How Does ESG Shape Consumption?*

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Abstract

Exploiting 150 million points of purchase by US households, we examine how negative ESG shocks ripple through product market and shape consumption. We show that the sales of affected products drop by an average of 5 - 10%, comparing with that of unaffected products consumed by the same households during the same period of time. The observed contraction is mainly demand-driven, rather than a reflection of the manufacturer's decision to phase out production. This effect is strongest among millennial, middle-class households, and for more severe ESG shocks. Furthermore, we find that salience about climate issues heterogeneously affects the household's response. Lastly, we map the shocks to a set of well-defined ESG issues and identify significant heterogeneity among consumer's reaction to these issues. In summary, we present the first comprehensive product-level evidence on the financial materiality of ESG, via the household consumption channel.

JEL classification: G50, M14, E20, D10

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1 Introduction

In recent years, Environmental, Social and Governance ('ESG', hereafter) issues have increasingly influenced investor behavior and corporate actions. Billions of dollars have flowed into investment vehicles and lending facilities that promote a wide range of environmental and social goals. In turn, companies have faced both direct and indirect pressure from institutional investors (Dimson, Karakaş, and Li (2015), Bialkowski and Starks (2016), Dyck et al. (2019), and Chen, Dong, and Lin (2020)), creditors (Chava (2014), Houston and Shan (2022), and Seltzer, Starks, and Zhu (2022)), corporate customers (Schiller (2018) and Dai, Liang, and Ng (2021)), and employees (Edmans (2011) and Krueger, Metzger, and Wu (2021)) to be more environmentally and socially responsible.[1]

At the same time, in some quarters, there has been an increasing backlash against ESG-related initiatives. On the investor side, there is concern about fees and the impact of these initiatives on financial performance. These concerns have led some states to pressure public pension funds to steer clear of ESG consideration when investing public funds. For example, in August 2022, the attorneys general of 19 states, including Texas, Georgia, Arizona, Utah, and Ohio, sent a strongly worded letter to the CEO of BlackRock, accusing the firm of using "the hard-earned money of our states' citizens to circumvent the best possible return on investment."[2] Likewise, some investors have criticized companies for not going far enough and for relying on "greenwashing" and other cosmetic gestures. Underlying all these concerns, are key questions related to the financial materiality of ESG-related activities and performance.

Missing in all this analysis are direct insights on how ESG-related actions influence consumption, which directly turns into the revenue and profit of corporations. Arguably, a fundamental test of how society values ESG initiatives is to examine the influence of ESG on consumer spending. Moreover, the extent to which ESG policies influence customer sales provides valuable insights into the channel in which these policies affect overall corporate

[1] For a more comprehensive overview of the topic, see Gillan, Koch, and Starks (2021).

[2] *Wall Street Journal*, "The ESG Investing Backlash Arrives," August 15, 2022

performance.

Building upon these ideas, a growing theoretical literature has suggested various possible links between customer behavior and ESG-related performance. Some papers assume that consumers gain utility from consuming goods aligned with their social preferences, and that these preferences can give rise to the prominence of an ESG factor in asset returns (Heinkel, Kraus, and Zechner (2001), Pástor, Stambaugh, and Taylor (2021), and Goldstein et al. (2022)). Somewhat relatedly, Pedersen, Fitzgibbons, and Pomorski (2021) develop a model that focuses directly on investor utility and assumes that there is a group of ESG-conscious investors who derive utility from holding assets with better ESG profiles. Another approach has modeled firm ESG investments as a means of differentiating its product to increase its market power (Albuquerque, Koskinen, and Zhang (2019)). In this framework, the prediction is that firms with better ESG ratings will have more loyal customers, which translates into a less elastic consumer demand.

Given the interest in these issues, it is notable that they have not received much attention in the empirical literature. In this paper, we take the important initial step of connecting ESG issues to consumer behavior by linking detailed product-level purchases to the revelation of ESG scandals. Our analysis relies heavily on two key databases. To capture consumer purchases, we utilize the Nielsen Homescan Consumer Panel (Consumer Panel) provided by the Kilts Nielsen Data Center at the University of Chicago Booth School of Business. This data tracks detailed shopping behaviors of approximately 40,000 - 60,000 U.S. households that the Nielsen company continually surveyed from 2004 to 2019. The sufficient granularity of the data enables us to observe detailed product-level purchasing prices and quantities for frequent shopping trips made by all surveyed households.

To identify negative ESG events, we utilize the RepRisk database, which tracks news incidents of firms from January 2008 to June 2020. Comparing with other leading ESG databases, RepRisk is uniquely suited for our analysis for its methodology, coverage and classification. First, Reprisk adopts an approach that captures only *negative* news from *external* sources, which minimizes the concerns that our event sample is driven by greenwashing and/or endogenous disclosures. Second, it offers unparalleled coverage on more than 200,000 firms, with majority being private firms. The coverage on private firms is critical when we aim to understand household consumption, given a lot of product manufacturers are private, local firms. Exploiting the ESG databases that focus only on public firms inevitably introduces selection problems that bias the analysis. Third, RepRisk presents detailed classifications of the types of ESG incidents, allowing us to decompose the broad impact of ESG across a broad range of well-defined issues. Moreover, we can exclude ESG scandals that expose product safety/quality problems so that our results do not merely stem from a mechanical link between compromised product quality and reduced consumer spending. To facilitate the empirical analysis, we use algorithmic name matching to connect firms involved in all ESG scandals included in Reprisk with the product manufacturers in the Nielson Consumer Panel. The merged sample allows us to identify both the manufacturers and the products affected by the negative ESG news coverage.

We first conduct a univariate analysis on the merged RepRisk-Nielsen sample to identify the affected products. We then present the trend of their monthly sales from six months before to six months after the ESG shock. To construct the control group, we calculate the monthly product sales of the unaffected products during the same window. We define unaffected products as those not involved in the ESG scandals and also require such products to come from a different, unrelated product group. In the graphic analysis, we find a significant decrease in the sales of the affected products, following a parallel trend in the sales of both affected products and unaffected products. We then formally test this relationship by conducting a battery of product-month level regressions. In the analysis, we incorporate all negative ESG incidents for consumer goods manufacturers and apply "stacked" Difference-in-Differences (DiD) regressions to study variations in product-level purchases surrounding the months of negative ESG news revelation. Consistent with the finding in the univariate analysis, we show that the total sales of the affected products decrease by 9% post the ESG shock, relative to that of the unaffected products.

The exploratory analysis above leads us to further investigate the connection between ESG issues and product consumption. We, however, recognize that there are some limitations to empirical tests at the product level. Using unrelated products as a control group is not ideal since such products may present a different latent utility to consumers. This approach thus raises the concern that the control products are not really comparable to the affected products in a DiD setting. Additionally, we are not able to disentangle the demand and supply effects by analyzing product sales, which are jointly determined by the time-varying demand of consumers and the production decisions of the manufacturers.

To overcome the limitations of the aggregated product-level analysis, we use the Nielsen Consumer Panel to analyze detailed household product purchases surrounding ESG incidents covered by Reprisk database. Specifically, we leverage the rich household shopping trip-level information to conduct a set of *within-household* and *within-product-group* regressions. The spirit of the experiment is to study the changes in the *same* household's shopping behaviors if a manufacturer whom they frequent with is involved in an ESG scandal. To conduct a proper comparison of purchasing decisions, we analyze the same household's consumption of a similarly-priced product within the same product group. Specifically, the control group consists of products manufactured by unaffected firms, but belonging to the same product category and purchased by the same household. This step ensures that the products in the treatment and control groups present similar latent utility to the same household, and are frequently consumed in the same location. We further require that both the affected and control products are purchased at least once in the six months period before the scandal revelation to make sure that all products are available and known to the studied households. The resultant sample consists of millions of product purchases by U.S. households between 2008 and 2019, allowing us to draw accurate inferences from big data.

Using household data, we can include high dimensional ESG Shock × Household × Month fixed effects in our econometric models. The adoption of such fixed effect models eliminates the impact of several unobservable confounding factors, such as 1) time-varying household-specific orientation towards certain ESG scandals, 2) time-varying changes in household demand, budget and family composition, and 3) the ensuing impact of local economic and political shocks. In robustness tests, we also include the ESG Shock × Household × Product fixed effects to control for time-invariant heterogeneity across the household's demand/appetite towards different products. Our results are robust to these variations.

In the baseline results, we find that negative ESG shocks have a significant effect on customer actions. Overall, the average reputation shock triggers a 5 - 10 % drop in customer purchases that extends for at least six months. Further analysis shows that consumer purchases drop further in more severe ESG scandals. In subsequent tests, we decompose the changes in consumer purchases into price-induced and quantity-induced variation and identify declining trends in both prices and purchasing quantities - for the same household, in the same market. These patterns are consistent with a reduction in consumer demand for products with ESG scandals rather than the firm's strategic decision to phase out production or recall products in face of negative ESG news revelation. On balance, these results provide compelling evidence that customers do take ESG considerations into account and that the corresponding drop in expected sales may induce many companies to take proactive steps to mitigate ESG-related controversies.

While these aggregate results are interesting, we might expect there to be considerable heterogeneity within the results. Fortunately, the granularity of both the Nielsen and RepRisk databases enables us to explore how these effects vary over time, across different customers, and across different types of ESG shocks. Specifically, we find that the negative links between ESG shocks and consumption are more pronounced for higher-income households and younger (millennial) households. Additionally, we also find that consumers react more strongly to negative ESG news (especially scandals related to environmental risks) when they have salient experiences of weather-related natural disasters during the six-month period prior to the ESG scandals.

