When I Know Your Taste:

Retail Customers' Environmental Preferences and Firm Pollution

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Abstract

I examine whether and how firms incorporate retail customers' environmental preferences into their pollution decisions. Leveraging the staggered revelations of firms' environmental negative news and the granularity of household grocery shopping records, I quantify local customers' heterogeneous environmental preferences based on the extent of product sales declines following the news events. In line with the conjecture that firms factor in rewards and penalties from customers and strategically reduce their pollution, I find a significant improvement in air quality near event firms' facilities located in markets where local customers reveal the strongest environmental preferences. This effect is more pronounced when news events are more salient and when ex-ante information frictions between firms and customers are greater. Furthermore, I find no changes in firm-level pollution, and air quality significantly worsens in facilities located in markets where customers have weaker environmental preferences, corroborating firms' pollution-shifting strategy. Overall, my findings shed light on retail customers' role in firms' environmental resource allocation.

Keywords: Environmental preferences, ESG preferences, Retail customers, Stakeholders, Pollution shifting, ESG resource allocation

JEL classifications: D83, M14, M41, Q50

1. Introduction

Shifting toward more sustainable patterns of consumption and production is essential for pollution reduction (United Nations Environment Programme, 2017). Theoretically, sustainable consumption drives market demand for products with less negative environmental impact, which in turn gives firms incentives to produce in a more responsible manner (Kitzmueller and Shimshack 2012; Besley and Persson 2023).[1] The intertwined consumption and production decisions suggest that the billions of small daily purchasing choices made by individual customers are likely to have an important influence on firms' pollution. Anecdotally, retail customers are showing increasingly strong environmental preferences. According to the 2023 U.S. Brand Sustainability Benchmark Report, one in two consumers have changed their choices of food and grocery brands based on sustainability considerations.[2] However, prior studies focus more on the influence that investors and regulators have on firms' pollution (Riedl and Smeets 2017; Dyck et al. 2019; Azar et al. 2021; Dasgupta et al. 2023; Tomar 2023), and empirical studies on the role played by retail customers are relatively scarce. In this paper, I examine whether and how retail customers' environmental preferences shape firms' pollution decisions.

As pollution reduction is costly and consumes substantial corporate resources, firms trade off pollution reduction costs against the expected penalties from stakeholders (Shapira and Zingales 2017; Xu and Kim 2022). Retail customers with strong environmental preferences can penalize firms by factoring their environmental practices into purchasing choices. Specifically, when customers perceive a firm's environmental efforts as inadequate, they divert their spending to more sustainable alternatives, resulting in decreased demand and revenue loss for the firm (Duan

[1] In a recent survey conducted by United Nations, 68% of CEOs state that customers are the most impactful stakeholders that influence their firms' sustainability agenda (United Nations Global Compact 2023).
[2] See: https://campaign.glowfeed.com/srs_foodgrocery_us.

et al. 2023; Dube et al. 2023; Houston et al. 2023; Meier et al. 2023). Besides, environmentally conscious customers can deter firms' excessive pollution by actively engaging in actions like protests and class-action lawsuits, which impose litigation and reputational risks on polluting firms (Eesley and Lenox 2006). However, whether the penalties from retail customers are sufficient to change firms' pollution decisions hinges on the proportion of environmentally conscious customers in firms' customer base, and the strength of their environmental preferences (Broccardo et al. 2022).

To empirically capture retail customers' environmental preferences, I develop a novel measure guided by revealed preference theory. The revealed preference theory suggests that individual customers' environmental preferences can be derived by comparing the purchasing decisions made by the *same* customer for the *same* product when they are informed about the firm's environmental practices versus when they are not informed. Therefore, the magnitude of the change in customers' spending reflects the weight they place on a product's environmental attributes in their utility function, indicating how strong their environmental preferences are. Empirically, I use the release and dissemination of firm-level negative environmental news to capture retail customers' awareness of firms' environmental misconduct. I then measure the various reactions of customers in different local markets to the same environmental news using their grocery spending on the same products before and after they become aware of the environmental news. I refer to this as "the revealed preference measure."

To ensure that the revealed preference measure captures retail customers' environmental preferences, I first show that it is positively correlated with other measures used in prior studies, such as Americans' beliefs in global warming, Democratic votes, median income, and educational background (e.g., Howe et al. 2015; Albuquerque et al. 2019). However, the revealed preference measure is more relevant to firms' pollution decisions than these other measures, and directly speaks to the effect of retail customers for three reasons. First, while retail customers may intend to buy environmentally friendly products, their actual choices are subject to factors such as budget constraints and local product availability, creating a large discrepancy between stated and realized preferences (Hainmueller et al. 2015; Pigors and Rockenbach 2016).[3] Derived from customers' actual purchases, the revealed preference measure captures realized preferences instead of stated ones. It is the realized preferences that directly affect product demand and, consequently, have the potential to shape firms' decisions. Second, the firm-specific, event-based revealed preference measure allows customers to value environmental attributes differently across various product categories, consistent with survey evidence showing that retail customers weigh a firm's environmental practice most heavily when buying baby care products and least when selecting pet products.[4] In contrast, measures from prior studies implicitly assume homogeneous environmental preferences across different products, which fails to capture the variations that could provide additional information for individual firms. Third, the revealed preference measure reflects the environmental preferences of a firm's customer base, rather than those of the general resident population. This distinction is important because other measures, such as income and education level, are based on average or median values from all residents, who are not necessarily customers of the focal firm. As a result, these measures could be subject to sampling bias, misrepresenting the preferences of the firm's actual customers.

After validating the revealed environmental preference measure, I examine whether and how retail customers' environmental preferences shape firms' pollution decisions using a sample of

[3] According to a survey from the Harvard Business Review, 65% of consumers said they want to buy purpose-driven brands that advocate sustainability, yet only about 26% actually do so. See: https://hbr.org/2019/07/the-elusive-green-consumer.
[4] See: https://campaign.glowfeed.com/srs_foodgrocery_us.

U.S. consumer-facing firms over the period of 2004–2016. Specifically, I measure the pollution level of firms' facilities in different local markets and consider the local markets of event firms as having strong environmental preferences if the magnitude of the sales drop in a market is the largest following the news event (i.e., within the bottom decile of the sample distribution). Using the staggered timing of negative environmental news events and a stacked difference-in-differences (DiD) specification (Cengiz et al. 2019), I examine the change in pollution levels of the event firms' facilities located in local markets with strong environmental preferences (i.e., treated facilities) relative to that of control facilities after the news event. The control facilities are facilities owned by the event firms but located elsewhere, or facilities of non-event firms that are in the same county and in the same industry as the treated facilities. The use of these control facilities mitigates the confounding effects of unobservable time-varying firm characteristics and local socioeconomic factors on firms' pollution decisions.

Consistent with the prediction that firms will factor in expected penalties from retail customers when making pollution decisions, I find that facilities located in markets where customers have strong environmental preferences reduce their pollution by 0.9%, relative to control facilities, in the first three years following the news event. This is equivalent to a 3.6% standard deviation change in facilities' pollution level or an 11% within fixed effects standard deviation change (see Breuer and deHaan 2023).

Next, I conduct two sets of cross-sectional tests to strengthen the inferences. First, the revealed preference measure is built upon the premise that retail customers are aware of firms' negative environmental news. Because prominent and widely circulated information is more likely to reach retail customers (Hirshleifer and Teoh 2003; Blankespoor et al. 2020), I examine whether the local pollution reduction varies with the salience level of news events. Consistent with the expectation, I find that the results are more pronounced when the triggering news events are more salient. Second, the necessity to adjust pollution emissions following a news event is determined by the extent of the *ex-ante* misalignment between local pollution level and local customers' environmental preferences. From the customers' side, retail customers are more likely to have access to information about corporate environmental practices when firms are more transparent in their ESG disclosures, creating a richer information environment. Informed customers can express their preferences through their purchasing decisions independently of news events, enabling firms to adjust their pollution decisions, even before any news event occurs. From the firms' side, geographic proximity can improve information exchange between headquarters and local markets (Campbell et al. 2009). When headquarters are geographically close to local markets, this proximity facilitates private information channels, allowing firms to better understand the environmental preferences of their local customers. In such cases, the revealed preferences contain limited incremental information. Consistent with this prediction, I find that the results are less pronounced when a firm's ESG disclosure score prior to a news event is above the sample median and when the distance between a firm's headquarters and its local facilities is below the sample median.

I further investigate the mechanism through which firms achieve reductions in local pollution levels. There are two primary strategies they can employ. One way that firms can reduce their pollution levels in markets where customers have strong environmental preferences is by increasing their local abatement investments, without making any changes to operations elsewhere. Alternatively, firms can reduce local pollution by shifting it to other facilities. To shed light on the mechanism, I begin by showing that firm-level pollution remains unchanged after negative news events. Second, I find an increase in local pollution levels in markets with weak environmental preferences following such events. Third, I show a monotonic pattern between increases in pollution and local environmental preferences. That is, the smaller the local sales drop after negative news events, the greater the increase in local pollution level.

Finally, to provide more support for the pollution-shifting mechanism, I conduct two sets of cross-sectional analyses. First, I expect managers to be particularly incentivized to cater to local customers with strong environmental preferences and to shift pollution away when facing higher expected penalties and marginal costs for failing to do so. Specifically, I find that the effect of local pollution reduction is more pronounced when the local market is the firm's major market, when the level of local product market competition is higher, and when the majority of the local population resides in rural areas where the facilities are most likely to be located. Second, the feasibility of pollution shifting depends on the "pollution slack" of the facilities in areas with weaker environmental preferences. I expect the reduction in pollution for facilities in markets with strong environmental preferences to be more pronounced when other facilities have excess production capacity and are under less stringent environmental regulations, allowing them to absorb this redirected pollution (Bartram et al. 2022; Thomas et al. 2022). The empirical results are consistent with these predictions. Collectively, these findings support the pollution-shifting mechanism, whereby firms redistribute their pollution internally based on the environmental preferences of local markets.

This study makes three main contributions to the literature. First, it enhances our understanding of retail customers as an underexplored stakeholder group. While prior studies have documented corporate customers' influence on suppliers' ESG practices (e.g., Dai et al. 2021), the inherent power imbalance between individual customers and firms makes it unclear whether the conclusions drawn from corporate customers can be generalized to retail customers. Several concurrent working papers, utilizing Nielsen data or foot-traffic data, show that retail consumers react negatively to at least some ESG incidents (Christensen et al. 2023; Duan et al. 2023; Dube et al. 2023; Houston et al. 2023; Meier et al. 2023). While some of these studies show that customers' reactions vary with residents' political leanings, income, and educational level (Duan et al. 2023; Dube et al. 2023; Houston et al. 2023), they have not explored whether and how firms factor in the variation of local customers' environmental preferences into their decision-making. My paper differs from these studies as I quantify the heterogeneity in local customers' environmental preferences at the county level and investigate firms' responses by exploiting the pollution levels of local facilities. In doing so, I highlight that retail customers' environmental preferences are a key input for firms' environmental resource allocation decisions.

