Earnings Management via Product Information: Evidence from Solicited Amazon Reviews

Shawn X. Huang*
Arizona State University
shawn.huang@asu.edu

Wenting Zheng
Arizona State University
w.zheng@asu.edu

Yuqing Zhou
The Chinese University of Hong Kong
yuqingzhou@cuhk.edu.hk

Abstract: This study examines whether firms use online product reviews to manage product information and meet earnings targets. Using a unique dataset on review solicitation activities and a machine learning approach, we develop a novel measure to identify products associated with solicited reviews on Amazon.com. We find that firms under pressure of meeting analyst earnings forecasts engage in more review solicitation, particularly during the fourth quarter. We also provide direct evidence that solicited reviews increase product sales. Further cross-sectional analyses reveal that firms with stronger operating performance and broader product portfolios engage less in review solicitation, whereas financially distressed firms and those facing greater credit pressure from suppliers are more likely to do so. Additionally, we find that firms tend to solicit reviews for products with lower visibility, greater competition, and higher prices. Overall, our study documents a previously underexplored channel of earnings management through review solicitation.

Keywords: Product Information, Solicited Product Reviews, Amazon Reviews, Analyst Earnings Forecasts, Earnings Management

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"When you're in a brick-and-mortar store, you can see the inventory. If it's a couch, you can sit on it. If it's a TV, you can watch it. But when you're shopping online, it's much harder to know what you're actually buying. That's why reviews are so crucial. If 500 other people have bought something and say it works, you can have a lot more confidence. But what if those people were paid to leave those positive reviews?…"

– Lina M. Khan, chair, Federal Trade Commission, 2022

1. Introduction

Over the past several decades, accounting research has extensively examined earnings manipulation as a strategy through which firms achieve various objectives. Central to this literature is the notion that accounting numbers are widely used by stakeholders to assess firms' and managers' performance in both informal and formal contracts (Watts and Zimmerman, 1986; Holthausen and Watts, 2001; Graham, Harvey, and Rajgopal 2005). As a result, managers have strong incentives to manage earnings to align reported performance with desired targets, whether to meet analysts' forecasts, influence stock prices prior to important corporate events, or meet contractual obligations (Erickson and Wang, 1999; Brown and Caylor, 2005; Dichev and Skinner, 2002; Louis, 2004; Franz, Hassabelnaby and Lobo, 2014). To date, most research has focused on the manipulation of financial information (e.g., accruals) and real operating activities. In this study, we explore a different channel: whether firms manage product information to achieve earnings targets. Specifically, we investigate whether firms at risk of missing analyst earnings forecasts solicit product reviews to boost product sales and reported earnings.[1]

This issue is particularly important in the online retail environment. The rapid growth of e-commerce has increased firms' reliance on online sales. According to the U.S. Census Quarterly Retail E-Commerce Sales Report, e-commerce accounted for 16.3 percent of total U.S. retail sales

[1] In this study, we use the term "product reviews" to refer specifically to consumer-generated reviews posted on online platforms (e.g., Amazon.com), which constitute the primary form of publicly observable review content in modern retail settings. Offline product reviews (such as face-to-face word-of-mouth or in-store comments) are outside the scope of our analysis, in part due to their private nature.

in the second quarter of 2025. In online markets, however, consumers often face greater uncertainty about product quality and reliability, which can deter them from making purchases (Pocchiari, Proserpio, and Dover 2025). Product information that helps resolve such uncertainty will increase consumer confidence and improve sales. Therefore, online consumer reviews have become a central component of product information. Star ratings and textual reviews communicate buyers' ex post experiences with a product or seller, reducing search costs and mitigating adverse selection for prospective buyers (Dellarocas 2003). Consistent with this informational role, Chevalier and Mayzlin (2006) show that more favorable reviews are associated with higher product sales. It is worth noting that the influence of online product reviews is not limited to online transactions, as many consumers consult online reviews even when they intend to buy in physical stores. For example, Bazaarvoice (2018) reports that 45% of brick-and-mortar sales begin with an online review and that 62% of shoppers use their phones to look up reviews before making in-store purchases.[2]

Nonetheless, only about 1.5% to 18.6% of consumers (mostly on the lower end of this range) write a review after making a purchase (Anderson and Simester, 2014; Brandes and Dover, 2022; Brandes et al., 2022; Weise, 2017; Zhou, 2024). Moreover, reviews are disproportionately written by consumers with extreme experiences, potentially distorting the overall product information environment (Brandes et al. 2022). Given the impact of reviews on sales, firms have strong incentives to shape the review-generation process, particularly by actively soliciting reviews from customers (Floyd et al. 2014). In doing so, firms can control who participates and what type of information is provided (Dellarocas 2003). Prior research shows that unincentivized review solicitation, such as reminder emails, increases review volume (Karaman 2021), and more

[2] Similarly, in a U.S. survey, Pew Research Center (2016) reports that 45% of Americans have used their phone inside a physical store to look up online reviews, and that among those aged 18 to 49 this share rises to 62%.

importantly that review solicitation accompanied by financial incentives (i.e., free products, monetary payments or gift cards) is even more effective (Burtch et al. 2018).

Not surprisingly, financially incentivized review solicitation has become a pervasive feature of the online review ecosystem.[3] Using Amazon review data from September 2016, Park, Shin and Xie (2023) document that, out of 654,463 Amazon reviews, 241,831 (approximately 37 percent) are solicited reviews with financial incentives. Figure 1 provides an example of disclosed solicited reviews for a public company's product. Although financial incentives are effective in increasing review volume (Sun et al. 2017; Burtch et al. 2018), recent research shows that such incentives can inflate review ratings as well (Mayzlin et al. 2014; Qiao et al. 2020), thereby biasing online product reviews. Park et al. (2023) show that incentivized reviews are, on average, roughly half a star higher than comparable verified-purchase reviews. Qiao and Rui (2023) further find that platform-initiated incentivized reviews, such as Amazon's Vine program, also exhibit upwardly biased ratings.[4] More importantly, marketing research indicates that financially incentivized review solicitation is an economically viable strategy for increasing product demand (Babić Rosario et al. 2016; Burtch et al. 2018). Park et al. (2023) find that the presence of incentivized reviews increases product sales by about 9%. Together, these studies suggest that financially incentivized review solicitation is economically meaningful and capable of shifting both review ratings and realized sales.

While such effects make review solicitation an attractive tool for boosting sales,[5] it is not without cost. Inflated reviews can raise consumers' expectations above true product quality. When

[3] In this study, we focus on reviews that are both solicited and financially incentivized. For ease of exposition, we refer to these as "solicited reviews" and use the terms "solicited reviews" and "incentivized reviews" interchangeably.
[4] Amazon Vine reviews are product reviews written by trusted Amazon customers ("Vine Voices") who receive free products (provided/sponsored by firms) in exchange for their honest feedback, marked with a "Vine Customer Review of Free Product" badge for transparency.
[5] He et al. (2022) document that the impact of solicited reviews is most pronounced within the first two weeks following solicitation, during which products experience an average 16% improvement in sales ranks.

actual experiences fall short, dissatisfied consumers who feel misled by solicited reviews may leave negative feedback, damaging long-term reputation and repeat business. Park et al. (2023) show that products with incentivized reviews subsequently receive more poor product reviews (e.g., one-star reviews) from verified purchasers than comparable products without such reviews. In more extreme cases, where review solicitation crosses the line into deception or fraud, firms also face regulatory and legal risk. For example, in 2020, the Federal Trade Commission (FTC) fined Sunday Riley Modern Skincare, LLC, for requesting employees to post reviews on a major retailer's website, which resulted in not only legal costs but also widespread negative media attention. Therefore, these potential long-term costs may deter some firms from fully exploiting solicited reviews, making it an open empirical question when and to what extent public firms use review solicitation as a tool to manage earnings.

In this study, we focus on the setting in which firms facing pressure to meet analyst earnings forecasts, as prior research documents that there are significant adverse consequences when a firm's reported earnings fall short of analyst expectations, which provide managers with strong incentives to manage earnings and make the short-term benefits of boosting sales are especially valuable (Graham et al., 2005).[6] Firms may manage product reviews on many online platforms, but we choose Amazon.com because it is the largest digital market place with the most product reviews available. We utilize the Amazon product review data, such as review texts, ratings, and posting dates, to construct review features. Then, we employ a feature-based machine learning approach, which uses a manually collected ground truth dataset from He et al. (2022) and a Random Forest model to identify products involved in solicited reviews on Amazon.com.

[6] The adverse effects include negative stock price reactions (Skinner and Sloan, 2002), lower management credibility, higher litigation risks (Bartov, Givoly, and Hayn 2002), lower CEO compensation (Matsunaga and Park, 2001), and a higher probability of forced management turnover (Mergenthaler, Rajgopal, and Srinivasan 2012).