Lastly, we delve deeper into the specific issue underlying each ESG scandal. We separately examine each of the ESG issues classified by RepRisk. Our analysis shows that controversies related to issues related to social discrimination, corruption, and discrimination in employment prompt the greatest consumer backlash. Furthermore, by removing ESG issues related to "product fallacy" from the empirical analysis, our results can speak directly to the preferences of consumers, who are increasingly unwilling to associate themselves with ESG scandal-inflicted products that do not align with their environmental, social, or political beliefs

Altogether, our paper contributes to two lines of research in the intersection of ESG, firm performance, and household consumption. We add to the long-standing literature on the financial materiality of firm ESG performance dating back to Berle (1932) and Friedman (1970). We demonstrate the financial materiality of ESG matters directly through the lens of consumers, via the household consumption channel. Our study presents the micro-level evidence on the revenue/profitability of corporations, by mapping firm sales to a comprehensive set of ESG drivers. Our results are also related to a nascent strand of the literature that suggests corporate ESG commitments can lower downside risks (Lins, Servaes, and Tamayo (2017) and Hoepner et al. (2018)) to help firms to achieve better financial performance (Eccles, Ioannou, and Serafeim (2014)). Specifically, a prominent channel through which sustainable practices can create value for shareholders is by reducing the risks of being litigated (Akey and Appel (2021), Bellon (2020), and Bellon (2021)). We contribute to this line of research by documenting that corporate ESG practices can also reduce the risks of losing customers.

Our paper also contributes to the developing literature on how individuals, in their capacity as investors or consumers, shape societal ESG initiatives (Bénabou and Tirole (2010)).

There is considerable debate on whether and how individuals incorporate social objectives and societal well-being into their investment and consumption decisions. For example, Moss, Naughton, and Wang (2020) show that retail investors are largely unresponsive to ESG disclosures while Bauer, Ruof, and Smeets (2021) and Hartzmark and Sussman (2019) suggest that investors place great emphasis on ESG-related factors. In a similar vein, there is little conclusive evidence that directly connects consumer behaviors to ESG issues, partly due to the difficulty of observing detailed consumer purchasing decisions surrounding significant changes in producers' ESG profiles. In related studies on consumer foot traffic, Gurun, Nickerson, and Solomon (2021) and Painter (2020) find that corporate initiation on certain ESG objectives, such as gun control or providing public amenities to non-investor stakeholders, can result in a decrease in consumer store visits. In contrast to these studies, our paper conducts a within-household, product-level analysis to examine the heterogeneity across various ESG drivers and different types of products. More importantly, product-level information allows us to decompose the demand and supply effects by tracking the changes in price and quantity. In summary, our paper presents the first comprehensive product-level analysis encompassing the broad ESG landscape. In a concurrent paper, Cen et al. (2022) focus on a specific aspect of ESG - workplace equality, and show that household's total spending on poor-performing manufacturers decreases following the breakouts of #MeToo and Black Lives Matter movements.

2 Data

2.1 Nielson Retail Data

We use the Nielsen Homescan Consumer Panel (Consumer Panel) provided by the Kilts-Nielsen Data Center at the University of Chicago Booth School of Business to study consumer purchases. The data tracks detailed shopping behaviors of approximately 40,000 - 60,000 U.S.

households that the Nielsen company continually surveyed from 2004 to 2019. Specifically, the surveyed households use in-home scanners or mobile apps to record all their purchases from any outlet intended for personal and in-home use. For each shopping trip, the data provides detailed transaction information for each product purchased (e.g., product identity, quantity, price, deals, and coupons). The products are assigned unique barcodes (UPCs) and organized into multiple well-defined product groups. Figure 1 lists the product groups covered in our analysis. Most product groups are items frequently bought by households in grocery stores. The largest category is "DRY GROCERY", which includes candy, cookies, cereal, other baked goods, etc.

In addition to product purchase information, the Consumer Panel provides rich demographics for the entire household, such as household size, income, age, employment, education, marital status, etc. It is worth mentioning that the surveyed households are geographically dispersed and demographically balanced. For example, Figure 2 lists the geographic distribution of all surveyed households in our sample.

The Consumer Panel is particularly relevant to our research question. We can exploit the high-frequency nature of shopping trips to do event studies on consumer purchases surrounding adverse ESG shocks. To connect consumer purchases with the changes in the producer's ESG profile, we use the company prefix data from GS1 US to trace the producers of all products in the Consumer Panel through their barcodes. GS1 US is the single official source that assigns barcodes to consumer goods, allowing manufacturers to obtain unique digital identities for their products. With this matching, we can compare products whose producer experiences an ESG scandal with similar products purchased by the same consumer. As we illustrate below, the granularity of the data set sharpens the identification of ESG shocks and enables us to explore heterogeneity at the consumer and product level.

2.2 RepRisk Data

We identify the negative shocks to a firm's reputation related to its ESG and business conduct using the RepRisk database. The database tracks negative news incidents of firms from January 2008 to June 2020.[3] It adopts an "outside-in" approach that only considers *negative* news from *external* sources. This approach, compared with those used by other leading ESG databases, alleviate the endogeneity concerns that changes in a firm's perceived reputation may be driven by green-washing activities and/or discretionary disclosures. This methodological advantage is evidenced by Reprisk's increasing popularity among researchers in studying how negative ESG shocks affect firm strategies, the equity market, and other corporate stakeholders (See Derrien et al. (2021), Houston and Shan (2022), Gantchev, Giannetti, and Li (2022), and Glossner (2021) among others).

Specifically, a dedicated team of analysts leverages a combination of artificial intelligence and curated human analysis to track a universe of over 200,000 firms globally. Over 100,000 public sources and stakeholders in 23 languages are screened on a daily basis. Once an incident is identified, analysts conduct additional analysis to (1) confirm that the incident is indeed related to the firm's ESG activities or business conduct, (2) remove possible duplicate media coverage on the same incident to make sure each risk event only enters once into the RepRisk Platform, and (3) identify the specific nature of the incident, by mapping it to 28 issues and 73 topics including "discrimination in employment", "controversial products", and "tax evasions", etc. Each incident is assigned three proprietary scores based on severity (harshness), reach (influence), and novelty (newness). Finally, the monthly RepRisk Index is updated, with the *change* reflecting the ensuing impact of the news incident on the firm's perceived reputation. The RepRisk Index is a non-broken, monthly time-series variable ranging from 0 to 100, with 100 representing the worst perceived reputation.

[3] The sample period of the merged database between Nielson and RepRisk starts in January 2008 and ends in December 2019. The starting year is restricted by the coverage in RepRisk, while the ending year is restricted by the coverage in Nielson.

We capture the negative reputation shock to a firm by exploiting the changes in its RepRisk Index. We consider a manufacturer and its products as "Treated", if its RepRisk Index increases by more than 25 from month T to month T+1. In Table 8, we also experiment with an alternative threshold - a monthly change over 50 - to define an ESG reputation shock. Our results are robust to this variation. As the threshold signals the severity of the shocks, we show that the spending on affected products contracts more significantly following the second set of incidents. Lastly, we map the ESG shocks to their underlying issues. We consider a shock to be mainly driven by a specific issue, if the total number of news coverage related to this issue is higher than the number of news coverage on other issues, as observed from month T to month T+1.

2.3 Summary of Statistics

We merge the RepRisk database with the Nielson Consumer Panel using shared firm (manufacturer) names, and summarize the statistics in Table 1. Each observation is the total spending by a household (i) on a product (p) in month (t). In the balanced panel, $Total\_Spending$ equals zero if the household didn't make any purchase of the product in the month. The mean level of $Total\_Spending$ is 0.57 dollar. However, if we only consider the household-product-month with non-missing purchases, the average monthly spending by a household on a product is 4.1 dollars. Note that in the merged DiD sample, we include the products 1) from the same product category, 2) priced within a +/-20% range, and 3) purchased by the same household, as control products. The ratio between treatment and control products in our sample is roughly 1:2. In terms of household composition, the majority of the households are headed by the Boomer Generation (Figure 2 Panel b) and about 40% of the households in our sample make an annual income between 50k and 100k (Figure 2 Panel c).

3 Univariate Results and Product-level Analysis

3.1 Univariate Results

We start with a visual analysis of consumers' product consumption trends when goods in their shopping basket experience an ESG scandal. Our objective is to examine whether the revelation of negative ESG news has a discernible effect on consumer choices. In Figure 3, we plot the average consumption of products affected by ESG scandals and a control group consisting of other unrelated products covered by the Consumer Panel. Panel a (b) of Figure 3 plots the percentage changes in the average dollar (unit) purchases relative to the pre-shock level in months $[T-6,\ T-1]$, where T is the month of negative ESG news coverage.

Both panels reveal a striking pattern of consumption changes following negative ESG shocks. As is evident from the post-event consumption trends, the average purchases of affected products experience a consistent decrease following the onset of the negative ESG shock (Panel a). This trend continues for at least six months and shows no sign of reversal. The level of purchasing decrease amounts to about 10% at the end of the six-month window. At the same time, the consumption trend of the control group is mostly flat before and after the ESG scandal. The results on product quantity in Panel b echo the findings in dollar consumption.

The graphical analysis suggests that adverse ESG shocks on manufacturers significantly influence consumers' choice of these firms' products. Recall that the largest product groups in our sample are consumer staples that are purchased rather frequently (Figure 1). The fact that consumers choose to avoid affected products for several months points to a significant change in consumption behaviors.