Second, this study adds to the growing literature on how stakeholders' nonpecuniary preferences shape firms' ESG practices. Prior literature has documented that institutional investors' prosocial preferences can affect firms' ESG practices either through direct engagement or through the threat of divestment (e.g., Dimson et al. 2015; Dyck et al. 2019; Gantchev et al. 2022). These studies almost exclusively rely on the World Value Survey to capture cross-country E&S preference divergence. To sharpen the identification and pin down the role of retail customers' environmental preferences, I construct a novel and more refined measure by exploring local customers' different responses to the same firm-specific negative environmental news and document that firms strategically shift their local pollution to cater to revealed local customers' environmental preferences. My findings thus directly answer the call for "understanding whose preferences influence a firm's CSR activities" (Hanlon et al. 2022, p.1160).

Third, this study builds on recent theoretical work investigating whether individual decisions in responsible investment or consumption can promote corporate social responsibility. While the impact of each responsible individual is small and can be offset by irresponsible counterparts (e.g., Heinkel et al. 2001), recent models suggest that when individual consumers, particularly those with warm-glow preferences, act collectively in a coordinated manner, their aggregated efforts can influence corporate behavior (Hakenes et al. 2021; Kaufmann et al. 2024). By analyzing county-level retail customer demand as a unit of aggregation and documenting firms' responses in reducing local pollution, the empirical findings of this study support these theoretical insights and highlight the crucial role of collective consumer action.

The remainder of the paper is organized as follows. Section 2 develops hypotheses. Section 3 describes the estimation of retail customers' revealed environmental preferences. Section 4 explains the research design of the main hypothesis. Section 5 presents the main results, and Section 6 reports the results of additional analyses. Section 7 concludes.

2. Hypothesis development

2.1. Retail customers' environmental preferences and firms' pollution decisions

Firms' investments in pollution reduction, despite being costly, are not necessarily value-decreasing. In fact, a firm can benefit from pollution reduction if it increases demand or if customers are willing to pay more for products from firms that actively manage their environmental impact. From a value maximization perspective, a company will invest in pollution reduction when the expected profit increase outweighs the cost of the investment and up to the point at which marginal benefits and marginal costs balance (McWilliams and Siegel 2001).

However, firms face uncertainty when evaluating the payoffs from pollution reduction investments (Roychowdhury et al. 2019), partly because customers' environmental preferences vary widely and change over time,[5] making it difficult to assess the benefits of catering to these

[5] For example, Hainmueller et al. (2015) conduct a field experiment in which fair-trade labels are randomly attached

customers and the costs of not doing so. To mitigate this uncertainty, firms can either directly survey customers or infer their environmental preferences from their observed purchasing behavior. However, direct surveys can be costly and inefficient, as the difference between stated and realized preferences can be large. In contrast, customers' purchasing decisions reflect their knowledge about a product's attributes and the importance they place on these attributes in their utility function. Nevertheless, customers' purchasing decisions reveal their environmental preferences only when customers are informed about firms' environmental practices. Yet, it is difficult, if not impossible, for consumers to determine whether a firm harms the environment solely through the purchase and use of a firm's products.[6] Furthermore, collecting information on a firm's environmental practices can be excessively costly for individuals.[7] Therefore, in the absence of additional independent information about firms' environmental practices, customers make uninformed purchasing decisions that do not reflect whether and to what extent environmental considerations weigh in their utility-maximizing choices. The uninformed purchasing decisions thus impede a useful channel for firms to learn about the environmental preferences of their customer base (Hayek 1945).

I argue that the release and dissemination of firms' environmental negative news by third

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to bulk coffee bins in grocery stores. While the overall sales of fair-trade labelled coffees increase, they observe significant heterogeneity in the weight that different consumers place on ethical sourcing when making their purchasing decisions. Simon-Kucher (2021) finds that 45% of respondents who previously identified their attitudes towards sustainability as negative or neutral, now cite environmental sustainability as a higher priority when it comes to purchasing decisions.

[6] In the information economics view of customer purchasing behavior, when consumers base their purchasing decisions on a firm's operating practices, the output of the firm is a credence good (Darby and Karni 1973; Feddersen and Gilligan 2001). The responsible production of a product is a "credence" attribute, which remains undetectable even after consumption. There are two classes of product attributes in addition to credence attributes. Search attributes, such as price and color, are product characteristics that are discoverable through inspection and can be evaluated before purchase. Experience attributes, such as quality and durability, are product characteristics that can be assessed after consumption (Nelson 1970).

[7] EY's Future Consumer Index shows that 55% of customers say that a lack of information deters them from buying a sustainable product and 61% want more information for better sustainable shopping choices. See: https://www.ey.com/en_gl/consumer-products-retail/redesign-consumer-ecosystems-to-scale-sustainability.

parties creates an information channel between firms and retail customers. When learning negative environmental news, customers who give more weight to a product's environmental attributes in their utility function experience a greater disutility. This leads to a decline in demand as the product becomes less desirable compared with alternatives. In contrast, other customers may not be as responsive to the negative news, either because they have weak innate environmental preferences or because they cannot voice their environmental demands due to budget constraints or limited product availability (Pigors and Rockenbach 2016). As a result, firms update their beliefs about customers' heterogeneous environmental preferences by observing how changes in product demand in response to negative environmental news vary across different local markets. This enables firms to develop more precise estimates of the expected penalties for pollution emissions and rewards for pollution reduction in local areas and adjust their pollution reduction efforts accordingly. Specifically, firms have greater incentives to cut pollution in areas where customers reveal strong environmental preferences. First, the reduced product demand poses a direct threat to firms' sales revenue. Second, environmentally conscious customers are prone to undertake actions such as protests and civil lawsuits, heightening litigation and reputational risk (Eesley and Lenox 2006). Moreover, customers' high environmental preferences can affect firms indirectly through local governments translating voter preferences into regulatory interventions (Kitzmueller and Shimshack 2012). Therefore, the expected penalties for polluting in areas where customers have strong environmental preferences are likely to exceed the costs of pollution reduction, leading firms to cut emissions. I state my main hypothesis in the alternative form below:

> *H1: Firms will reduce pollution emissions in facilities located in areas where retail customers reveal strong environmental preferences after the release of firms' negative environmental news.*

2.2. The role of news salience

The main hypothesis is built upon the premise that retail customers are aware of firms' negative environmental news and able to efficiently process the information content. Owing to individuals' limited attention and processing capacity constraints, information that is prominent and widely circulated is likely to be absorbed more easily (Hirshleifer and Teoh 2003; Blankespoor et al. 2020). From the firms' perspective, attribution theory suggests that salient events or factors are more likely to be perceived as the cause of an outcome (Kelley 1973). In other words, while various market factors can lead to fluctuations in sales, salient negative news makes the managers of the firms more confident in attributing the sales change to the specific news event. Collectively, changes in product sales following a salient negative environmental news event are therefore expected to be more informative about local customers' underlying environmental preferences and thus more likely to be factored in firms' pollution decisions. This leads to my second hypothesis:

> *H2: Pollution reduction in facilities located in areas where retail customers reveal strong environmental preferences is more pronounced if firms' negative environmental news is more salient.*

2.3. The role of ex-ante information frictions

Before the revelation of firms' environmental negative news, retail customers are likely to have incomplete information about firms' environmental practices, and firms also face information uncertainty in terms of their customers' environmental preferences. These information frictions between the two parties give rise to the possibility of *ex-post* pollution emission adjustments. Thus, I expect the effect of the pollution reduction induced by retail customers' revealed preferences to be stronger when customers face greater *ex-ante* information asymmetry about firms' environmental practices. In other words, news events are more useful to retail customers if they have limited knowledge of firms' environmental practices before the events. Similarly, I expect the effect to be stronger when firms' information uncertainty about retail customers' environmental preferences is higher. For example, if the local market is further away from a firm's headquarters, it is more challenging for the managers of the firm to accurately assess retailor customers' environmental preferences (Campbell et al. 2009). As a result, the revealed preferences are likely to be more informative. This leads to my third hypothesis:

H3: Pollution reduction in facilities located in areas where retail customers reveal strong environmental preferences is more pronounced when ex-ante information frictions are greater.

Nevertheless, there are reasons why I might not observe the predicted outcomes. First, some firms may lack the expertise or resources to actively monitor changes in customers' purchasing behavior and assess their environmental preferences. Second, firms need time and capacity to adjust their pollution decisions, and it may take time for the pollution reduction efforts to manifest.

3. Empirical measure of retail customers' environmental preferences

In this section, I describe the estimation of retail customers' revealed environmental preferences and report the descriptive statistics, alongside a validity test for the measure.

To address empirical challenges associated with the unobservable nature of environmental preferences, I examine changes in customer demand following the revelation of firms' negative environmental news. Drawing on revealed preference theory, I infer customers' realized preferences by comparing their purchasing behavior before and after they gain knowledge of a firm's environmental practices. Specifically, I expect that customers with stronger environmental preferences will reduce their spending more significantly on products of the firm involved in the environmental news after the news breaks. Therefore, by assuming that the information of one news event is constant for all customers in different local markets, I argue that the heterogeneity in retail customers' environmental preferences can be approximated by the relative extent of product sales declines during the short window surrounding the negative environmental news event.

3.1. Data and sample

To estimate customers' revealed preferences, I combine retail customers' grocery shopping records from the NielsenIQ HomeScan database with firm-level environmental negative news data from the RepRisk database.[8]

The NielsenIQ HomeScan database provides daily grocery shopping records from a demographically representative sample of approximately 60,000 U.S. households, across 52 Scantrack markets from 2004 to 2020.[9] Each household is assigned a unique panelist ID, and detailed geographical information is recorded, including Federal Information Processing Standard (FIPS) county code and Scantrack market code.[10] Households are asked to scan their daily purchases with provided barcode scanners, generating detailed transaction-level data including purchase dates, Universal Product Codes (UPCs),[11] prices, and quantities. This dataset is uniquely suited to the estimation of individual customers' preferences because NielsenIQ has tracked the purchasing behavior of these households over a reliably long period.[12] I match company names in the NielsenIQ dataset with those in Compustat using fuzzy matching; over 24 million UPCs are successfully merged with 1,122 U.S.-headquartered firms in Compustat.[13] Appendix A provides further details of the database and the matching and cleaning procedures.

I obtain firm-level negative environmental news events from RepRisk, which performs daily screenings of over 100,000 sources to detect negative ESG incidents from 2007 to 2022. Each

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[8] The researcher owns analyses calculated (or derived) based in part on data from Nielsen Consumer LLC and marketing databases provided through the NielsenIQ Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the NielsenIQ data are those of the researcher and do not reflect the views of NielsenIQ. NielsenIQ is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

[9] Scantrack markets are geographical market areas designated by NielsenIQ. There are in total 52 Scantrack markets in the U.S., each typically covering a central city and the surrounding counties.