Consistent with our prediction, we find that firms under pressure to meet analyst earnings forecasts solicit more product reviews than other firms. The effect is economically significant as well. For example, the percentage of products with solicited reviews is 4.2% higher for firms just meeting analyst forecasts compared to those without the pressure of meeting forecasts, representing an 8.0 % increase relative to the sample mean. We also find that firms increase review solicitation in the fourth quarter (even after we exclude firm-years where the fiscal year end is in December). This result is consistent with prior findings that consumers may give poor ratings after they feel misled by solicited reviews. If firms solicit reviews in early quarters, the resulting lower ratings from organic reviews would defeat the purpose of review solicitation. Therefore, firms tend to manipulate reviews in the quarter closest to earnings announcements. Furthermore, we provide direct evidence that solicited reviews effectively boost product sales, confirming the mechanism through which review solicitation can help managers meet analyst earnings expectations. Consistent with this mechanism, we also document that firms facing greater pressure to meet analysts' *sales* forecasts engage in more review solicitation, reinforcing the view that solicited reviews are a strategic tool for driving sales.

We further explore the scenarios in which the relationship between meeting analyst earnings targets and review solicitation is amplified or muted. We find that larger firms engage in less review solicitation, possibly due to reputation concerns. Moreover, firms with higher profits (*ROA*) are less likely to resort to review solicitation to meet earnings targets, as they are already achieving favorable performance targets. In contrast, firms under credit pressure from suppliers may need strong sales to ease suppliers' concerns and thus are more prone to review solicitation. Additionally, firms with better financial health exhibit low levels of review solicitation, possibly because the market often perceives these firms as more stable and reliable, and this positive market perception decreases the scrutiny on short-term earnings fluctuations. Finally, firms with broader product portfolios engage in less review solicitation, suggesting that sales diversification reduces reliance on any single product and that the costs of soliciting reviews across multiple product lines make such activities less feasible.

We conduct additional analyses to further investigate the types of products that are more susceptible to review solicitation. Our findings indicate that firms are more likely to manage reviews for newer products and products with fewer existing reviews, where solicited reviews are likely to have a greater impact on consumer perception compared to products with longer track records. We also find that solicited reviews are more concentrated among expensive products, as the marginal impact of solicited reviews on sales is more pronounced among these goods. Lastly, we find that products in more concentrated markets are less likely to be involved in review solicitation, possibly because they face fewer competitive threats or have already established market dominance, which mitigates their reliance on review solicitation to influence consumer perception.

Finally, we conduct two robustness checks. First, we expand the threshold for firms narrowly meeting analyst forecasts from one cent to two cents and five cents. The results are qualitatively similar, indicating that our findings are not driven by a specific threshold. Second, we apply alternative machine learning classification algorithms (Logistic Regression and Support Vector Machine) to identify solicited reviews and continue to find that firms at risk of missing analyst earnings forecasts engage in more review solicitation.

This study makes two important contributions to the literature. First, we contribute to the accounting literature by introducing a new way to align earnings with strategic targets, namely product information management. Traditionally, accounting studies have focused on accrual-based earnings management, in which managers directly manipulate accounting numbers to meet earnings targets (Healy, 1985; Guidry et al., 1999; Defond and Jiambalvo, 1994; Teoh et al., 1998a; Teoh et al., 1998b; Kasznik, 1999). Since the enactment of the Sarbanes-Oxley Act (SOX, 2002), with the increased scrutiny of accruals management, the focus has been shifted to real earnings management, in which firms manipulate their real operating activities to achieve earnings targets (Roychowdhury, 2006; Cohen et al., 2008; Cohen and Zarowin, 2010; Choi et al., 2018). Our study departs from extant research by presenting new evidence that firms can solicit product reviews to improve sales and meet analyst earnings forecasts. We provide novel insights into earnings management facilitated by product information management. This contribution is particularly important given the rapid growth of the digital economy, which underscores the need to understand firms' behaviors in digital environments.

Second, our study contributes to the growing research on product information management. Prior literature in economics and marketing primarily focuses on the immediate outcomes of solicited reviews in product markets, such as increased firm sales and deteriorated consumer welfare (Dellarocas, 2006; Mayzlin et al., 2014; Park et al., 2023). Our study provides evidence that the reach of solicited reviews extends well beyond product markets. These solicited reviews can facilitate firms' ability to meet analyst earnings benchmarks, affecting capital-market performance metrics used by investors. Our findings should be of particular interest to investors and regulators and call for greater scrutiny of solicited reviews.

The rest of this paper proceeds as follows: Section 2 reviews the relevant literature on earnings management and review manipulation. Section 3 describes the data and presents the summary statistics. Section 4 provides the research design and main results. Section 5 presents the cross-sectional results based on firm-level and product-level characteristics. Section 6 reports robustness tests. Finally, Section 7 concludes the paper with a summary of key insights and suggestions for future research.

2. Literature Review and Hypothesis Development

2.1. Managerial Incentives to Engage in Earnings Management to Meet Earnings Targets

Public firms face significant pressure to meet earnings benchmarks, such as analysts' forecasts, prior-year earnings, management forecasts, and non-negative earnings. These benchmarks are critical because they directly affect stock prices, investor confidence, and market perceptions of firm performance and managerial abilities (Graham et al., 2005; Roychowdhury, 2006; Cohen et al., 2008; Cohen et al., 2010; Gunny, 2010; Zang, 2012; Ertan, 2022). Graham et al. (2005) provide survey evidence that chief financial officers (CFOs) consider earnings as the most important financial metric for external stakeholders. As a result, managers often prioritize short-term earnings over long-term value creation and are willing to make economic sacrifices to avoid missing these critical earnings targets.

This pressure is amplified during major corporate events (e.g., seasoned equity offerings), when firms seek to present strong financial performance to facilitate successful completion of these transactions (Cohen and Zarowin, 2010). To meet earnings benchmarks, managers can engage in accrual management or activities that temporarily improve earnings. For example, Ertan (2022) documents that publicly traded banks that narrowly meet or beat earnings benchmarks tend to increase syndicated loan initiation in the last month of the fiscal quarter to polish their financial standing.

2.2. Accrual and Real Earnings Management in Meeting Earnings Targets

Healy and Wahlen (1999, page 368) define earnings management as occurring "when managers use judgment in financial reporting and in structuring transactions to alter financial reports to either mislead some stakeholders about the underlying economic performance of the company, or to influence contractual outcomes that depend on reported accounting numbers." That is, earnings management is typically categorized into accrual-based and real earnings management.

Accrual earnings management involves adjusting accruals to influence reported financial outcomes, such as altering revenue or expense accruals or changing accounting estimates or methods (Badertscher, 2011; Zang, 2012). Prior research shows that firms engage in accrual-based earnings management to meet or exceed analysts' earnings forecasts (Degeorge, Patel, and Zeckhauser 1997; Payne and Robb, 2000). This behavior is largely motivated by the asymmetric payoff associated with meeting versus missing these forecasts. For example, Skinner and Sloan (2002) find that the market penalty for failing to meet analyst earnings expectations is significantly greater than the reward of meeting them. Additionally, managerial equity compensation incentives can further amplify this pressure (Myers et al., 2007). With respect to other earnings targets, prior studies have investigated how firms engage in accruals management around major corporate transactions. Rangan (1998) and Teoh et al. (1998b) show that firms tend to manage earnings upward through positive abnormal accruals to inflate stock prices prior to seasoned equity offerings (SEOs). Similarly, Erickson and Wang (1999) and Louis (2004) find that acquirers inflate accruals prior to merger and acquisition (M&A) announcements to temporarily boost share prices, especially in stock-for-stock mergers, thereby reducing their cost of acquiring target firms.

Following the enactment of the 2002 Sarbanes-Oxley Act (SOX), which aimed to curb corporate financial misconduct and restore financial reporting integrity, real earnings management came to light and drew increased attention in academia (Graham et al., 2005; Cohen et al., 2008;

Cohen and Zarowin, 2010). Unlike accruals manipulation, real earnings management involves altering actual operating activities. Roychowdhury (2006, page 337) describes this practice as "departures from normal operational practices, motivated by managers' desire to mislead at least some stakeholders into believing that certain financial reporting goals have been met in the normal course of operations." In general, real earnings management does not violate Generally Accepted Accounting Principles (GAAP), making it less likely to be scrutinized by external monitors and carrying lower legal risk compared to accruals management (Cohen et al., 2008; Choi et al., 2018). This lower level of scrutiny further makes real earnings management a more attractive option for firms facing higher litigation risk, especially when they are involved in significant corporate events that are subject to regulatory oversight (Zang, 2012). Consistent with this substitution view, Cohen et al. (2008) show that firms rely more heavily on real earnings management after SOX, particularly when meeting important earnings benchmarks. Cohen and Zarowin (2010) further find that real activities manipulation contributes more to post-SEO performance declines than accrual-based management.

