12] 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 older).

[13] The data on county-level education is obtained from the 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.

county where the education level or the fraction of old population is above median in each state-year. We then conduct subsample tests for the effect of ESG incidents on store visits and report the results in Panels B and C of Table 6, respectively. Consistent with the prediction of the preference channel, 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).

Collectively, these results are more consistent with the preference channel that the negative response to ESG incidents is driven by consumers with a preference for corporate sustainability.

3.5 The Moderating Effect of Local Competition and Firms' Past ESG Behavior

In this subsection, we examine the role of local product market competition and firms' past ESG behavior in moderating the effect of ESG incidents on consumer store visits. Firstly, we conjecture that the negative response to ESG incidents should be stronger when consumers can more easily switch to peer stores in the same county to purchase similar products. 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) developed by Hoberg and Phillips (2016) to identify product market peers.

Table 7 reports the results. Consistent with our conjecture, the decrease in consumer store visits following negative ESG incidents is indeed larger when peer stores are available in the same county. For example, column (1) ((2)) shows that 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 indicate that the difference in the coefficients of *Ln (ESG incidents+1)* between the two subsamples is statistically significant for both the number of visits and visitors.

Our second test exploits the heterogeneity in firms' past ESG behavior. The idea is that ESG incidents incurred by firms with good past ESG standings should be less expected to consumers and hence elicit stronger consumer reaction (Serafeim and Yoon, 2022). To that end, we split firms into two groups based on their past ESG standings, as measured by whether the firm experienced any ESG incidents over the past 12 months. We then conduct baseline regression for the two subsamples and report the results in Table 8. We find the decrease in consumer store visits in response to ESG incidents is indeed stronger for firms with better past ESG behavior. For example, column (1) ((2)) shows the coefficient of *Ln(ESG incidents+1)* is -0.073 (-0.018) in the subsample of firms without (with) any ESG incidents over the past 12 months. The *F*-statistics indicate that the differences in the coefficients of *Ln (ESG incidents+1)* between the two subsamples are statistically significant for both the number of visits and visitors (p-value =0.000). This result is consistent with the notion that consumers' purchasing behavior changes more dramatically when ESG incidents are less expected.

3.6 Does Consumer Reaction Trigger Adjustments to Firms' Future ESG Performance?

Finally, we study whether ESG incidents and the associated negative reaction from end-consumers trigger any adjustments to the firm's future ESG performance. We use the RepRisk Index (*RRI*) to measure firm ESG performance. 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. A lower *RRI* value reflects better ESG performance. We also create a dummy variable, *Decline of consumer visits (visitors)*, which equals one if the change of firm-level store visits (visitors) belongs to the bottom quartile of all firms in the industry and month, and zero otherwise. To test whether the negative consumer reaction helps pressure firms with ESG incidents to repair their ESG reputation subsequently, we regress firms' future ESG performance on the interaction of ESG incidents with the dummy indicating *Decline of consumer visits.*

Table 9 reports the results. The dependent variable is *Ln (RRI+1)* in month *m*+1. The independent variable of interest is the interaction between a dummy variable *Decline of firm visits* (*visitors*) in month *m* and *Ln (ESG incidents+1)* in month *m*-1. Not surprisingly, we find a positive and significant coefficient of *Ln (ESG incidents+1)*, reflecting the fact that firms' ESG performance deteriorates after they experience ESG incidents. More importantly, column (1) reports a significantly positive coefficient of the interaction term *Decline of firm visits * Ln (ESG incidents+1)*. This is consistent with our conjecture that firms under the threat of losing consumers improve their ESG performance relative to those facing less pressure. Column (2) reports similar findings with a positive and significant coefficient of *Decline of firm visitors * Ln (ESG incidents+1)*. Overall, the results suggest that consumers could be a powerful group of stakeholders that promote better corporate ESG practices.

4. Robustness Checks and Additional Analyses

In this section, we first examine whether our main results are robust when we use several alternative measures of ESG performance. We then examine whether the negative consumer reaction to ESG incidents also extends to their online shopping interest and has material impact on firm-level sales and profits. Lastly, we perform additional robustness checks.