[10] Throughout the paper, I refer to Scantrack markets as local markets.

[11] UPCs, commonly known as barcodes, are a series of black lines and accompanying numbers encoded to uniquely identify products.

[12] Currently, NielsenIQ retains about 80% of its active panel each year.

[13] The matching results are comparable to those of Hajda and Nikolov (2022), who also link Nielsen data to U.S. Compustat firms.

verified incident is logged with an event date and tagged with one (or more) of the 28 predefined ESG issues, which are broadly classified into environmental, social, governance, or cross-cutting categories. I focus on all negative news in the environmental category and "Products (health and environmental issues)" in the cross-cutting category. To effectively compare customer behavior changes across markets, I include news events reported by national and global media and exclude those only covered by local media to ensure sufficient readership.

I link firms in RepRisk to Compustat firms using the shared ISIN variable in both databases. I then merge Nielsen data with RepRisk data using the GVKEY identifier. The final sample for estimating retail customers' environmental preferences includes 232 negative environmental news events covering 80 firms between 2007 and 2015.[14] Firms in the sample are mainly large, consumer-facing firms in the retail industry, such as Abbott Laboratories, the Campbell Soup Company, and Kellogg's. Panel A of Table 1 presents the sample selection process.

3.2. Research design

Following the research design of Houston et al. (2023), I construct a balanced panel dataset that tracks household purchases at the product level in the [-2, +2] quarterly window around a firm's environmental negative news event. The treatment group includes products of news event firms, whereas the control group includes products of non-event firms that belong to the same product groups as the treatment products and are purchased by the same households. The unaffected firms are those that have either never experienced ESG incidents or whose first ESG incident occurs after the end of the post-event window.[15]

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[14] The sample of news events starts in 2007 and ends in 2015. The sample starts in 2007 because RepRisk started coverage in that year, and it ends in 2015 because air quality data are available up to 2016, allowing for at least one year of data post-event to observe the effect on firms' pollution decisions.

[15] In selecting the control group, I account for all negative news events in the RepRisk database, regardless of news type, severity, and readership, etc., to avoid potential confounding effects from other types of negative news and ensure a cleaner control group.

I run a Poisson regression with high-dimensional fixed effects to examine changes in customer spending following negative environmental news.[16] For each negative environmental news event and for each local market, I estimate the following model:

$$\begin{aligned} Spending_{h,j,p,q} &= \beta_0 + \beta_1\, Treat_j \times Post_{h,q} + \beta_2\, SalePrice_{j,p,q} + Product\ FE \\ &+ Household\ FE\ + Year - Quarter\ FE + \varepsilon_{h,j,p,q}, \end{aligned} \tag{1}$$

where subscripts h, j, p, and q represent household h, firm j, product p, and quarter q, respectively. $Spending_{h,j,p,q}$ is the total spending of household h on product p of firm j in quarter q. $Treat_j$ is a treatment dummy equal to one if product p belongs to the event firm in the focal environmental news, and zero otherwise. $Post_{h,q}$ equals one for the first two quarters after the news event, and zero otherwise. I exclude observations in the event quarter. To account for the effect of product price on customer spending, I include $SalePrice_{j,p,q}$ as a control variable, calculated as the average transaction price of product p of firm j in quarter q in the local market. I also include household and product fixed effects to rule out time-invariant household and product characteristics, and year-quarter fixed effects to control for the time trend. I use heteroskedasticity-robust standard errors clustered by firm to calculate *t*-statistics.

The coefficient of interest, β_1, captures the average decrease in spending on the event firm's products due to the negative environmental news. I denote β_1 as the revealed environmental preferences (*Pref*) of retail customers in a particular local market in response to the focal news event. To identify local markets with strong environmental preferences, Equation (1) is estimated for each news event and for each individual local market. Next, for each news event, all the β_1s estimated for different local markets are sorted into deciles. *High_Pref* is an indicator variable

[16] The choice of model is based on Cohn et al.' s (2022) argument that Poisson models provide unbiased and consistent estimates when the outcome variable is count-based and has many zero values.

equal to one if the local market is in the bottom decile, and zero otherwise. Local markets with *High_Pref* equal to one are defined as having strong environmental preferences as retail customers in these areas significantly decrease their purchases of the event firm's products.

3.3. Descriptive statistics and validation test for the revealed preference measure

First, Table 2 reports the descriptive statistics for the revealed environmental preference measure (*Pref*). I obtain 8,989 event-market-level revealed environmental preferences regarding 232 negative environmental news events about 80 firms. The median and average of *Pref* are close to zero. This is consistent with the finding that retail consumers on average do not respond to negative environmental news events (Christensen et al. 2023). *Pref* varies, with a standard deviation of 0.78, suggesting that firms may face uncertainty about customers' environmental preferences. As a robustness check, I estimate Equation (1) using ordinary least squares (OLS) regression. Table 2 shows the summary statistics of these OLS estimates, denoted by *Pref_OLS*, which are similar to those derived from the Poisson regression.

Next, I plot the geographical distribution of revealed environmental preferences in Figure 1. I calculate local market-level environmental preferences by averaging event-market-level preferences across all events in the sample for each local market. I then sort the aggregated environmental preferences into deciles and illustrate the distribution on the map. Figure 1 shows that Boston, Washington DC, Miami, Richmond, and Buffalo-Rochester are the most environmentally conscious markets, while Birmingham, Nashville and New Orleans-Mobile are among the least environmentally conscious markets.

Lastly, to ensure that the revealed preference measure captures retail customers' environmental preferences, I show that the measure is positively correlated with other measures used in prior studies, namely Americans' beliefs in global warming, the share of votes for the

Democratic Party in presidential elections, income per capita, and the proportion of residents with a bachelor's degree or higher (e.g., Howe et al. 2015; Albuquerque et al. 2019).[17] Figure 2 displays the binned scatter plots of the revealed preference measure and the four other measures of environmental preferences. For each negative environmental news event, counties with stronger revealed environmental preferences tend to be those with more respondents who agree that global warming is a concern, with higher percentages of votes for the Democratic Party, higher income per capita, and more educated residents.

4. The effect of retail customers' environmental preferences on firms' pollution

4.1. Data

To examine the effect of customers' revealed preferences on firms' pollution decisions (H1) and to overcome data limitations concerning facility-level pollution emissions,[18] I match the location of firms' facilities with high-resolution satellite-based $PM_{2.5}$ data.

I obtain a facility's historical location information (FIPS county code, longitude and latitude coordinates), its parent company's name, its annual sales, and number of employees from the National Establishment Time-Series (NETS) database. This database is produced by Walls and Associates and provides annual time-series information for over 78 million facilities owned by U.S. listed firms from 1990 to 2020. I then match parent firms in NETS with Compustat firms that are in the NielsenIQ database using their historical names, supplemented with manual checking.[19]

[17] I obtain data on climate beliefs from the Yale Climate Opinion Maps, votes in the presidential election from the MIT Election Data and Science Lab, income per capita from the U.S. Bureau of Economic Analysis (BEA), and the share of residents with a bachelor's degree or higher from the U.S. Census.
[18] Existing studies that examine facility-level pollution mostly rely on firms' self-reported emissions data from the U.S. EPA, such as the Toxic Release Inventory program and the Greenhouse Gas Reporting Program. These databases predominantly contain data from manufacturing and utility sectors, with limited coverage of customer-facing industries.
[19] Facilities with fewer than 10 employees are excluded from the analysis due to the high imputation rates in this size class, as documented by Barnatchez et al. (2017).

I use satellite-based $PM_{2.5}$ concentration data from NASA's Socioeconomic Data and Applications Center (SEDAC), which provides annual $PM_{2.5}$ concentrations at 1 km by 1 km resolution for the contiguous U.S. from 2000 to 2016.[20] This dataset was developed by integrating advanced remote sensing technology and machine learning predictive tools and has been used in economics studies as a proxy for fine-grained local pollution exposure (e.g., Currie et al. 2023).[21] To create an annual facility-level air quality measure, I match annual $PM_{2.5}$ concentration data with NETS facility location data. Specifically, I calculate the geographic distance from the centroid of each 1-km grid cell to each facility using their latitudes and longitudes. Facility-level air quality is the average of the annual $PM_{2.5}$ levels from grid cells falling within a 1-km radius of the facility.

4.2. Research design

To examine whether firms will reduce pollution in areas where customers reveal strong environmental preferences (H1), I estimate the following stacked DiD model:

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\begin{aligned}
Log(PM_{2.5})_{i,j,c,e,t} &= a_0 + a_1\, High\_Pref_{i,j,c,e} \times Post_{e,t} + Facility\ Controls \\
&\quad + Firm\ Controls + County\ Controls + Event \times Facility\ FE \\
&\quad + Event \times Year\ FE + \varepsilon_{i,j,c,e,t},
\end{aligned} \tag{2}
$$

where subscripts i, j, c, e, and t represent facility i, firm j, county c, event e, and year t, respectively. $Log(PM_{2.5})_{i,j,c,e,t}$ is the pollution level at facility i, owned by firm j and located in county c in year t. Specifically, it is calculated as the natural logarithm of the average annual $PM_{2.5}$ concentrations of the 1-km grid cells that are within a 1-km radius of facility i. $High\_Pref_{i,j,c,e}$ equals one if facility

[20] The dataset is developed by a team of researchers from Harvard University's T.H. Chan School of Public Health, led by Dr. Joel Schwartz; for more details, see Di et al. (2019).

[21] The basic idea of this dataset is to build a predictive model for $PM_{2.5}$ by correlating *in-situ* EPA monitor data with the observable predictors of air pollution using machine learning techniques. Researchers then apply this model to predict out-of-sample air pollution levels for the entire U.S., including areas without existing EPA monitors but with satellite measurements. It is important to note that these pollution data are *estimates* of ground-level pollution concentrations. These estimates perform well as they match the "ground truth" from EPA monitors with very high in-sample measures of fit.

i is located in county c, which is defined as having strong environmental preferences in firm j's event e. $Post_{e,t}$ equals one for all years following the year of event e. The estimation window is from year t-3 to year t+3. H1 predicts that the coefficient on the interaction term $High\_Pref \times Post$ (a_1) is negative.

I use a stacked DiD research design because the sample includes multiple staggered negative environmental news events in the sample. The stacked regression approach avoids biased estimates in the presence of heterogeneous treatment effects (Baker et al. 2022). This approach treats each negative environmental news event as a separate event and creates a dataset for each news event. It then stacks the news event-specific datasets and estimates the average treatment effect across all news events.

To create a clean control group, for each news event and each treated facility, I match facilities of the event firm that are located elsewhere and facilities located in the same county as the treated facility and owned by non-event firms that have never been involved in negative environmental news. I require both the treated and control facilities to belong to the same 2-digit SIC industry. In addition, I require facilities to have at least one year of data before and after the event to mitigate any survivorship bias concerns.

