# When Does Corporate Philanthropy Pay? An Information Perspective*†

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## Abstract

We examine corporate philanthropy as a signal of firm product quality under limited attention. Linking local charitable donations to sales, we find no average effect but a strong fourth-quarter (Q4) lift. This pattern aligns with product market seasonality and is more pronounced for firms with greater Q4-seasonal product mixes. The Q4 effect is also larger when the signal is likely more valuable: in weaker local economies where product quality matters more for consumer utility; in more competitive markets where differentiation relies more on non-pricing signals; for firms with more geographically concentrated sales where attribution is clearer; and after negative product incidents when uncertainty about quality is higher. Overall, the results highlight an informational role of charitable donations, but only when consumers attend to and value such information.

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# 1 Introduction

Corporate philanthropy is widespread yet difficult to reconcile with shareholder value maximization, placing it squarely in the debate between shareholder primacy and stakeholder capitalism. Since Milton Friedman's (1970) influential *New York Times* op-ed (Friedman (1970)), this debate has crystallized into three broad views. The first holds that maximizing shareholder value ("so long as it stays within the rules of the game," as Friedman put it) is sufficient to discipline firms to invest optimally in stakeholders; any deviation risks value destruction (e.g., Jensen, 2001; Denis, 2016; Bebchuk and Tallarita, 2020; Fama, 2020). A second view stresses that emphasizing stakeholder goals can enhance shareholder value because uncertainty and measurement challenges make positive NPV stakeholder investments difficult to justify ex ante (e.g., Edmans, 2020a, 2023). A third view argues that because some shareholders have non-pecuniary objectives, firms should maximize shareholder welfare rather than value (e.g., Hart and Zingales, 2017; Hart, 2020).

Despite their differences, the three views share a common skepticism toward charitable donations as a value-creating tool. Under shareholder primacy, such giving is simply wasteful. Even stakeholder-friendly accounts argue that writing checks is rarely first best. For example, Edmans (2020b) emphasizes that firms' comparative advantage lies in embedding stakeholder considerations into operating decisions, such as product design and workplace practices, rather than transferring resources to external organizations. Similarly, Hart and Zingales (2017) argue that when shareholders object to a firm-generated externality (e.g., if Walmart's shareholders oppose the retailer selling guns), it is more efficient for the firm to address the practice directly (an ex ante operation change) than to maximize profits and then offset the harm through donations (an ex post redistribution).

The discussion above motivates our question: if corporate philanthropy neither follows from shareholder value maximization nor is a first-best way to advance stakeholder aims, why is it so prevalent, and can it create value under some conditions? We propose and examine an informational role of corporate philanthropy, focusing on when it serves as a credible signal that improves product market outcomes. Philanthropy is a natural setting: while charitable donations do not mechanically increase sales by lowering prices, improving product features, or expanding distribution, they can credibly convey that a firm cares about consumers and other stakeholders and that this concern extends to how the firm designs, produces, and stands behind its products.

Conveying such care is not always easy, as statements like "we value our customers" may be dismissed as cheap talk. Instead, firms can rely on costly donations (e.g., toy companies supporting children's hospitals or food retailers funding local food banks) to make such claims credible.[1] As such, giving serves as a costly signal of product quality that shapes consumer beliefs (Spence, 1973). We argue that the effectiveness of this signal depends on consumer attention. In canonical signaling models such as Spence (1973), signals are fully observable and costlessly processed, so credibility hinges solely on differences in signaling costs across types. More recent theories relax these assumptions by allowing limited attention. This literature suggests two channels through which inattention arises: (i) exogenous cognitive or information constraints that limit intended recipients' ability to observe or process signals, regardless of their information value (e.g., Dow, 1991; Hirshleifer and Teoh, 2003); and (ii) endogenous attention choices when information processing is costly, as in rational inattention models (e.g., Sims, 2003; Peng and Xiong, 2006; Matějka and McKay, 2015). Under either form of inattention, even credible, costly signals may fail to affect consumer beliefs if they are rarely observed or if the expected value of attending to them is low.[2]

This reasoning is well suited to our setting because charitable donations are low-salience signals that consumers do not routinely monitor. Many consumers may be unaware of firms' giving activities, and even when aware, may not attend to them unless circumstances make such information valuable. When inattention stems from cognitive or informational constraints, exogenous shifts in the visibility of the signal, such as seasonal spikes in consumer attention, can increase awareness of donations without changing their informational content. When inattention reflects consumers' rational choices, attention instead arises endogenously from consumers' demand for information. Intuitively, the value of information about product quality is higher when consumers place greater weight on product quality in their utility function, when the signal is perceived to be more precise, and when prior beliefs about product quality are more uncertain. As the value of information rises,

[1] Anecdotal evidence suggests that firms can face substantial reputational and legal costs when charity-linked claims are not backed by actual donations. For example, a 2018 class action against Thrive Causemetics alleged that the firm failed to fulfill its donation promise, misleading consumers into believing that its charitable campaign reflected genuine care for women's well-being. Likewise, Pandorogate, an Italian scandal that began with a 2021-2022 charity-linked marketing campaign and continued through regulatory and legal proceedings into 2026, concerned pandoro products promoted as supporting a children's hospital even though the donation was in fact a pre-existing, one-off contribution unrelated to sales. The firm later made additional donations as part of resolving the legal dispute.

[2] Corporate giving may also signal financial strength, because only firms with sufficient cash and profitability can sustain donations and benefit from related tax deductions. We focus on giving as a signal of product quality because firms have more direct ways to signal financial strength to investors (such as payout policies) and because this interpretation maps naturally to the product market outcomes we examine.

consumers become more likely to attend to charitable giving as a signal of product quality and update their beliefs accordingly.

To assess the effect of charitable donations on sales, we link data from Candid's Foundation Directory Online, which tracks grant-level donations and recipient locations, with NielsenIQ Retail Measurement Services data, which report weekly point-of-sale prices and quantities for products sold across retail outlets. In NielsenIQ, a *group* represents a broad product category (e.g., cheese) and a *module* represents a subcategory within a group (e.g., mozzarella). This linkage allows us to align where firms donate with where they sell their products.

We begin by estimating the average effect as a baseline. Given the data frequency, we regress a firm's quarterly sales in a state and product module on its same-year donations in that state, with both variables scaled by lagged assets and log-transformed. With firm–quarter–module (or group) or state–quarter–module (group) fixed effects included, donations are positively associated with sales. However, once we add firm–state fixed effects, the association becomes economically small and statistically insignificant. This pattern suggests that the baseline relation reflects persistent firm–state differences: firms donate more where they already have a stronger product market presence, rather than donations causally increasing sales within a firm–state.

If charitable giving acts as a low-salience signal of product quality, its effect on sales may vary with consumer attention. As is well documented, product markets exhibit strong seasonality. Macro work such as Barsky and Miron (1989) shows large, predictable intra-year swings in economic activity, including a pronounced fourth-quarter (Q4) boom tied to holiday spending. Using NielsenIQ data, Butters et al. (2025) document strong seasonality in retail demand, with Q4 as the peak quarter and December as the peak month. To the extent that seasonality shifts consumer attention (either by increasing the salience of the signal or the value consumers place on product quality), the donations-sales relation may also exhibit similar seasonality.

We explore this possibility by augmenting the baseline specification with interactions between annual donation intensity and quarter indicators. Because the baseline result highlights the importance of controlling for firm–state differences, we include fixed effects at this level. We further include either firm–quarter–module (group) or state–quarter–module (group) fixed effects; these fixed effects absorb time-varying firm characteristics, ensuring they do not drive our findings. The donation coefficients are statistically insignificant in the first three quarters, but the Q4 interaction

is significantly positive. Economically, a one-standard-deviation increase in donations-to-assets at the firm–state–year level (1.09) is associated with a 1.16 percent increase in Q4 sales-to-assets at the firm–state–quarter–module level. To better gauge economic magnitude, we estimate an analogous regression using unscaled sales and donations. A back-of-the-envelope calculation suggests that, for every dollar donated to a state, the firm gets roughly 75 cents of extra sales in that state, aggregated across product modules. In further analysis, we show that the Q4 lift is stronger among firms with more Q4-seasonal product mixes. These patterns support a signaling channel under limited attention: donations matter most when consumer attention is predictably higher.

Next, we present three sets of cross-sectional analyses that speak to consumers' endogenous attention to product quality information. First, we examine two settings in which the donation signal likely matters more for consumer utility. We find that the Q4 donations-sales effect is significantly stronger in weaker local economic environments; this contrast is more pronounced when local economic conditions are measured using the level of real per capita personal income rather than its growth rate. The Q4 effect is also more pronounced in more competitive product markets, where differentiation relies more on non-pricing signals. These results suggest that charitable giving is a more effective signal of product quality when such information plays a larger role in consumers' utility function.

Second, we examine whether the Q4 effect varies with signal precision. We use firms' geographic sales concentration as a proxy for how clearly consumers can attribute local giving to the firm. Consistent with this notion, the Q4 effect is concentrated among firms with more geographically concentrated sales, where attribution is cleaner and the signal is more precise.

Third, we examine whether the Q4 effect strengthens when prior beliefs about product quality are more uncertain. We proxy for heightened uncertainty using increases in negative product-related incidents, which plausibly make consumers less certain about a firm's quality and more responsive to quality signals. Indeed, the Q4 lift is larger when product-related incidents increase relative to the prior quarter. Combined, these results suggest that charitable donations affect sales not on average, but when consumers are more attentive and when the informational value of the signal is higher.

This paper makes three contributions. First, it informs the debate on shareholder primacy versus stakeholder capitalism by adding to the empirical literature on the value implications of corporate

social responsibility ("CSR"). Prior evidence is mixed: CSR spending may be a value-enhancing intangible investment (e.g., Edmans, 2011; Lins et al., 2017) or reflect agency problems that reduce shareholder value (e.g., Masulis and Reza, 2015; Cheng et al., 2023; Flugum and Souther, 2025).

Prior literature has emphasized two channels through which CSR may create value: building social capital (see Servaes and Tamayo (2017) for a review) and appealing to consumers' pro-social preferences (Andreoni, 1989, 1990). As social capital is often defined in terms of trust, cooperation, and norms of reciprocity (Putnam, 1993), the first view is closely related to reciprocity-based theories (e.g., Rabin, 1993), where stakeholders respond to perceived corporate "good actions" with supportive behavior. Under this view, CSR builds trust, which can elicit stakeholder reciprocity and translate into value when actions are visible such as during advertising campaigns (e.g., Servaes and Tamayo, 2013) and when trust is scarce such as during financial crises (e.g., Lins et al., 2017). However, as discussed earlier, cash donations may be less efficient at creating stakeholder value than other forms of CSR spending (Edmans, 2020b; Hart and Zingales, 2017). In contrast, the preference-based view holds that CSR spending affects demand by catering to consumers' pro-social preferences. Andreoni (1989, 1990) formalize this idea through exogenous warm-glow preferences, whereby individuals derive utility from the act of giving itself in addition to its impact. Unlike the reciprocity-based view, which operates through stakeholders' beliefs about the firm's behavior, this mechanism operates through consumers' intrinsic preferences and therefore requires consumers to attach non-pecuniary value to purchasing from socially responsible firms.