4.1 Alternative Measures of ESG Performance

In Table IA.2 of the Internet Appendix, we examine the robustness of the baseline results by using several alternative measures of ESG performance. First, we look at the impacts of environmental, social, and governance incidents separately to see whether consumers respond differently to different dimensions of corporate sustainability. Panel A presents the results. Columns (1) - (3) (columns (4) - (6)) report the results using *Ln(E incidents+1)*, *Ln(S incidents+1)* and *Ln(G incidents+1)* as key variables of interest, respectively.[14] We find that the decrease in consumer store visits following environmental incidents is the strongest, followed by social incidents. Consumer reaction to governance-related incidents is much weaker, both economically and statistically. For example, column (1) reports that the coefficient of *Ln(E incidents+1)* is -0.022 (*t*-stats = -24.68), implying that a firm experiences approximately 0.99% decrease in monthly store visits after being associated with one environmental incident. By comparison, the coefficient of *Ln(G incidents+1)* in column (3) is -0.006 (*t*-stats = -8.09), indicating that a firm experiences only 0.25% decrease in monthly store visits after conducting one governance-related incident. The evidence further suggests that the environmental and social preferences, rather than information about firm quality, drive the results.

Second, we use the RepRisk Index as an alternative measure of firm ESG performance. 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*

[14] Noted that one ESG incident could be associated with more than one category of E/S/G incidents. As a result, the total number of ESG incidents does not necessarily equal to the sum of the number of environmental, social, and governance incidents.

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.2. The negative and highly significant coefficients of *Ln(RRI increase+1)* for both *Ln(Visits)* and *Ln(Visitors)* suggest that our main finding is robust to using the RepRisk Index that considers the reach and severity of the incidents.

Third, we use the monthly ESG risk ratings provided by Sustainalytics as an alternative measure of firm ESG reputation and re-run the baseline regressions. Panel C of Table IA.2 shows that our main results are also robust to using this alternative measure of firm ESG performance.

4.2 ESG Incidents and Online Consumer Shopping Interests

One caveat about the foot-traffic data is that it only captures part of consumer demand. In particular, it does not capture consumers' online shopping activities, which nowadays is a non-trivial part of total consumer spending. To test whether shocks to a firm's ESG reputation also influence consumers' online shopping interest for its products, we use the shopping-related search volume index (SVI) of brand names from Google Trends to measure consumers' online shopping interest.

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.[15] Marketing studies show that Google searches capture consumers' prepurchase information acquisition well and Google searches of firm products provide information about firm sales that is incremental to reported sales growth in financial statements (Hu, Du, and Damangir, 2014; Chiu et al., 2020). Following Hu, Du, and Damangir (2014) and Sun (2017), we use additional procedures to obtain a more precise measure of consumer

[15] For example, existing studies in finance (e.g., Da, Engelberg, and Gao, 2011) use Google SVI of the stock ticker to capture retail investor attention.

interest. First, we focus on the SVI of brand names so that the search activities are more likely conducted by consumers. Second, we use the advanced functions of Google Trends by selecting the "shopping" category to isolate consumer interest from other types of online interest.

Table IA.3 reports the effect of ESG incidents on online shopping 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 *m* minus its average SVI in the past three months. The independent variable of interest is *Ln(ESG incidents+1)* measured in month *m*-1. The unit of observation is at brand-year-month level, and we control for the same set of firm variables as in the baseline specification. 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 statistically significant. In terms of the economic magnitude, the coefficient estimate in column (4) implies that a firm with one ESG incident in a month experiences approximately a 0.12 decrease in *SVI_adjusted* relative to firms without ESG incidents, which represents about 1% of the standard deviation of *SVI_adjusted*. Overall, we conclude that the negative effect of ESG incidents on consumer demand also extend to firms' e-commerce businesses.