2.3 Solicited Product Reviews

As digital marketplaces have become more popular, firms are increasingly relying on user-generated online sentiment to drive sales. Among various forms of user-generated content, online product reviews have emerged as one of the most important ways to shape consumer sentiment, because they are highly visible at the point of purchase. The importance of online reviews is underscored in Nielsen's 2013 Global Trust in Advertising report, which reveals that 70 percent of customers worldwide (28,000 survey respondents in 56 countries) trust online reviews, ranking them second only to word-of-mouth from family and friends. Yet, consumer participation in review writing is limited. To address this challenge, many firms have begun to incentivize consumers to write reviews (sometimes explicitly encouraging positive reviews) by offering rewards such as coupons, discounts, gifts, free products, or monetary payments, often without full disclosure (Murphy, 2020).

Focusing on these incentivized reviews, Burtch, Hong, Bapna, and Griskevicius (2018) show that financial incentives are more effective than simple requests in generating new reviews. However, Khern-am-nuai, Kannan, and Ghasemkhani (2018) find that such incentives can lead to more positive but lower-quality reviews, adversely affecting review usefulness. Similarly, Woolley and Sharif (2021) document that incentivized reviews contain more positive emotional content than unincentivized reviews, arguing that incentives make the writing process more enjoyable for consumers. To further explain positive bias in incentivized reviews, Garnefeld et al. (2020) offer a reciprocity argument: reviewers may feel obliged to "pay back" the firm and therefore exaggerate their ratings upward. Extending beyond individual reviews, Park, Aziz, and Lee (2022) argue and find spillover effects, whereby incentivized reviews act as biased public signals that subsequent reviewers herd on, inflating average ratings. Consistent with these findings, Park, Shin, and Xie (2023) document substantial rating inflation in incentivized reviews and show that the presence of such reviews increases short-run product sales. Taken together, this literature suggests that solicited reviews frequently involve financial incentives, which systematically bias product information and hence increase product sales.

From an accounting perspective, solicited reviews represent a form of strategic information management analogous to accrual earnings management: rather than altering accounting numbers, managers seek to influence non-financial, product-related information that affects customers' purchase decisions. However, solicited reviews are not cost-free. Firms incur expenses for soliciting these reviews, which could otherwise be allocated to advertising or promotions, representing a departure from normal operational practices. In this respect, review solicitation also bears some characteristics of real earnings management. It is worth noting that like other earnings management strategies, engaging in review solicitation does not require direct involvement by top executives such as CEOs or CFOs. Prior research emphasizes that senior executives set performance targets and establish the "tone at the top," while operational decisions are often executed by lower-level managers. When firms face pressure to meet earnings benchmarks, this pressure can cascade through the organization, shaping incentives at multiple levels.

Given the effectiveness of solicited reviews in shaping consumer perceptions and product sales, we posit that firms under pressure to meet analysts' forecasts may have incentives to engage in review solicitation to boost sales and earnings. The preceding arguments form the basis for our hypothesis, stated in the alternative form:

H1: Ceteris paribus, firms that are under risk of missing analyst earnings forecasts engage in more review solicitations than other firms.

3. Data, Variable Construction, and Summary Statistics

3.1 Amazon Data

To identify products involved in solicited reviews, we use a dataset collected by McAuley Lab, which contains around 500 million reviews on Amazon.com from 2000 to 2021 (Hou et al., 2024). This dataset provides comprehensive coverage of user reviews (including ratings, text, and review dates) as well as item metadata such as product descriptions, prices, and images across 38 different product categories.

Following the matching procedure of Zeng and Zhou (2025), we link Amazon products to public firms. We first standardize brand and company names and then match product brand names from the Amazon dataset to trademarks registered with the United States Patent and Trademark

Office. Using the CorpWatch dataset, we identify companies owning these trademarks and match them to Compustat firms. Figure 2 provides an example on the matching process. To ensure accuracy, we only keep exact matches and exclude cases where a brand is matched to multiple companies, as it is unclear which company owns the brand.[7] After further excluding observations with missing financial or control variable data, our final sample consists of 3,926 firm-year observations during the period 2000-2021. Table 1 Panel A provides the sample selection procedure.

3.2. Data on Review Solicitation Activities

We obtain data on review solicitation activities from He et al. (2022), who manually collect postings from private Facebook groups in which sellers offer financial incentives (e.g., Amazon gift cards) in exchange for product reviews. Specifically, He et al. (2022) track the 30 largest and most active product review-related Facebook groups, each averaging about 16,000 members. The authors joined these groups and collected review solicitation postings on a weekly basis from October 2019 to June 2020. Their final sample includes approximately 1,500 unique products involved in these review requests.[8] For each product, they identified two competing products that were not involved in review solicitation and appeared most frequently in Amazon search results within 7 days before and after the initial Facebook posting. This procedure yields 2,714 unique

[7] To further ensure that the identified Amazon products are directly associated with the matched public firms rather than independent third-party marketplace sellers, we compare the store name and brand name for each product. We observe a 97.83% consistency between store and brand names in our final matched sample. This high degree of consistency suggests that the reviews we analyze are primarily linked to the brand-owning firm, thereby mitigating concerns that our results are driven by unrelated third-party sellers. The remaining 2.17% of cases do not necessarily indicate the absence of brand ownership. In practice, brand-owning firms may operate storefronts under names that differ from the registered brand name, particularly when managing multiple brands, which can generate apparent discrepancies in the store–brand name matching.

[8] It is important to note that He et al. (2022) identify only products associated with review solicitation postings and do not observe which specific reviews were subsequently posted by incentivized reviewers.

competitor products, which serve as a control sample. Together, these products form a ground-truth dataset used to train and validate our review-solicitation detection model.

3.3 Detecting Products with Solicited Reviews

To identify products involved in solicited reviews, we begin by constructing review features likely associated with review solicitation.[9] Prior research suggests that signs of firms soliciting reviews often include: (1) a surge of reviews within a short time period, (2) consistently favorable ratings, (3) similar language across reviews, and (4) photos accompanying reviews (He et al., 2022). To capture these signals, we extract a comprehensive set of review features from the Amazon review dataset. The first category of features captures temporal patterns of reviews, measured using the total number of reviews and the average, minimum, maximum, and standard deviation of the time intervals (in days) between them. The second category focuses on favorable ratings, incorporating features like average review ratings, the proportion of reviews with helpful votes, the proportion of one-star reviews, and the proportion of five-star reviews. The third category captures content similarity, measured by the average text similarity between reviews (TF-IDF similarity) and variation in review length.[10] The final feature involves the presence of photos in reviews.

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[9] The detection methodology employed in this study focuses on identifying review solicitation at the product level, rather than at the individual review level. For example, the feature capturing the time intervals between reviews is aggregated across all reviews for a product within a given period to identify abnormal patterns. Products exhibiting unusually consistent or irregular review timing may reflect potential review manipulation.

[10] TF-IDF (Term Frequency-Inverse Document Frequency) is a statistical measure that evaluates the importance of a word in a document compared to a collection of documents. It is computed as the product of term frequency (TF) and inverse document frequency (IDF). TF calculates how frequently a term t appears in a document d, normalized by the document length. IDF quantifies how rare the term is across a collection of documents D, with common terms (e.g., “the” or “and”) receiving lower weights. To compute the text similarity between reviews, we transform a product’s reviews in a given fiscal year into TF-IDF weighted word vectors. Then, we calculate cosine similarity for each review pair and take the average similarity across all review pairs. If a product has only one review or no reviews, the similarity is set to 0 since pairwise similarity cannot be calculated.

Using these review features/patterns, we train three supervised machine learning models on 80% of the ground truth dataset to classify products as being associated with solicited reviews or not. We then evaluate these models' performance on the remaining 20% of the dataset. The three machine learning models are Random Forest, Logistic Regression, and Support Vector Machine (SVM), which are widely used in prior literature. Among the three models, the Random Forest model demonstrates the best performance. Next, we apply the trained Random Forest model to identify products with solicited reviews in the Amazon dataset for each sample year. Appendix A provides detailed procedures of detecting products with solicited reviews and performance comparisons among the three machine learning models.

It is important to note that our machine learning approach does not rely on how sellers recruit reviewers (e.g., emails, Facebook postings, or public relations firms).[11] Instead, the algorithm identifies abnormal review patterns that emerge once review solicitation occurs. To the extent that financially incentivized reviews, regardless of the initiating party, generate similar statistical footprints in timing, rating distributions, textual similarity, or photo usage, the trained classifier remains effective in detecting review solicitation.

This product-level detection approach also allows us to capture solicited reviews more comprehensively than detection approaches that rely solely on textual analysis at the individual-review level. This is because review writers rarely disclose whether their reviews are solicited, and as a result, ground truth data at the individual-review level is generally unavailable. This lack of verified solicited reviews makes it challenging not only to train reliable machine learning models but also to evaluate their accuracy and effectiveness.

[11] Public firms may use third-party marketing or public relations firms to coordinate review solicitation. Similar outsourcing arrangements have been documented in other settings. For example, Kogan et al. (2023) document instances in which firms used public relations firms to hire external writers to publish fake financial news articles on Seeking Alpha.