Our study departs from prior literature in two ways. First, we examine the product market implications of corporate charitable donations rather than broad firm-year CSR or Environmental, Social, and Governance (ESG) measures. This focus yields a cleaner empirical setting, and our use of granular data on donations and product-level sales, together with stringent fixed effects, helps mitigate concerns that broad ESG metrics are correlated with firm fundamentals (e.g., Aswani et al., 2024; Zhang, 2025) and that time-varying firm characteristics such as advertising intensity drive our results. Second, our mechanism differs from both the social capital- and preference-based channels. In particular, recent work by Meier et al. (2026) shows that firms with higher E&S ratings exhibit greater local sales, especially when consumers are more informed through advertising or media coverage. They interpret this relation as evidence consistent with consumer preferences for socially responsible firms. By contrast, we conceptualize charitable giving as a periodic, attention-

contingent signal of product quality. Consistent with this information-based mechanism, we find no average effect of donations on sales, but a sharp Q4 increase, especially for firms with more Q4-seasonal product mixes. This seasonal pattern is difficult to reconcile with either a slow-moving social-capital mechanism, in which donations gradually build trust, or a persistent preference-based mechanism, in which consumers derive stable non-pecuniary utility from purchasing from donating firms. The cross-sectional evidence points in the same direction: the effect is stronger in more competitive product markets and following negative product incidents, precisely when credible signals of product quality are more valuable. While we do not rule out that charitable giving may also foster reciprocity or induce warm-glow responses, our results suggest that these channels are not sufficiently strong or persistent to generate a uniform demand effect throughout the year.

Second, our paper contributes to the signaling literature by examining corporate philanthropy as a costly signal of product quality. Our framework differs from existing signaling theories of charitable giving. Prior work emphasizes donations as signals of the donor's type, such as wealth or social status (Glazer and Konrad, 1996), or more broadly as expressions of social-image and self-image concerns (Bénabou and Tirole, 2006, 2010). In these models, giving primarily conveys information about the donor's type rather than about firm attributes or product quality.

In corporate settings, Fisman et al. (2008) model corporate philanthropy as a signal that separates firms led by socially minded managers from those led by purely profit-driven managers. Signaling is less costly for the former because they derive warm-glow utility from giving. In contrast, we adopt a standard Spence (1973)-style single-crossing logic: when product quality is otherwise difficult to observe, higher-quality firms face lower effective costs of sustaining costly giving because they can recoup more of the signaling cost through increased consumer demand. This framework does not require managerial preference heterogeneity. Our mechanism also relates to Aghamolla et al. (2026), who show that seemingly myopic investment cuts can credibly signal financial strength, thereby improving price efficiency despite reducing real efficiency. Similarly, charitable donations may appear wasteful, yet they can credibly reveal otherwise unobservable product quality.

Finally, we complement the recent empirical literature that examines corporate philanthropy. For example, Vansteenkiste (2026) shows that acquirers increase targeted donations (toward target-insider–affiliated charities, employee communities, and locations with regulatory presence) around mergers and acquisitions (M&A) to facilitate stakeholder support and improve deal outcomes. Like

our study, this paper views charitable giving as strategically directed to settings in which it is most likely to create value: in Vansteenkiste (2026), by building stakeholder support around M&As, and in our setting, by signaling product quality. Firms also adjust charitable giving following adverse shocks, such as natural disasters (Liang and Vansteenkiste, 2025; Rice and Schiller, 2025) and data breaches (Akey et al., 2026). Other studies show that donations can reflect agency problems (Masulis and Reza, 2015) or rent extraction by executives (Cai et al., 2021). In these settings, philanthropy is viewed as a strategic, stakeholder-targeted tool to elicit reciprocity, repair reputation, or reflect governance distortions.

By contrast, far less is known about the direct product market consequences of routine charitable donations outside special corporate events or crises. Even when product market outcomes are examined, the evidence is mixed and largely associational.[3] Our focus on consumer-facing firms with products sold through NielsenIQ-covered retail channels makes this a particularly suitable setting to capture the product-signaling channel, because product quality is arguably more central to consumer demand in our sample. By contrast, in heavy industrial sectors, charitable giving may be more likely to reflect reputation repair following environmental controversies.

# 2 Data

## 2.1 Local Product Sales

We obtain product-store-level data from the NielsenIQ Retail Measurement Services (RMS) dataset, which begins in 2006 and is available to us through 2020. This dataset contains weekly point-of-sale information on prices and quantities for products identified by Universal Product Codes (UPCs) across participating retail outlets in the U.S.[4] The NielsenIQ data provide economically meaningful coverage of household goods spending. Because goods account for roughly 34% of total household expenditures, spending on consumer goods tracked by NielsenIQ represents about 8.57% to 13.39% of total household spending (or 25% to 40% of goods expenditures) (Jaravel, 2019). In aggregate,

[3]For example, Lev et al. (2010) show, using Granger causality tests, that increases in corporate giving are followed by higher sales growth, especially in consumer-facing industries. However, such evidence remains vulnerable to time-varying firm-level factors that may jointly drive giving and sales.

[4]A UPC is a barcode encoded as a Global Trade Item Number (GTIN) that uniquely identifies a product. When scanned at the point of sale, the code allows the system to recognize the item and retrieve its price; see Figure IA1 in the Online Appendix for an illustrative example.

the covered goods generated $143.5 billion in sales in 2020. Coverage is also broad across income groups, ranging from 12.04% to 17.42% of total expenditures for households in the lowest income quintile and from 6.69% to 11.15% for households in the highest income quintile (Jaravel, 2019). This breadth of coverage explains why NielsenIQ data are widely used in prior literature to study firms' product market outcomes (e.g., Fracassi et al., 2022; Sharma, 2026).

The NielsenIQ RMS dataset enables analyses of granular sales patterns at the local retail level. The data are compiled from approximately 30,000 to 50,000 retail outlets (including grocery stores, drug stores, mass retailers, and other retail formats) and cover a broad set of product categories (including food, non-food grocery items, health and beauty products, and other general merchandise). Products are organized into a hierarchical taxonomy consisting of ten departments (e.g., Dairy, Alcoholic Beverages, and Health and Beauty), 125 groups (e.g., Cheese and Spread), and 1,075 modules (e.g., American Cheddar and Mozzarella). Our analysis focuses on the most granular level of this taxonomy, the module level.

Although the RMS dataset provides detailed information on retail sales, it does not contain identifiers for product manufacturers. To address this limitation, we merge the NielsenIQ data with information from GS1 US, a standards organization that maintains the registry of company prefixes used in UPCs and provides the names of product manufacturers. This step allows us to link UPCs to the manufacturers that supply products to retailers, matching approximately 5 million products to roughly 50,000 manufacturers. We then link manufacturers to firms using a combination of fuzzy name matching, supervised machine learning techniques, and manual verification, ultimately identifying around 300 publicly listed firms.

### 2.2 Local Charitable Donations

We obtain data on charitable donations from Candid's Foundation Directory Online (FDO). FDO compiles grant-level information on donations made by foundations to U.S. nonprofit organizations from multiple sources, including Internal Revenue Service Form 990 filings, press releases, newspaper reports, and submissions from funders and recipient organizations. The dataset reports detailed information on each grant, including the grant year, the donation amount, the name of the donating foundation, and the name and city of the recipient nonprofit organization. We study donations from 2006 to 2020 to align with the coverage of the NielsenIQ data. This starting year is also appropriate

because FDO coverage improves substantially after 2006 following the introduction of mandatory electronic filing requirements for large foundations with assets exceeding $10 million. Following prior literature (e.g., Rice and Schiller, 2025; Vansteenkiste, 2026), we exclude donor-advised funds (DAFs), for which giving decisions are more likely to reflect individual preferences (e.g., those of employees) rather than corporate choices. This exclusion helps ensure that the donations in our sample more plausibly capture firm giving policies rather than stakeholder-directed philanthropy.

Like the NielsenIQ data, the FDO database enables analyses of granular local donations but does not contain firm identifiers. Given our research interest, we seek to link donating foundations to public firms where possible. Because the FDO database contains far more donating foundations than there are public firms, we use Russell 1000 firms as a benchmark when reporting descriptive statistics on the donation data and manually identify associated foundations by matching corporate and foundation names.[5] Within the Russell 1000 universe, we identify 503 firms with foundations tracked by the FDO database, of which 402 make at least one non-DAF donation of $10,000 or more during our 2006–2020 sample period. An initial analysis of such donations by these 402 firms suggests that corporate charitable giving is both widespread and economically meaningful.

These 402 firms span 44 industries based on the Fama-French 49 industry classification, indicating that corporate philanthropy is broadly practiced rather than concentrated in a narrow set of sectors. Firm size also varies substantially, with a mean market capitalization of $51.68 billion and a standard deviation of $87.55 billion. While some of the largest contributions come from household names such as Walmart Inc., JPMorgan Chase & Co., and Dell Technologies Inc., meaningful donations are also made by smaller firms outside prominent sectors (e.g., retail, finance, and technology). For example, substantial charitable contributions are also observed among less well-known firms like XPO Inc., a transportation and logistics company, and Brunswick Corporation, a manufacturer of recreational marine products and equipment.

The magnitude of the donations made by these firms is also economically meaningful: the mean annual donation is approximately $3.91 million with a standard deviation of $11.78 million, while the median is lower at $0.47 million. Consistent with right-skewness, donations at the 99th percentile reach $70.35 million. These figures suggest that corporate giving can represent a costly

[5]To the extent that some foundations cannot be identified because their names do not closely align with corporate names, our estimates likely understate both the prevalence and the economic magnitude of charitable donations.

action for many firms. Consistent with this firm-level evidence from our sample, reported aggregate corporate philanthropy in the U.S. has grown substantially over time: total charitable giving by U.S. corporations nearly tripled over the past two decades, rising from roughly $13 billion in 2003 to more than $40 billion in 2023 (e.g., Giving USA, 2024; Vansteenkiste, 2026)

### 2.3 Sample and Variable Construction

To link a firm's local charitable donations to its local product sales, we begin with the public firms identified in the NielsenIQ dataset. For each firm, we search FDO to determine whether the firm operates a corporate foundation and whether that foundation makes charitable donations. This procedure yields a matched sample of 105 public firms that appear in both NielsenIQ and FDO from 2006 to 2020, including 59 Russell 1000 firms and 46 firms outside the Russell 1000. Russell 1000 firms in the sample are substantially larger than non-Russell 1000 firms, with mean total assets of $65,190 million versus $6,842 million and mean sales of $55,318 million versus $9,537 million, consistent with the index's focus on the largest U.S. public firms. Although the number of public firms in the matched sample is modest, the roughly even split between Russell 1000 and non-Russell 1000 firms suggests that our sample provides broad market coverage. Moreover, the highly granular sales and donation data render the effective sample size much larger than the firm count alone would suggest.

We then construct two main variables for each firm in this matched sample. First, using NielsenIQ data, we aggregate weekly UPC-level sales, defined as quantities sold multiplied by average prices, across retailers for products produced by firm $i$ to the firm $i$–state $s$–calendar quarter $q$–product module $m$ level. We then define our measure of local sales as the natural logarithm of firm–state–quarter–module sales (in dollars) scaled by the firm's total assets at the end of the previous fiscal year (in millions of dollars), denoted as $\ln(Sales_{i,s,q,m}/AT_{i,y-1})$; we refer to this variable as quarterly sales-to-assets. Because sales are aggregated by calendar quarter whereas firm financial data are reported by fiscal quarter and fiscal year, we align each calendar quarter with the corresponding fiscal quarter and fiscal year using Compustat's calendar–fiscal quarter mapping, which assigns each calendar quarter to the fiscal quarter with the greatest overlap in days. This variable serves as the dependent variable in our quarterly panel regressions. Constructing sales at this level of granularity allows us to exploit variation across firms, locations, time, and product

categories while controlling for rich fixed effects. Our aggregation approach follows prior literature using NielsenIQ data (e.g., Fracassi et al., 2022; Chen et al., 2025).