4.3 ESG Incidents and Firm-level Sales and Profits

As we document significant declines in both offline and online consumer activities, it is natural to expect that the effect of ESG incidents on consumer demand should also manifest at the firm level. We use firm sales growth as a proxy for change in firm-level consumer demand. Given the strong positive correlation between store visits and firm-level sales shown in Table 2, we expect to find a significant decline in the sales growth of firms experiencing ESG incidents. For this test, as we use quarterly data with a limited number of observations within a firm, we only include industry-by-year-quarter fixed effects. Consistent with our hypothesis, column (1) of Table IA.4 in the Internet Appendix reports a negative and significant coefficient of *Ln(ESG incidents+1)* when the dependent variable is quarterly sales growth. In column (2), we find a strong negative effect of ESG incidents on firm profitability, as measured by return-on-assets (*ROA*). This suggests that the lower consumer demand translates into lower profitability of the affected firm. Overall, the analysis using firm-level sales and profits is consistent with our main results based on store visits.

4.4 Other Robustness Tests

The negative effects of ESG incidents on subsequent store visits could be driven by confounding non-ESG news or events at the firm level. In Table IA.5 of the Internet Appendix, we examine this possibility by including several commonly used proxies of non-ESG news, including earnings news (SUE), analyst forecast revisions (FREV), and short interest ratio.[16] The results show that the coefficient of *Ln(ESG incidents+1)* is still highly significant, with an

[16] Earnings surprises, analyst earnings forecast revisions, and short interest ratio are commonly used measures of firm fundamentals and quality (Dechow et al., 2001; Easton and Monahan, 2005; and Da and Warachka, 2009). We also include the earnings announcement month dummy because Noh, So and Zhu (2021) document that consumer store visits increase during earnings announcement window.

economic effect similar to that in Table 3. To the extent that our measures capture non-ESG news comprehensively, this result suggests that the effect of ESG incidents on consumer behavior is unlikely confounded by non-ESG news.

Can reduction in advertising expenses explain our results? To examine this possibility, we add a variable *Ad_Exp*, defined as advertising expenses scaled by sales, as an additional control in the baseline regression. Panel A of Table IA.6 of the Internet Appendix reports the results. We find the coefficient of *Ln(ESG incidents+1)* remains significant after controlling for advertising expenditures, suggesting that our key finding of a negative consumer reaction to ESG news is unlikely driven by firms cutting advertising expenses after experiencing ESG incidents.

Population mobility in the U.S. is severely restricted during the early stage of COVID-19 and the degree of restriction varies significantly across U.S. states (Painter and Qiu, 2021). In Panel B of Table IA.6, we re-run the baseline regression by removing the sample period after the outbreak of COVID-19 (from March 2020 and onwards). The negative effect of ESG incidents on consumer store visits still holds, suggesting that our main results are not explained by mobility restrictions imposed on consumers during COVID-19 period.

In Panel C of Table IA.6, we conduct another robustness test by removing all ESG incidents related to product issues and find our main result still holds. This suggests that the negative consumer reaction to ESG incidents is not likely explained by consumers' direct response to firm product issues.

5. Conclusion

Using micro-level data on consumer shopping activities, this paper investigates end-consumers' attitude toward firms' ESG behavior, and as importantly, the ability of consumers to affect firms' policy concerning sustainability issues. We find that consumers care about firms' ESG standings, and consumers' behavior can impact firms' attitudes.

Our empirical approach exploits consumers' reaction to ESG incidents as a proxy for their attitude to ESG. We find that following the occurrence of negative ESG news, consumers significantly reduce visits to firms' commerce locations. The reduction in consumer foot traffic lasts for several months and has material impacts on firm sales and profits. We find similar evidence that firms' ESG news influences consumers' online shopping activities. Consumers' attitude toward ESG has a real impact: firms under the threat of losing consumers subsequently improve their ESG performance. Using abnormally high temperature as a shock to consumer awareness of sustainability issues, we show the effect of ESG incidents is plausibly causal and unlikely driven by omitted firm characteristics.

We test the channels underlying our main findings. Exploiting county-level demographic information, we find that the decreases in consumer store visits are more pronounced in areas with a greater percentage of educated and younger residents, and for consumers living in Democratic counties, consistent with the notion that consumers have a preference for firms with good ESG standing and are willing to punish firms with bad ESG behavior.

Given the limited impacts of shareholders in driving changes in firm ESG policies and inaction of governments in addressing environmental externalities, ESG advocates have increasingly turned to other stakeholders as a disciplining mechanism that could pressure corporations to act in a socially responsible manner. Our findings suggest that end-consumers are an important group of stakeholders that can potentially improve corporate ESG practices. Possibly, greater transparency of firms' ESG policies and clearer and more comprehensive reporting by firms can lead to better ESG outcomes through consumers' impact on firms' policies.