The clean control group and the fixed effects structure help me address three key endogeneity concerns. First, by comparing treated facilities with other facilities of the same firm that are located elsewhere, I control for unobserved time-varying firm-level characteristics, especially mitigating the concern that the observed decrease in pollution is a result from the firm's overall corrective behavior after the negative news event. Second, by comparing treated facilities with those located in the same county and owned by non-event firms, I control for unobserved time-varying local socioeconomic factors and mitigate the concern that the observed decrease in pollution is due to local regulators' heightened intervention following the negative news event. Third, I include event-facility and event-year fixed effects to control for unobserved facility characteristics and time trends. This largely addresses the selection concern that customers show high environmental preferences because local facilities have high pollution levels initially, which leaves firms with more room for subsequent improvement.

I draw on prior literature and include a set of facility-, firm-, and county-level control variables that may affect pollution emissions (Bartram et al. 2022; Heese et al. 2022). Facility characteristics include facility age and the number of employees; firm characteristics include firm size, Tobin's Q, ROA, leverage, and R&D stock; county characteristics include the natural logarithm of the annual GDP of the county and unemployment rates. Appendix B provides detailed variable definitions. I winsorize all continuous variables at the 1st and 99th percentiles within each event-specific sample. Standard errors are clustered at the event-facility level.

The sample for estimating Equation (2) begins with the merged data between NETS and NielsenIQ from 2004 to 2016. First, the sample starts in 2004 because RepRisk started coverage in 2007 and I require three pre-event years to estimate Equation (2), and the sample ends in 2016 because the satellite-based pollution data are available up to 2016. Second, I exclude facilities located outside Nielsen Scantrack markets because I cannot reliably assess customers' environmental preferences in these local markets. Third, after merging the data with the revealed preference measure estimated in Section 3, I further filter facilities to retain those in markets with strong environmental preferences (i.e., the treated facilities) and the clean control facilities, as described earlier. Lastly, I exclude facility observations with missing control variables. The final sample consists of 458,192 facility-year observations, covering 45,126 distinct facilities owned by 380 firms. Panel B of Table 1 details the sample selection process.

Table 3 provides the summary statistics of the final regression sample after removing the duplicates introduced by the stacked DiD design. The average $PM_{2.5}$ concentration is 9.92 $\mu g/m^3$ with a standard deviation of 2.37 $\mu g/m^3$. On average, the facilities in the sample have an age of 11.6 years and 76 employees. The average firm in the sample has total assets of US$ 33.0 billion, is profitable (*ROA* of 0.16), and has a *Tobin's Q* of 1.82, *Leverage* of 0.23, and *R&D Stock* of 0.08 million. The average county in the sample has an annual GDP of US$11.7 billion with an unemployment rate of 6.9%.

5. Main results

5.1. Retail customers' environmental preferences and firm pollution

In this subsection, I test H1 on the effect of customers' revealed environmental preferences on firms' pollution decisions. Table 4 presents the results of estimating Equation (2). Column (1) presents the results without any control variables, Column (2) includes facility-level control variables, Column (3) includes both facility- and firm-level control variables, and Column (4) additionally controls for county-level control variables and estimates the full specification of Equation (2). Across all specifications, the coefficient on *High_Pref* × *Post* is negative and statistically significant at the 1% level (*t*-stats range from -7.98 to -6.75), consistent with hypothesis H1 that firms reduce their pollution emissions in facilities located in areas where retail customers have strong environmental preferences. In terms of economic magnitude, event firms' facilities located in markets where customers have strong environmental preferences reduce pollution by 0.9% ($= e^{-0.009} - 1$), relative to other facilities of the same firm that are located elsewhere and facilities in the same county owned by non-event firms, following the release of firms' negative environmental news. This represents a 3.6% standard deviation change in facilities' logged pollution (*Log($PM_{2.5}$))* or a 11.1% within-fixed-effect standard deviation change (see Breuer and deHaan 2023).[22] In untabulated analyses, I conduct a "horse race" between the revealed preference measure and the aforementioned environmental preferences measures used in prior studies. Specifically, I further include three interaction terms between *Post* and three indicator variables to Equation (2). Each indicator variable equals one when the share of votes for the Democratic Party, income level, and education level for a county-year is in the top decile of that year, respectively. I find that the coefficient on *High_Pref* × *Post* remains negative and significant at the 1% level and the magnitude of the coefficient does not change, suggesting that the revealed preferences measure provides unique and incremental information that is useful in firms' pollution decisions.

For control variables, I find that the coefficient on *Tobin's Q* is positively significant, suggesting that facilities owned by firms with higher *Tobin's Q*, i.e., having better growth opportunities, tend to produce higher levels of pollution. Furthermore, facilities located in counties with higher GDP and lower unemployment rates also tend to pollute more.

The DiD methodology relies on similar pre-trends for the treated and control facilities. To inspect the validity of this parallel trend assumption, Figure 3 presents the dynamic effect on facilities' pollution level before and after the release of firms' negative environmental news. Using the pollution level in year *t*-1 as a benchmark, the pollution level of treated facilities is not significantly different from that of control facilities before the news event, supporting the parallel trend assumption. In the year of the news event, the pollution level of treated facilities shows an increase, though statistically insignificant, relative to control facilities. A discernible reduction in pollution at the treated facilities occurs only after the news release and the revelation of customers' environmental preferences, and the effect becomes significant in years *t*+2 and *t*+3.

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[22] For comparison, Zou (2021) finds that the level of PM pollution increases by 2.2% following the retirement of EPA monitoring sites.

Overall, the results in Table 4 and Figure 3 indicate that firms factor in rewards and penalties from customers and strategically reduce their pollution to cater to local customers with strong environmental preferences.

5.2. *The role of news salience*

An important assumption underlying the main hypothesis is that retail customers are aware of the news event and able to efficiently process the information content to make informed purchasing decisions that reveal their environmental preferences. In this subsection, I test this premise by investigating whether the pollution reduction in facilities located in areas where retail customers have strong environmental preferences is more pronounced if the firms' negative environmental news is more salient (H2).

I exploit the *Severity* and *Reach* measures provided by RepRisk to identify the salience of news events. In the RepRisk database, each piece of negative environmental news is assigned scores for severity (*Severity*) and reach (*Reach*) to reflect its perceived impact and readership, respectively. *Severity* and *Reach* are each graded on a three-tier scale: 1 indicates low, 2 indicates medium, and 3 indicates high. Local media coverage corresponds to low reach, national media coverage to medium reach, and global media coverage to high reach.

A news event is categorized as *High_Severity* when assigned a *Severity* score of 2 or 3, and as *Low_Severity* with a score of 1. Similarly, a news event is categorized as *High_Reach* with a *Reach* score of 3, and as *Low_Reach* with a score of 2.[23] To test H2, I expand Equation (2) and split *High_Pref* × *Post* into *High_Pref* × *Post* × *High_Salience* and *High_Pref* × *Post* × *Low_Salience*.

[23] News events with a *Reach* score of 1, indicating local media coverage, are excluded from the analysis in the sample selection process outlined in Section 3.1.

Table 5 presents the regression results. In Column (1), news salience is defined by severity, with *High_Salience* set to one when *High_Severity* is equal to one. In Column (2), news salience is based on reach, with *High_Salience* set to one when *High_Reach* is equal to one. In Column (3), news salience is determined by both severity and reach, with *High_Salience* set to one when both *High_Severity* and *High_Reach* are equal to one.

Across all specifications, the coefficients on both *High_Pref* × *Post*× *High_Salience* and *High_Pref* × *Post*× *Low_Salience* are negative and statistically significant at the 1% level. However, the magnitude of the coefficient on *High_Pref* × *Post*× *High_Salience* is significantly larger than that on *High_Pref* × *Post*× *Low_Salience* at the 1% level in all three columns, suggesting that the pollution reduction in facilities where retail customers have strong environmental preferences is more pronounced for negative environmental news events that are more salient.

5.3. The role of ex-ante information frictions

H3 proposes that the pollution reduction in facilities located in areas where retail customers have strong environmental preferences is more pronounced when *ex-ante* information frictions between firms and customers are greater. For customers, the news events are more useful if they have limited knowledge of firms' environmental practices prior to the events. Arguably, customers know little about firms' environmental practices if firms do not have transparent ESG disclosure policies. I use the industry-adjusted ESG disclosure score in year t-1 obtained from Bloomberg, *ESG_Disclosure,* as a proxy for the extent of retail customers' incomplete information about firms' environmental practices.[24]

For firms, the news events are more useful if their information uncertainty about retail

[24] I adjust the raw ESG disclosure score obtained from Bloomberg by subtracting the industry mean ESG disclosure score that excludes the focal firm in the same year.

customers' environmental preferences is higher. I use the distance between the headquarters and facilities as a proxy for how familiar managers are with local retail customers (Campbell et al. 2009). I obtain historical local information about headquarters and facilities from NETS and calculate the distance between each facility and its headquarters (*Headq_Dist*).

To test H3, I split *High_Pref* × *Post* in Equation (2) into *High_Pref* × *Post*× *High_Friction* and *High_Pref* × *Post*× *Low_Friction*. Table 6 presents the regression results. Panel A reports the results for the information frictions of retail customers, where *High_Friction* is equal to one when *ESG_Disclosure* is below the sample median. Panel B reports the results for the information frictions of firms, where *High_Friction* is equal to one when *Headq_Dist* is above the sample median.

In both panels, the coefficients on both *High_Pref* × *Post*× *High_Friction* and *High_Pref* × *Post*× *Low_ Friction* are negative and statistically significant at least at the 5% level. However, the magnitude of the coefficient on *High_Pref* × *Post*× *High_Friction* is significantly larger than that on *High_Pref* × *Post*× *Low_ Friction* at the 1% level, consistent with H3 that *ex-post* pollution reduction is more pronounced when *ex-ante* information frictions are greater.

6. Additional analyses

6.1. The mechanism of local pollution reduction

So far, I have shown that firms reduce their pollution in facilities located in markets where customers have strong revealed environmental preferences. In this subsection, I investigate the mechanisms through which firms achieve reductions in the local pollution levels. There are two primary strategies they can employ. One way that firms can reduce their pollution levels in markets where customers have strong environmental preferences is by increasing their local abatement investments, without making any changes to operations elsewhere. Alternatively, firms can reduce local pollution by shifting it to other facilities.