3.2 Product-level Analysis

In this subsection, we conduct a battery of product-level regressions to formally test the divergence in product sales documented in the graphical analysis above. For each ESG shock, we calculate the monthly product sales of the affected products. Our control group consists of the product sales from a different product group. We conduct DiD regression analysis following the specification below:

$$\begin{aligned} Product\_Sales_{j,p,t} =& \beta_1 Treat_{j,p} + \beta_2 Post_{i,t} + \\ & \beta_3 Treat_{j,p} \times Post_{i,t} + \alpha_{j,p,t} + \epsilon_{i,j,p,t}, \end{aligned} \tag{1}$$

In this model, j denotes ESG scandals, p denotes products, and t denotes calendar months. The $Treat_{j,p}$ dummy equals one for products involved in the ESG scandal, while $Post_{j,t}$ is set to one for the six months after a negative ESG shock. $\alpha_{j,p,t}$ are a set of fixed effects that we specify to control for time-invariant or time-varying unobservable product characteristics. The coefficient β_3 on the interaction term reflects the average change in the dollar consumption of affected products, relative to the sales of other products in unrelated product groups. In subsequent tests, we replace the dollar value with the natural logarithm of product sales, in which case β_3 captures the percentage change in product sales, relative to that of other products in unrelated product groups.

Table 2 reports the results from regressions. In column 1, we include the Product, Shock and Time fixed effects. The specification in column 2 is more stringent, where we include interactive shock-time fixed effects and shock-product fixed effects. In essence, these high-dimensional fixed effects converts the model to a stack of "canonical" DiD regressions with unit fixed effects and time fixed effects. As can be expected from such models, both the $Treat$ dummy and the $Post$ dummy are absorbed by the interactive fixed effects. In addition, we cluster standard errors at the ESG scandal level to account for the correlation between error terms within each event. We find that the total product sales of affected products, on average, decrease by 207 thousands per month. In columns 3 and 4, we replace the dependent variable with the natural logarithm of product sales, and show that the sales of affected products decrease by about 9% relative to the percentage change in sales of unaffected products. In summary, the findings from the product-level regression analysis is consistent with that of the univariate graphical analysis reported in section 3.1.

4 Identification Strategy and Results

While the visualization of raw data and the product-level regressions above are generally considered a straightforward and transparent way to establish the negative relationship between ESG shocks and product sales, they are subject to several limitations. First, we are not able to disentangle the demand and supply effects by analyzing product-level sales, which is jointly determined by the time-varying demand of consumers and production decisions of the manufacturers. Examining the average product price does not help us answer the question either, as it is likely weighted across purchases in different geographical locations over time. Second, the control products in the analysis above are not perfect. For each affected product, we pair it with an unaffected control product from a distant product group. This choice gives us a benchmark of unaffected product sales, but also raises concerns that the control product presents a different latent utility to consumers - and thus not really comparable to the affected products in a Difference-in-Differences (DiD) setting.

In this section, we leverages the rich household shopping trip-level information to conduct a set of *within-household* and *within-product-group* regressions. We study the changes in the *same* household' shopping behaviors if a manufacturer whom they frequent with was involved in an ESG scandal. We compare it with the household's consumption on a similarly-priced product within the same product group. We further require that the household has purchased both the affected and control products at least once in the six months period before the scandal revelation, which implicitly confirms that both products are readily available options serving similar customer needs and falling under the similar budget requirement.

4.1 Baseline Regressions

Central to this research design is the use of extensive data sets to account for the heterogeneity across products and consumers in periods spanning ESG scandals. To this end, we create a balanced panel data set that tracks surveyed households' product-level purchases surrounding all ESG scandals in our sample period. We include the products affected by the ESG scandal (treatment products) and the products classified under the same product groups, whose prices are within a $\pm$ 20% range of the treatment product's price (control products). Figure 4 illustrates the construction of the treatment and control sample using three different product groups: Dairy, Beverage, and Cosmetics. For each treatment product, we track and compare its purchase to that of the control products in the same consumers' shopping baskets within a six-month window. We then repeat this process for all products, all surveyed households, and all ESG scandals, resulting in a data set with about 150 million observations. The oversized data is due to the rich cross-sections of products, households, and ESG scandals in our sample period.

We estimate a "stacked" difference-in-differences model (see, e.g., Gormley and Matsa (2011) and Cengiz et al. (2019)) to study consumer spending following staggered ESG scandals. In a nutshell, the "stacked" approach estimates the average treatment effect across multiple "canonical" DiD regressions with two groups and clean pre- and post-periods. In a recent evaluation of econometric methodologies applied in staggered events, Baker, Larcker, and Wang (2022) show that the "stacked" regression produces an efficient estimator that can uncover the aggregated treatment effect via OLS. As such, this method is not subject to the critiques of applying two-way fixed effects DiD regressions in dynamic treatment settings

Goodman-Bacon (2021).

$$
\begin{aligned}
Total\_Spending_{i,j,p,t} = & \beta_1 Treat_{j,p} + \beta_2 Post_{i,t} + \\
& \beta_3 Treat_{j,p} \times Post_{i,t} + \alpha_{j,p,t} + \epsilon_{i,j,p,t},
\end{aligned}
\tag{2}
$$

In this model, i denotes surveyed households, j denotes ESG scandals, p denotes products, and t denotes calendar months. The $Treat_{j,p}$ dummy equals one for products involved in the ESG scandal, while $Post_{i,t}$ is set to one for the six months after a negative ESG shock. $\alpha_{j,p,t}$ are a set of fixed effects we later specify in the each section. The coefficient β_3 on the interaction term reflects the average change in the dollar consumption of affected products (compared to similar products) across all products, households, and ESG scandals. In subsequent tests, we extend this baseline model to study the heterogeneous responses for different product attributes, household demographics, and types of ESG scandals.

Table 3 reports our baseline results. We start with the first three models. Model (1) is our main specification with interactive event-time-household fixed effects. We cluster the standard errors by each product in this model. Model (2) is the same as Model (1) except that we double cluster standard errors by household and time to account for correlation in household purchasing decisions for a specific household in a month. Model (3) is the most stringent specification, where we include interactive event-time fixed effects and event-household-product fixed effects. In essence, these high-dimensional fixed effects converts the model to a stack of "canonical" DiD regressions with unit fixed effects and time fixed effects. As can be expected from such models, both the treatment dummy and the post dummy are absorbed by interactive fixed effects. In using a series of models, we can observe the changes in the coefficient across multiple fixed effects that aim to absorb unobservable heterogeneity across events, households, and products.

We find that the estimated results to be both statistically and economically significant. Across all models, the coefficient β_3 is negative and highly significant (t-stats range from -7 to -12). The economic magnitudes of the treatment effects are also sizable. We estimate the economic magnitude of the contraction in spending triggered by ESG shocks as the coefficient of the interaction term, divided by the sum of the constant term and the coefficient of the $Treat$ term. Take Model (5) for example, the sales of affected products drop by an average of 5%, relative to similarly-priced merchandise consumed by the same household during the same period of time. The magnitude inceases to 10% in Model (6) when we apply the most granulary fixed effects.

We note that the empirical model above hinges on the accurately identifying the timing of ESG scandals and defining the $Post$ variable. It is possible, however, that a significant increase in the Reprisk index value is triggered by news sources that transpired the official assignment of the Reprisk score. For example, analysts can mark up the Reprisk index in month t+1 based on ESG scandals in month t. As a result, we cannot precisely define the date of ESG scandal occurrence since the finest data source by Reprisk is at a monthly frequency. To address this issue, we define a "shock period" as the months t and t+1 of a significant increase in Reprisk index value occurring in month t. Removing this "shock period" yields a cleaner set of shopping trips before and after ESG scandals. Models (4) to (6) report estimated results based on this smaller sample using the same set of fixed effects applied in the first three regressions. We find that our main conclusion remains unchanged if we remove the "shock period" from the test sample. In general, the economic magnitudes of the treatment effect become larger in this sample.

4.2 Disentangling the Demand and Supply Effects

Our results have thus far pointed to a consistent decrease in consumer purchases following ESG scandals. One potential confounding interpretation, however, is that these findings are mainly driven by supply side issues rather than consumers' willingness to pay. In face of ESG scandals, firms can make strategic responses to product lines, such as production scale-down, product redesign, or even product recalls. These changes can eventually result in a reduction in purchases of focal products in ESG scandals. While it is plausible that both supply and demand factors can be at play, we believe our findings thus far are largely attributable to changes in consumer decisions during ESG scandals. For example, we document the changes in purchasing behaviors in the months immediately following ESG scandals. For a supply-side channel to be the main factor, firms hit by ESG scandals have to make adequate changes to product lines across the nation in a very short horizon.

In this section, we attempt to further disentangle supply and demand effects by observing changes in both prices and quantities. We note that supply-driven consumption changes are likely associated with a reduction in purchasing quantities but an increase in equilibrium prices. On the contrary, if faltering consumer demand is the main factor underlying our findings, we expect to observe a decrease in both prices and quantities as the demand curve shifts to the left.

In Table 4, we study product prices and purchasing quantities using DiD models similar to the previous sections. In Models (1) and (2), we use product prices and quantities as dependent variables and cluster standard errors at the product level. We find that the purchasing quantity of consumers decreases sing following the ESG scandal. The DiD estimate on the price component is negative but not statistically significant at conventional levels (t=-1.309). In the remaining two models, we also adopt the same econometric specification to study samples outside the "shock period." The results are largely unchanged – purchasing quantity decreases significantly while the estimated product price differences between treatment and control group is negative but not statistically significant. An interesting contrast between the price and quantity regressions lies in the explanatory power of the fixed effect model – the magnitudes of adjusted R^2 of the price models is close to 70% and less than 10% for the quantity regression. This finding is consistent with the "price rigidity" phenomenon, where sellers do not adjust prices quickly in response to changing economic conditions.