After identifying products with solicited reviews, we compute the proportion of a firm's products having solicited reviews in a given year, *Solicited_Ratio*, which is calculated as follow:

$$Solicited\_Ratio_{i,t} = \frac{Number\ of\ Products\ with\ Solicited\ Reviews_{i,t}}{Total\ number\ of\ Products_{i,t}}$$

3.4 Firms under Pressure to Meet Analyst Earnings Forecasts

Graham et al. (2005) note that managers treat analyst earnings forecasts as one of the most important earnings benchmarks. Following Roychowdhury (2006), Zang (2012), and Cheng et al. (2016), we identify suspect firm-years as those in which managers are likely under pressure to manipulate earnings to meet analyst forecasts. Specifically, these are firm-years where the actual Earnings Per Share (EPS) equals or just exceeds the median forecasted EPS by one cent. We expect suspect firms-years to be positively associated with our solicited review measure.

3.5 Other Financial Data

Actual Earnings Per Share (EPS) and analyst earnings forecasts are obtained from the IBES database, while firm-level financial information is collected from Compustat. Institutional ownership is extracted from Thomson/Refinitiv 13F filings, and firm credit ratings are retrieved from Capital IQ S&P Ratings.

3.6 Summary Statistics

Table 1, Panel B presents summary statistics comparing key variables between the suspect and non-suspect samples. The suspect sample consists of 418 firm-years, while the non-suspect sample includes 3,508 firm-years. For each variable, we report the mean, median, and standard deviation, as well as the differences between the two groups. *Solicited_Ratio* is higher in the suspect sample, with a mean of 0.582, compared to 0.521 in the non-suspect sample. The difference of 0.061 is both statistically and economically significant, representing approximately a 12% increase relative to the non-suspect sample. Although the level of *Solicited_Ratio* appears relatively high, it is important to note that our classification operates at the product level rather than the individual-review level. A product is coded as associated with review solicitation if it exhibits abnormal review patterns consistent with incentivized review activity, even when only a subset of its reviews are solicited. As a result, this measure captures the prevalence of products exposed to solicitation practices, rather than the share of reviews that are directly incentivized. Our finding is consistent with prior evidence suggesting that incentivized review solicitation is widespread. For context, Park et al. (2023) document that approximately 37 percent of Amazon reviews in September 2016 were incentivized reviews, indicating that financially incentivized review solicitation is not uncommon and may span a broad set of products.

Regarding the control variables, suspect firms are larger, have higher growth opportunities, and are more profitable than non-suspect firms. Additionally, advertising expenses (*AD*) are significantly higher for suspect firms, suggesting that these firms adopt a more aggressive marketing approach. The differences in other control variables between the two groups are statistically insignificant, indicating that suspect and non-suspect firms have similar levels of financial leverage, discretionary spending, and product variety.

Table 1, Panel C presents a correlation matrix for the key variables. It is worth noting that *Solicited_Ratio* is positively correlated with *Suspect* ($p <= 0.01$), providing univariate evidence that firms under pressure to meet analyst forecasts engage in more review solicitation.

4. Main Results

4.1 Research Design

We employ the following regression model to test our hypothesis that firms at risk of missing analyst earnings forecasts solicit more reviews than other firms:

$$Solicited\_Ratio_{\,i,t} = \beta_1 Suspect_{i,t} + \sum \gamma\, Control_{i,t} + FirmFE + YearFE + \varepsilon_{i,t}$$

where $Solicited\_Ratio_{\,i,t}$ is the dependent variable measuring the extent to which firms engage in review solicitation for their amazon products. *Suspect* identifies firm-years during which firms just meet or beat analyst earnings forecasts by one cent. Firm and year fixed effects are included to control for unobserved firm-level characteristics and time-specific factors. We also cluster standard errors at the firm level.

Following prior research, we construct a set of control variables to account for factors that may influence a firm's decision to manage earnings. These controls include firm size, the presence of long-term debt during the year, the market-to-book ratio, and return on assets (ROA) (Healy and Wahlen, 1999; Fields et al., 2001; Roychowdhury, 2006). Additionally, we control for institutional ownership, selling, general, and administrative expenses (*SG&A*), advertising expenses, and the number of products listed by a given firm on Amazon. Appendix C provides the detailed definitions of these variables.

Larger firms may have more resources to engage in review solicitation but also face greater scrutiny. Thus, we do not make a directional prediction on the effect of firm size. Firms with long-term debt may have greater incentives to solicit product reviews to improve earnings, avoiding covenant violations or lowering borrowing costs (Zang, 2012; Cheng et al., 2016). Growth firms, proxied by high market to book ratios, may have greater incentives to manipulate product reviews, as their stock prices are more sensitive to negative earnings surprises (Skinner and Sloan, 2002). Conversely, firms with higher ROA may not have pressure to engage in such practices to meet analyst earnings forecasts (Cohen and Zarowin, 2010). Cohen and Zarowin (2010) also find that institutional investors tend to focus on long-term performance, indicating that they may not pressure managers to meet short-term performance targets set by analysts. To a large extent, greater

SG&A and advertising expenses can signal firms' effort to promote their products through normal marketing channels (Roychowdhury 2006), which can potentially mitigate the need for soliciting product reviews to improve sales. Lastly, on one hand, firms with more products on Amazon may have greater opportunities to manipulate product reviews. On the other hand, because their sales are diversified and not dependent on any single product, these firms would need to manipulate reviews across all their product lines to meaningfully boost overall sales, which can be costly and deter them from engaging in such review practices.

4.2 Main Results

Table 2 presents the main regression results. In Column (1), we do not include any fixed effects and find that the coefficient on *Suspect* is significantly positive, consistent with our univariate evidence (0.059, $P < 0.01$). In Column (2), after including the firm and year fixed effects, we continue to find the coefficient on *Suspect* to be significantly positive (0.042, $P < 0.01$). This result suggests that the percentage of products with solicited reviews is 4.2% higher for firms just meeting analyst forecasts compared to other firms, representing an 8.0 % increase relative to the sample mean. Regarding the control variables, *SGA* is negatively associated with *Solicited_Ratio*, suggesting that firms focus on normal marketing channels may be less inclined to manage product reviews. Other control variables, such as firm size (*SIZE*), *HasDebt*, *MTB*, and *ROA*, do not show significant associations with *Solicited_Ratio*, indicating that these factors may not be primary drivers of review solicitation. Overall, our findings are consistent with the hypothesis that firms under earnings management pressure may strategically manage product information through review solicitation to achieve their performance objectives.

4.3 Quarterly Pattern

To further explore the timing of review solicitation, we apply the same machine learning model used in the firm-year level analysis to firm-quarters. The results, presented in Table 3, reveal an interesting quarterly pattern in review solicitation. The coefficient on *Suspect* is positive but not statistically significant in the first three quarters (Q1–Q3). In contrast, Column (4) shows that in the fourth fiscal quarter, when earnings pressure is most acute, the coefficient on *Suspect* is significantly positive (0.027, $p = 0.05$). To address concerns that this fourth-quarter effect merely reflects seasonal demand during the holiday shopping period, we exclude firms with December fiscal year-ends. As shown in Column (5) of Table 3, the coefficient on *Suspect* remains statistically significant in the fourth fiscal quarter and increases in magnitude (0.047, $p = 0.05$), indicating that the effect is unlikely to be driven solely by holiday seasonality.

This quarterly pattern is consistent with evidence that solicited reviews can affect sales rapidly. He et al. (2022) document that review solicitation can immediately influence Amazon sales within approximately two weeks. As fiscal year-end approaches and opportunities for accrual-based or operational adjustments narrow, firms under pressure to meet annual earnings targets may find such a quick demand-enhancing strategy particularly attractive, even if the benefits are temporary. The quarterly pattern is also consistent with Park et al. (2023), who show that the impact of incentivized reviews is largely short-term. If firms were to solicit reviews earlier in the fiscal year, subsequent negative organic reviews from dissatisfied customers could erode the initial sales gains before earnings are finalized.

To shed light on the immediate and temporary effect of solicited reviews on Amazon product sales, we use data collected by He et al. (2022) from the Keepa.com API and analyze changes in weekly Amazon Best Seller Ranks, where lower ranks indicate higher sales.[12] Our analysis focuses on the ground-truth dataset and examines the four weeks before and after the first Facebook post associated with each product. Figure 3 plots log-transformed sales ranks over the

[12] Because Amazon does not publicly disclose product-level dollar sales, we use Best Seller Ranks as a proxy for sales performance.

eight-week window, with Week 0 corresponding to the week of the first Facebook post. The figure shows a sharp improvement in sales ranks between Week −1 and Week 0, suggesting an immediate increase in sales following review solicitation. Sales ranks remain relatively stable through Weeks 1 and 2, indicating persistence of the short-term effect. Beginning in Week 3, however, sales ranks gradually deteriorate, consistent with the view that the sales impact of review solicitation is temporary.[13] Together, these results suggest that as the fiscal year closes, managers may turn to review solicitation as a last resort to quickly influence short-term performance.