To investigate the local pollution reduction mechanism, I conduct three sets of analyses. Table 7 presents the results. First, I examine whether firm-level pollution is reduced following negative environmental news events. If local pollution reduction is achieved through increased abatement investments, I expect firm-level pollution to decrease following a news event. Alternatively, if reduction is achieved by shifting pollution to a firm's other facilities, its overall firm-level pollution should remain unchanged. Using a stacked DiD research design, for each event year (i.e., cohort), I define the treatment group as firms involved in negative environmental news, and the control group as firms that never experienced negative news throughout the sample period. The datasets specific to each event year (i.e., cohort) are then stacked together. The estimation window is $[-3, +3]$. Column (1) reports the results using firm-level pollution as the dependent variable, calculated as the average pollution level of all facilities owned by the firm. These results show that firm-level pollution remains unchanged following the news event, as the coefficient on *Event_Firm* × *Post* is 0.002 (*t*-statistic = 0.44).

Second, I examine pollution emissions of facilities located in markets where customers reveal weak environmental preferences. If firms strategically shift their pollution and incorporate the penalties and rewards from retail customers into their pollution decisions, then markets with customers who have the weakest environmental preferences are arguably the locations with the lowest expected costs for dumping pollution. Therefore, I expect to observe an increase in the pollution levels of facilities located in such areas following a news event. To test this prediction, I apply the same methodology used to test H1. Specifically, *Low_Pref* is equal to one if the estimated β_1 ranks in the top decile, and zero otherwise. The regression sample includes event firms' facilities that are located in counties where *Low_Pref* is equal to one (treated facilities) and other facilities of the same firms that are located elsewhere as well as facilities in the same county owned by non-event firms (control facilities). Column (2) reports the results. The coefficient on *Low_Pref* × *Post* is 0.016 (*t*-statistic = 9.49), indicating that the pollution emissions of facilities located in markets with weak environmental preferences increase by 1.6% following news events, relative to the control facilities.

Third, one may worry that the results of low-environmental-preference facilities' pollution is simply a flip side of the results of high-environmental-preference facilities' pollution. To address this concern, I reconstruct the main sample by focusing on facilities owned by event firms and directly test how the pollution of facilities in local markets with different environmental preferences changes following news events, using the within-firm sample. The results are presented in Column (3) of Table 7. I include a set of interaction terms by interacting decile indicators of environmental preferences with the *Post* dummy, in addition to the control variables and fixed effects in Equation (2). Specifically, I separate the two extreme deciles (i.e., the decile of environmental preferences equal to 1 and 10) and split the remaining eight deciles into four decile group indicators in rank. The interaction term of *High_Pref* × *Post* is omitted because I use facilities located in markets with the strongest environmental preferences as a benchmark. The coefficients on the other interaction terms thus represent the pollution changes of facilities located in markets with environmental preferences, as indicated by the corresponding decile group indicators, relative to the pollution changes of facilities located in areas with the strongest environmental preferences. The coefficients on the interaction terms in Column (3) of Table 7 show an almost *monotonic* pattern: the increase in pollution relative to the pollution changes of facilities located in areas with the strongest environmental preferences after a negative environmental news event is greater when the local markets are less environmentally sensitive. I plot the coefficients on the interaction terms in Figure 4.

Collectively, the results in Table 7 support the pollution-shifting mechanism, whereby firms redistribute their pollution internally based on the environmental preferences of local markets.

6.2. Cross-sectional analyses of pollution shifting

To provide more support for the pollution-shifting mechanism, I conduct two sets of cross-sectional analyses. First, I expect managers to be particularly incentivized to cater to local customers with strong environmental preferences and to shift pollution away when facing high expected penalties and marginal costs for failing to do so. Second, the feasibility of pollution shifting depends on the "pollution slack" at facilities in areas with weaker environmental preferences. I expect a more pronounced pollution reduction in facilities located in markets with strong environmental preferences when other facilities have excess production capacity, so they can handle more production activities (i.e., production slack), and are under less stringent environmental regulations, and thus able to absorb this redirected pollution (i.e., regulatory slack) (Bartram et al. 2022; Thomas et al. 2022).

To test the incentive prediction, I expand Equation (2) and split *High_Pref* × *Post* into *High_Pref* × *Post*× *High_Incentive* and *High_Pref* × *Post*× *Low_Incentive*. I use several proxies to capture the potential costs of failing to meet the environmental demands of local markets. First, I expect firms to have greater incentives to shift pollution away if the local market with strong environmental preferences is also the firm's major market, given that the potential loss of such a market would have a material adverse impact on the firm's sales revenue and profitability. Empirically, sales from the previous year for a firm in each local market are sorted into quintiles. *High_Incentive* is equal to one if the local market falls into the top quintile and *Low_Incentive* is equal to one if the local market falls into the remaining quintiles. Similarly, firms are more likely to cater to customers in local markets with strong environmental preferences when these markets are highly competitive (Flammer 2015). Failing to meet customers preferences in such markets can raise significant business risk, as these markets are characterized by low brand-switching costs for consumers and high re-entry barriers for firms. To measure local product market competitiveness, I first calculate the Herfindahl–Hirschman Index (HHI) of product sales for each product group in each local market, and I define a firm's competition level in the local market as the average of its product group-level HHIs. *High_Incentive* (*Low_Incentive*) is equal to one if the average HHI is below (above) the sample median. Lastly, the expected penalties for excessive pollution are greater if local customers are directly exposed to the sources of pollution, placing their health at stake. I therefore expect the likelihood of pollution shifting is higher when the majority of the local population resides in rural areas where the facilities are most likely to be located. I use county rurality level data from the U.S. Census, and *High_Incentive* (*Low_Incentive*) is equal to one if more (less) than 50 percent of the county's population lives in rural areas.

Panel A of Table 8 presents the results. Consistent with the prediction, the coefficients on *High_Pref* × *Post*× *High_Incentive* are significantly negative and of larger magnitude than the coefficients on *High_Pref* × *Post* × *Low_Incentive* across three different proxies. More importantly, the difference between *High_Pref* × *Post*× *High_Incentive* and *High_Pref* × *Post*× *Low_Incentive* is significant at the 1% level.

Turning to the feasibility prediction, to assess the production slack of facilities located in markets with weak environmental preferences, I first calculate facility-level excess production capacity as end-of-year employees per million dollars of sales, following Bartram et al. (2022). I then aggregate the facility-level measure to the firm level by taking the average across all facilities located in markets with relatively weaker environmental preferences, denoted by *Capacity*.

High_Feasibility (*Low_Feasibility*) is set to one when *Capacity* is above (below) the sample median. To measure regulatory slack, I assume that a facility that is located outside the EPA's designated nonattainment counties is subject to less regulatory oversight. I then calculate the proportion of a firm's low-environmental-preference facilities that are located outside the EPA's designated nonattainment counties, denoted as *Unregulated*. *High_Feasibility* (*Low_Feasibility*) is set to one when *Unregulated* is above (below) the sample median. To test the prediction, I expand Equation (2) and split *High_Pref* × *Post* into *High_Pref* × *Post* × *High_Feasibility* and *High_Pref* × *Post* × *Low_Feasibility*.

Panel B of Table 8 presents the results. Consistent with the prediction, the coefficients on *High_Pref* × *Post*× *High_Feasibility* are significantly negative and of larger magnitude than the coefficients on *High_Pref* × *Post*× *Low_Feasibility*. More importantly, the difference between *High_Pref* × *Post* × *High_Feasibility* and *High_Pref* × *Post* × *Low_Feasibility* is significant at the 1% level. Taken together, the results in Table 8 further corroborate the pollution-shifting mechanism.

6.3. Alternative measures and specifications

Table 9 reports the robustness checks for the baseline results using alternative measures and specifications. First, in Panel A, I use $PM_{2.5}$ concentrations in a 3-km radius of the facility to measure its pollution level. The results are almost identical to those of the main results when using this alternative facility pollution measure, with the coefficient on *High_Pref* × *Post* being -0.010 (*t*-statistic = -7.76).

Second, I run an OLS regression to estimate customers' environmental preferences in Equation (1). I sort local markets analogously as described in Section 3.2. I show that the results are robust to this choice in Column (1) of Panel B. The coefficient on *High_Pref* × *Post* is significantly negative (t-statistic = -6.85), and the magnitude is almost the same as that of the main results.

Third, I examine whether the results are sensitive to choosing 10% as a cut-off threshold when defining *High_Pref*. Column (2) and Column (3) of Panel B show that the results remain qualitatively similar when using 5% and 20% as cut-off points. Compared to Column (4) of Table 4, the magnitude of the coefficient on *High_Pref* × *Post* is larger (smaller) when using 5% (20%) as the cut-off point.

Fourth, I use a stacked DiD regression as the main specification and find that the main results are not sensitive to the choice of specifications in Panel C. I run a TWFE estimator in Column (1) and the Sun and Abraham (2021) estimator in Column (2). The coefficients on *High_Pref* × *Post* are significantly negative in both Column (1) and Column (2) of Panel C (t-statistic = -5.06 and -2.59, respectively).

Taken together, the results in Table 9 show that the main results are robust to alternative choices of measures and empirical specifications.

7. Conclusion

I examine whether and how firms incorporate retail customers' environmental preferences into their pollution decisions. I construct a revealed environmental preference measure using the extent of product sales declines following the release of firms' negative environmental news. Using a stacked DiD design, I find that firms reduce their local pollution in areas where customers reveal strong environmental preferences following the news event. This finding is robust to alternative measures and specifications. The reduction in local pollution is more pronounced when news events are more salient and when *ex-ante* information frictions between firms and retail customers are greater. Consistent with firms shifting their pollution to align with retail customers' environmental preferences, I find no pollution reduction at the firm-level and that pollution increases relatively in markets with weaker environmental preferences.

Overall, the findings in this paper suggest that firms actively adjust their local pollution levels according to retail customers' heterogeneous environmental preferences. The study sheds light on the underexplored influence of retail customers on firms' environmental decision-making and contributes to the literature on how stakeholders' nonpecuniary preferences can shape firms' ESG practices.

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Appendix A
Data Description for the NielsenIQ Homescan Database

I obtain retail customers' grocery shopping records from the NielsenIQ HomeScan database. The data were collected from a demographically representative sample of approximately 60,000 households across 52 Scantrack markets in the U.S. from 2004 to 2020.

NielsenIQ categorizes UPCs into 1,075 product modules, 125 product groups, and 10 departments. Each UPC is associated with its brand code. Following Handbury (2021), I aggregate UPCs into a classification that I call "product," defined as a set of UPCs within a product module that share the same brand code and GVKEY. For example, within the "SOFT DRINKS-CARBONATED" product module, 64 UPCs associated with the brand "COCA-COLA CLASSIC R" (where R stands for regular, as opposed to diet) are classified as the same product. The analysis, therefore, abstracts from other product characteristics, such as flavor. Differentiating between products along these dimensions results in many UPCs with sales shares that are too low to allow for the matrix inversions required in the preference estimation procedure.