Unlike sales data, grant-level donation data in the FDO database are only available annually. We therefore aggregate donations across all grants made by foundations in FDO that can be attributed to firm $i$ in state $s$ during fiscal year $y$. We then define our measure of local donations as the natural logarithm of one plus firm-state-year donations (in dollars) scaled by the firm's total assets at the end of the previous fiscal year (in millions of dollars), denoted as $\ln(1 + Donation_{i,s,y}/AT_{i,y-1})$; we refer to this variable as annual donations-to-assets, or briefly, donation intensity. This variable serves as our main independent variable of interest.

### 2.4 Summary Statistics

To provide an overview of corporate charitable donation patterns in our sample, we begin by analyzing 1,208 firm–year observations of 105 U.S. publicly listed firms with product sales data in the NielsenIQ RMS dataset and charitable donations recorded in the FDO database. Figure 1 plots total charitable donations aggregated across sample firms by year and reveals substantial intertemporal variation. Donations generally rise through 2016, increasing from \$117 million in 2006 to a peak of \$459 million in 2013, with a temporary dip back to \$117 million in 2009. After remaining elevated through 2016, donations decline sharply to \$121 million in 2017 before gradually recovering to \$320 million in 2020. The dip in 2009 likely reflects the aftermath of the Global Financial Crisis. The sharp decline in 2017 may reflect reduced incentives for corporate giving following the Tax Cuts and Jobs Act of 2017, or pressures faced by the more consumer-oriented firms in the NielsenIQ sample due to growing competition from e-commerce.

Table 1 reports additional descriptive statistics for donating firms in the sample. As shown in Panel A, average annual donations are \$2.65 million across all sample donating firms, \$4.18 million for Russell 1000 firms, and \$0.69 million for non-Russell 1000 firms. Medians are much lower, at \$0.23 million, \$0.55 million, and \$0.06 million, respectively, indicating a highly right-skewed distribution. Consistent with this skewness, the 99th percentile reaches \$34.88 million for the full sample, \$62.83 million for Russell 1000 firms, and \$12.3 million for non-Russell 1000 firms.[6] The

[6]Notably, the distribution of total annual donation amounts for the Russell 1000 firms in our final sample closely resembles that of the full Russell 1000 sample reported in Section 2.2, suggesting that the 59 Russell 1000 firms in our analysis are representative of the index with respect to corporate giving.

number of states receiving donations is similarly right-skewed: firms donate in 3.4 states per year on average, but the median is just over one. Russell 1000 firms donate across more states, with a mean (median) of 4.8 (1.6), compared with 1.6 (0.5) for non-Russell 1000 firms. Overall, these patterns suggest that corporate giving is geographically concentrated for most firms.

Panel B of Table 1 further reports yearly patterns in corporate donations. The time-series pattern in average annual donations is consistent with that shown in Figure 1: donations generally rise during the first half of the sample period (with a dip in 2009), peak in 2013, remain elevated through 2016, drop sharply in 2017, and gradually recover through 2020. At its peak in 2013, average annual donations represent about 0.11% of the firm's average year-end cash balance (this ratio ranges from approximately 0.03% to 0.11% in the sample), suggesting that corporate giving is economically meaningful. The average number of states receiving donations is also relatively stable over time, ranging from about 2.5 to 5.3 states across years, although the median (unreported) is closer to one. The average donation per recipient state ranges between \$0.10 million and \$0.39 million.

As discussed earlier, underlying our analysis is a single-crossing condition: when product quality is difficult to observe, firms with higher product quality incur lower effective costs of sustaining costly giving than firms with lower product quality, presumably because they can recoup a greater portion of the signaling cost. Although this condition is difficult to test directly, precisely because product quality is not readily observable, Panel C of Table 1 offers suggestive evidence. As shown, firms in the top quartile of donation level have higher net income-to-sales ratios and higher earnings per share than firms in the bottom three quartiles, consistent with the idea that, despite making larger donations, the former are better able to translate sales into profits and create shareholder value. To be clear, higher profitability is not a necessary condition for the signaling mechanism we posit: if charitable giving indeed leads consumers to revise their beliefs upward about a firm's product quality, it can increase sales and/or improve profitability.

Finally, Panel D of Table 1 reports summary statistics for the two main variables used in the regression analysis. The sample comprises 2,119,619 firm–state–quarter–product-module observations for 105 firms over 60 calendar quarters from 2006 to 2020. Quarterly sales-to-assets, $\ln(Sales_{i,s,q,m}/AT_{i,y-1})$, has a mean of -1.45 and a median of -1.92. Annual donation intensity, $\ln(1 + Donation_{i,s,y}/AT_{i,y-1})$, has a mean of 0.57 and a median of 0. Therefore, the distribution

of both variables is right-skewed.

# 3 Empirical Findings

## 3.1 Charitable Donations and Sales: Baseline

We hypothesize that corporate giving serves as a signal of product quality under limited attention. To assess its effectiveness, we begin by examining whether charitable donations are associated with higher sales on average. This baseline analysis is a useful starting point because, if donations credibly convey information about product quality and consumers broadly attend to that information, we should observe a positive relationship between donations and sales even before considering the role of attention. By contrast, if charitable giving is a low-salience signal that consumers do not routinely monitor, its average effect may be weak even if it matters in certain settings.

Specifically, we run the following ordinary least squares (OLS) regression:

$$\ln(Sales_{i,s,q,m}/AT_{i,y-1}) = \alpha + \beta \ln(1 + Donation_{i,s,y}/AT_{i,y-1}) + \lambda(\text{Fixed Effects}) + \varepsilon_{i,s,q,m}, \quad (1)$$

where the dependent variable, $\ln(Sales_{i,s,q,m}/AT_{i,y-1})$, is the natural logarithm of firm $i$'s sales at the state $s$–calendar quarter $q$–product module $m$ level, scaled by total assets at the end of the previous fiscal year. The independent variable of interest, $\ln(1 + Donation_{i,s,y}/AT_{i,y-1})$, is the natural logarithm of one plus firm $i$'s donations to state $s$ in fiscal year $y$, scaled by the same lagged assets. Section 2.3 provides further details on these two variables. We estimate equation (1) with various fixed effects and cluster standard errors by firm and year-calendar quarter.

Column (1) of Table 2 reports the regression results including firm–quarter–group fixed effects ($\lambda_{i,q,g}$) and state–quarter–group fixed effects ($\lambda_{s,q,g}$). Including $\lambda_{i,q,g}$ is useful to absorb firm-specific shocks in a given quarter for a product group. These fixed effects also absorb time-varying firm characteristics at the firm-quarter level (e.g., size, growth, profitability, and advertising intensity), assuming their effects on the donations–sales relation are common across all product groups the firm carries. Moreover, including $\lambda_{s,q,g}$ absorbs local state demand/supply shocks in a given quarter for a product group. Column (2) of Table 2 reports the regression results including firm–quarter–module

fixed effects ($\lambda_{i,q,m}$) and state–quarter–module fixed effects ($\lambda_{s,q,m}$). Recall that a module is a more granular product subcategory than a group, so including these two sets of fixed effects helps absorb firm-specific and state-specific shocks at the quarter–module level. With these fixed effects included, annual donations are positively associated with the same-year quarterly sales, as evidenced by the statistically significant coefficient estimate on $\ln(1 + Donation_{i,s,y}/AT_{i,y-1})$.

While these specifications control for firm- and state-specific shocks that vary across quarters and product categories, they do not account for persistent heterogeneity in a firm's operations across states. One concern is that firms simply donate more to the states where they sell more. To address this concern, we further include firm–state ($\lambda_{i,s}$) fixed effects in columns (3)–(4). These added fixed effects absorb all time-invariant characteristics of a given firm–state pair, such as market presence, persistent local demand conditions, and unobserved stickiness in firm–state relationships. Therefore, identification comes from within–firm–state variation over time.

Once firm–state fixed effects are included, the coefficient estimate on donation intensity becomes economically small and statistically insignificant. This result suggests that the positive association observed in columns (1)–(2) is largely driven by persistent differences across firm–state pairs rather than by within–firm–state changes over time. In other words, the positive relation between donations and sales may merely reflect that firms donate more to states where they already have a stronger product market presence, rather than that increases in donations within a firm–state pair lead to contemporaneous increases in sales.

Table IA1 of the Online Appendix repeats the analysis in Table 2 using the firm's annual sales-to-assets ratio as the dependent variable and yields qualitatively similar results. Taken together, the baseline results suggest that charitable giving does not operate as an effective signal of product quality on average. This conclusion appears somewhat at odds with the prevalence and economic significance of charitable donations documented in Section 2.2. We therefore examine whether the effectiveness of this signal varies predictably with conditions under which consumers are more likely to notice and respond to it in the analyses below.

### 3.2 Charitable Donations and Sales: Seasonality

Section 3.1 finds no average effect of corporate donations on sales. However, if charitable giving indeed operates as a low-salience signal of product quality, as we hypothesize, its effect may arise

only when consumers are more attentive or when such information is more valuable to them. A natural way to explore this possibility is through seasonality in product markets. A large literature documents predictable within-year fluctuations in economic activity, especially a pronounced fourth-quarter increase in retail demand tied to holiday spending (e.g., Barsky and Miron, 1989). Using the same NielsenIQ data underlying our sales measures, Butters et al. (2025) show that retail demand peaks in Q4, with December being the most common peak-demand month. If this seasonality heightens consumer attention or increases the value consumers place on product quality, then the relation between donations and sales may also exhibit similar seasonality.

We test for this seasonality by augmenting equation (1) with interactions between annual donation intensity and quarter indicators. Specifically, we estimate the following OLS regression:

$$\begin{aligned} \ln(\mathit{Sales}_{i,s,q,m}/\mathit{AT}_{i,y-1}) = \alpha &+ \beta_1 \ln(1 + \mathit{Donation}_{i,s,y}/\mathit{AT}_{i,y-1}) \\ &+ \sum_{k\in\{2,3,4\}} \beta_k \left[Q_k \times \ln(1 + \mathit{Donation}_{i,s,y}/\mathit{AT}_{i,y-1})\right] \\ &+ \lambda\,(\text{Fixed Effects}) + \varepsilon_{i,s,q,m}, \end{aligned} \tag{2}$$

where $\ln(\mathit{Sales}_{i,s,q,m}/\mathit{AT}_{i,y-1})$ and $\ln(1 + \mathit{Donation}_{i,s,y}/\mathit{AT}_{i,y-1})$ are defined above. $Q_k$, for $k = 2, \ldots, 4$, are indicators for the second through fourth calendar quarters, with the first quarter being the omitted category. The independent variables of interest are the interaction terms between $Q_k$ and $\ln(1 + \mathit{Donation}_{i,s,y}/\mathit{AT}_{i,y-1})$; the standalone variable of donation intensity corresponds to its interaction with Q1. We include $\lambda_{i,s}$ in all specifications because the baseline results demonstrate the importance of these effects, and then add alternative fixed effects across specifications. As in the baseline analysis, we cluster standard errors by firm and year-calendar quarter.