4.4 The Impact of Solicited Reviews on Sales

Our hypothesis rests on the assumption that solicited reviews effectively boost firm sales, thereby increasing earnings and enabling managers to meet analyst expectations. This assumption is widely supported by prior research (e.g., Park et al., 2023). In this section, we use our own data to provide direct evidence on this assumption.

We begin by examining whether solicited reviews translate into increased firm sales. Table 4 presents regression results where the dependent variable is *SALE*, defined as total sales scaled by lagged total assets. The coefficient on *Solicited_Ratio* is positive and statistically significant at the 10% level, indicating that firms with higher levels of solicited reviews tend to have stronger sales performance, supporting our assumption. The magnitude of the effect reported in Table 4 is also economically meaningful. Specifically, a 1% increase in *Solicited_Ratio* is associated with an increase in gross profits of approximately $2.29 million, which corresponds to an increase in gross profit *per share* of about 1 cent.[14] This effect supports our main findings, as firms often just need a few cents per share to meet or narrowly beat analyst earnings forecasts.

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[13] He et al. (2022) provide causal evidence that products involved in review solicitation experience approximately a 16 % short-term improvement in sales ranks.

[14] Given that the coefficient estimate on *Solicited_Ratio* is 0.044, a 1% increase in this variable is associated with a 0.00044 increase in *Sale*, where *Sale* is scaled by lagged assets. To translate this into raw dollar terms, we multiply 0.00044 by the mean lagged assets of our sample ($12,213.91 million), resulting in a $5.37 million increase in sales.

We further examine whether soliciting reviews is a viable strategy for firms aiming to meet analyst *sales* forecasts. Table 5 presents regression results using the proximity of firm sales to analyst sales forecasts to define suspect firm-years. Specifically, we adopt the approach of Ittner and Michels (2017) and measure forecast errors as the absolute deviation between actual and forecasted sales, scaled by actual sales. Based on this measure, we construct *Suspect_1%*, which equals one for firm-years in which realized sales meet or exceed forecasted sales by no more than 1% of actual sales. We find that the coefficient on the suspect indicator is positive and statistically significant (0.023, P = 0.05), suggesting that firms narrowly meeting sales targets are more likely to engage in review solicitation.

In summary, the findings in Tables 4 and 5 provide direct evidence supporting increased sales as the mechanism through which solicited reviews help firms meet analyst earnings forecasts.

5. Additional Tests

5.1 Cross-Sectional Results: Operating Characteristics

In this section, we examine cross-sectional variation in review solicitation to better understand the incentives and constraints underlying this strategic behavior. We first explore how firms' operating characteristics influence their decisions to engage in review solicitation. Specifically, we examine factors such as firm size and profitability. While larger firms often have more economic resources that allow them to fund review solicitation, they are also subject to greater external scrutiny (Healy and Palepu, 2001). Given the potential reputation costs associated with solicited reviews, larger firms may engage in less review solicitation. Firm size (*SIZE*) is

Applying the mean gross profit rate of 42.71% yields an estimated increase in gross profit of $2.29 million. Finally, dividing this amount by the average number of common shares outstanding (287.09 million) gives an increase in gross profit per share of approximately $0.008, or close to 1 cent.

computed as the natural logarithm of a firm's market capitalization. Firms with higher *ROA* typically exhibit higher operating efficiency and stronger profitability, which reduces the need to engage in review solicitation for improving short-term earnings performance. As such, firms with higher *ROA* are expected to be involved in less review solicitation.

Table 6 presents the cross-sectional results related to firm operating characteristics. The coefficient on the interaction term, *Suspect_SIZE*, in Column (1) is significantly negative, indicating that the relation between suspect firms and review solicitation is less pronounced among larger firms. This finding suggests that larger firms are concerned about potential reputation costs, which mitigate their incentives to engage in review solicitation. Similarly, the coefficient on *Suspect_ROA* in Column (2) is significantly negative, suggesting that profitable firms do not need to engage in the meeting analyst expectations game.

5.2 Cross-Sectional Results: Other Firm Characteristics

In this section, we investigate how credit pressure from suppliers, financial health, and product portfolios impact the extent of a firm's review solicitation. Current liabilities are obligations a firm must settle within a year, and accounts payable often constitute a major part of these obligations. Unlike other forms of debt, accounts payable represent amounts a firm owes to its suppliers for goods or services that have been received but not yet paid for. A high level of current liabilities generally indicates that firms rely on credit from suppliers to maintain their operations. When a firm's earnings fall short of analyst forecasts, suppliers may be concerned about the firm's growth prospects and thus the ability to pay for goods and services in the future. In response, suppliers may tighten credit terms, demand quicker payments, or reduce credit availability, putting extra pressure on firms to demonstrate strong earnings in order to ease suppliers' concerns. We expect that suspect firms with higher current liabilities (*CL*) engage in more review solicitation.

Firms with stronger financial health are typically under less pressure to manipulate earnings to meet analyst forecasts or market expectations. The market tends to view these firms as more stable and reliable, making it more willing to look past short-term earnings fluctuations. In contrast, previous studies have shown that financially distressed firms are more likely to engage in earnings management to meet earnings benchmarks (Graham et al., 2005; Roychowdhury, 2006). To assess financial health, we compute the Altman Z-scores (*Altman_Z*), which combine various financial ratios to predict the likelihood of bankruptcy. A higher Altman Z-score indicates greater financial stability and a lower risk of bankruptcy. We expect suspect firms with higher Altman Z-scores to engage in less review solicitation.

Firms with a larger product portfolio (*Count*) are less likely to engage in review management because they have built up their reputation in the product market and enjoy diverse revenue streams from different product lines. Luca (2011) finds that Yelp ratings significantly impact independent restaurants, with a one-star improvement leading to a 5-9% increase in revenue. However, chain restaurants do not experience the same effect, likely because they already have established reputations, and consumers rely less on online reviews when deciding whether to visit them. Furthermore, large product portfolios suggest that sales are not reliant on a single product, and soliciting reviews across multiple product lines to significantly boost sales may be costly for these firms.

Table 7 presents the regression results. The coefficient on the interaction term, *Suspect_CL*, in Column (1) is significantly positive, consistent with our expectation that firms relying on credit from suppliers are more prone to review solicitation. In Column (2), the coefficient on the interaction term, *Suspect_Altman_Z*, is significantly negative, suggesting that firms with stronger financial health engage in less review solicitation. Finally, in Column (3), the significantly negative coefficient on *Suspect_Count* indicates that firms with a larger number of products exhibit a low level of review management.

5.3 Product Characteristics

In this section, we examine the types of products for which firms are more likely to solicit reviews. Given limited budgets, firms may be selective in choosing their products for review solicitation. We explore whether this prioritization is influenced by factors such as the number of reviews in the previous year, product age, price, and the level of market competition. Unlike the main analyses, these tests are conducted at the firm-product-year level. The dependent variable, *Solicited_Dummy*, is a dummy variable that equals one if a product has solicited reviews in a given year, and zero otherwise.

To conduct the analyses, we employ the following regression specification:

$$
\begin{aligned}
Solicited\_Dummy_{i,j,t} &\\
&= \beta_1 Suspect_{i,t} + \beta_2 Suspect_{i,t} * \ Product\_Characteristics_{i,j,t} \\
&+ \beta_3 Product\_Characteristics_{i,j,t} + \sum \gamma \ Control_{i,t} + ProductFE + YearFE \\
&+ \varepsilon_{i,j,t}
\end{aligned}
$$

where $Solicited\_Dummy_{i,j,t}$ is the dependent variable indicating whether firm *i*'s product *j* is involved in solicited reviews in year *t*. *Suspect* denotes whether firm *i* in year *t* is classified as a firm under pressure to meet analyst earnings forecasts. The coefficient of interest, β_2, captures whether the likelihood of product *j* involved in solicited reviews varies with product-specific characteristics. As discussed above, we focus on four product-level characteristics constructed using median splits: *Reviews_Lag* (an indicator for higher prior-year review volume), *ASIN_Age* (an indicator for products with longer listing histories), *Price* (an indicator for higher-priced products), and *HHI_Product* (an indicator for higher product market concentration). The control variables remain the same as those used in the main analysis. We include product and year fixed effects to further account for unobserved product-level characteristics and time-specific factors. Robust standard errors are clustered at the product level.

In general, products with fewer reviews in the past are more likely to benefit from solicited reviews, as firms can quickly alter consumer perceptions by inserting a few positive product reviews compared to products with substantial consumer feedback. Table 8, Column (1) reports the results. We find that the coefficient on the interaction term between *Suspect* and *Reviews_Lag*, is significantly negative, supporting our prediction that firms tend to choose products with limited consumer feedback for review management.