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 m	SafeGraph
Ln(Visitors)	The natural logarithm of the number of unique visitors to a store in month m	SafeGraph
Ln(Visits)_Month 1 to 4	The natural logarithm of the cumulative number of visits to a store from month m+1 to m+4	SafeGraph
Ln(Visits)_Month 5 to 9	The natural logarithm of the cumulative number of visits to a store from month m+5 to m+9	SafeGraph
Ln(Visitors)_Month 1 to 4	The natural logarithm of the cumulative number of unique visitors to a store from month m+1 to m+4	SafeGraph
Ln(Visitors)_Month 5 to 9	The natural logarithm of the cumulative number of unique visitors to a store from month m+5 to m+9	SafeGraph
Ln(Firm visits)	The natural logarithm of the aggregate number of visits to all stores owned by a firm in month m (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 m (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
Decline of firm visits (visitors)	A dummy variable equal to one if the change of firm visits (visitors) belongs to the bottom quartile of all firms in the industry and month, and zero otherwise.	SafeGraph
ESG incidents variables		
Ln(ESG incidents+1)	The natural logarithm of one plus the number of negative ESG incidents in a firm-month	RepRisk
High (Low) severity Ln(ESG incidents+1)	The natural logarithm of one plus the number of high and median (low) severity negative ESG incidents in a firm-month	
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(G incidents+1)	The natural logarithm of one plus the number of negative governance 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 the month before. Negative and zero change of PRI is coded as zero	RepRisk
ESG incidents dummy	An indicator variable equal to one if a firm has at least one ESG incidents in the month, and zero otherwise.	
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)
Ln(RRI+1)	The natural logarithm of one plus RepRisk index (RRI) in a firm-month. The higher value of RRI reflect the higher ESG risk.	RepRisk
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 m-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		
Hot temperature shock	A dummy variable equal to one if the abnormal temperature of the county (location of the store) belongs to the top quintile of all counties in the month, and zero otherwise, where we follow Di Giuli et al. (2022) to measure abnormal temperature.	NOAA
Democratic (republic) counties	The subsample that stores located in counties in which the 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 in which the percentage of adults with bachelor's degrees (including adults completing some college or an 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 stores located in counties in which the percentage of adults older than 60 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
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)
High (low) ESG	The subsample of firms without (with) the negative ESG incidents in the prior twelve months.	RepRisk

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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.