Column (1) of Table 3 reports the regression results of estimating equation (2) including firm–state, firm–quarter–group, and state–quarter–group fixed effects. As discussed earlier, these fixed effects absorb persistent differences across firm–state pairs, firm-specific shocks at the product-group–quarter level, and state-specific shocks at the product-group–quarter level, respectively. The coefficients on the interactions between $\ln(1 + \mathit{Donation}_{i,s,y}/\mathit{AT}_{i,y-1})$ and the quarter indicators for Q1–Q3, with the standalone donation intensity variable capturing the Q1 effect, are all statistically insignificant and economically small; this result indicates that higher annual donation intensity is not associated with higher sales in the first three quarters. In contrast, the interaction between

annual donation intensity and the Q4 indicator is positive and statistically significant at the 5% level. This result provides initial evidence of seasonality in the donations-sales relation.

Column (2) of Table 3 reports the regression results including firm–state, firm–quarter–module, and state–quarter–module fixed effects. Because module is a finer product category than group, these fixed effects are even more stringent than those in column (1). Despite this, we continue to find a positive coefficient on the interaction between annual donation intensity and the Q4 indicator, significant at the 10% level. Although the statistical significance is modest, presumably because of the more demanding fixed-effects structure, the economic magnitude remains sizable. Based on the estimates in this column, a one-standard-deviation increase in annual donation intensity (1.09 in the sample) is associated with an approximately 1.16% increase in Q4 sales ($1.09 \times 0.0106$).[7]

We conduct three additional analyses. First, to better gauge the economic magnitude, we estimate an analogous regression directly using the natural logarithms of sales and donations, without scaling by lagged total assets. That is, we use $\ln(Sales_{i,s,q,m})$ and $\ln(1 + Donation_{i,s,y})$ in place of the scaled variables defined in equation (1). As shown in Table 4, the estimate suggests that a 1% increase in a firm's annual donations to a given state is associated with a 0.025% increase in the firm's Q4 sales in that state. A back-of-the-envelope calculation suggests that, for every dollar donated to a state, the firm gets roughly 75 cents of extra sales in that state, aggregated across product modules. This back-of-the-envelope calculation assumes that the estimated elasticity applies proportionally across the firm's product modules within a state.

Second, our baseline and seasonality analyses regress quarterly sales-to-assets on annual donation intensity because donation data are available only at the annual level. Using an annual measure in quarterly regressions implies that the donation variable is repeated across the four quarters within a year. One concern with this approach is that repeating the same donation measure across quarters may understate standard errors.

A related concern is that the annual measure provides no within-year variation, making it difficult to capture the quarterly distribution of donations. To be clear, equation (2) tests whether the slope on donations differs by quarter, rather than whether the level of donations differs by quarter. Accordingly, even if donations tend to be highest in Q4, this does not by itself imply that

[7]Because sales-to-assets enters the natural logarithm transformation as $\ln(x)$, whereas donations-to-assets (or donation intensity) enters as $\ln(1 + x)$, this calculation is only an approximation. However, the approximation is reasonable because the donation intensity is small relative to one in the transformation.

the effect of donations on sales is also strongest in Q4. To the extent that the average donating firm makes donations throughout the year, the annual variable effectively spreads the donation measure equally across quarters. This introduces measurement error, attenuates the estimated seasonal effect, and makes it harder to detect a Q4 lift, if one indeed exists in the data.

An alternative concern is that donating firms may make donations only in Q4. In that case, a stronger Q4 relation could merely reflect the timing of donation activity rather than a quarter-specific slope. Even so, this pattern need not be inconsistent with the mechanism we propose: firms may strategically concentrate donations in Q4 when investor or consumer attention is highest, thereby enhancing the signaling value of charitable giving. In practice, however, donations are unlikely to occur exclusively in a single quarter, as their timing may also reflect institutional constraints and the fundraising cycles and needs of recipient charities.

Nevertheless, to address the possibility of within-year concentration in donations, we approximate quarterly donation intensity. Specifically, we allocate annual donations across the four calendar quarters aligned with a fiscal year based on the relative share of the firm's cash and cash equivalents in each fiscal quarter of the year. The assumption is that charitable donations are more affordable, and therefore more likely, when firms hold more cash. Table 5 reports the results of estimating equation (2) using this imputed quarterly donation intensity, $\ln(1 + \widehat{Donation}_{i,s,q}/AT_{i,y-1})$, instead of the annual measure. The results continue to show that the positive relationship between quarterly donation intensity and quarterly sales-to-assets is concentrated in Q4.

Third, to further assess whether the Q4 effect in Table 3 is driven by seasonality in product markets, as documented in Butters et al. (2025), we examine whether the effect is more pronounced among firms with greater exposure to Q4-seasonal products. We construct this exposure measure in two steps. First, using the full sample of module-level NielsenIQ sales, we estimate module-level seasonality by regressing each module's share of total NielsenIQ module sales on calendar-quarter indicators, with Q1 omitted as the benchmark. We then retain the coefficient on the Q4 indicator, which captures the extent to which the module's share of total NielsenIQ sales increases in Q4 relative to Q1 and thus serves as a measure of the module's Q4 seasonality. Second, for each firm, we aggregate these module-level Q4 coefficients into a firm-level measure by taking a sales-weighted average across the modules in which the firm operates. Firms whose sales are more concentrated in modules with stronger Q4 seasonality are therefore considered to have greater exposure to Q4-

seasonal products.

Using this firm-level exposure measure, we split the sample at the median and reestimate equation (2) separately for firms with below-median and above-median exposure to Q4-seasonal products, where the above-median group includes observations at the median.[8] Table 6 reports the results including firm–state, firm–quarter–module, and state–quarter–module fixed effects. Consistent with our prediction, the interaction between the Q4 indicator and annual donation intensity is substantially stronger for the subsample with above-median exposure to Q4-seasonal products in column (2); the coefficient on the Q4–donation interaction is positive and statistically significant at the 5% level. The magnitude (0.0274) is more than twice the baseline Q4 effect reported in Table 3 column (2) (0.0106). In contrast, the corresponding coefficient for the subsample with below-median exposure is small (0.0038) and statistically insignificant in column (1). The difference between the two coefficients is statistically significant at the 10% level.

Taken together, the results thus far suggest that the average effect of donations on sales is close to zero, but this null result masks meaningful seasonal heterogeneity. Charitable giving appears to affect sales primarily in Q4, either because seasonal shifts in consumer attention increase the salience of donations as signals of product quality or because consumers place greater value on such signals during that period. These findings are also more difficult to reconcile with the view that donations operate mainly by building social capital or trust, since it is not clear why such a mechanism would matter only in Q4 and not in the first three quarters of the year.

### 3.3 The Value of Signaling: Cross-Sectional Evidence

The seasonal pattern in the donations-sales relation is consistent with a limited-attention interpretation: charitable giving may act as a low-salience signal of product quality that becomes effective only when consumers happen to be more attentive to the signal or when the information conveyed by the signal is more valuable. However, seasonality evidence alone cannot distinguish between two mechanisms. One possibility is that attention constraints are exogenous as in bounded rationality models (e.g., Dow, 1991; Hirshleifer and Teoh, 2003). In Q4, these constraints may be less binding, as holiday shopping could mechanically increase consumer engagement with product markets. Al-

[8] Our inferences are unchanged if we additionally require, for the above-median exposure subsample, that the Q4 coefficient exceed the corresponding coefficients on Q2 and Q3.

ternatively, attention may arise endogenously as in rational inattention models such that consumers optimally allocate attention to a signal when its expected value becomes higher (e.g., Sims, 2003; Peng and Xiong, 2006; Matějka and McKay, 2015). In Q4, the average value consumers place on product quality may also be higher, especially when some purchases have sentimental value.

In signaling models like Spence (1973), the value of a signal about product quality depends on several factors, including the importance of the information in consumers' utility functions, the precision with which the signal conveys information, and the degree of prior uncertainty about the information being conveyed. If charitable donations indeed operate as a signal of product quality, their effectiveness should therefore vary systematically along these dimensions under full rationality. In the analyses that follow, we examine settings that speak to the importance of product quality in consumers' utility functions, the precision with which donations are likely to signal firm product quality, and consumers' prior uncertainty about firm product quality.

### 3.3.1 Local Economic Conditions

The first setting that we examine speaks to the importance of product quality in consumers' utility functions. As we hypothesized earlier, a sizable donation may serve as a signal that a firm cares about consumers and that this concern extends to how the firm designs, produces, and stands behind its products. When local economic conditions are weak, consumers may face tighter budget constraints and thus place greater weight on product quality, including utility, durability, and after-sales customer care. In such environments, information that helps consumers assess product quality may become more valuable, increasing the likelihood that consumers attend to signals conveying such information. Accordingly, if charitable donations operate as a signal of product quality, their effect on sales should be stronger when local economic conditions are weaker.

We measure local economic conditions using state-year data from the U.S. Bureau of Economic Analysis Regional Economic Accounts. We focus on "real per capita personal income" expressed in chained 2017 dollars (i.e., inflation-adjusted using chain-type price indexes to reflect 2017 purchasing power), and construct measures of its level and annual growth rate. We merge these measures with our firm–state–quarter–module panel using geographic and time identifiers.

Using the merged sample, we examine whether the seasonal donations–sales relationship varies with local economic conditions. We first split the sample at the median level of real per capita

personal income (with observations at the median included in the above-median group) and reestimate equation (2) separately for the two subsamples. Columns (1)–(2) of Table 7 report the results, including firm–state, firm–quarter–module, and state–quarter–module fixed effects. The interaction between the Q4 indicator and annual donation intensity is both statistically and economically stronger in state-years with weaker economic conditions. For the subsample with below-median real per capita personal income, the coefficient on the Q4–donation interaction is positive and statistically significant at the 5% level. Its magnitude (0.0186) is also 75% larger than the baseline Q4 effect reported in Table 3 (0.0106). In contrast, for the subsample with above-median real per capita personal income, the corresponding coefficient is smaller in magnitude (0.0070) and statistically insignificant. The difference between the two coefficients is statistically significant at the 10% level.

We next split the sample at the median growth rate of real per capita personal income and repeat the analysis, including observations at the median in the above-median group. Columns (3)–(4) of Table 7 report the results. The Q4–donation interaction remains larger in the below-median subsample than in the above-median subsample (0.0149 vs. 0.0066), and is marginally significant only in the below-median subsample. However, the difference between the two coefficients is not statistically significant.

Taken together, these results suggest that local economic conditions shape the seasonal sales response to charitable donations, presumably because consumers in weaker economic environments place greater value on signals about firm product quality when evaluating product utility, durability, and after-sales customer care. Interestingly, the level of local income appears to matter more than its growth rate in shaping this pattern.

### 3.3.2 Product Market Competition

The second setting speaks to how the value of product quality signals may vary with product market competition. When consumers face a larger choice set, firms may be less able to differentiate themselves on price alone, increasing the importance of non-pricing signals about product quality. Accordingly, if charitable donations operate as signals of product quality, their effect on sales should be stronger in more competitive product markets.

We measure product market competition using the number of firms with positive sales in a

given state–quarter–module market. Using this measure, we split the sample at the median number of firms (with observations at the median included in the above-median group) and reestimate equation (2) separately for markets with below-median and above-median levels of competition. Table 8 reports the results, including firm–state, firm–quarter–module, and state–quarter–module fixed effects. For markets with above-median numbers of competing firms, the coefficient on the Q4–donation interaction is positive and statistically significant at the 10% level (0.0122), and is 15% larger than the baseline Q4 effect reported in Table 3 (0.0106). In contrast, the corresponding coefficient for markets with below-median numbers of competing firms is small (0.0026) and statistically insignificant. The difference between the two coefficients is economically meaningful, although it falls short of conventional significance levels ($t$ statistic = 1.63).