Matching with Compustat

I link each product purchased by households to its producer using linking files provided by GS1 U.S., the official source that issues barcodes to producers. These linking files record the company name and address associated with each UPC. I match the company name in GS1 U.S. to the firm's historical names in Compustat using fuzzy matching. Many public firms own multiple subsidiaries; consequently, the producer names in the product-producer data may be the subsidiaries' names instead of the ultimate parents' names. To address this, I obtain the subsidiaries' names from WRDS and pool the parent company names and subsidiary names together in the matching process. To ensure accuracy, I manually verify the matching results and use the Orbis online platform, which provides software that automatically matches firms based on their name and address and returns standardized identifiers such as ISIN and Ticker. In total, I am able to merge over 24 million UPCs with 1,122 U.S.-headquartered firms in Compustat.

Data Cleaning

The sample is cleaned to control for data recording errors. First, I drop any purchase observations for which the price paid for a UPC is greater than three times or less than a third of the median price paid per unit of any UPC within the same product module. Second, I limit the sample to products that are purchased by 20 or more households. Third, I require that firms' sales in NielsenIQ data account for at least 1% and no more than 150% of Compustat sales.

Appendix B
Variable Definitions

Variable Name	Definition	Source
Environmental Preference Variables		
Pref	The revealed environmental preferences of retail customers in a Scantrack market after the release and dissemination of an event firm's negative environmental news event estimated in Equation (1).	NielsenIQ, RepRisk
High_Pref	An indicator variable equal to one when an event firm's facilities are located in Scantrack markets in the bottom decile based on *Pref*, and zero otherwise.	NielsenIQ, RepRisk
Other Variables for Main Tests		
Log($PM_{2.5}$)	The natural logarithm of average annual $PM_{2.5}$ concentrations within a 1-km radius of a facility.	NASA's SEDAC
Facility Age	The natural logarithm of one plus facility age, calculated as the difference between the year of establishment and the current year.	NETS
Facility Employee	The natural logarithm of the number of employees in a facility.	NETS
Firm Size	The natural logarithm of total assets of a facility's parent firm (in millions of US$).	Compustat
Tobin's Q	Market value of assets (total assets plus market value of common equity minus common equity minus deferred taxes) divided the book value of assets of a facility's parent firm.	Compustat
ROA	Operating income before depreciation divided by the lagged total assets of a facility's parent firm.	Compustat
Leverage	Short-term debt plus long-term debt scaled by the total assets of a facility's parent firm.	Compustat
R&D Stock	Perpetual inventory method following Hall et al. (2005), measured as R&D expenses with a depreciation rate of 15%, scaled by the total assets of a facility's parent firm.	Compustat
Log(GDP)	The natural logarithm of the annual GDP of a facility's county (in thousands of US$).	BEA
Unemployment Rate	Annual unemployment rates of a facility's county.	BLS
Other Variables for Cross-sectional Tests		
Severity	The severity measure of a news event (1 = low, 2 = medium, and 3 = high), reflecting its consequence, impact, and reason (by accident or not), defined by RepRisk.	RepRisk
Reach	The reach measure of a news event (2 = covered by national media and 3 = covered by global media), reflecting its influence based on readership, defined by RepRisk.	RepRisk
ESG Disclosure	A facility's parent firm's industry-adjusted ESG disclosure score for the previous year, calculated as the sum of weighted ESG disclosure fields on which the firm provides information. The measure is	Bloomberg

	industry-adjusted by subtracting the 2-digit SIC industry mean (excluding the focal firm) in the same year.	
Headq_Dist	The geographic distance between a facility and its headquarters (in km).	NETS

Figure 1
Geographic Distribution of Retail Customers' Environmental Preferences

This figure plots the geographic distribution of retail customers' environmental preferences estimated using Equation (1) for the full sample over the 2007–2015 period. Retail customers' environmental preferences estimated using Equation (1) are at the event-market level. I aggregate retail customers' environmental preferences to the local market-level by averaging event-market-level preferences across all events in the sample for each local market. I then sort the aggregated environmental preferences into deciles and illustrate the distribution on the map.

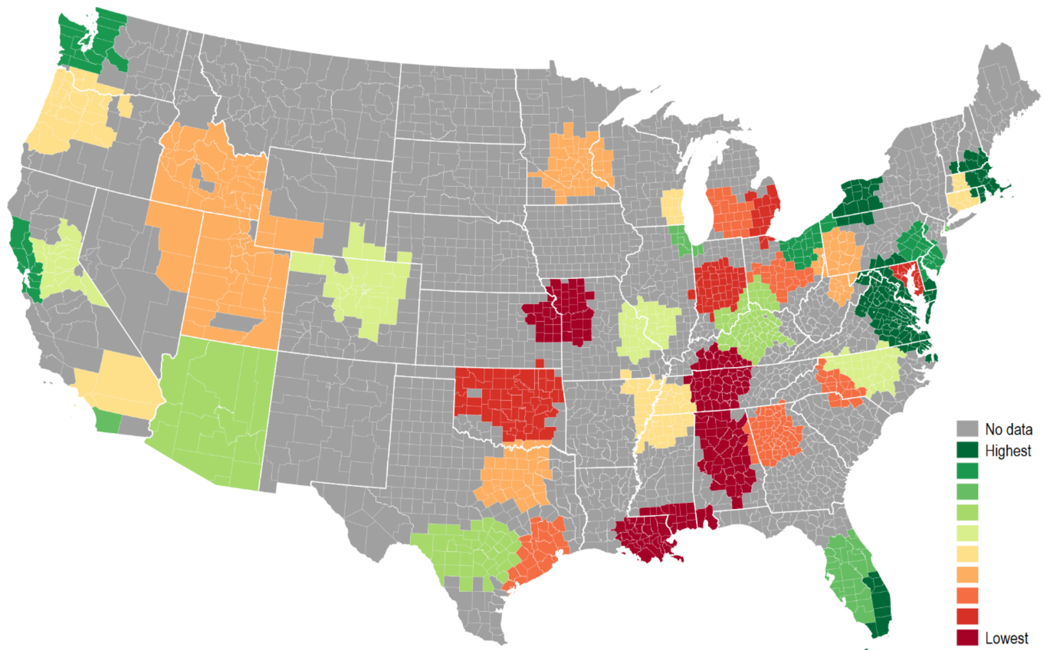
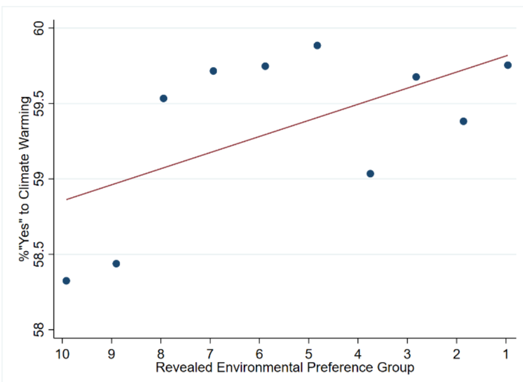


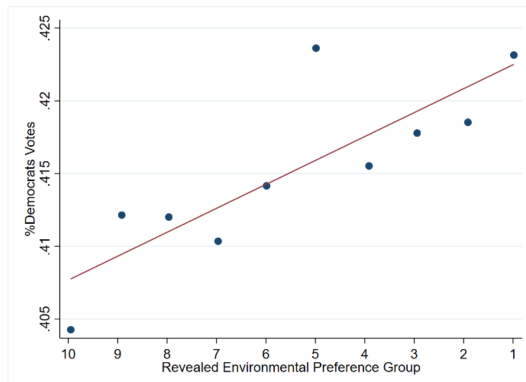
Figure 2
Correlation with Other Environmental Preferences Measures

This figure displays binned scatter plots between the inverse of retail customers' environmental preferences group and other environmental preferences measures used in the prior studies. Retail customers' environmental preferences across different local markets are sorted into deciles for each news event. The x-axis reports retail customers' environmental preferences group, with group 1 (group 10) having the strongest (weakest) environmental preferences. The y-axis in Panels A, B, C, and D report the percentage of respondents who agree that global warming is a concern, the share of votes to the Democratic Party in presidential elections, income per capita, and the proportion of residents with a bachelor's degree or higher, respectively.

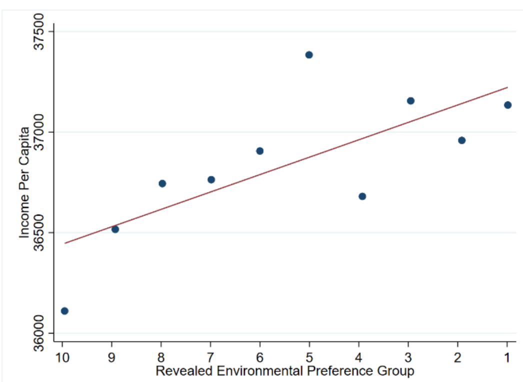
Panel A: Climate Beliefs



Panel B: Democratic Votes



Panel C: Income Per Capita



Panel D: Percentage of Bachelor or Higher degree

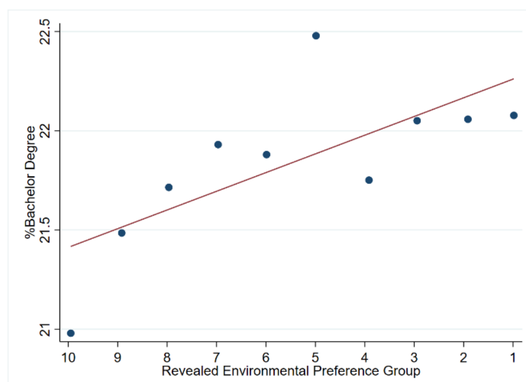


Figure 3
Dynamic Effects

This figure displays the dynamic version of Column (4) of Table 4. I plot the coefficients on a set of interaction terms by interacting *High_Pref* with indicator variables indicating the years relative to the event year and the corresponding 99% confidence intervals. I keep other control variables and fixed effects unchanged. Year 0 is the event year for each cohort; year -1 is omitted to avoid collinearity.