In Table 5, we attempt to further understand the dynamics of consumer consumption by analyzing month-by-month changes in prices and quantities surrounding ESG scandals. In this exercise, we focus on a sharp window $[T-2,\, T+3]$ to identity immediate reactions in customer purchases and firm's price setting strategies. The table presents models with the same fixed effects models in Table 4 on all observations within the $[T-2,\, T+3]$ window ("Full Sample") as well as a sub-sample with non-missing price observations. We substitute the $Treat \times Post$ with interactions between the treatment group indicator and individual time dummy variables capturing the months relative to the ESG scandal event.

In Model (1) of Table 5, we find that the prices of affected goods fall in the months after the ESG scandals ("Post-Shock"). The purchasing quantities also follow a declining trend but the drop occurs in the same months of the ESG scandal ("Shock-Period"), suggesting that consumer reacts more swiftly than the product manufacturers or retailers, the price setters. The fact that consumers are more responsive to ESG scandals suggests that consumer demand rather than producer market strategies is the main driver of our main results. In Models (3) and (4), we apply the same econometric models to a subsample containing non-missing price observations and document similar patterns in the trajectories of prices and quantities. Specifically, we note that quantities decrease (coefficient on the T dummy in Model (4), t=-2.257) still predate the responses in price changes (coefficients in periods $[T+1,\, T+3]$). In aggregate, the drops in both quantities and prices are in line with a demand-drive explanation of observed consumption changes following ESG scandals.

4.3 Cross-sectional Analysis

4.3.1 Household Social-economic Profiles

We now study how household wealth and age affect their perception of ESG scandals. To test the impact of these two attributes, we conduct a triple-difference analysis based on our baseline model. Specifically, we interact the double interaction term $Treat \times Post$ with variables capturing the household age and retail spending.

Table 6 analyzes how age affects the awareness of ESG scandals. The econometric model is similar to the baseline specification, except we include an interaction variable with the age of the household as well as dummy variables capturing whether the household age falls in the second, third, and fourth quartiles of all households ranked by age. In Model (1), we find that the triple-interaction term is negative and statistically significant at the 5% level, suggesting that older households are less likely to reduce consumption of goods in ESG scandals. This fining is confirmed by results in Model (2), where we only observe a positive and statistically significant triple interaction term with a dummy variable capturing households in the largest age bucket.

Turning to the analysis on household spending in Table 7 , we find that households are less reactive to ESG scandals when they have a larger budget, possibly indicating wealthier families. Specifically, we document a positive and significant coefficient on the triple interaction term with the logarithm of total household spending (Model (1)) and an interaction between $Treat \times Post$ and an indicator variable for households in the largest spending quartile.

These results highlight the important heterogeneity in ESG receptibility across both the age groups and household wealth. When viewed together, our results on household age heterogeneity are consistent with the notion that younger households are more reactive to ESG scandals. Additionally, we note that Millennials are more likely to belong to a low-income group but have the highest awareness of ESG issues.

4.3.2 Severity of ESG Shocks

As a validation of our baseline test, we study whether more severe ESG scandals are associated with more dramatic drops in affected products. Finding this relation would strengthen the credibility of our main results by examining the treatment intensity of the DiD test.

Table 8 presents our analysis of the severity of the ESG incidents. Our analysis is based on the Reprisk's proprietary rating of ESG scandals (RRI_Trend). We start by defining severe ESG scandals as those events triggering a more than 50 points drop in Reprisk's rating. We then assign a dummy variable (Sev) that equals to one for such events. In Model (1), the triple-interaction term with Sev is negative and statistically significant, consistent with the notion that more severe ESG scandals can lead to more precipitous drops in consumer purchases. In Models (2) and (3), we apply the baseline model to two subsamples of "Severe Shocks" and "Non Severe Shocks" based a cutoff of 50 points drop in Reprisk's rating. The results in the this part echo the triple-DiD model. Although the $Treat \times Post$ term is statistically significant in both models, the coefficient is more negative for more severe ESG scandals. As another validation, in Model (4), we document a negative and significant triple interaction term with the continuous measure of the Reprisk's rating (RRI_Trend). Overall, our results suggest that consumers react more strongly when a product manufacturer's reputation is significantly damaged in ESG scandals. These results also suggest that there are substantial cross-sectional differences between ESG scandals in our sample.

4.4 Salience and Consumer Responses

In this section, we analyze whether consumer salience of environmental issues affects their reaction to ESG scandals. We measure consumer salience using households' exposure to environmental disasters such as hurricanes and wildfires. We hypothesize that consumers in areas that experience severe environmental damage can react more significantly to ESG scandals due to their increasing awareness of ESG issues, particularly scandalous events regarding environmental factors.

We present the analysis between consumer salience and the changes in purchasing behaviors due to ESG scandals in Table 9. In the DiD model, We use the per capita cost of recent natural disasters at the consumer's residing county or the natural logarithm of this value to proxy for consumer salience. The triple interaction between this variable and the $Treat \times Post$ variable captures whether surveyed households are more sensitive to ESG incidents. Given that natural disasters is closely related to awareness of environmental issues, We restict our analysis to environmental-related ESG scandals. As placebo tests, we also separately study ESG scandals driven by social or governance issues. We would not expect find consumers affected by natural disasters to be more reactive in such scandals.

In Models (1) and (2), we find that consumers in areas with high environmental disaster-induced costs tend to further reduce the consumption of products in ESG scandals. This result is consistent with the notion that recent natural disaster experiences increase consumer awareness of ESG issues. Relatedly, the triple interaction term with environmental damage costs is not significantly different from zero in Models (3) to (6), where we use alternative samples including ESG scandals driven by social or governance issues. We view these results as a validation to the measurement on consumer awareness in environmental issues.

5 Heterogeneity Across ESG Issues

In this section, we classify ESG shocks by the underlying violating issues. We follow the classification system in RepRisk, and break down the negative exposure along the Environmental, Social - External, Social - Internal, Governance and Cross-cutting issues. The external social issues involve conflicts with external communities while the internal ones relate to conflicts with employees. The former includes human rights abuses, social discrimination, while the latter includes pay equality, labor conditions etc. Cross-cutting issues are those spanning across E, S, and G dimensions.

Specifically, for each ESG shock, we calculate the number of news incidents on each of the issues, during month t-1 and month t. We consider the most heavily exposed issue during the shock period as the driving issue. In the fourth column of Table 10, we show that

33.79% of the shocks are driven by product scandals that cause health and/or environmental damage. Pollution, Climate Change, Human Rights Abuse follow as the other commonly exposed problems.

We then repeat the analysis in Equation 2 using all sub-samples. Each sub-sample consists the control and treatment product purchases from six months before to six months after a specific type of shocks. In columns 5, 6 and 7, we report the coefficients of the constant, $Treat$ and interaction terms respectively. We estimate the contraction in the spending on treatment products as the coefficient of the interaction term, divided by the sum of the constant term and the coefficient of the $Treat$ term. The last column reports whether the treatment effect is statistically significant.

For ESG scandals that result in a statistically significant change in consumer purchases, issues related to social discrimination, corruption, and discrimination in employment trigger the most significant backlash from consumers. Consumers also react significantly to frequent ESG issues in our sample, such as product-related health and environmental issues, climate changes, and local pollution, suggesting our baseline results are unlikely driven by events with rare occurrences. Interestingly, we find scandals involving that social and governance issues have a stronger impact on consumption than scandals on environmental issues. This result suggests that the baseline result in this paper does no merely stem from the risks of consuming products affected by ESG scandals such as pollution. ESG issues that are relevant to consumer's social preferences can also shape consumers' purchasing decisions.

6 Conclusion

In this paper, we have studied the impact that negative ESG events have on consumption behavior. Our study explores the effects of more than 1600 negative events captured from the RepRisk database, on 150 million point-of-sale consumption observations obtained from the Nielsen Homescan Consumer Panel.

Our baseline findings show that the average negative event generates a 5 - 10 % decrease in sales for the affected product in the six months following the event. These findings strongly suggest that consumers take ESG issues into account when making consumption decisions. This behavior also illustrates a specific consumption channel through which firm ESG policies ultimately affect firm performance in a meaningful way. Taking a deeper dive into these issues, we find that there is considerable heterogeneity in consumer responses, and that the average response varies considerably depending on consumer demographics and the nature of the ESG-related reputation shock.