Taken together, these results suggest that competition strengthens the seasonal sales response to charitable donations. This pattern is consistent with charitable donations serving as a signal of firm product quality that becomes more valuable when consumers face a larger choice set and rely more on non-pricing signals to differentiate among competing products.

#### 3.3.3 Firms' Geographic Concentration

The third setting speaks to the precision with which charitable donations may signal firm product quality. When firms operate in fewer geographic markets, their charitable activities may be more visible and easier for consumers in those markets to attribute to the firm. In contrast, when firms operate across many states, consumers may face greater difficulty linking charitable donations to a specific firm, rendering the signal less precise. Accordingly, we predict the effect of charitable donations on sales to be stronger for firms with more geographically concentrated operations.

We measure firms' geographic dispersion using the number of states in which a firm sells a given product module in a given quarter. Using this measure, we split the sample at the median number of states (with observations at the median included in the above-median group) and reestimate equation (2) separately for firms with below-median and above-median geographic dispersion. Table 9 reports the results, including firm–state, firm–quarter–module, and state–quarter–module fixed effects.

For firms with below-median geographic dispersion, the coefficient on the Q4–donation interaction (0.0192) is statistically significant at the 5% level, 80% larger than the baseline Q4 effect

reported in Table 3 (0.0106). In contrast, the corresponding coefficient for firms with above-median geographic dispersion is small (0.0018) and statistically insignificant. The difference between the two coefficients is positive and statistically significant at the 5% level. As a robustness check, Table IA2 in the Online Appendix reconstructs geographic dispersion at the firm–group–quarter level, and the results remain qualitatively similar.

Taken together, these results suggest that the seasonal sales response to charitable donations is stronger when firms operate in more geographically concentrated markets. This pattern is consistent with charitable donations serving as a signal of product quality that becomes more precise when consumers can more easily attribute the firm's charitable activities to the products they purchase.

### 3.3.4 Product-Related Incidents

The final setting aims to capture consumers' prior uncertainty about product quality at the time the signal arrives. We argue that negative product-related incidents heighten concerns about a firm's products and thereby increase consumers' uncertainty about product quality. Our focus on negative incidents is motivated by the well-documented asymmetry that negative shocks increase firm uncertainty and return volatility more than positive shocks (e.g., Glosten et al., 1993). In a signaling framework, when uncertainty about product quality is higher, consumers should place greater value on signals that help them infer firm quality. We therefore predict that the relation between donations and sales is stronger during periods with more product-related incidents.

We obtain firm-level incident data from RepRisk, which systematically monitors corporate incidents and controversies using more than 80,000 public media, stakeholder, and third-party sources worldwide. We focus on incidents related to firms' products and operations, including controversial products and services and product-related health and environmental concerns. We aggregate the monthly data to the quarterly level and measure the quarter-to-quarter change in the frequency of product-related incidents.

Using this measure, we split the sample according to whether product-related incidents increase or decrease relative to the previous quarter and reestimate equation (2) separately for the two subsamples. Table 10 reports the results, including firm–state, firm–quarter–module, and state–quarter–module fixed effects. When product-related incidents increase, the coefficient on the Q4–donation interaction is positive and statistically significant at the 1% level (0.0267), more than

doubling the baseline Q4 effect reported in Table 3 (0.0106). In contrast, when product-related incidents decrease, the corresponding coefficient is smaller (0.0081) and statistically insignificant. The difference between the two coefficients is statistically significant at the 10% level.

Taken together, these results suggest that the seasonal sales response to charitable donations is stronger when negative product-related incidents increase. This pattern is consistent with charitable donations serving as a signal of product quality that becomes more valuable when consumers face greater uncertainty about firms' products.

# 4 Conclusion

Charitable donations are widely practiced in Corporate America, yet they fit uneasily within standard frameworks in corporate finance. Unlike direct product market actions, donations do not alter product attributes, prices, or distribution outlets. They also differ from conventional advertising expenditures that are explicitly designed to communicate product quality or pricing information to consumers. For this reason, corporate philanthropy is frequently invoked in the debate between shareholder primacy and stakeholder capitalism. Under shareholder primacy, charitable giving is often viewed as a wasteful use of corporate resources or as a channel through which managers pursue personal utility at shareholders' expense (e.g., Friedman, 1970; Jensen, 2001; Bebchuk and Tallarita, 2020). Even stakeholder-oriented views generally regard charitable giving as an inefficient way to advance stakeholder objectives (e.g., Edmans, 2023; Hart and Zingales, 2017). As such, existing explanations for corporate philanthropy tend to focus on altruistic motives, agency concerns, or the accumulation of trust and social capital (e.g., Servaes and Tamayo, 2017).

In this paper, we study whether charitable donations can instead function as an indirect signal of firm product quality. Our premise is that corporate giving may convey information about a firm's commitment to product quality and customer care. Because such information is difficult to communicate directly, charitable donations may serve as a costly but observable action that helps consumers update their beliefs about a firm's products. To the extent consumers do not routinely monitor this signal, its effectiveness may be limited by attention, whether due to cognitive constraints or rational inattention.

To examine this possibility, we assemble granular data linking local charitable donations to

product market outcomes. These data allow us to implement an identification strategy that controls for time-varying firm-quarter characteristics as well as firm- and state-specific demand and supply shocks. Our results reveal a pronounced Q4 lift in the donations–sales relation, precisely when consumer activity peaks in many product categories. Moreover, the strength of this relation varies predictably with conditions that affect the value or credibility of product-quality signals. Specifically, the effect is stronger in economically weaker environments, in more competitive product markets, among firms with more geographically concentrated operations, and when product-related incidents increase.

Broadly, our results suggest that charitable giving plays a strategic signaling role in product markets that extends beyond traditional interpretations rooted in altruism or corporate social responsibility. Unlike trust- or social-capital-based explanations, which would predict a cumulative, slow-moving effect of charitable giving on sales, our evidence instead points to a periodic, attention-contingent informational effect. Recognizing this signaling role helps reconcile the prevalence of corporate philanthropy with economic incentives and shows that these seemingly costly, non-product-related activities can create shareholder value by improving product market outcomes.

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**Figure 1:** Total Charitable Donations by Year

This figure plots the annual total charitable donations (in millions of dollars) aggregated across sample firms by year. The sample consists of 1,208 firm-year observations from 105 U.S. publicly listed firms with product sales data available in the NielsenIQ Retail Measurement Services dataset and charitable donation data obtained from Candid's Foundation Directory Online database from 2006 to 2020.

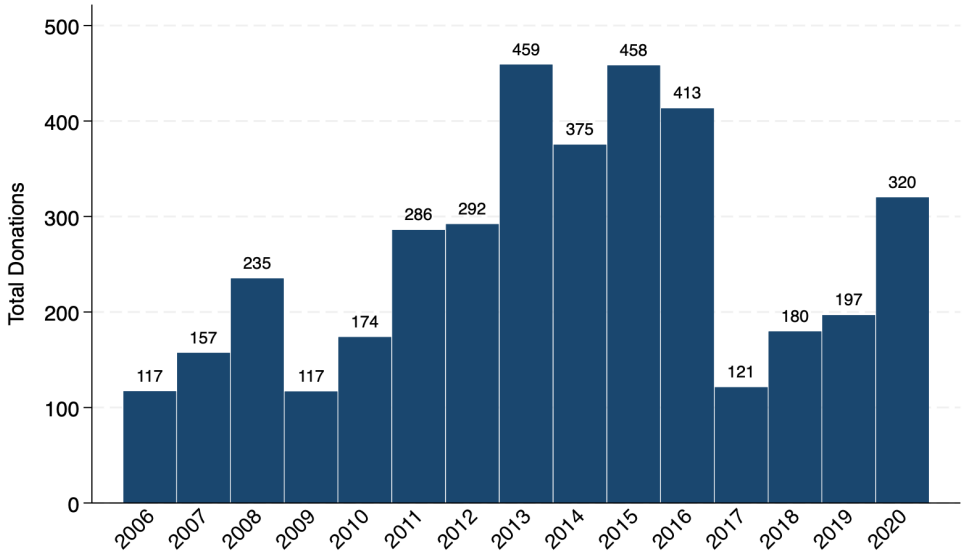


**Table 1:** Descriptive Statistics

Panel A reports descriptive statistics on charitable donations in the full sample of donating firms. The sample used in this panel consists of 1,208 firm-year observations from 105 U.S. publicly listed firms with product sales data available in the NielsenIQ Retail Measurement Services dataset and charitable donation data obtained from Candid's Foundation Directory Online database from 2006 to 2020. For each firm, we compute firm-year measures of total donations (in millions of dollars) and the number of recipient states and then average these measures across years. We report summary statistics for these firm-level averages for the full sample, the Russell 1000 subsample, and the non-Russell subsample. Using the same sample, Panel B reports annual statistics, including the average total donations (in millions of dollars), the average number of recipient states, the average donation per recipient state, and the average firm cash balance.

**Panel A: Charitable Donations in the Full Sample**

| | N | Mean | SD | P25 | P50 | P75 | P99 |
|---|---|---|---|---|---|---|---|
| *Full sample* | | | | | | | |
| Average total donations ($ million) | 105 | 2.65 | 8.09 | 0.02 | 0.23 | 0.92 | 34.88 |
| Average number of recipient states | 105 | 3.41 | 5.56 | 0.13 | 1.07 | 3.47 | 23.33 |
| *Russell 1000* | | | | | | | |
| Average total donations ($ million) | 59 | 4.18 | 10.39 | 0.05 | 0.55 | 2.86 | 62.83 |
| Average number of recipient states | 59 | 4.80 | 6.56 | 0.20 | 1.60 | 5.87 | 25.27 |
| *Non-Russell 1000* | | | | | | | |
| Average total donations ($ million) | 46 | 0.69 | 2.26 | 0.00 | 0.06 | 0.35 | 12.30 |
| Average number of recipient states | 46 | 1.63 | 3.20 | 0.07 | 0.50 | 1.73 | 18.50 |

**Panel B: Charitable Donations by Year**

| Year | Average total donations ($ million) | Average number of recipient states | Average donations per recipient state ($ million) | Average firm cash balance ($ million) |
|---|---|---|---|---|
| 2006 | 1.54 | 3.22 | 0.10 | 3,440 |
| 2007 | 1.99 | 3.41 | 0.13 | 3,031 |
| 2008 | 2.94 | 3.70 | 0.20 | 3,165 |
| 2009 | 1.48 | 2.54 | 0.10 | 3,867 |
| 2010 | 2.17 | 3.00 | 0.15 | 4,214 |
| 2011 | 3.53 | 3.31 | 0.25 | 4,015 |
| 2012 | 3.43 | 3.27 | 0.25 | 4,425 |
| 2013 | 5.47 | 4.88 | 0.39 | 4,814 |
| 2014 | 4.22 | 4.17 | 0.31 | 4,758 |
| 2015 | 5.39 | 5.21 | 0.39 | 4,940 |
| 2016 | 4.86 | 4.98 | 0.35 | 4,875 |
| 2017 | 1.60 | 3.37 | 0.10 | 5,227 |
| 2018 | 2.30 | 4.06 | 0.16 | 4,831 |
| 2019 | 2.62 | 4.33 | 0.18 | 4,875 |
| 2020 | 4.21 | 5.28 | 0.30 | 6,373 |

**Table 1:** Descriptive Statistics (Continued)

Panel C reports net income-to-sales and earnings-per-share, averaged across firm-year observations, for sample firms in the top quartile of charitable donations and those in the bottom three quartiles, along with their differences and the two-sided $t$-statistics testing these differences. The sample used in this panel is the same as that used in Panels A and B. Panel D reports descriptive statistics for the two main variables used in the regression analysis: $\ln(Sales_{i,s,q,m}/AT_{i,y-1})$ is the natural logarithm of firm $i$'s sales revenue in state $s$–calendar quarter $q$–product module $m$, scaled by the firm's total assets at the end of the fiscal year preceding the year to which quarter $q$ belongs (i.e., $y-1$), and $\ln(1+Donation_{i,s,y}/AT_{i,y-1})$ is the natural logarithm of one plus firm $i$'s annual donations to state $s$ in year $y$, scaled by total assets at the end of year $y-1$. Both variables are winsorized at the 1% and 99% levels. The sample used in this panel consists of 2,119,619 firm–state–quarter–module observations from 2006 to 2020.