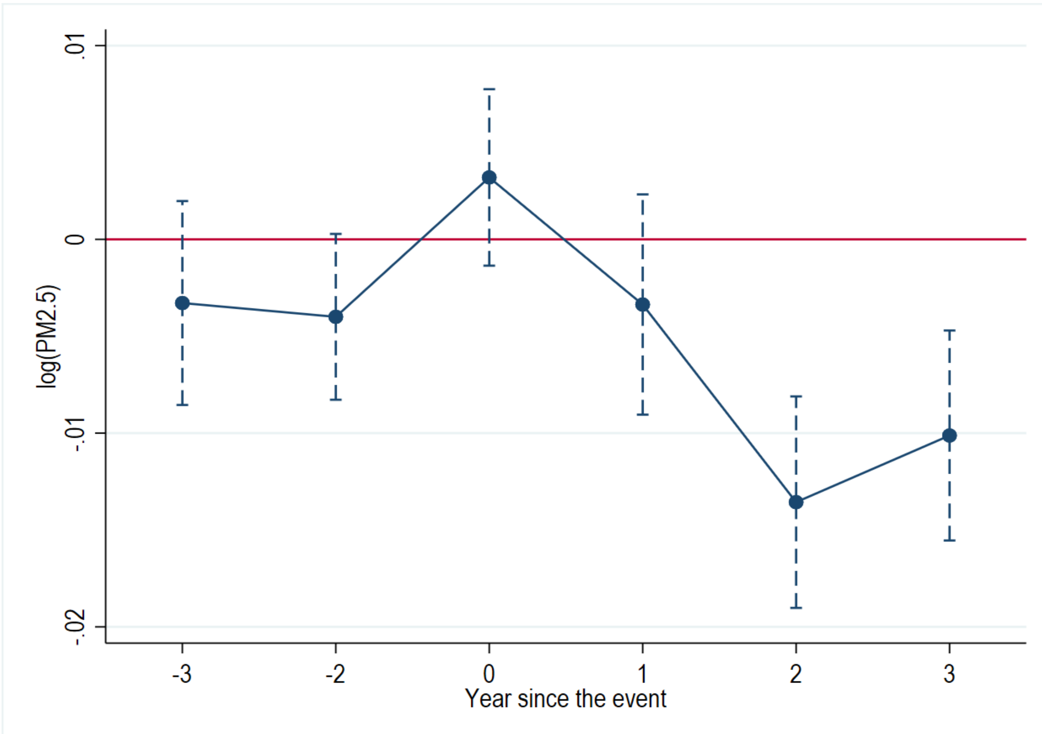


Figure 4
Shifting Pollution by Retail Customers' Environmental Preferences

This figure displays the coefficients on a set of interaction terms that interact decile group indicators with the *Post* dummy reported in Column (3) of Table 7. Facilities located in local markets with the strongest environmental preferences (i.e., decile of retail customers' environmental preferences = 1) serve as the benchmark.

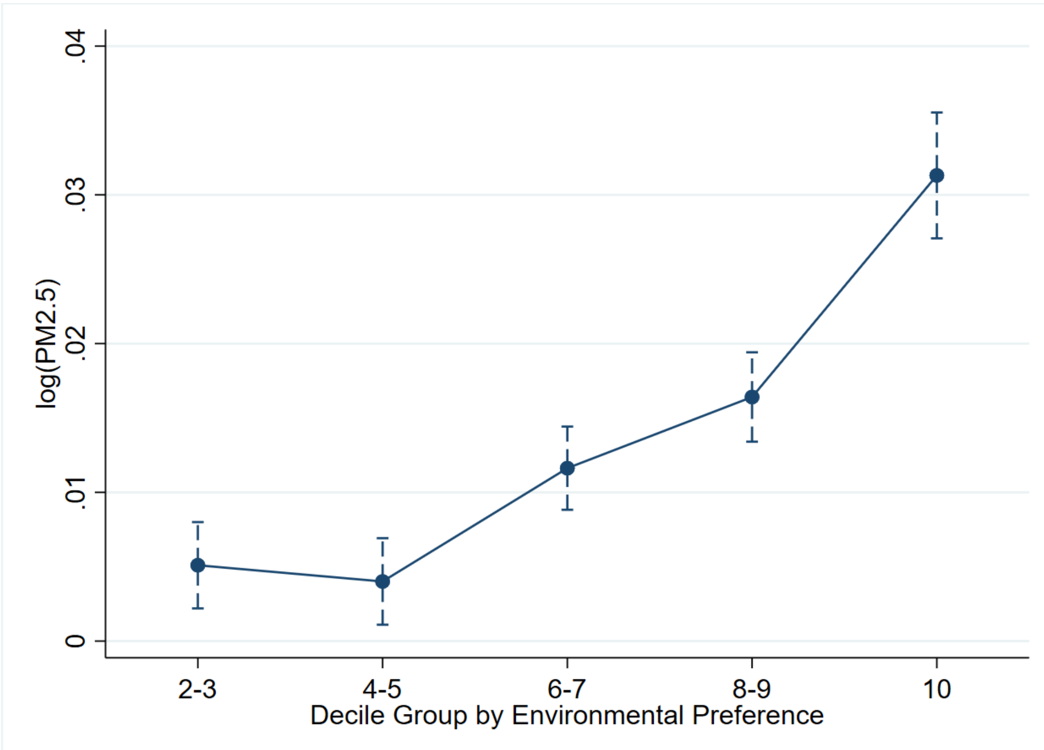


Table 1
Sample Selection

This table presents the sample selection process. Panel A and Panel B display the construction of the negative environmental news events used in the analysis and the facility-level sample, respectively. The final news event sample includes 117 negative environmental news events from 71 firms in the 2007–2015 period. The facility-level sample includes 458,192 facility-year observations, covering 45,126 facilities from 380 firms, in the 2004–2016 period.

Panel A: Construction of the sample of negative environmental news events

Selection Criteria	# Events	# Firms
Negative environmental news events:		
Negative environmental news events of U.S. listed firms from 2007 to 2015	3,927	1,584
Keep news events of firms covered by the NielsenIQ Homescan database from 2007 to 2015	232	80
Keep news events satisfying the minimum three-year gap from 2007 to 2015	117	71

Panel B: Construction of the facility-level sample

Selection Criteria	# Facility-year	# Facilities	# Firms
Facilities:			
Facilities merged with NielsenIQ's firms from 2004 to 2016	2,246,889	313,760	882
Keep facilities having pollution data from 2004 to 2016	2,233,305	311,781	882
Keep facilities in Scantrack markets from 2004 to 2016	1,652,284	268,121	869
Keep facilities satisfying the stacked DiD design described in Section 4.2 from 2004 to 2016	515,905	47,156	457
Keep facilities with non-missing control variables from 2004 to 2016	458,192	45,126	380

Table 2
Summary Statistics for Retail Customers' Environmental Preferences

This table presents the summary statistics for retail customers' environmental preferences at the event-market level for the full sample over the 2007–2015 period. *Pref* is retail customers' environmental preferences estimated using Poisson regression in Equation (1); *Pref_OLS* is retail customers' environmental preferences estimated using OLS in Equation (1). See Appendix B for variable definitions.

Variable	N	Mean	Std. Dev.	P25	Median	P75
Pref	8,989	0.007	0.780	-0.216	-0.006	0.205
Pref_OLS	9,584	-0.057	1.174	-0.280	-0.018	0.217

Table 3
Summary Statistics

This table presents the summary statistics for the variables used in the main analysis. Panel A reports the summary statistics for facility-level, firm-level and county-level variables, respectively. See Appendix B for variable definitions.

Variable	N	Mean	Std. Dev.	P25	Median	P75
Panel A: Facility-level Variables						
PM2.5 (1km) ($\mu g/m^3$)	311,672	9.924	2.366	8.262	9.844	11.426
PM2.5 (3km) ($\mu g/m^3$)	311,672	9.805	2.374	8.138	9.741	11.346
Log(PM2.5) (1km)	311,672	2.266	0.247	2.112	2.287	2.436
Log(PM2.5) (3km)	311,672	2.252	0.253	2.097	2.276	2.429
High_Pref × Post	311,672	0.039	0.193	0.000	0.000	0.000
Facility Age	311,672	11.627	7.135	5.000	11.000	17.000
Facility Employee	311,672	75.872	200.744	15.000	28.000	75.000
Panel B: Firm-level Variables						
Total Assets (US$ billions)	3,339	32.965	144.472	1.272	4.772	19.612
Firm Size	3,339	8.580	1.836	7.345	8.470	9.880
Tobin's Q	3,339	1.819	0.876	1.202	1.572	2.189
ROA	3,339	0.158	0.077	0.105	0.149	0.204
Leverage	3,339	0.231	0.150	0.113	0.224	0.334
R&D Stock	3,339	0.078	0.153	0.000	0.000	0.083
Panel C: County-level Variables						
GDP (US$ billions)	12,531	11.684	35.781	0.997	2.301	6.776
Log(GDP)	12,531	14.961	1.428	13.830	14.684	15.735
Unemployment Rate	12,531	6.874	2.538	5.000	6.300	8.400

Table 4
Retail Customers' Environmental Preferences and Firm Pollution

This table reports the regression results of facility-level pollution in response to the revealed environmental preferences after the negative news event. Column (1) reports the results without any control variables. Columns (2)–(4) report the results with facility-level control variables, facility- and firm-level control variables, and the full set of control variables, respectively. The sample consists of 458,192 event-facility-year observations with data on regression variables over the 2004–2016 period. Heteroskedasticity-robust *t*-statistics clustered at the event-facility level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, based on two-sided tests. See Appendix B for variable definitions.

Dependent Variable	*Log($PM_{2.5}$)*			
	(1)	(2)	(3)	(4)
High_Pref × Post	-0.010***	-0.010***	-0.010***	-0.009***
	(-7.96)	(-7.97)	(-7.98)	(-6.75)
Facility Age		0.002*	0.002	0.002
		(1.66)	(1.57)	(1.30)
Facility Employee		0.000	0.000	0.000
		(0.17)	(0.12)	(0.28)
Firm Size			0.001	0.001
			(1.08)	(1.39)
Tobin's Q			0.002***	0.002***
			(4.23)	(3.87)
ROA			-0.014	-0.016*
			(-1.60)	(-1.82)
Leverage			0.040***	0.035***
			(7.77)	(6.90)
R&D Stock			-0.014	-0.019
			(-0.48)	(-0.64)
Log(GDP)				0.022***
				(8.27)
Unemployment Rate				-0.007***
				(-29.40)
Event-Year FE	Yes	Yes	Yes	Yes
Event-Facility FE	Yes	Yes	Yes	Yes
N	458,192	458,192	458,192	458,192
Adj. R^2	0.864	0.864	0.864	0.864

Table 5
Cross-Sectional Analyses: News Salience

This table reports the cross-sectional results for the effect of news salience. Column (1) reports the results that separate events into *High_Severity* (*Severity* = 2 or 3) and *Low_Severity* (*Severity* = 1) groups. Column (2) reports the results that separate events into *High_Reach* (*Reach* = 3) and *Low_Reach* (*Reach* = 2) groups. Column (3) reports the results that separate events into *High_Severity_Reach* (*High_Severity* = 1 and *High_Reach* = 1) and *Low_Severity_Reach* (otherwise) groups. *High_Severity*, *High_Reach*, and *High_Severity_Reach* indicate that the event is salient (i.e., *High_Salience*). The sample consists of 458,192 event-facility-year observations with data on regression variables over the 2004–2016 period. Heteroskedasticity-robust *t*-statistics clustered at the event-facility level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, based on two-sided tests. See Appendix B for variable definitions.