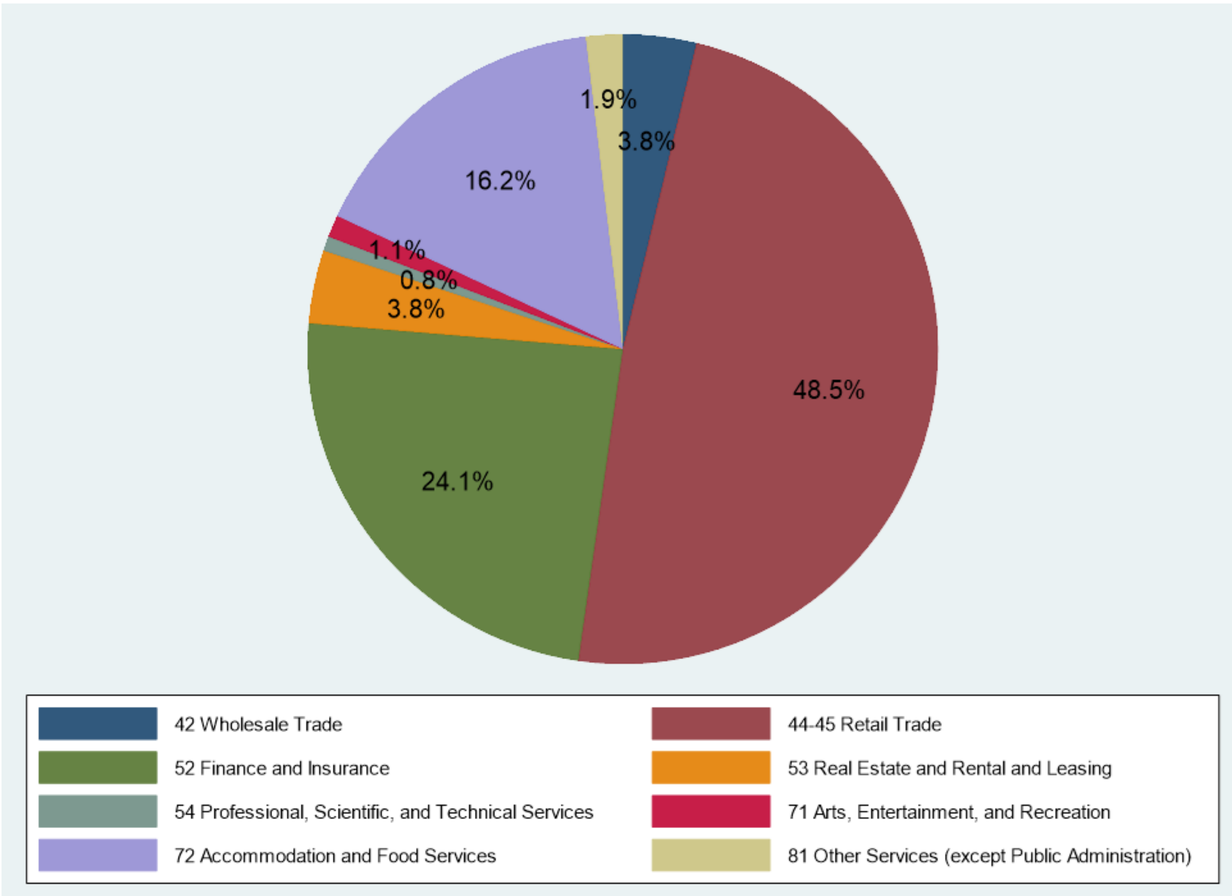

Table 1 Summary statistics

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 4	11,106,513	6.732	6.967	1.443	6.026	7.653
Ln(Visits)_Month 5 to 9	11,008,873	7.015	7.225	1.402	6.315	7.905
Ln(Visitors)_Month 1 to 4	11,106,513	6.303	6.513	1.415	5.568	7.244
Ln(Visitors)_Month 5 to 9	11,008,873	6.581	6.770	1.379	5.852	7.496
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(G incidents+1)	8,314	0.147	0.000	0.421	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 and stock return

This table reports panel regression of quarterly firm-level sales and sales growth on quarterly firm-level store visits, and regression of monthly firm-level stock return on monthly firm-level store visits. The dependent variables are *Ln(Sales)* and *Sales growth* in quarter q, and *Stock return* in month m. The independent variable of interest is *Ln(Firm visits), Ln(Firm visitors), Firm visits growth,* and *Firm visitors growth* in quarter q, and *Ln(Firm visits)* and *Ln(Firm visitors)* in month m. The unit of observation is at firm-year-quarter level for columns (1) to (4), and at firm-year-month level for columns (5) and (6). 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		Stock return	
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Firm visits)	0.435***				0.012**	
	(7.146)				(2.296)	
Ln(Firm visitors)		0.487***				0.009*
		(8.551)				(1.722)
Firm visits growth			0.420***			
			(10.857)			
Firm visitors growth				0.440***		
				(12.323)		
Cash	-0.171	-0.146	-0.061	-0.047	0.046	0.045
	(-1.017)	(-0.857)	(-0.426)	(-0.327)	(0.737)	(0.726)
Market-to-book	0.024	0.022	0.021	0.020	-0.014***	-0.014***
	(0.841)	(0.777)	(1.581)	(1.580)	(-3.326)	(-3.344)
Leverage	-0.052	-0.049	0.163**	0.160**	0.086**	0.087**
	(-0.442)	(-0.429)	(2.074)	(2.061)	(2.002)	(2.012)
ROA	-0.044	-0.003	-0.122	-0.143	0.030	0.029
	(-0.107)	(-0.008)	(-0.463)	(-0.565)	(0.384)	(0.372)
Ln(Sales)					-0.013	-0.013
					(-0.507)	(-0.508)
Return_12m	0.110***	0.105***	0.035***	0.031**	-0.048***	-0.047***
	(5.601)	(5.327)	(2.797)	(2.564)	(-6.841)	(-6.806)
Firm FEs	YES	YES	YES	YES	YES	YES
Year-Quarter FEs	YES	YES	YES	YES	NO	NO
Year-Month FEs	NO	NO	NO	NO	YES	YES
Adjusted R2	0.988	0.989	0.366	0.384	0.365	0.365
Observations	2,668	2,668	2,399	2,399	8,298	8,298