**Panel C: Profitability of Firms with High versus Low Donations**

| | Donation High | Donation Low | Difference | $t$-stat |
|---|---|---|---|---|
| Average total donations ($ million) | 12.65 | 0.09 | 12.56 | 16.96 |
| Net Income-to-sales | 0.09 | 0.06 | 0.03 | 4.25 |
| Earnings-per-share | 3.00 | 2.34 | 0.66 | 3.31 |

**Panel D: Variables Used in the Main Analysis**

| | N | Mean | SD | P25 | P50 | P75 | P99 |
|---|---|---|---|---|---|---|---|
| $\ln(Sales_{i,s,q,m}/AT_{i,y-1})$ | 2,119,619 | -1.45 | 3.69 | -4.08 | -1.02 | 1.38 | 5.46 |
| $\ln(1+Donation_{i,s,y}/AT_{i,y-1})$ | 2,119,619 | 0.57 | 1.09 | 0.00 | 0.00 | 0.71 | 4.76 |

**Table 2:** Baseline Effect of Annual Charitable Donations on Quarterly Sales (Scaled)

This table reports the ordinary least squares (OLS) regression results examining the relationship between annual charitable donations and quarterly sales. The dependent variable, $\ln(Sales_{i,s,q,m}/AT_{i,y-1})$, is the natural logarithm of firm $i$'s sales revenue in state $s$–calendar quarter $q$–product module $m$, scaled by the firm's total assets at the end of the fiscal year preceding the year to which quarter $q$ belongs (i.e., $y-1$). The independent variable, $\ln(1+Donation_{i,s,y}/AT_{i,y-1})$, is the natural logarithm of one plus firm $i$'s annual donations to state $s$ in year $y$, scaled by total assets at the end of year $y-1$. Columns (1)–(4) differ in their inclusion of fixed effects (FE), as indicated in the table; "Quarter" denotes year-calendar quarter fixed effects. The sample consists of 2,119,619 firm–state–quarter–module observations from 2006 to 2020. All continuous variables are winsorized at the 1% and 99% levels. $t$-statistics are reported below coefficients in parentheses, and standard errors are two-way clustered by firm and year-calendar quarter. $^{***}$, $^{**}$, and $^{*}$ denote statistical significance at the 1%, 5%, and 10% levels, respectively.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dependent variable | | $\ln(Sales_{i,s,q,m}/AT_{i,y-1})$ | | |
| $\ln(1+Donation_{i,s,y}/AT_{i,y-1})$ | 0.0379** | 0.0495** | 0.0005 | -0.0002 |
| | (2.32) | (2.09) | (0.16) | (0.04) |
| Firm × State FE | No | No | Yes | Yes |
| Firm × Quarter × Group FE | Yes | N.A. | Yes | N.A. |
| State × Quarter × Group FE | Yes | N.A. | Yes | N.A. |
| Firm × Quarter × Module FE | No | Yes | No | Yes |
| State × Quarter × Module FE | No | Yes | No | Yes |
| N (observations used) | 2,073,054 | 1,333,988 | 2,073,036 | 1,333,965 |
| $R^2$ | 0.652 | 0.945 | 0.657 | 0.952 |

**Table 3:** Seasonal Effect of Annual Donations on Quarterly Sales (Scaled)

This table reports the OLS regression results examining the seasonality in the relationship between annual charitable donations and quarterly sales. The dependent variable, $\ln(Sales_{i,s,q,m}/AT_{i,y-1})$, is the natural logarithm of firm $i$'s sales revenue in state $s$–calendar quarter $q$–product module $m$, scaled by the firm's total assets at the end of the fiscal year preceding the year to which quarter $q$ belongs (i.e., $y-1$). The independent variables include: $\ln(1 + Donation_{i,s,y}/AT_{i,y-1})$, the natural logarithm of one plus firm $i$'s annual donations to state $s$ in year $y$, scaled by total assets at the end of year $y-1$; $Q_k$, for $k = 2, \ldots, 4$, indicator variables for the second through fourth calendar quarters; and the interaction terms between the two. Columns (1)–(2) differ in their inclusion of fixed effects (FE), as indicated in the table; "Quarter" denotes year-calendar quarter fixed effects. The sample consists of 2,119,619 firm–state–quarter–module observations from 2006 to 2020. All continuous variables are winsorized at the 1% and 99% levels. $t$-statistics are reported below coefficients in parentheses, and standard errors are two-way clustered by firm and year-calendar quarter. $^{***}$, $^{**}$, and $^{*}$ denote statistical significance at the 1%, 5%, and 10% levels, respectively.

| | (1) | (2) |
|---|---|---|
| Dependent variable | $\ln(Sales_{i,s,q,m}/AT_{i,y-1})$ | |
| $\ln(1 + Donation_{i,s,y}/AT_{i,y-1})$ | -0.0037 | -0.0041 |
| | (1.11) | (0.89) |
| $Q2 \times \ln(1 + Donation_{i,s,y}/AT_{i,y-1})$ | 0.0014 | 0.0024 |
| | (0.85) | (0.56) |
| $Q3 \times \ln(1 + Donation_{i,s,y}/AT_{i,y-1})$ | 0.0031 | 0.0027 |
| | (1.32) | (0.52) |
| $Q4 \times \ln(1 + Donation_{i,s,y}/AT_{i,y-1})$ | 0.0124** | 0.0106* |
| | (2.53) | (1.71) |
| Firm × State FE | Yes | Yes |
| Firm × Quarter × Group FE | Yes | N.A. |
| State × Quarter × Group FE | Yes | N.A. |
| Firm × Quarter × Module FE | No | Yes |
| State × Quarter × Module FE | No | Yes |
| N (observations used) | 2,073,036 | 1,333,965 |
| $R^2$ | 0.657 | 0.952 |

**Table 4:** Seasonal Effect of Annual Donations on Quarterly Sales (Unscaled)

This table reports the OLS regression results examining the seasonality in the relationship between annual charitable donations and quarterly sales. The dependent variable, $\ln(Sales_{i,s,q,m})$, is the natural logarithm of firm $i$'s sales revenue in state $s$–calendar quarter $q$–product module $m$. The independent variables include: $\ln(1 + Donation_{i,s,y})$, the natural logarithm of one plus firm $i$'s annual donations to state $s$ in year $y$; $Q_k$, for $k = 2, \ldots, 4$, indicator variables for the second through fourth calendar quarters; and the interaction terms between the two. Columns (1)–(2) differ in their inclusion of fixed effects (FE), as indicated in the table; "Quarter" denotes year-calendar quarter fixed effects. The sample consists of 2,119,619 firm–state–quarter–module observations from 2006 to 2020. All continuous variables are winsorized at the 1% and 99% levels. $t$-statistics are reported below coefficients in parentheses, and standard errors are two-way clustered by firm and year-calendar quarter. $^{***}$, $^{**}$, and $^{*}$ denote statistical significance at the 1%, 5%, and 10% levels, respectively.

| | (1) | (2) |
|---|---|---|
| Dependent variable | $\ln(Sales_{i,s,q,m})$ | |
| $\ln(1 + Donation_{i,s,y})$ | -0.0008 | -0.0007 |
| | (1.06) | (0.61) |
| $Q2 \times \ln(1 + Donation_{i,s,y})$ | 0.0005 | 0.0004 |
| | (0.63) | (0.45) |
| $Q3 \times \ln(1 + Donation_{i,s,y})$ | 0.0011 | 0.0008 |
| | (1.45) | (0.81) |
| $Q4 \times \ln(1 + Donation_{i,s,y})$ | 0.0034*** | 0.0025* |
| | (2.68) | (1.89) |
| Firm × State FE | Yes | Yes |
| Firm × Quarter × Group FE | Yes | N.A. |
| State × Quarter × Group FE | Yes | N.A. |
| Firm × Quarter × Module FE | No | Yes |
| State × Quarter × Module FE | No | Yes |
| N (observations used) | 2,188,941 | 1,446,639 |
| $R^2$ | 0.636 | 0.948 |

**Table 5:** Seasonal Effect of Imputed Quarterly Donations on Quarterly Sales (Scaled)

This table reports the OLS regression results examining the seasonality in the relationship between imputed quarterly charitable donations and quarterly sales. The dependent variable, $\ln(Sales_{i,s,q,m}/AT_{i,y-1})$, is the natural logarithm of firm $i$'s sales revenue in state $s$–calendar quarter $q$–product module $m$, scaled by the firm's total assets at the end of the fiscal year preceding the year to which quarter $q$ belongs (i.e., $y-1$). The independent variables include $\ln(1+\widehat{Donation}_{i,s,q}/AT_{i,y-1})$, the imputed quarterly donations constructed by allocating the firm's annual donations across four quarters according to its relative quarterly cash holdings within the year; $Q_k$, for $k=2,\ldots,4$, indicator variables for the second through fourth calendar quarters; and the interaction terms between the two. Columns differ in their inclusion of fixed effects (FE), as indicated in the table; "Quarter" denotes year-calendar quarter fixed effects. The sample consists of 2,119,619 firm–state–quarter–module observations from 2006 to 2020. All continuous variables are winsorized at the 1% and 99% levels. $t$-statistics are reported below coefficients in parentheses, and standard errors are two-way clustered by firm and year-calendar quarter. $^{***}$, $^{**}$, and $^{*}$ denote statistical significance at the 1%, 5%, and 10% levels, respectively.

| | (1) | (2) |
|---|---|---|
| Dependent variable | $\ln(Sales_{i,s,q,m}/AT_{i,y-1})$ | |
| $\ln(1+\widehat{Donation}_{i,s,q}/AT_{i,y-1})$ | -0.0045 | 0.0014 |
| | (0.91) | (0.25) |
| $Q2\times\ln(1+\widehat{Donation}_{i,s,q}/AT_{i,y-1})$ | 0.0011 | 0.0015 |
| | (0.26) | (0.26) |
| $Q3\times\ln(1+\widehat{Donation}_{i,s,q}/AT_{i,y-1})$ | 0.0042 | 0.0003 |
| | (1.47) | (0.04) |
| $Q4\times\ln(1+\widehat{Donation}_{i,s,q}/AT_{i,y-1})$ | 0.0162** | 0.0126* |
| | (2.38) | (1.65) |
| Firm × State FE | Yes | Yes |
| Firm × Quarter × Group FE | Yes | N.A. |
| State × Quarter × Group FE | Yes | N.A. |
| Firm × Quarter × Module FE | No | Yes |
| State × Quarter × Module FE | No | Yes |
| N (observations used) | 2,073,036 | 1,333,965 |
| $R^2$ | 0.657 | 0.952 |

**Table 6:** Seasonal Effect of Annual Donations on Quarterly Sales (Scaled): Heterogeneity in Firm Exposure to Q4-Seasonal Products