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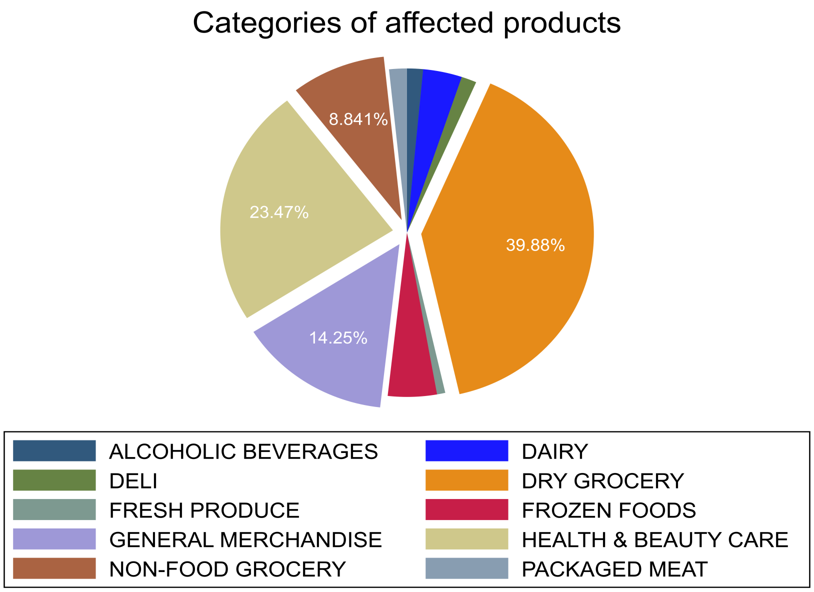
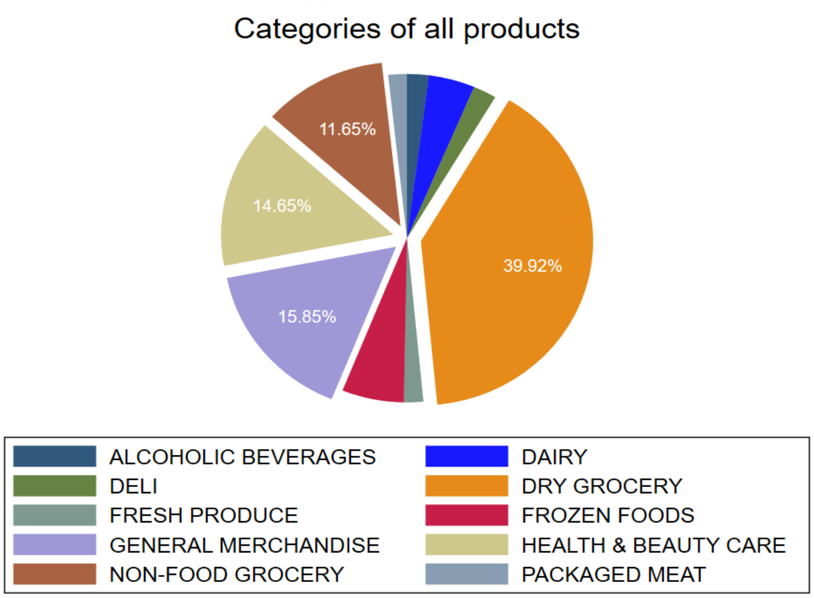
Figure 1. Distribution of Products

(a) Products Affected by ESG Shocks



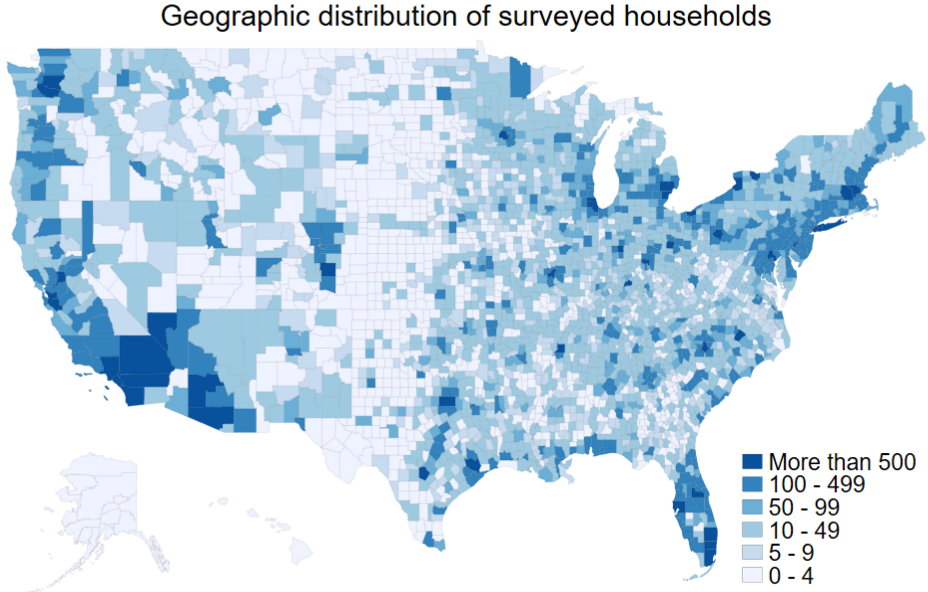
(b) All Products



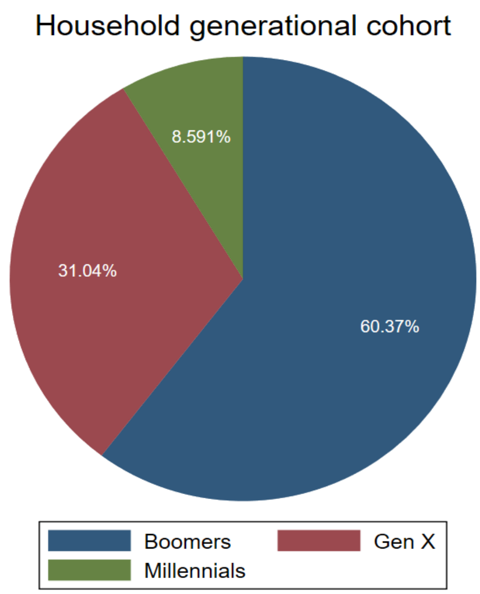
The figures plot the distribution of the products purchased by the surveyed households, by their affiliated product categories. Figure (a) shows the breakdown of the products affected by ESG incidents. Figure (b) shows the breakdown of all products covered in the sample. The classifications are based on the product categories defined by Nielsen.

Figure 2. Distribution of Households

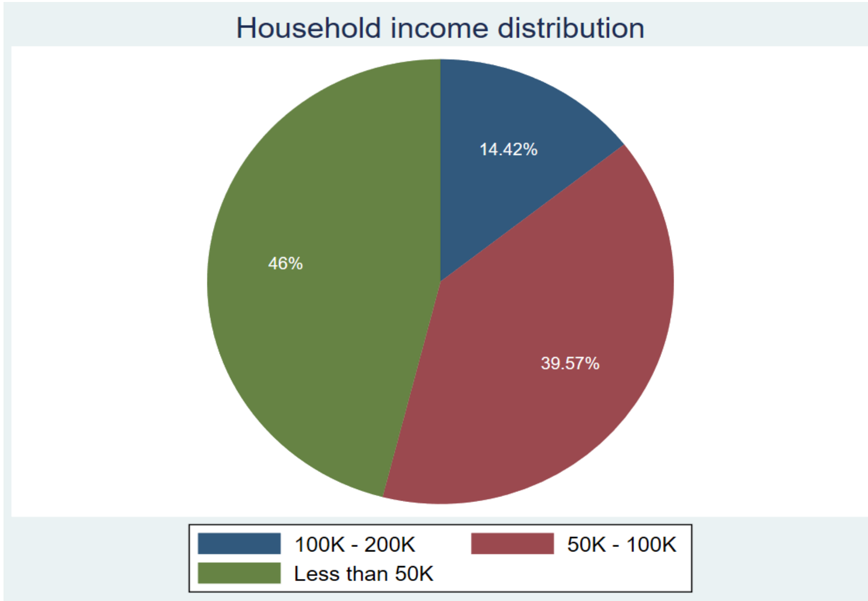
(a) By Location



(b) By Age



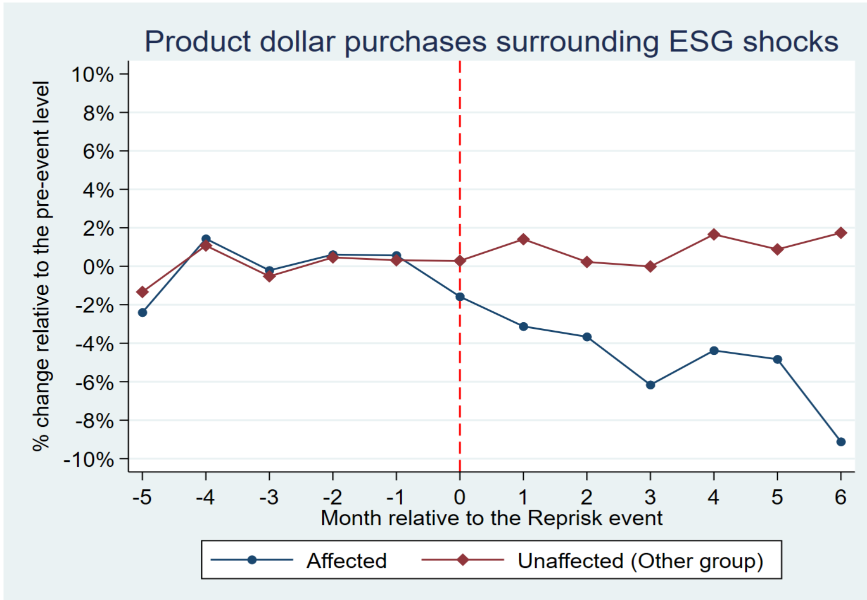
(c) By Income



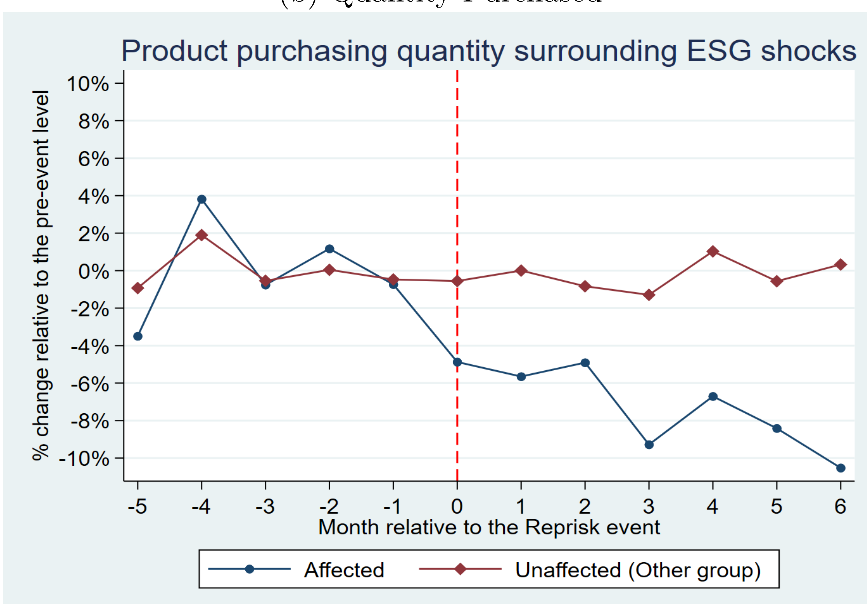
The figures plot the distribution of the surveyed households by location, age and income. We only include the households in our treatment and control groups. In figure (a), areas of the heat map filled with darker blue are populated with higher number of surveyed households. Figure (b) shows the distribution of the surveyed households by the average of the ages of household heads. The Boomer Generation is defined as the group born before 1964. Generation X includes the group born after 1964 but before 1980. Millennial Generation includes the group born after 1980 but before 1994. Figure (c) shows the distribution of the surveyed households by household income, across the groups with less than 50K, between 50K and 100K, and above 100K, respectively.