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 4*, *Ln(Visits) over Month 5 to 9*, *Ln(Visitors) over Month 1 to 4*, and *Ln(Visitors) over Month 5 to 9*, 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 4	Ln(Visits) over Month 5 to 9	Ln(Visitors) over Month 1 to 4	Ln(Visitors) over Month 5 to 9
	(1)	(2)	(3)	(4)
Ln(ESG incidents+1)	-0.005***	-0.001**	-0.005***	-0.001
	(-12.430)	(-2.269)	(-12.550)	(-1.490)
Controls	YES	YES	YES	YES
Store FEs	YES	YES	YES	YES
Industry-County-YM FEs	YES	YES	YES	YES
Adjusted R^2	0.953	0.954	0.960	0.961
Observations	11,106,513	11,008,873	11,106,513	11,008,873

Table 5 ESG incidents and store visits: the impact of abnormally high temperature

This table reports the effect of ESG incidents on consumer store visits conditional on high temperature shock. 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 the interaction between *Ln(ESG incidents+1)* in month *m*-1, and a dummy indicating *High temperature shock* in month *m*-2. 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.

Variable	Ln(Visits)		Ln(Visitors)	
	(1)	(2)	(3)	(4)
Ln(ESG incidents+1)*High temperature shock	-0.001*	-0.002***	-0.001*	-0.002***
	(-1.750)	(-4.915)	(-1.888)	(-5.243)
Ln(ESG incidents+1)	-0.017***		-0.016***	
	(-28.757)		(-29.237)	
Control variables	YES	NO	YES	NO
Store FEs	YES	YES	YES	YES
Industry-County-YM FEs	YES	YES	YES	YES
Firm-YM FEs	NO	YES	NO	YES
Adjusted R^2	0.933	0.941	0.942	0.950
Observations	11,295,944	11,295,944	11,295,944	11,295,944

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 county-level average 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 county-level population 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 Subsample tests conditional on local product market competition

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 Classifications (TNIC) 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 8 Subsample tests conditional on firms' past ESG behavior

This table repeats the effect of ESG incidents on consumer store visits conditional on firms' past ESG behavior. We classify firms as good ESG behavior if a firm does not have any negative ESG news in the past twelve months, and as poor ESG behavior 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)	
	Good ESG Behavior	Poor ESG Behavior	Good ESG Behavior	Poor ESG Behavior
	(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 9 ESG incidents, consumer store visits, and future ESG performance

This table reports the impact of change in consumer store visits on the future ESG performance of firms with ESG incidents. The sample period runs from January 2018 to September 2020. The dependent variable is *Ln(RRI+1)* in month m+1. The independent variable of interest is the interaction between a dummy indicating *Decline of firm visits* (*visitors*) in month m and *Ln(ESG incidents+1)* in month m-1. 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 county-year-month level. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively.

Variables	Ln(RRI+1)	
	(1)	(2)
Decline of firm visits*Ln (ESG incidents+1)	-0.042***	
	(-2.662)	
Decline of firm visitors*Ln (ESG incidents+1)		-0.040**
		(-2.590)
Decline of firm visits	0.042**	
	(2.073)	
Decline of firm visitors		0.042**
		(2.225)
Ln (ESG incidents+1)	0.377***	0.376***
	(11.327)	(11.318)
Controls	YES	YES
Firm FEs	YES	YES
YM FEs	YES	YES
Adjusted R^2	0.704	0.704
Observations	7,957	7,957