Newer products often lack consumer awareness and feedback, making them more likely to benefit from solicited reviews. He et al. (2022) also highlight how solicited reviews help newer products overcome the "cold-start problem," where a lack of reviews limits visibility and sales. In addition, it is relatively easy to manipulate reviews of newer products to enhance their market visibility given that there are not many existing reviews. In Column (2) of Table 8, the coefficient on the interaction term, *Suspect_ASIN_Age*, is negative and statistically significant, supporting our prediction.

Expensive products generally offer higher profit margins, making them attractive targets for review solicitation. However, consumers often invest considerable time and effort in researching costly items before making purchase decisions, which may reduce their susceptibility to the influence of solicited reviews. Thus, we do not offer a directional prediction on whether firms are more or less likely to solicit reviews for higher-priced products. Column (3) of Table 8 reports the coefficient estimate for the interaction term, *Suspect_Price*, which is positive and statistically significant. This finding indicates that firms are, in fact, more inclined to engage in review solicitation for products with higher price tags.

Product market competition can also shape a firm's incentives to manipulate product reviews. In a more competitive, less concentrated market, consumers have access to a wider range of similar products, prompting firms to manipulate reviews to make their products stand out and maintain or grow their market shares. In contrast, products in a more concentrated market face fewer competitive threats or have already established market dominance, which reduces their reliance on review management. That is, the marginal benefit of soliciting reviews increases with product market competition. Consistent with this notion, the coefficient estimate for the interaction term, *Suspect_HHI_Product*, in Column (4) of Table 8 is negative and statistically significant, indicating that firms are less likely to solicit reviews for products in more concentrated markets (higher *HHI_Product*). Together, the results in this section reveal how firms allocate their limited resources to maximize the impact of review solicitation on earnings.

6. Robustness Tests:

6.1 Alternative Suspect Threshold

To evaluate the robustness of our findings, we redefine the *Suspect* variable by expanding the threshold to include firms beating analyst forecasts by two cents and five cents. This adjustment captures the dynamic nature of the "meet or beat" analyst forecast game, where analysts, anticipating earnings management by firms, may revise forecasts upward, further incentivizing firms to engage in more earnings management.

Table 9 presents the regression results using the two alternative *Suspect* proxies. In Columns (1) and (2), we define *Suspect* as firms whose earnings per share (EPS) meet or exceed analyst forecasts by two cents and five cents, respectively. When the threshold is set at two cents, the coefficient on *Suspect* is 0.027 (p = 0.03). At the five-cent threshold, the coefficient remains positive but diminishes slightly to 0.018 (p = 0.09). Overall, the robustness tests rule out the possibility that our findings are driven by certain thresholds used to define suspect firms.

6.2 Alternative Machine Learning Models

In the main analysis, we use the Random Forest model for machine learning because of its overall accuracy (see Appendix A Table A2). To evaluate whether our main findings are robust across different classification algorithms and to ensure that the results are not overly dependent on the choice of the Random Forest model, we also conduct robustness analyses using the other two machine learning models: Logistic Regression (LR) and Support Vector Machine (SVM).

Table 10 presents the results of the robustness tests. In Columns (1) and (2), we report the findings for the LR and SVM models, respectively. In both models, *Suspect* continues to have a significantly positive impact on *Solicited_Ratio*, with coefficients of 0.024 (p = 0.06) for LR and 0.040 (p = 0.01) for SVM. Because different algorithms rely on distinct functional forms and decision boundaries, the consistency of results across Random Forest, Logistic Regression, and SVM mitigates concerns that our findings are driven by idiosyncrasies of a specific training structure.

7. Conclusion

This study examines a previously underexplored area of earnings management, the use of solicited product reviews to influence sales and meet earnings benchmarks. While financial reporting manipulation has received substantial attention from regulators and researchers, less is known about how firms manage product information, particularly in the form of product reviews, to achieve strategic objectives. Unlike traditional earnings management, review solicitation does not violate GAAP or significantly disrupt normal business operations; instead, it relies on using biased reviews to shape the information environment in which consumers make purchase decisions and hence boost sales. We document evidence that firms under earnings pressure engage in more review solicitation. Furthermore, we find that this behavior is more pronounced among firms with poorer operating performance and financial health, greater credit pressure from suppliers, and narrower product portfolios. We also show that firms tend to solicit reviews for products with limited track records, higher prices, and those in highly competitive markets. Collectively, these findings suggest that review solicitation is deployed strategically when the marginal benefit of boosting short-term sales is greatest.

Our study makes two important contributions. First, it deepens our understanding of the toolset firms use to manipulate earnings. Second, our findings shed light on the broader implications of product information. The influence of solicited product reviews extends beyond the product market, affecting the capital market and leading to inefficient resource allocation and eroded investor confidence. Our findings should be of particular interest to regulators and investors. Future research should further investigate the long-term effects of review solicitation on firm performance and consumer behavior, as well as the effectiveness of regulatory interventions in curbing such practices.

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Table 1 Sample Selection and Descriptive Statistics

Panel A: Sample Selection

Criterion	Unique Firms	Firm-Years
Initial firm-year sample with Product Sales on Amazon from 2000 to 2021.	1,671	11,189
Missing financial variables (SIZE, HasDebt, MTB, ROA).	-421	-2,025
Missing additional variables (InstOwn, SGA, AD, Count).	-655	-5,238
Final sample		3,926

Note: This panel provides the sample selection process for Compustat firms with product sales on Amazon.com.

Panel B: Univariate Comparisons

	Suspect Sample (n = 418)			Non-Suspect Sample (n = 3,508)			Full Sample (n = 3,926)			Difference	
	Mean	Median	Std	Mean	Median	Std	Mean	Median	Std	Mean	Median
Solicited_Ratio	0.582	0.551	0.283	0.521	0.500	0.285	0.527	0.500	0.285	0.061***	0.051***
SIZE	8.291	8.320	1.969	7.798	7.760	2.049	7.851	7.828	2.046	0.493***	0.560***
HasDebt	0.861	1.000	0.346	0.873	1.000	0.333	0.872	1.000	0.335	-0.012	0.000
MTB	2.306	1.852	1.592	1.966	1.449	1.661	2.002	1.498	1.657	0.340***	0.403***
ROA	0.155	0.146	0.107	0.120	0.122	0.113	0.124	0.125	0.113	0.035***	0.024***
InstOwn	0.740	0.802	0.204	0.733	0.800	0.220	0.733	0.800	0.218	0.007	0.002
SGA	0.314	0.281	0.202	0.331	0.262	0.947	0.329	0.264	0.897	-0.017	0.019
AD	3.704	3.842	2.304	3.149	3.261	2.427	3.208	3.330	2.420	0.555***	0.581***
Count	2.704	2.441	2.080	2.779	2.565	2.001	2.771	2.565	2.009	-0.075	-0.124

Note: This panel presents summary statistics and comparisons between the suspect and non-suspect samples. The suspect sample includes 418 firm-years in which firms just meet or beat analyst earnings forecasts by one cent, following the methodology of Roychowdhury (2006). The non-suspect sample comprises 3,508 firm-years. The full sample contains 3,926 firm-years. The table reports the mean, median, and standard deviation for each variable. Additionally, differences in means and medians between the two groups are tested using t-tests and Mann-Whitney U tests, respectively. All variables are winsorized at the 1% and 99% levels. Statistical significance of the differences is indicated by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

Panel C: Pearson Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Solicited_Ratio	1.00									
(2) Suspect	0.07***	1.00								
(3) SIZE	-0.09***	0.07***	1.00							
(4) HasDebt	-0.05***	-0.01	0.24***	1.00						
(5) MTB	-0.07***	0.06***	0.31***	-0.07***	1.00					
(6) ROA	0.02	0.10***	0.38***	0.03	0.23***	1.00				
(7) InstOwn	-0.05***	0.01	0.34***	0.14***	0.04***	0.24***	1.00			
(8) SGA	-0.02	-0.01	-0.05***	-0.03**	0.11***	-0.23***	-0.04**	1.00		
(9) AD	-0.03*	0.07***	0.73***	0.23***	0.00	0.29***	0.21***	-0.06***	1.00	
(10) Count	-0.13***	-0.01	0.32***	0.12***	0.02	0.13***	0.07***	-0.06***	0.31***	1.00

Note: This panel presents the Pearson correlation matrix for the key variables used in the analysis. The sample includes all firm-year observations from the full sample (n = 3,926). Statistical significance of the correlation is indicated by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

Table 2 Pressure to Meet Analyst Earnings Forecasts and Solicited Reviews

	(1) Solicited_Ratio	(2) Solicited_Ratio
Suspect	0.059***	0.042***
	(0.00)	(0.00)
SIZE	-0.014**	0.010
	(0.01)	(0.44)
HasDebt	-0.025	0.007
	(0.20)	(0.77)
MTB	-0.010**	0.002
	(0.01)	(0.70)
ROA	0.167**	-0.044
	(0.02)	(0.64)
InstOwn	-0.046	-0.024
	(0.16)	(0.66)
SGA	-0.004*	-0.004***
	(0.06)	(0.00)
AD	0.008*	-0.007
	(0.05)	(0.54)
Count	-0.018***	-0.004
	(0.00)	(0.71)
Firm FE	No	Yes
Year FE	No	Yes
Observations	3,926	3,926
R-squared	0.037	0.467

Note: This table presents the regression results of the relationship between solicited reviews and the pressure to meet analyst earnings forecasts. The dependent variable is *Solicited_Ratio*, which measures the proportion of products with solicited reviews relative to the total number of products for each firm-year. The key independent variable, *Suspect*, captures firm-years where firms meet or beat analyst earnings forecasts by just one cent. Columns (1) and (2) differ based on whether the model includes firm and year fixed effects. All control variables are winsorized at the 1% and 99% levels. Standard errors are clustered at the firm level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively, with p-values reported in parentheses.