Figure 3. Total Spending and Quantity Purchased for Affected and Control Products

(a) Total Spending

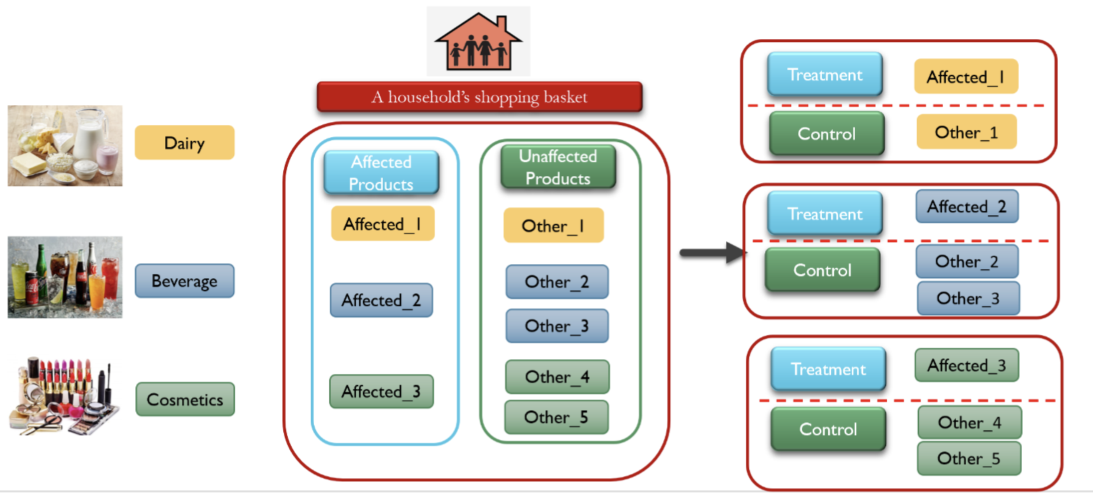


(b) Quantity Purchased



The figures plot the time-series variations in spending and quantity sold for affected products and unaffected products from other product groups. Figure (a) shows the percentage change in spending on the affected products, and non-affected products from other product groups, from 6 months before to 6 months after the ESG shock. In figure (b), we repeat the analysis in figure (a), but use the quantity sold instead of total spending as the variable of interest.

Figure 4. The Conceptual Framework of the Empirical Strategy



The figure visualizes the construction of treatment and control groups within the same household's shopping basket. Our empirical strategy builds on a time-varying, within-household analysis.

Table 1. Summary Statistics

This table reports the summary of statistics for the key variables. The level of observation is on the household-month-product level. The 10th percentile, 90th percentile, median, mean and standard deviation are reported. Detailed variable definitions are available in Appendix A.1.

Var	Obs	p10	p50	p90	Mean	Std
Total_Spending	151,727,000	0.00	0.00	1.96	0.57	2.62
Price	141,181,511	0.98	2.29	4.89	2.79	2.89
Quantity	151,727,000	0.00	0.00	1.00	0.24	1.04
Treat	151,727,000	0.00	0.00	1.00	0.36	0.48
Age	144,136,856	39.00	55.00	71.00	55.15	12.25
Ln Spending	144,348,973	8.32	9.07	9.72	9.04	0.54
Dmg per capita	151,727,000	0.00	0.00	0.01	0.02	0.33
Dmg	151,727,000	0.00	0.00	0.27	0.72	15.60

Table 2. Product Sales and ESG Shocks

In this table, we regress the monthly product sales on the *Treat*, *Post* and the interaction term in a Difference-in-Differences setting. The analysis is based on a balanced panel, where each observation is the total spending on a product (p) in month (t). *Product_Sales* is the total dollar value of product sales (in $1,000) observed among all households tracked by Nielson. *Treat* is a dummy variable that turns on when the product is manufactured by a firm involved in an ESG scandal that happened during the shock period (month (T) and month ($T+1$)). We only include the monthly observations from six months before to six months after a specific scandal. The *Post* is a dummy variable that equals one for every t that falls between $[T+1, T+6]$, and equals zero for every t that falls between $[T-5, T]$. In column 1, we include the Shock, Product and Time FEs. In column 2, we include the Shock × Time and Shock × Product fixed effects that absorb the variations in both *Treat* and *Post*. Standard errors are clustered at the ESG scandal level. In columns 3 and 4, we repeat the analysis in columns 1 and 2 using the same set of specifications, but replace the *Product_Sales* with *Ln_Product_Sales*. t-statistics are shown in parentheses. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively. Detailed variable definitions are available in Appendix A.1.

	(1)	(2)	(3)	(4)
	Product_Sales (in $1,000)		Ln_Product_Sales	
Treat × Post	-207.271**	-207.261**	-0.089***	-0.090***
	(-2.099)	(-2.099)	(-6.767)	(-6.779)
Post	104.798**		0.036**	
	(2.115)		(5.333)	
Observations	1,650,583	1,650,559	1,330,882	1,330,388
Shock FE	Yes		Yes	
Time FE	Yes		Yes	
Product FE	Yes		Yes	
Shock × Time FE		Yes		Yes
Shock × Product FE		Yes		Yes
Cluster by Shock	Yes	Yes	Yes	Yes
Adjusted R-squared	0.999	0.999	0.997	0.997

Table 3. Baseline Regressions: Within Household Analysis

In this table, we regress the total spending on the $Treat$, $Post$ and the interaction term in a Difference-in-Differences setting. The analysis is based on a balanced panel, where each observation is the total spending by a household (i) on a product (p) in month (t). $Total\_Spending$ equals zero if the household didn't make any purchase of the product in the month. $Treat$ is a dummy variable that turns on when the product is manufactured by a firm involved in an ESG scandal that happened during the shock period (month (T) and month ($T+1$)). We only include the monthly observations from six months before to six months after a specific scandal. The $Post$ is a dummy variable that equals one for every t that falls between $[T+1,\, T+6]$, and equals zero for every t that falls between $[T-5,\, T]$. In column 1 and 2, we include the fixed effects that fully absorb the variation in $Post$. In column 3, we include the fixed effects that absorb the variations in both $Treat$ and $Post$. Standard errors are clustered at the product level in columns 1 and two-way clustered at the product and household × time (Year-month) levels in columns 2 and 3. In columns 4-6, we repeat the analysis in columns 1-3 using the same set of specifications, but use the sub-sample after carving out the observations during the shock period (month (T) and month ($T+1$)). t-statistics are shown in parentheses. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively. Detailed variable definitions are available in Appendix A.1.

	(1)	(2)	(3)	(4)	(5)	(6)
		[T-5, T+6]			[T-5, T-1] & [T+2, T+6]	
	Total_Spending	Total_Spending	Total_Spending	Total_Spending	Total_Spending	Total_Spending
Treat × Post	-0.0232***	-0.0232***	-0.0597***	-0.0267***	-0.0267***	-0.0640***
	(-7.251)	(-7.531)	(-12.112)	(-7.079)	(-7.371)	(-11.707)
Treat	0.0358***	0.0358***		0.0393***	0.0393***	
	(4.920)	(5.202)		(5.160)	(5.454)	
Observations	145,431,915	145,431,915	151,721,400	119,952,383	119,952,383	125,185,094
Shock × Time FE			Yes			Yes
Shock × Time × Household FE	Yes	Yes		Yes	Yes	
Shock × Household × Product FE			Yes			Yes
Cluster by Product	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by Household × Time		Yes	Yes		Yes	Yes
Adjusted R-squared	0.176	0.176	0.320	0.176	0.176	0.317

Table 4. Decomposing the Demand and Supply Effects

In this table, we regress the price and quantity sold for both treated and control products in a Difference-in-Differences setting. The analysis is based on a balanced panel, where each observation is the price and quantity of the product (p) purchased by a household (i) in month (t). *Quantity* equals zero if the household didn't make any purchase of the product in the month - and in this case, we assign the value of *Price* as the same product's average price paid by other households in the same county. *Treat* is a dummy variable that turns on when the product is manufactured by a firm involved in an ESG scandal that happened during the shock period (month (T) and month ($T+1$)). We only include the monthly observations from six months before to six months after a specific scandal. The *Post* is a dummy variable that equals one for every t that falls between $[T+1,\ T+6]$, and equals zero for every t that falls between $[T-5,\ T]$. In columns 4-6, we repeat the analysis in columns 1-3 using the same set of specifications, but use the sub-sample after carving out the observations during the shock period (month (T) and month ($T+1$)). The specifications in all columns include the Shock × Household × Product fixed effects that absorb the variations in the *Post* dummy. Standard errors are two-way clustered at the product and Household × Time (Year-month) levels. t-statistics are shown in parentheses. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively. Detailed variable definitions are available in Appendix A.1.