This table reports the OLS regression results examining how the seasonal effect of annual charitable donations on quarterly sales varies with the firm's exposure to Q4-seasonal products. The dependent variable, $\ln(Sales_{i,s,q,m}/AT_{i,y-1})$, is the natural logarithm of firm $i$'s sales revenue in state $s$–calendar quarter $q$–product module $m$, scaled by the firm's total assets at the end of the fiscal year preceding the year to which quarter $q$ belongs (i.e., $y-1$). The independent variables include: $\ln(1+Donation_{i,s,y}/AT_{i,y-1})$, the natural logarithm of one plus firm $i$'s annual donations to state $s$ in year $y$, scaled by total assets at the end of year $y-1$; $Q_k$, for $k=2,\ldots,4$, indicator variables for the second through fourth calendar quarters; and the interaction terms between the two. The inclusion of fixed effects (FE) is as indicated in the table; "Quarter" denotes year-calendar quarter fixed effects. Columns (1) and (2) report results for firms with below- and above-sample-median exposure to Q4-seasonal products, respectively. We measure a firm's exposure to Q4-seasonal products in two steps. First, using the full sample, we run module-quarter regressions to estimate module-level Q4 coefficient estimates. A module's Q4 coefficient estimate captures the increase in its share of total NielsenIQ module sales in Q4 relative to Q1. Second, for each firm, we calculate a sales-weighted average of these module-level Q4 coefficient estimates. The "coefficient difference" line reports the difference in the Q4 coefficients between the below- and above-median groups and the two-sided $t$-statistic for testing the difference. The sample consists of 2,119,619 firm–state–quarter–module observations from 2006 to 2020. All continuous variables are winsorized at the 1% and 99% levels. $t$-statistics are reported below coefficients in parentheses, and standard errors are two-way clustered by firm and year-calendar quarter. $^{***}$, $^{**}$, and $^{*}$ denote statistical significance at the 1%, 5%, and 10% levels, respectively.

| | (1) | (2) |
|---|---|---|
| Dependent variable | $\ln(Sales_{i,s,q,m}/AT_{i,y-1})$ | |
| | Below-median Q4 exposure | Above-median Q4 exposure |
| $\ln(1+Donation_{i,s,y}/AT_{i,y-1})$ | 0.0013 | -0.0003 |
| | (0.21) | (0.03) |
| $Q2 \times \ln(1+Donation_{i,s,y}/AT_{i,y-1})$ | -0.0005 | 0.0097 |
| | (0.12) | (0.87) |
| $Q3 \times \ln(1+Donation_{i,s,y}/AT_{i,y-1})$ | 0.0019 | 0.0185 |
| | (0.41) | (1.62) |
| $Q4 \times \ln(1+Donation_{i,s,y}/AT_{i,y-1})$ | 0.0038 | 0.0274** |
| | (0.97) | (2.58) |
| Coefficient Difference ($Q4$ Interaction) | 0.0236* | |
| | (1.95) | |
| Firm × State FE | Yes | Yes |
| Firm × Quarter × Module FE | Yes | Yes |
| State × Quarter × Module FE | Yes | Yes |
| N (observations used) | 763,149 | 196,102 |
| $R^2$ | 0.943 | 0.967 |

**Table 7:** Seasonal Effect of Annual Donations on Quarterly Sales (Scaled): Heterogeneity in Local Economic Conditions

This table reports the OLS regression results examining how the seasonal effect of annual charitable donations on quarterly sales varies with local economic conditions. The dependent variable, $\ln(Sales_{i,s,q,m}/AT_{i,y-1})$, is the natural logarithm of firm $i$'s sales revenue in state $s$–calendar quarter $q$–product module $m$, scaled by the firm's total assets at the end of the fiscal year preceding the year to which quarter $q$ belongs (i.e., $y-1$). The independent variables include: $\ln(1+Donation_{i,s,y}/AT_{i,y-1})$, the natural logarithm of one plus firm $i$'s annual donations to state $s$ in year $y$, scaled by total assets at the end of year $y-1$; $Q_k$, for $k=2,\ldots,4$, indicator variables for the second through fourth calendar quarters; and the interaction terms between the two. The inclusion of fixed effects (FE) is as indicated in the table; "Quarter" denotes year-calendar quarter fixed effects. Columns (1) and (2) report results for observations with below- and above-sample-median real per capita personal income, respectively. Columns (3) and (4) report results for observations with below- and above-sample-median real per capita personal income growth, respectively. The "coefficient difference" line reports the differences in the Q4 coefficients between the below- and above-median groups and the two-sided $t$-statistic for testing the differences. The sample consists of 2,119,619 firm–state–quarter–module observations from 2006 to 2020. All continuous variables are winsorized at the 1% and 99% levels. $t$-statistics are reported below coefficients in parentheses, and standard errors are two-way clustered by firm and year-calendar quarter. $^{***}$, $^{**}$, and $^{*}$ denote statistical significance at the 1%, 5%, and 10% levels, respectively.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dependent variable | $\ln(Sales_{i,s,q,m}/AT_{i,y-1})$ | | | |
| | Real per capita personal income | | Real per capita income growth | |
| | Below-median | Above-median | Below-median | Above-median |
| $\ln(1+Donation_{i,s,y}/AT_{i,y-1})$ | -0.0055 | -0.0039 | -0.0031 | -0.0027 |
| | (0.77) | (0.73) | (0.44) | (0.43) |
| $Q2 \times \ln(1+Donation_{i,s,y}/AT_{i,y-1})$ | 0.0025 | 0.0015 | 0.0002 | 0.0030 |
| | (0.38) | (0.44) | (0.02) | (0.60) |
| $Q3 \times \ln(1+Donation_{i,s,y}/AT_{i,y-1})$ | 0.0073 | 0.0019 | 0.0024 | 0.0014 |
| | (1.00) | (0.44) | (0.33) | (0.22) |
| $Q4 \times \ln(1+Donation_{i,s,y}/AT_{i,y-1})$ | 0.0186$^{**}$ | 0.0070 | 0.0149$^{*}$ | 0.0066 |
| | (2.59) | (1.22) | (1.72) | (1.11) |
| Coefficient Difference ($Q4$ Interaction) | 0.0117$^{*}$ | | 0.0083 | |
| | (1.84) | | (0.97) | |
| Firm × State FE | Yes | Yes | Yes | Yes |
| Firm × Quarter × Module FE | Yes | Yes | Yes | Yes |
| State × Quarter × Module FE | Yes | Yes | Yes | Yes |
| N (observations used) | 570,156 | 750,609 | 518,305 | 800,820 |
| $R^2$ | 0.956 | 0.953 | 0.956 | 0.952 |

**Table 8:** Donations and Sales: Heterogeneity by Competition

This table reports the OLS regression results examining how the seasonal effect of annual charitable donations on quarterly sales varies with product market competition. The dependent variable, $\ln(Sales_{i,s,q,m}/AT_{i,y-1})$, is the natural logarithm of firm $i$'s sales revenue in state $s$–calendar quarter $q$–product module $m$, scaled by the firm's total assets at the end of the fiscal year preceding the year to which quarter $q$ belongs (i.e., $y-1$). The independent variables include: $\ln(1+Donation_{i,s,y}/AT_{i,y-1})$, the natural logarithm of one plus firm $i$'s annual donations to state $s$ in year $y$, scaled by total assets at the end of year $y-1$; $Q_k$, for $k=2,\ldots,4$, indicator variables for the second through fourth calendar quarters; and the interaction terms between the two. The inclusion of fixed effects (FE) is as indicated in the table; "Quarter" denotes year-calendar quarter fixed effects. Columns (1) and (2) report results for observations with below- and above-sample-median product market competition, respectively. We measure product market competition as the number of firms ($n_firms$) in a given state–quarter–module market. The "coefficient difference" line reports the differences in the Q4 coefficients between the below- and above-median groups and the two-sided $t$-statistic for testing the differences. The sample consists of 2,119,619 firm–state–quarter–module observations from 2006 to 2020. All continuous variables are winsorized at the 1% and 99% levels. $t$-statistics are reported below coefficients in parentheses, and standard errors are two-way clustered by firm and year-calendar quarter. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

| | (1) | (2) |
|---|---|---|
| Dependent variable | $\ln(Sales_{i,s,q,m}/AT_{i,y-1})$ | |
| | Below median $n_firms$ | Above median $n_firms$ |
| $\ln(1+Donation_{i,s,y}/AT_{i,y-1})$ | -0.0079 | -0.0037 |
| | (1.19) | (0.76) |
| $Q2 \times \ln(1+Donation_{i,s,y}/AT_{i,y-1})$ | -0.0009 | 0.0028 |
| | (0.12) | (0.88) |
| $Q3 \times \ln(1+Donation_{i,s,y}/AT_{i,y-1})$ | 0.0018 | 0.0034 |
| | (0.25) | (0.63) |
| $Q4 \times \ln(1+Donation_{i,s,y}/AT_{i,y-1})$ | 0.0026 | 0.0122* |
| | (0.37) | (1.82) |
| Coefficient Difference ($Q4$ Interaction) | -0.0096 | |
| | (1.63) | |
| Firm × State FE | Yes | Yes |
| Firm × Quarter × Module FE | Yes | Yes |
| State × Quarter × Module FE | Yes | Yes |
| N (observations used) | 521,972 | 791,448 |
| $R^2$ | 0.964 | 0.946 |

**Table 9:** Donations and Sales: Heterogeneity by Geographic Dispersion

This table reports the OLS regression results examining how the seasonal effect of annual charitable donations on quarterly sales varies with firms' geographic dispersion. The dependent variable, $\ln(Sales_{i,s,q,m}/AT_{i,y-1})$, is the natural logarithm of firm $i$'s sales revenue in state $s$–calendar quarter $q$–product module $m$, scaled by the firm's total assets at the end of the fiscal year preceding the year to which quarter $q$ belongs (i.e., $y-1$). The independent variables include: $\ln(1+Donation_{i,s,y}/AT_{i,y-1})$, the natural logarithm of one plus firm $i$'s annual donations to state $s$ in year $y$, scaled by total assets at the end of year $y-1$; $Q_k$, for $k=2,\ldots,4$, indicator variables for the second through fourth calendar quarters; and the interaction terms between the two. The inclusion of fixed effects (FE) is as indicated in the table; "Quarter" denotes year-calendar quarter fixed effects. Columns (1) and (2) report results for observations with below- and above-sample-median geographic dispersion, respectively. We measure geographic dispersion as the number of states ($n_states$) in which firm $i$ sells module $m$ in quarter $q$. The "coefficient difference" line reports the differences in the Q4 coefficients between the below- and above-sample-median groups and the two-sided $t$-statistic for testing the differences. The sample consists of 2,119,619 firm–state–quarter–module observations from 2006 to 2020. All continuous variables are winsorized at the 1% and 99% levels. $t$-statistics are reported below coefficients in parentheses, and standard errors are two-way clustered by firm and year-calendar quarter. $^{***}$, $^{**}$, and $^{*}$ denote statistical significance at the 1%, 5%, and 10% levels, respectively.