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

Table IA.1 The impacts of ESG incidents severity

This table repeats the effect of ESG incidents on consumer store visits conditional on the severity of ESG incidents. We decompose ESG incidents into two parts: high severity ESG incidents and low severity ESG incidents. The independent variables are *High severity Ln(ESG incidents+1)* and *Low severity Ln(ESG incidents+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)
High severity Ln(ESG incidents+1)	-0.018***	-0.017***
	(-19.717)	(-19.152)
Low severity Ln(ESG incidents+1)	-0.009***	-0.008***
	(-14.589)	(-14.789)
Cash	0.131***	0.130***
	(20.120)	(20.994)
Market-to-book	0.038***	0.035***
	(47.522)	(46.135)
Leverage	0.043***	0.059***
	(16.052)	(23.472)
ROA	-0.240***	-0.188***
	(-27.380)	(-21.995)
Ln(Sales)	0.067***	0.042***
	(27.730)	(18.370)
Return_12m	0.088***	0.091***
	(34.574)	(35.345)
Store FEs	YES	YES
Industry-County-YM FEs	YES	YES
Adjusted R^2	0.933	0.942
Observations	11,361,099	11,361,099

Table IA.2 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 governance 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-level ESG scores from Sustainalytics (*Ln(ESG_Sustainlytics)*) to measure firms' ESG performance. The sample period for Panel A and B runs from January 2018 to September 2020, and from January 2018 to December 2019 in Panel C. 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, social and governance 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(G incidents+1)			-0.006***			-0.007***
			(-8.092)			(-10.367)
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 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 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.3 ESG incidents and consumers' online shopping 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 R^2	0.070	0.070	0.107	0.107
Observations	75,908	75,908	75,908	75,908

Table IA.4 ESG incidents and firm-level sales and profits

This table reports panel regressions of quarterly firm-level sales growth and return-on-assets on firm ESG incidents. The dependent variables are *Sales Growth* and *ROA* in quarter q. The independent variable of interest is *Ln(ESG incident+1)* 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	Sales Growth	ROA
	(1)	(2)
Ln(ESG incidents+1)	-0.005**	-0.002***
	(-2.079)	(-2.622)
Cash	0.062	-0.006
	(1.416)	(-0.766)
Market-to-book	0.013***	0.007***
	(3.308)	(10.313)
Leverage	0.008	0.004*
	(0.895)	(1.852)
ROA	-0.177***	
	(-3.286)	
Ln(Sales)		0.002***
		(3.832)
Return_12m	0.019*	0.015***
	(1.894)	(10.155)
Industry-YQ FEs	YES	YES
Adjusted R^2	0.287	0.437
Observations	2,631	2,643

Table IA.5 Controlling for non-ESG news

This table reports the effect of ESG incidents on consumer store visits, controlling several proxies of non-ESG news at firm level. 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 IA.6 Other robustness tests

This table reports results from several robustness tests. Panel A reports the regression of monthly store visits on *Ln(ESG incidents +1)* in month *m*-1 after controlling for advertising expenses scaled by sales (*Ad_Exp*). Panel B reports the baseline results by excluding the sample after the outbreak of COVID-19 (from March 2020 and onwards). Panel C reports the results by excluding the product-related ESG incidents (i.e., controversial products and services, health, and environmental issues). 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: Controlling advertising expenses

Variables	Ln(Visits) (1)	Ln(Visitors) (2)
Ln(ESG incidents+1)	-0.016***	-0.016***
	(-28.635)	(-29.126)
Controls	YES	YES
Store FEs	YES	YES
Industry-County-YM FEs	YES	YES
Adjusted R2	0.933	0.942
Observations	11,231,243	11,231,243

Panel B: Excluding the sample period after COVID-19

Variable	Ln(Visits) (1)	Ln(Visitors) (2)
Ln(ESG incidents+1)	-0.007***	-0.006***
	(-15.491)	(-15.262)
Controls	YES	YES
Store FEs	YES	YES
Industry-County-YM FEs	YES	YES
Adjusted R^2	0.954	0.962
Observations	8,992,949	8,992,949

Panel C: Excluding product-related ESG incidents

Variables	Ln(Visits) (1)	Ln(Visitors) (2)
Ln(ESG incidents+1)	-0.007***	-0.007***
	(-11.162)	(-10.974)
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