	(1)	(2)	(3)	(4)
	[T-5, T+6]		[T-5, T-1] & [T+2, T+6]	
	Price	Quantity	Price	Quantity
Treat × Post	-0.0069	-0.0033**	-0.0080	-0.0057***
	(-1.309)	(-2.271)	(-1.227)	(-3.229)
Treat	0.1358***	0.0117***	0.1362***	0.0143***
	(10.471)	(4.397)	(10.086)	(4.986)
Observations	135,050,622	145,431,915	110,528,133	119,952,383
Shock × Time × Household FE	Yes	Yes	Yes	Yes
Cluster by Product	Yes	Yes	Yes	Yes
Cluster by Household × Time	Yes	Yes	Yes	Yes
Adjusted R-squared	0.697	0.0931	0.696	0.0940

Table 5. Dynamic Analysis

In this table, we regress the price and quantity sold for both treated and control products in a dynamic Difference-in-Differences setting. We focus on a sharp window centered on the shock period. In columns 1 and 2, *Quantity* equals zero if the household didn't make any purchase of the product in the month - and in this case, we assign the value of *Price* as the same product's average price paid by other households in the same county. In columns 3 and 4, we only include the observations with non-missing price information (i.e., the household purchased the product at least once in the month). *Treat* is a dummy variable that turns on when the product is manufactured by a firm involved in an ESG scandal that happened during the shock period (month (T) and month ($T+1$)). Six monthly dummies are included, with two in the pre-shock period, two in the shock period, and two in the post-shock periods, respectively. The specifications in all columns include the Shock × Household × Product fixed effects that absorb the variations in the *Post* dummy. Standard errors are two-way clustered at the product and Household × Time (Year-month) levels. t-statistics are shown in parentheses. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively. Detailed variable definitions are available in Appendix A.1.

	(1)	(2)	(3)	(4)
	Full Sample		Non-missing Price	
	Price	Quantity	Price	Quantity
Pre-Shock				
Treat × T-2				
Treat × T-1	-0.0005	-0.0025	-0.0035	-0.0001
	(-0.146)	(-0.762)	(-0.410)	(-0.020)
Shock-Period				
Treat × T	-0.0095	-0.0152***	0.0037	-0.0160**
	(-1.436)	(-4.245)	(0.281)	(-2.257)
Treat × T+1	-0.0112	-0.0089***	-0.0313**	0.0078
	(-1.586)	(-2.850)	(-1.962)	(1.093)
Post-Shock				
Treat × T+2	-0.0146**	-0.0060*	-0.0528***	0.0096
	(-2.069)	(-1.909)	(-3.227)	(1.396)
Treat × T+3	-0.0149**	-0.0074**	-0.0364**	0.0140*
	(-2.164)	(-2.348)	(-2.372)	(1.810)
Treat	0.1440***	0.0162***	0.1167***	-0.0209***
	(10.601)	(3.958)	(6.385)	(-2.611)
Observations	69,845,198	72,614,953	21,118,674	21,118,674
Shock × Time × Household FE	Yes	Yes	Yes	Yes
Cluster by Product	Yes	Yes	Yes	Yes
Cluster by Household × Time	Yes	Yes	Yes	Yes
Adjusted R-squared	0.702	0.0898	0.636	0.240

Table 6. Generational Gap

In this table, we regress the total spending on household characteristics in the triple Difference-in-Differences setting. The analysis is based on a balanced panel, where each observation is the total spending by a household (i) on a product (p) in month (t). $Total\_Spending$ equals zero if the household didn't make any purchase of the product in the month. $Treat$ is a dummy variable that turns on when the product is manufactured by a firm involved in an ESG scandal that happened during the shock period (month (T) and month ($T+1$)). We only include the monthly observations from six months before to six months after a specific scandal. The $Post$ is a dummy variable that equals one for every t that falls between $[T+1, T+6]$, and equals zero for every t that falls between $[T-5, T]$. Age is a continuous variable that equals the average age of the household heads. Age_Q2, Age_Q3 and Age_Q4 are dummy variables that equal one if the Age falls in the second, third and fourth quartiles of all households ranked by age. Note that the variations in $Post$, Age and their interaction terms are fully absorbed by the fixed effects, so their coefficients are not reported. Standard errors are two-way clustered at the product and household $\times$ Time (Year-month) levels. t-statistics are shown in parentheses. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively. Detailed variable definitions are available in Appendix A.1.

	(1) Total Spending	(2) Total Spending
Treat × Post × Age	0.0003**	
	(2.222)	
Treat × Post × Age_Q2		-0.0018
		(-0.540)
Treat × Post × Age_Q3		0.0013
		(0.348)
Treat × Post × Age_Q4		0.0086**
		(2.223)
Treat × Age	-0.0005**	
	(-2.377)	
Treat × Age_Q2		-0.0036
		(-0.875)
Treat × Age_Q3		-0.0048
		(-0.821)
Treat × Age_Q4		-0.0203***
		(-3.106)
Treat × Post	-0.0373***	-0.0251***
	(-5.181)	(-6.435)
Treat	0.0637***	0.0433***
	(6.364)	(7.032)
Observations	138,361,521	145,431,915
Shock × Time × Household FE	Yes	Yes
Cluster by Product	Yes	Yes
Cluster by Household × Time	Yes	Yes
R-squared	0.175	0.176

Table 7. Social-Economic Gap

In this table, we regress the total spending on household characteristics in the triple Difference-in-Differences setting. The analysis is based on a balanced panel, where each observation is the total spending by a household (i) on a product (p) in month (t). $Total\_Spending$ equals zero if the household didn't make any purchase of the product in the month. $Treat$ is a dummy variable that turns on when the product is manufactured by a firm involved in an ESG scandal that happened during the shock period (month (T) and month ($T+1$)). We only include the monthly observations from six months before to six months after a specific scandal. The $Post$ is a dummy variable that equals one for every t that falls between $[T+1, T+6]$, and equals zero for every t that falls between $[T-5, T]$. $LnSpending$ is a continuous variable that equals the natural algorithm of the dollar value of a household's total spending. $Spending\_Q2$, $Spending\_Q3$ and $Spending\_Q4$ are dummy variables that equal one if the $LnSpending$ falls in the second, third and fourth quartiles of all households ranked by yearly spending. Note that the variations in $Post$, $LnSpending$ and their interaction terms are fully absorbed by the fixed effects, so their coefficients are not reported. Standard errors are two-way clustered at the product and household $\times$ Time (Year-month) levels. t-statistics are shown in parentheses. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively. Detailed variable definitions are available in Appendix A.1.

	(1) Total Spending	(2) Total Spending
Treat × Post × Ln Spending	0.0057**	
	(2.109)	
Treat × Post × Spending_Q2		-0.0016
		(-0.526)
Treat × Post × Spending_Q3		0.0012
		(0.312)
Treat × Post × Spending_Q4		0.0104***
		(2.656)
Treat × Ln Spending	0.0011	
	(0.154)	
Treat × Spending_Q2		0.0041
		(1.090)
Treat × Spending_Q3		0.0023
		(0.459)
Treat × Spending_Q4		-0.0010
		(-0.090)
Treat × Post	-0.0229***	-0.0255***
	(-7.031)	(-8.166)
Treat	0.0367***	0.0352***
	(5.094)	(7.574)
Observations	138,555,497	138,555,497
Shock × Time × Household FE	Yes	Yes
Cluster by Product	Yes	Yes
Cluster by Household × Time	Yes	Yes
R-squared	0.175	0.175

Table 8. Severity of ESG Scandals

In this table, we regress the total spending on the heterogeneity of ESG shocks in the triple Difference-in-Differences setting. The analysis is based on a balanced panel, where each observation is the total spending by a household (i) on a product (p) in month (t). $Total\_Spending$ equals zero if the household didn't make any purchase of the product in the month. $Treat$ is a dummy variable that turns on when the product is manufactured by a firm involved in an ESG scandal that happened during the shock period (month (T) and month ($T+1$)). We only include the monthly observations from six months before to six months after a specific scandal. The $Post$ is a dummy variable that equals one for every t that falls between $[T+1,\ T+6]$, and equals zero for every t that falls between $[T-5,\ T]$. Sev is the dummy variable that equals to one if the ESG shock is accompanied with a monthly increase in the RepRisk index that is greater than 50. RRI_Trend is a continuous variable that equals the monthly change in the firm's RepRisk index. In column 1, we report the triple-DiD analysis by including the indicator variable Sev, while in column 2 and 3, we report the DiD analysis using the sub-samples consisting of severe ESG shocks (Sev¿0) and non-severe ESG shocks, respectively. In column 4, we report the triple-DiD analysis by replacing Sev with RRI_Trend. Note that the variations in $Post$, Sev, RRI_Trend and their interaction terms are fully absorbed by the fixed effects, so their coefficients are not reported. Standard errors are two-way clustered at the product and household × Time (Year-month) levels. t-statistics are shown in parentheses. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively. Detailed variable definitions are available in Appendix A.1.