| | (1) | (2) |
|---|---|---|
| Dependent variable | $\ln(Sales_{i,s,q,m}/AT_{i,y-1})$ | |
| | Below median $n_states$ | Above median $n_states$ |
| $\ln(1+Donation_{i,s,y}/AT_{i,y-1})$ | -0.0043 | -0.0036 |
| | (0.59) | (0.90) |
| $Q2 \times \ln(1+Donation_{i,s,y}/AT_{i,y-1})$ | 0.0009 | -0.0019 |
| | (0.11) | (0.64) |
| $Q3 \times \ln(1+Donation_{i,s,y}/AT_{i,y-1})$ | 0.0024 | -0.0021 |
| | (0.28) | (0.57) |
| $Q4 \times \ln(1+Donation_{i,s,y}/AT_{i,y-1})$ | 0.0192** | 0.0018 |
| | (2.05) | (0.56) |
| Coefficient Difference ($Q4$ Interaction) | 0.0173** | |
| | (2.60) | |
| Firm × State FE | Yes | Yes |
| Firm × Quarter × Module FE | Yes | Yes |
| State × Quarter × Module FE | Yes | Yes |
| N (observations used) | 350,540 | 437,664 |
| $R^2$ | 0.955 | 0.947 |

**Table 10:** Donations and Sales: Heterogeneity by Product-Related Incidents

This table reports the OLS regression results examining how the seasonal effect of annual charitable donations on quarterly sales varies with product-related incidents. The dependent variable, $\ln(Sales_{i,s,q,m}/AT_{i,y-1})$, is the natural logarithm of firm $i$'s sales revenue in state $s$–calendar quarter $q$–product module $m$, scaled by the firm's total assets at the end of the fiscal year preceding the year to which quarter $q$ belongs (i.e., $y-1$). The independent variables include: $\ln(1+Donation_{i,s,y}/AT_{i,y-1})$, the natural logarithm of one plus firm $i$'s annual donations to state $s$ in year $y$, scaled by total assets at the end of year $y-1$; $Q_k$, for $k=2,\ldots,4$, indicator variables for the second through fourth calendar quarters; and the interaction terms between the two. The inclusion of fixed effects (FE) is as indicated in the table; "Quarter" denotes year-calendar quarter fixed effects. Columns (1) and (2) report results for observations with decreases and increases in product-related incidents in quarter $q$ relative to the previous quarter $(q-1)$, respectively. Product-related incidents are aggregated at the quarterly level and include (i) controversial products and services and (ii) products related to health and environmental issues. The "coefficient difference" line reports the differences in the Q4 coefficients between the decrease and increase groups and the two-sided $t$-statistic for testing the differences. The sample consists of 2,119,619 firm–state–quarter–module observations from 2006 to 2020. All continuous variables are winsorized at the 1% and 99% levels. $t$-statistics are reported below coefficients in parentheses, and standard errors are two-way clustered by firm and year-calendar quarter. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

| | (1) | (2) |
|---|---|---|
| Dependent variable | $\ln(Sales_{i,s,q,m}/AT_{i,y-1})$ | |
| | Product Incidents Decrease | Product Incidents Increase |
| $\ln(1+Donation_{i,s,y}/AT_{i,y-1})$ | -0.0010 | -0.0021 |
| | (0.16) | (0.30) |
| $Q2 \times \ln(1+Donation_{i,s,y}/AT_{i,y-1})$ | -0.0015 | 0.0027 |
| | (0.12) | (0.27) |
| $Q3 \times \ln(1+Donation_{i,s,y}/AT_{i,y-1})$ | -0.0032 | -0.0025 |
| | (0.65) | (0.24) |
| $Q4 \times \ln(1+Donation_{i,s,y}/AT_{i,y-1})$ | 0.0081 | 0.0267*** |
| | (1.57) | (2.78) |
| Coefficient Difference ($Q4$ Interaction) | -0.0186* | |
| | (1.77) | |
| Firm × State FE | Yes | Yes |
| Firm × Quarter × Module FE | Yes | Yes |
| State × Quarter × Module FE | Yes | Yes |
| N (observations used) | 246,344 | 276,081 |
| $R^2$ | 0.957 | 0.958 |

# Online Appendix

**Figure IA1:** UPC Identifier: An Example

This figure shows an illustrative example of a UPC barcode.

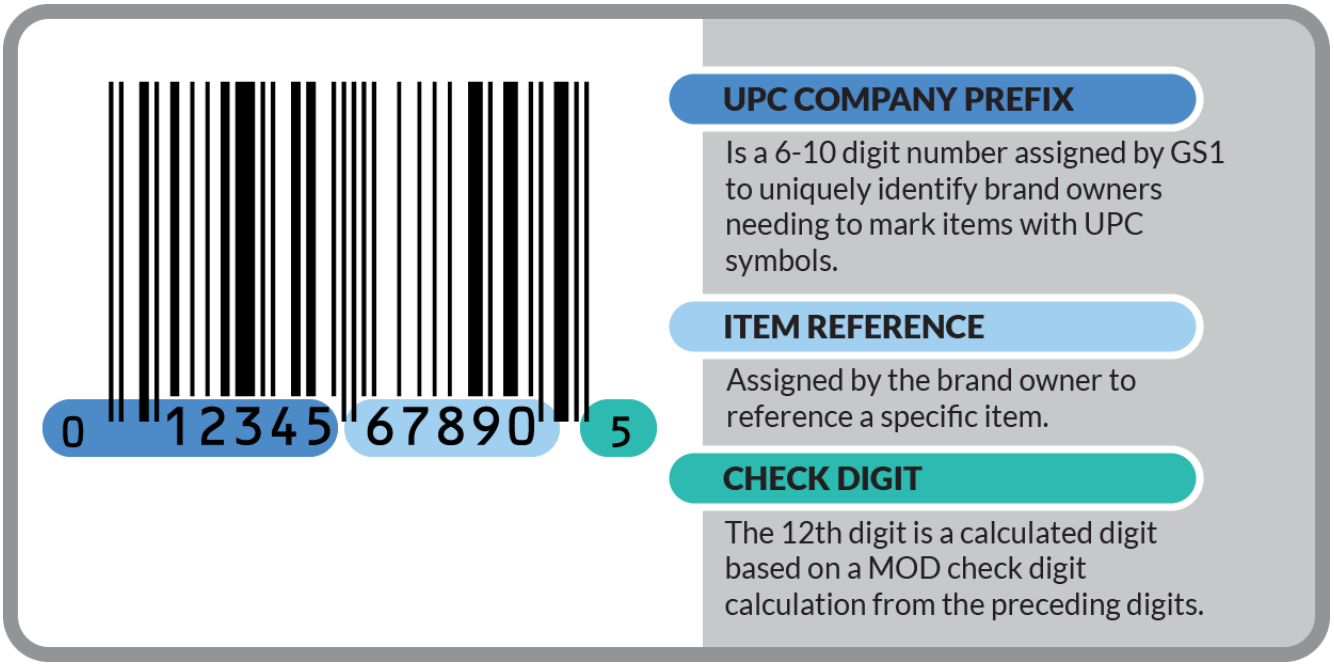


**Table IA1:** Robustness for Table 2: Donations and Sales (Yearly Regressions)

This table reports the ordinary least squares (OLS) regression results examining the relationship between annual charitable donations and annual sales. The dependent variable, $\ln(Sales_{i,s,y,m}/AT_{i,y-1})$, is the natural logarithm of firm $i$'s sales revenue in state $s$–year $y$–product module $m$, scaled by the firm's total assets at the end of the fiscal year preceding year $y$ (i.e., $y-1$). The independent variable, $\ln(1+Donation_{i,s,y}/AT_{i,y-1})$, is the natural logarithm of one plus firm $i$'s annual donations to state $s$ in year $y$, scaled by total assets at the end of year $y-1$. Columns (1)–(4) differ in their inclusion of fixed effects (FE), as indicated in the table. The sample consists of 631,459 firm–state–year–module observations from 2006 to 2020. All continuous variables are winsorized at the 1% and 99% levels. $t$-statistics are reported below coefficients in parentheses, and standard errors are two-way clustered by firm and year. $^{***}$, $^{**}$, and $^{*}$ denote statistical significance at the 1%, 5%, and 10% levels, respectively.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dependent variable | | $\ln(\text{Sales}_{i,s,y,m}/\text{AT}_{i,y-1})$ | | |
| $\ln(1+Donation_{i,s,y}/AT_{i,y-1})$ | 0.0506** | 0.0633** | 0.0033 | 0.0064 |
| | (2.21) | (2.20) | (0.44) | (0.79) |
| Firm × State FE | No | No | Yes | Yes |
| Firm × Group × Year FE | Yes | No | Yes | No |
| State × Group × Year FE | Yes | No | Yes | No |
| Firm × Module × Year FE | No | Yes | No | Yes |
| State × Module × Year FE | No | Yes | No | Yes |
| N (observations used) | 590,969 | 398,483 | 590,933 | 398,418 |
| $R^2$ | 0.650 | 0.945 | 0.656 | 0.953 |

**Table IA2:** Robustness for Table 9: Geographic Dispersion (Firm–Group–Quarter Level)

This table reports the OLS regression results examining how the seasonal effect of annual charitable donations on quarterly sales varies with firms' geographic dispersion. The dependent variable, $\ln(Sales_{i,s,q,m}/AT_{i,y-1})$, is the natural logarithm of firm $i$'s sales revenue in state $s$–calendar quarter $q$–product module $m$, scaled by the firm's total assets at the end of the fiscal year preceding the year to which quarter $q$ belongs (i.e., $y-1$). The independent variables include: $\ln(1 + Donation_{i,s,y}/AT_{i,y-1})$, the natural logarithm of one plus firm $i$'s annual donations to state $s$ in year $y$, scaled by total assets at the end of year $y-1$; $Q_k$, for $k = 2, \ldots, 4$, indicator variables for the second through fourth calendar quarters; and the interaction terms between the two. The inclusion of fixed effects (FE) is as indicated in the table; "Quarter" denotes year-calendar quarter fixed effects. Columns (1) and (2) report results for observations with below- and above-sample-median geographic dispersion, respectively. We measure geographic dispersion as the number of states ($n_states$) in which a firm operates at the firm–group–quarter level. The "coefficient difference" line reports the differences in the Q4 coefficients between the below- and above-sample-median groups and the two-sided $t$-statistic for testing the differences. The sample consists of firm–state–quarter–module observations from 2006 to 2020. All continuous variables are winsorized at the 1% and 99% levels. $t$-statistics are reported below coefficients in parentheses, and standard errors are two-way clustered by firm and year-calendar quarter. $^{***}$, $^{**}$, and $^{*}$ denote statistical significance at the 1%, 5%, and 10% levels, respectively.

| | (1) | (2) |
|---|---|---|
| Dependent variable | $\ln(Sales_{i,s,q,m}/AT_{i,y-1})$ | |
| | Below median $n_states$ | Above median $n_states$ |
| $\ln(1 + Donation_{i,s,y}/AT_{i,y-1})$ | -0.0003 | -0.0017 |
| | (0.04) | (0.28) |
| $Q2 \times \ln(1 + Donation_{i,s,y}/AT_{i,y-1})$ | 0.0073 | 0.0008 |
| | (0.64) | (0.25) |
| $Q3 \times \ln(1 + Donation_{i,s,y}/AT_{i,y-1})$ | 0.0075 | 0.0017 |
| | (0.64) | (0.37) |
| $Q4 \times \ln(1 + Donation_{i,s,y}/AT_{i,y-1})$ | 0.0302** | -0.0003 |
| | (2.61) | (0.08) |
| Coef. Diff. ($Q4$ Interaction) | 0.0305*** | |
| | (3.04) | |
| Firm × State FE | Yes | Yes |
| Firm × Quarter × Module FE | Yes | Yes |
| State × Quarter × Module FE | Yes | Yes |
| N (observations used) | 360,132 | 403,086 |
| $R^2$ | 0.964 | 0.936 |