Table 3 Quarterly Patterns of Solicited Reviews

	(1)	(2)	(3)	(4)	(5)
	Quarter 1	Quarter 2	Quarter 3	Quarter 4	Quarter 4 (Excluding December Fiscal Year-Ends)
Suspect	0.011	0.007	0.005	0.027**	0.047**
	(0.44)	(0.61)	(0.79)	(0.05)	(0.05)
SIZE	-0.018	-0.015	0.007	-0.014	-0.011
	(0.15)	(0.28)	(0.53)	(0.33)	(0.65)
HasDebt	0.021	0.028	-0.018	-0.005	0.004
	(0.38)	(0.27)	(0.38)	(0.83)	(0.92)
MTB	0.002	-0.008	0.002	0.003	-0.005
	(0.73)	(0.23)	(0.71)	(0.58)	(0.64)
ROA	-0.109	0.168	0.029	-0.016	0.177
	(0.32)	(0.11)	(0.78)	(0.88)	(0.45)
InstOwn	0.045	0.013	-0.072	-0.004	0.041
	(0.46)	(0.82)	(0.16)	(0.95)	(0.65)
SGA	-0.064	0.007***	0.045**	0.007***	0.004
	(0.47)	(0.00)	(0.05)	(0.00)	(0.98)
AD	0.018	0.007	-0.011	-0.001	-0.006
	(0.14)	(0.57)	(0.29)	(0.95)	(0.75)
Count	-0.003	-0.015	-0.007	-0.011	-0.010
	(0.76)	(0.17)	(0.46)	(0.24)	(0.55)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	3,201	3,246	3,332	3,427	1,200
R-squared	0.375	0.368	0.398	0.382	0.326

Note: This table presents the regression results of the relationship between solicited reviews and the pressure to meet analyst earnings forecasts across different fiscal quarters. The dependent variable is *Solicited_Ratio*, which measures the proportion of products with solicited reviews relative to the total number of products for each firm-year. The key independent variable, *Suspect*, captures firm-years where firms meet and beat analyst earnings forecasts by just one cent. Columns (1) through (4) represent the regression results for each fiscal quarter, respectively. Column (5) excludes firms with December fiscal year-ends from fourth-quarter observations. All control variables are winsorized at the 1% and 99% levels. Standard errors are clustered at the firm level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively, with p-values reported in parentheses.

Table 4 The Impact of Solicited Reviews on Firm Sales

	SALE
Solicited_Ratio	0.044*
	(0.09)
SIZE	-0.056*
	(0.05)
HasDebt	0.009
	(0.81)
MTB	0.050***
	(0.00)
ROA	1.682***
	(0.00)
InstOwn	-0.294***
	(0.01)
SGA	-0.011***
	(0.00)
AD	-0.011
	(0.64)
Count	-0.020
	(0.17)
Constant	1.581***
	(0.00)
Firm FE	Yes
Year FE	Yes
Observations	3,438
R-squared	0.883

Note: This table reports regression results on whether high levels of solicited reviews improve firms' sales performance. The dependent variable is *SALE*, defined as total sales scaled by lagged total assets. The key independent variable, *Solicited_Ratio*, measures the intensity of solicited reviews across a firm's product portfolio. All control variables are winsorized at the 1% and 99% levels. Standard errors are clustered at the firm level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively, with p-values reported in parentheses.

Table 5 Solicited Reviews and Meeting Analyst Sales Forecasts

	Solicited_Ratio
Suspect_1%	0.023**
	(0.05)
SIZE	-0.004
	(0.80)
HasDebt	0.014
	(0.57)
MTB	0.004
	(0.57)
ROA	0.070
	(0.48)
InstOwn	0.003
	(0.96)
SGA	-0.004***
	(0.00)
AD	0.003
	(0.78)
Count	-0.007
	(0.54)
Constant	0.528***
	(0.00)
Firm FE	Yes
Year FE	Yes
Observations	3,098
R-squared	0.471

Note: This table presents the regression results of the relationship between solicited reviews and the pressure to meet analyst *sales* forecasts. The dependent variable is *Solicited_Ratio*, defined as the proportion of products containing solicited reviews. The key independent variable is *Suspect_1%*, which captures firms that just meet or narrowly beat analyst *sales* expectations by 1% of actual sales in a given year. All control variables are winsorized at the 1% and 99% level. Standard errors are clustered at the firm level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively, with p-values reported in parentheses.

**Table 6 Cross-Sectional Analysis of Solicited Reviews:
The Role of Operating Characteristics**

	(1)	(2)
Suspect_SIZE	-0.020***	
	(0.00)	
Suspect_ROA		-0.301*
		(0.06)
Suspect	0.204***	0.088***
	(0.00)	(0.01)
SIZE	0.010	
	(0.40)	
ROA		-0.018
		(0.85)
Control	Yes	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
Observations	3,926	3,926
R-squared	0.468	0.467

Note: This table presents the results of regression analyses exploring how firm size and profitability moderate the relationship between solicited reviews and the pressure to meet analyst earnings forecasts. The dependent variable is *Solicited_Ratio*. All control variables are winsorized at the 1% and 99% levels. Standard errors are clustered at the firm level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively, with p-values reported in parentheses.

Table 7 Cross-Sectional Analysis of Solicited Reviews:
The Role of Other Firm Characteristics

	(1)	(2)	(3)
Suspect_CL	0.352***		
	(0.01)		
Suspect_Altman_Z		-0.017*	
		(0.07)	
Suspect_Count			-0.024***
			(0.00)
Suspect	-0.039	0.082***	0.109***
	(0.21)	(0.00)	(0.00)
CL	-0.072		
	(0.41)		
Altman_Z		0.005	
		(0.60)	
Count			-0.000
			(0.98)
Control	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	3,843	3,837	3,926
R-squared	0.475	0.474	0.469

Note: This table presents the results of regression analyses examining how credit concerns from suppliers, financial health, and product line diversity moderate the relationship between solicited reviews and the pressure to meet analyst earnings forecasts. The dependent variable is *Solicited_Ratio*. The interaction terms, *Suspect_CL* (Column 1), *Suspect_Altman_Z* (Column 2), and *Suspect_Count* (Column 3), capture how current liabilities (*CL*), financial health (measured by the Altman Z-score), and the number of product lines affect suspect firms' review solicitation. All control variables are winsorized at the 1% and 99% levels. Standard errors are clustered at the firm level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively, with p-values reported in parentheses.

Table 8
The Role of Product Characteristics

	(1)	(2)	(3)	(4)
Suspect_ Reviews_Lag	-0.019*			
	(0.06)			
Suspect_ASIN_Age		-0.039***		
		(0.00)		
Suspect_Price			0.026***	
			(0.00)	
Suspect_HHI_Product				-0.016***
				(0.01)
Suspect	0.014	0.038***	-0.008	0.016***
	(0.13)	(0.00)	(0.13)	(0.00)
Reviews_Lag	0.040***			
	(0.00)			
ASIN_Age		-0.058***		
		(0.00)		
Price			-0.007	
			(0.39)	
HHI_Product				-0.021***
				(0.00)
Control	Yes	Yes	Yes	Yes
Product FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	233,163	397,611	218,232	397,611
R-squared	0.359	0.364	0.343	0.363

Note: This table presents the results of regression analyses exploring which types of products are more susceptible to review solicitation. The dependent variable is *Solicited_Ratio*. The interaction terms, *Suspect_ Reviews_Lag* (Column 1), *Suspect_ASIN_Age* (Column 2), *Suspect_Price* (Column 3), and *Suspect_HHI_Product* (Column 4), examine how product characteristics such as the number of previous reviews, product age, price, and market concentration (measured by the Herfindahl-Hirschman Index, HHI) influence suspect firms' product choices for review solicitation. All control variables are winsorized at the 1% and 99% levels. Standard errors are clustered at the product level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively, with p-values reported in parentheses.