	(1) Total Spending Full Sample	(2) Total Spending Severe Shocks	(3) Total Spending Non Severe Shocks	(4) Total Spending Full Sample
Treat × Post × Sev	-0.0398***			
	(-2.793)			
Treat × Post × RRI_Trend				-0.0031***
				(-6.561)
Treat × Sev	0.0605***			
	(3.611)			
Treat × RRI_Trend				0.0082***
				(7.866)
Treat × Post	-0.0226***	-0.0624***	-0.0226***	0.0726***
	(-7.226)	(-4.482)	(-7.226)	(4.829)
Treat	0.0349***	0.0954***	0.0349***	-0.2167***
	(4.993)	(6.241)	(4.993)	(-6.197)
Observations	145,431,915	1,803,512	143,628,403	145,431,915
Shock × Time × Household FE	Yes	Yes	Yes	Yes
Cluster by Product	Yes	Yes	Yes	Yes
Cluster by Household × Time	Yes	Yes	Yes	Yes
Adjusted R-squared	0.176	0.150	0.177	0.176

Table 9. Salience about ESG and Consumption Decisions

In this table, we regress the total spending on the heterogeneity of the consumers' past exposure to environmental problems in the triple Difference-in-Differences setting. The analysis is based on a balanced panel, where each observation is the total spending by a household (i) on a product (p) in month (t). *Total_Spending* equals zero if the household didn't make any purchase of the product in the month. *Treat* is a dummy variable that turns on when the product is manufactured by a firm involved in an ESG scandal that happened during the shock period (month (T) and month ($T+1$)). We only include the monthly observations from six months before to six months after a specific scandal. The *Post* is a dummy variable that equals one for every t that falls between $[T+1, T+6]$, and equals zero for every t that falls between $[T-5, T]$. *Dmg per capita* is the county-level property damage per capita caused by natural disasters that happened during the six months period prior to the ESG shock. *Dmg* is the county-level property damage caused by natural disasters that happened during the six months period prior to the ESG shock. In column 1 and 2, we report the triple-DiD analysis using the full sample. In column 3 and 4, we report the triple DiD analysis using the sub-sample consisting of ESG shocks involving environmental issues. In column 5 and 6, we report the triple DiD analysis using the sub-sample consisting of ESG shocks driven entirely by environmental issues. Note that the variations in *Post*,*Dmg per capita*, *Dmg* and their interaction terms are fully absorbed by the fixed effects, so their coefficients are not reported. Standard errors are two-way clustered at the product and household × Time (Year-month) levels. t-statistics are shown in parentheses. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively. Detailed variable definitions are available in Appendix A.1.

	(1)	2	3	4	5	6
	The Placebo Tests					
	Environmental-Related Scandals		Social-Related Scandals		Governance-Related Scandals	
	Total Spending	Total Spending	Total Spending	Total Spending	Total Spending	Total Spending
Treat × Post × Ln Dmg per capita	-0.057513**		-0.059117		0.002516	
	(-1.97008)		(-0.95102)		(0.19025)	
Treat × Ln Dmg per capita	0.073600**		0.111401		-0.000090	
	(2.43029)		(1.53822)		(-0.00627)	
Treat × Post × Dmg per capita		-0.092597**		-0.072117		-0.005944
		(-2.08222)		(-0.94994)		(-0.25759)
Treat × Dmg per capita		0.116975**		0.139615		0.002952
		(2.47673)		(1.61962)		(0.11177)
Treat × Post	-0.017087**	-0.016816**	-0.014444**	-0.014434**	-0.026887***	-0.026800***
	(-2.37861)	(-2.34328)	(-2.05465)	(-2.04360)	(-7.37288)	(-7.36491)
Treat	0.033683***	0.033342***	0.041593***	0.041538***	0.032280***	0.032250***
	(3.74321)	(3.70700)	(2.73674)	(2.72200)	(4.01497)	(4.00849)
Observations	27,585,023	27,585,023	25,118,392	25,118,392	96,826,764	96,826,764
Shock × Time × Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by Product	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by Household × Time	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.206	0.206	0.136	0.136	0.166	0.166

Table 10. 28 ESG Issues

In 28 sub-samples, we regress the total spending on the $Treat$, $Post$ and the interaction term in a Difference-in-Differences setting. Each sub-sample consists of the ESG shocks driven by one of the 28 ESG issues categorized by RepRisk. The analysis is based on a balanced panel, where each observation is the total spending by a household (i) on a product (p) in month (t). $Total\_Spending$ equals zero if the household didn't make any purchase of the product in the month. $Treat$ is a dummy variable that turns on when the product is manufactured by a firm involved in the ESG scandal driven by a specific ESG issue that happened in month (s). We only include the monthly observations from six months before to six months after a specific scandal. The $Post$ is a dummy variable that equals one for every t that falls between $[s+1,\ s+6]$, and equals zero for every t that falls between $[s-6,\ s-1]$. We exclude the monthly observations observed in month s. The magnitude of the constant term, the coefficients of the Treat and Treat $\times$ Post terms are reported in each row. We estimate the average contraction in the spending on treatment products as the coefficient of Treat $\times$ Post, divided by the sum of the constant term and coefficient of the Treat term. The Standard errors are two-way clustered at the product and household $\times$ time (Year-month) levels.

Issue Classification	Issues	of Incidents	% of Incidents	Constant	Coefficient of Treat	Coefficient of Treat × Post	% Contraction in Spending (Magnitude)	Statistical Significance (lower than 5%)
E	CLIMATE GHG	115	7.12	0.571	0.0003	-0.0221	-3.87%	Y
E	LOCAL POLLUTION	140	8.66	0.6404	0.0447	-0.0228	-3.33%	Y
E	IMPACTS ON LANDSCAPES	53	3.28	0.4192	0.0051	-0.0030	-0.71%	
E	OVERUSE OF RESOURCES	1	0.06	1.0856	0.5452	-0.1663	-10.20%	
E	WASTE DISPOSAL ISSUES	10	0.62	0.8496	0.1318	-0.0496	-5.05%	
E	ANIMAL MISTREATMENT	29	1.79	0.6776	0.0402	-0.0397	-5.53%	Y
S - External	HUMAN RIGHTS ABUSES	107	6.62	0.6098	0.0648	-0.0446	-6.61%	Y
S - External	IMPACTS ON COMMUNITIES	40	2.48	0.9001	-0.0234	-0.0269	-3.07%	
S - External	LOCAL PARTICIPATION ISSUES	3	0.19	1.4702	2.2642	-0.8707	-23.32%	
S - External	SOCIAL DISCRIMINATION	6	0.37	0.8213	0.0763	-0.1091	-12.15%	Y
S - Internal	FORCED LABOR	6	0.37	0.7076	-0.3338	-0.0229	-6.13%	
S - Internal	CHILD LABOR	10	0.62	0.5617	-0.0179	-0.0291	-5.35%	
S - Internal	STRIKE COLLECTIVE BARGAIN	14	0.87	0.7585	0.1915	0.0909	9.57%	Y
S - Internal	DISCRIMINATION IN EMPLOYMENT	30	1.86	0.605	0.1095	-0.0495	-6.93%	Y
S - Internal	OCCUPATIONAL HEALTH	87	5.38	0.5643	-0.0659	0.0045	0.90%	
S - Internal	POOR EMPLOYMENT CONDITIONS	55	3.4	0.7494	-0.0586	-0.0335	-4.85%	Y
G	CORRUPTION BRIBERY EXTORTION	52	3.22	0.4702	0.0646	-0.0388	-7.26%	Y
G	EXECUTIVE COMPENSATION ISSUES	11	0.68	1.9724	0.0258	0.322	16.11%	Y
G	MISLEADING COMMUNICATION	87	5.38	0.5628	0.1037	-0.0443	-6.65%	Y
G	FRAUD	101	6.25	0.682	-0.0298	-0.0107	-1.64%	
G	TAX EVASION	4	0.25	0.4978	-0.1520	0.0934	27.01%	
G	TAX OPTIMIZATION	3	0.19	0.7083	-0.5000	0.0833	39.99%	
G	ANTI COMPETITITVE PRACTICES	62	3.84	0.4675	0.0419	-0.016	-3.14%	Y
Cross-Cutting	CONTROVERSIAL PROD SERVICES	25	1.55	4.6744	-0.4514	0.0705	1.67%	
Cross-Cutting	PROD HEALTH ENVIRON ISSUES	546	33.79	0.6297	-0.0146	-0.0359	-5.84%	Y
Cross-Cutting	VIOLATION OF INTL STANDARDS	0	0					
Cross-Cutting	VIOLATION OF NATL LEGISLATION	14	0.87	0.1577	0.6684	-0.6459	-78.19%	
Cross-Cutting	SUPPLY CHAIN ISSUES	5	0.31	0.2497	-0.0080	0.0265	10.96%	Y
	Total	1,616	100					

Appendix

Table A.1. Variable Definitions

Variable name	Description	Source
Total_Spending	A household-product-month level variable that equals the total spending by a household on a product in a month.	Nielson
Price	A household-product-month level variable that equals the average price paid by a household on a product in a month.	Nielson
Quantity	A household-product-month level variable that equals the total number (units) of a product purchased by a household in a month.	Nielson
Treat	A product-month level dummy variable that turns on when the product is manufactured by a firm involved in an ESG scandal that happened during the preceding six months.	RepRisk & Nielson
Inc_50k_100k	A dummy variable that equals one if the household has an annual incomebetween 50k and 100k.	Nielson
inc_100k_200k	A dummy variable that equals one if the household has an annual incomebetween 100k and 200k.	Nielson
Inc_gt_200k	A dummy variable that equals one if the household has an annual income greater than 200k.	Nielson
Boomers	A dummy variable that equals one if the household heads were born before 1964.	Nielson
Generation X	A dummy variable that equals one if the household heads were born between 1964 and 1980.	Nielson
Millennials	A dummy variable that equals one if the household heads were born between 1980 and 1996.	Nielson
Cnty_democratic	A dummy variable that equals one if the household was residing in a county which voted (more than 50%) for the Democratic Party in the presidential election. preceding the shock	Nielson
Durable	A dummy variable that equals one if the product affected is classified as durable products (i.e., low purchasing frequency).	Nielson
Dmg per capita	The county-level property damage per capita caused by natural disasters that happened during the six months period prior to the ESG shock.	FEMA
Dmg	The county-level property damage caused by natural disasters that happened during the six months period prior to the ESG shock.	FEMA