Dependent Variable		$Log(PM_{2.5})$	
News Salience Measure	*Severity*	*Reach*	*Severity and Reach*
	(1)	(2)	(3)
High_Pref × *Post*	-0.015***	-0.021***	-0.026***
× *High_Salience [a]*	(-6.26)	(-9.37)	(-9.60)
High_Pref × *Post*	-0.007***	-0.005***	-0.007***
× *Low_Salience [b]*	(-4.82)	(-3.07)	(-4.96)
Facility Age	0.002	0.002	0.002
	(1.35)	(1.35)	(1.43)
Facility Employee	0.000	0.000	0.000
	(0.29)	(0.27)	(0.28)
Firm Size	0.001	0.001	0.001
	(1.41)	(1.45)	(1.44)
Tobin's Q	0.002***	0.002***	0.002***
	(3.89)	(3.90)	(3.92)
ROA	-0.016*	-0.017**	-0.016*
	(-1.86)	(-2.02)	(-1.92)
Leverage	0.035***	0.036***	0.035***
	(6.86)	(7.00)	(6.89)
R&D Stock	-0.019	-0.017	-0.019
	(-0.63)	(-0.57)	(-0.63)
Log(GDP)	0.022***	0.022***	0.022***
	(8.23)	(8.33)	(8.26)
Unemployment Rate	-0.007***	-0.007***	-0.007***
	(-29.43)	(-29.47)	(-29.48)
p-value of [a] = [b]	0.006	<0.001	<0.001
Event-Year FE	Yes	Yes	Yes
Event-Facility FE	Yes	Yes	Yes
N	458,192	458,192	458,192
Adj. R^2	0.864	0.864	0.864

Table 6
Cross-Sectional Analyses: Information Frictions between Retail Customers and Firms

This table reports the cross-sectional results for the effect of information frictions between retail customers and firms. Panel A reports the results that separate firm-years into a *High_Friction* (*Low_Friction*) group if *ESG_Disclosure*, the industry-adjusted Bloomberg ESG disclosure score in year *t*-1, is below (above) the sample median. Panel B reports the results that separate facility-years into a *High_Friction* (*Low_Friction*) group if *Headq_Dist*, the geographic distance between the facility and its headquarters, is above (below) the sample median. The sample consists of 458,192 event-facility-year observations with data on regression variables over the 2004–2016 period. Heteroskedasticity-robust *t*-statistics clustered at the event-facility level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, based on two-sided tests. See Appendix B for variable definitions.

Panel A: Information Frictions of Retail Customers

Dependent Variable	*Log($PM_{2.5}$)*
Info Frictions Measure	*Previous ESG Disclosure*
	(1)
High_Pref × *Post* × *High_Friction [a]*	-0.017***
	(-5.75)
High_Pref × *Post* × *Low_Friction [b]*	-0.009***
	(-6.18)
p-value of [a] = [b]	0.007
Facility Controls	Yes
Firm Controls	Yes
County Controls	Yes
Event-Year FE	Yes
Event-Facility FE	Yes
N	458,192
Adj. R^2	0.864

Panel B: Information Frictions of Firms

Dependent Variable	*Log($PM_{2.5}$)*
Info Frictions Measure	*Distance to Headquarter*
	(1)
High_Pref × *Post* × *High_Friction [a]*	-0.013***
	(-6.65)
High_Pref × *Post* × *Low_Friction [b]*	-0.004**
	(-2.43)
p-value of [a] = [b]	<0.001
Facility Controls	Yes
Firm Controls	Yes
County Controls	Yes
Event-Year FE	Yes
Event-Facility FE	Yes
N	458,192
Adj. R^2	0.864

Table 7
The Mechanism of Local Pollution Reduction

This table reports the regression results for the mechanism of local pollution reduction. Column (1) reports the results of firm-level pollution, consisting of 12,194 cohort-firm-year observations with data on regression variables. *Event_Firm* is an indicator variable equal to one when a firm experiences a negative environmental event in the year-cohort. Column (2) reports the pollution results for facilities located in regions with weak environmental preferences, consisting of 418,894 event-facility-year observations with data on regression variables. *Low_Pref* is an indicator variable equal to one if a facility is in a market with weak environmental preferences (i.e., decile of environmental preferences = 10) after the release of negative environmental news events. Column (3) reports the results of within-firm analysis regressing facility-level pollution on a set of interaction terms by interacting indicator variables (i.e., decile indicators) indicating the environmental preferences of a facility's market with the *Post* dummy. *High_Pref* × *Post* is omitted in Column (3) so that the facilities located in regions with strong environmental preferences serve as the benchmark. The sample consists of 356,404 event-facility-year observations. The sample in Columns (1)–(3) covers the 2004–2016 period. Heteroskedasticity-robust *t*-statistics clustered at the cohort-firm (event-facility) level are reported in parentheses in Column (1) (Columns (2)–(3)). ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, based on two-sided tests. See Appendix B for variable definitions.

Dependent Variable		$Log(PM_{2.5})$	
	Firm Pollution	*Weak Environmental Preferences*	*Shifting within the Firm by Environmental Preferences*
	(1)	(2)	(3)
Event_Firm × Post	0.002		
	(0.44)		
Low_Pref × Post		0.016***	0.031***
		(9.49)	(14.49)
Pref(Decile=8&9) × Post			0.016***
			(10.69)
Pref(Decile=6&7) × Post			0.012***
			(8.14)
Pref(Decile=4&5) × Post			0.004***
			(2.68)
Pref(Decile=2&3) × Post			0.005***
			(3.43)
Facility Controls	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes
County Controls	Yes	Yes	Yes
Cohort-Year FE	Yes		
Cohort-Firm FE	Yes		
Event-Year FE		Yes	Yes
Event-Facility FE		Yes	Yes
N	12,194	418,894	356,404
Adj. R^2	0.913	0.857	0.859

Table 8
Cross-Sectional Analyses on Pollution Shifting

This table reports the cross-sectional results on pollution shifting based on firms' incentives and feasibility. Panel A reports the results based on incentives. Column (1) of Panel A reports the results that separates firm-market-years into *High_Incentive* (*Low_Incentive*) group if sales from the previous year for a firm in the local market are ranked in the top quintiles (the remaining quintiles). Column (2) of Panel A reports the results that separates firm-market-years into *High_Incentive* (*Low_Incentive*) group if the average HHI of a firm in the local market in a year is below (above) the sample median. Column (3) of Panel A reports the results that separates firm-market-years into *High_Incentive* (*Low_Incentive*) group if more (less) than 50 percent of the county's population lives in rural areas. Panel B reports the results based on feasibility. Column (1) of Panel B reports the results that separate firm-years into a *High_Feasibility* (*Low_Feasibility*) group if the excess production capacity of a firm in a year is above (below) the sample median. The excess capacity of a firm (*Capacity*) is computed as end-of-year employees per million dollars of sales at each facility, averaged across a firm's facilities with weak environmental preferences. Column (2) of Panel B reports the results that separate firm-years into a *High_Feasibility* (*Low_Feasibility*) group if the proportion of a firm's facilities with weak environmental preferences located outside the EPA's designated nonattainment counties in a year (*Unregulated*) is above (below) the sample median. The sample consists of 458,192 event-facility-year observations with data on regression variables over the 2004–2016 period. Heteroskedasticity-robust *t*-statistics clustered at the event-facility level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, based on two-sided tests. See Appendix B for variable definitions.

Panel A: Incentives

Dependent Variable		$Log(PM_{2.5})$	
Incentive Measure	*Major Market*	*Competition*	*County Rurality*
	(1)	(2)	(3)
High_Pref × *Post* × *High_Incentive [a]*	-0.010***	-0.055***	-0.021***
	(-7.22)	(-20.80)	(-5.13)
High_Pref × *Post* × *Low_Incentive [b]*	0.007**	0.004***	-0.008***
	(2.08)	(2.85)	(-5.99)
p-value of [a] = [b]	<0.001	<0.001	0.003
Facility, Firm, and County Controls	Yes	Yes	Yes
Event-Year FE	Yes	Yes	Yes
Event-Facility FE	Yes	Yes	Yes
N	458,192	458,192	458,192
Adj. R^2	0.864	0.865	0.864

Panel B: Feasibility

Dependent Variable	*Log(PM$_{2.5}$)*	
Feasibility Measure	*Capacity*	*Unregulated*
	(1)	(2)
High_Pref × Post × High_Feasibility [a]	-0.035***	-0.029***
	(-17.85)	(-3.99)
High_Pref × Post × Low_Feasibility [b]	0.007***	-0.009***
	(4.54)	(-6.54)
p-value of [a] = [b]	<0.001	0.005
Facility, Firm, and County Controls	Yes	Yes
Event-Year FE	Yes	Yes
Event-Facility FE	Yes	Yes
N	458,192	458,192
Adj. R^2	0.864	0.864

Table 9
Alternative Measures and Specifications

This table reports the regression results using alternative measures and specifications. Panel A reports the results using $PM_{2.5}$ concentrations within a 3-km radius of a facility as the alternative dependent variable to replicate Column (4) of Table 4. Column (1) of Panel B reports the results using local markets instead classified by environmental preferences estimated by OLS regression in Equation (1) to replicate Column (4) of Table 4. Column (2) and (3) of Panel B reports the results using 5% and 20% as cut-off points when defining *High_Pref*. Columns (1) and (2) of Panel C report the results using the TWFE estimator and the Sun and Abraham (2021) estimator to estimate the pollution response of treated facilities after local retail customers reveal their environmental preferences to the event firm. Heteroskedasticity-robust *t*-statistics clustered at the event-facility (facility) level are reported in parentheses in Panel A and Panel B (Panel C). ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, based on two-sided tests. See Appendix B for variable definitions.

Panel A: Alternative Measure of Pollution

Dependent Variable	*Log($PM_{2.5}$)* *$PM_{2.5}$ within 3 km*
	(1)
High_Pref × *Post*	-0.010***
	(-7.76)
Facility Controls	Yes
Firm Controls	Yes
County Controls	Yes
Event-Year FE	Yes
Event-Facility FE	Yes
N	458,192
Adj. R^2	0.885

Panel B: Alternative Measures of Retail Customers' Environmental Preferences

Dependent Variable	*Log($PM_{2.5}$)*		
	Environmental Preferences Estimated by OLS	*High_Pref defined using 5% as cut-off point*	*High_Pref defined using 20% as cut-off point*
	(1)	(2)	(3)
High_Pref × *Post*	-0.008***	-0.022***	-0.003***
	(-6.85)	(-11.76)	(-3.65)
Facility Controls	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes
County Controls	Yes	Yes	Yes
Event-Year FE	Yes	Yes	Yes
Event-Facility FE	Yes	Yes	Yes
N	482,019	406,880	558,630
Adj. R^2	0.871	0.863	0.866

Panel C: Alternative Specifications

Dependent Variable	*Log(PM2.5)*	
	TWFE	*Sun and Abraham*
	(1)	(2)
High_Pref × *Post*	-0.007***	-0.005***
	(-5.06)	(-2.59)
Facility Controls	Yes	Yes
Firm Controls	Yes	Yes
County Controls	Yes	Yes
Year FE	Yes	Yes
Facility FE	Yes	Yes
N	383,068	383,068
Adj. R^2	0.851	0.854