Table 9 Alternative Thresholds for Beating Analyst Forecasts

	(1) 2 Cents	(2) 5 Cents
Solicited_Ratio	0.027**	0.018*
	(0.03)	(0.09)
SIZE	0.010	0.010
	(0.44)	(0.43)
HasDebt	0.007	0.007
	(0.76)	(0.75)
MTB	0.003	0.002
	(0.67)	(0.70)
ROA	-0.043	-0.041
	(0.64)	(0.66)
InstOwn	-0.025	-0.024
	(0.65)	(0.66)
SGA	-0.004***	-0.004***
	(0.00)	(0.00)
AD	-0.007	-0.007
	(0.55)	(0.54)
Count	-0.004	-0.004
	(0.70)	(0.69)
Firm FE	Yes	Yes
Year FE	Yes	Yes
Observations	3,926	3,926
R-squared	0.466	0.465

Note: This table presents the results of robustness tests where we denote suspect firms as those meet and exceed analyst earnings forecasts by two cents (Column 1) and five cents (Column 2). The dependent variable is *Solicited_Ratio*, which measures the proportion of products with solicited reviews relative to the total number of products for each firm-year. All control variables are winsorized at the 1% and 99% levels. Standard errors are clustered at the firm level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively, with p-values reported in parentheses.

Table 10 Alternative Machine Learning Models

	(1) LR	(2) SVM
Solicited_Ratio	0.024*	0.040***
	(0.06)	(0.01)
SIZE	0.006	0.003
	(0.59)	(0.83)
HasDebt	-0.051***	-0.028
	(0.00)	(0.19)
MTB	-0.005	0.001
	(0.41)	(0.94)
ROA	0.014	-0.101
	(0.85)	(0.31)
InstOwn	-0.065	-0.058
	(0.14)	(0.27)
SGA	0.000	0.005***
	(0.91)	(0.00)
AD	0.001	-0.001
	(0.94)	(0.91)
Count	-0.002	0.009
	(0.82)	(0.32)
Firm FE	Yes	Yes
Year FE	Yes	Yes
Observations	3,926	3,926
R-squared	0.253	0.378

Note: This table presents the results of regression analyses using two different machine learning models to capture products involved in solicited reviews: Logistic Regression (LR) in Column 1 and Support Vector Machine (SVM) in Column 2. The dependent variable is *Solicited_Ratio*, which measures the proportion of products with solicited reviews relative to the total number of products for each firm-year. All control variables are winsorized at the 1% and 99% levels. Standard errors are clustered at the firm level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively, with p-values reported in parentheses.

Figure 1 Example of Disclosed Solicited Reviews on Sephora.com

Note: This figure provides evidence that public companies engage in review solicitation. Sephora tags certain reviews for the product Lancôme La Vie Est Belle Eau de Parfum as “Incentivized,” indicating that reviewers received compensation or free products in exchange for providing feedback. Lancôme is owned by L’Oréal, a publicly traded firm (EPA: OR). This example illustrates that financially incentivized reviews can arise even for products sold by large public companies.

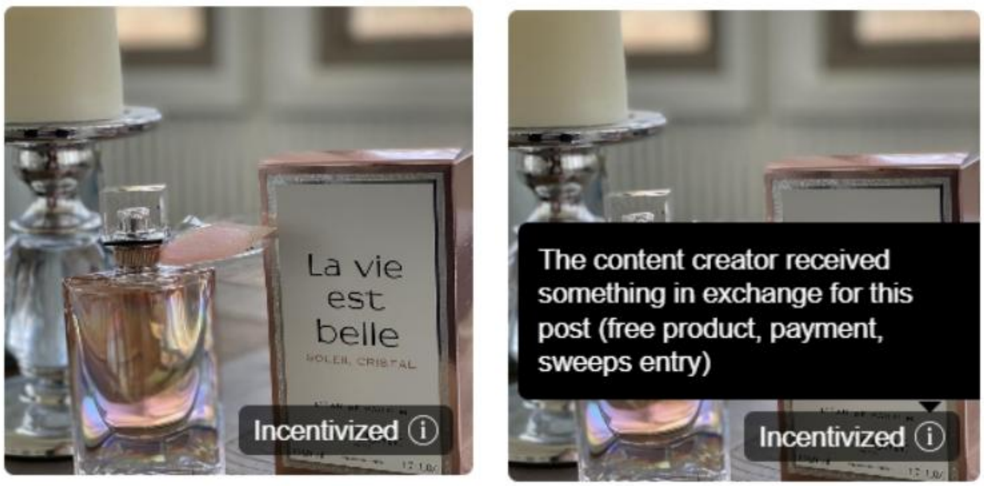
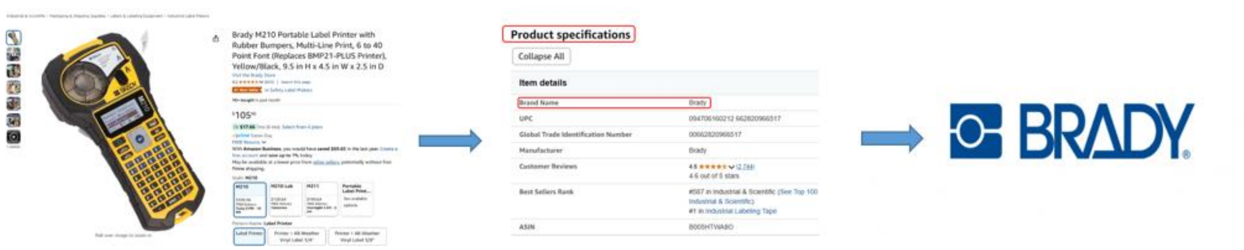


Figure 2: Linking Amazon Products to Public Firms

Note: This figure shows the procedure used to link Amazon products to publicly listed companies. The example shows a Brady M210 label printer listed on Amazon (left panel), where the brand name "Brady" is clearly stated. This allows the product to be matched to its manufacturer, Brady Corporation, and to a publicly traded firm (right panel).

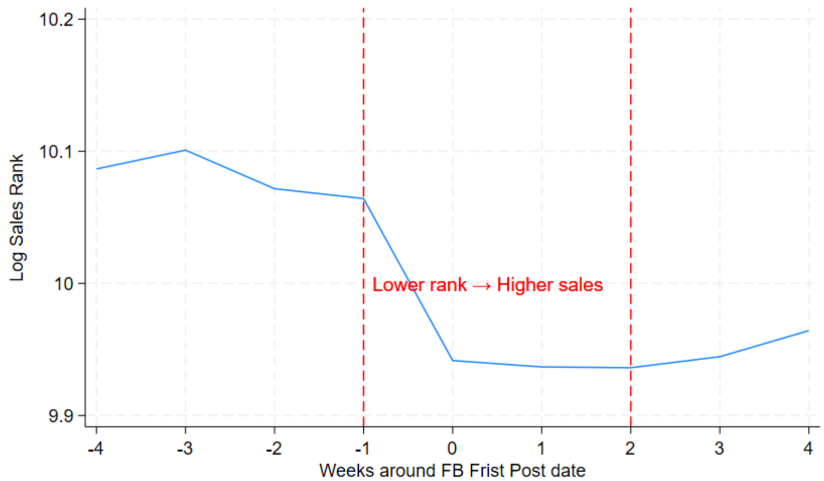


Amazon product listing for a Brady M210 label printer

Brand name "Brady" is identified in the product specifications

Brady is matched to the public firm Brady Corporation (Ticker: BRC)

Figure 3
Log Sales Rank Around the Facebook Post Requesting Fake Reviews [-4,4]



Note: This figure displays the natural logarithm of Amazon's sales ranks over an 8-week window, centered around the week of the Facebook post requesting reviews. The sharp decline in the log of sales ranks from Week -1 to Week 0 highlights the immediate positive impact of review solicitation on sales.

Appendix A
Detecting Products with Solicited Reviews

In this appendix, we provide a detailed description of the data used to identify products involved in solicited reviews on Amazon. The Amazon dataset collected by McAuley Lab has two main components: user reviews and product metadata.

He et al. (2022) identified and tracked 30 largest private Facebook groups, where sellers post requests for reviews, and created a ground truth dataset containing Amazon products with and without solicited reviews from October 2019 to June 2020. We match these products with the Amazon dataset to extract their reviews and compute review features. These review features fall into four categories. The first feature category is time patterns of reviews, measured by features such as the number of reviews, the average time (in days) between reviews, the minimum time (in days) between reviews, the maximum time (in days) between reviews, and the standard deviation of time (in days) between reviews. The second category focuses on favorable ratings, incorporating features like average review ratings, the share of reviews with helpful votes, the share of reviews of one-start ratings, and the share of reviews with five-star ratings. The third category captures content similarity, measured by the average text similarity between reviews (TF-IDF similarity) and variations in review lengths. The final feature involves the presence of photos in reviews. We expect these review features to help algorithms capture the signals of review-solicitation campaigns: (1) a surge of reviews within a short period, (2) consistently favorable ratings, (3) similar language across reviews, and (4) photos accompanying reviews (He et al., 2022). Table A1 provides detailed definitions of these review features.

To detect products with solicited reviews, we adopt three machine learning models: Random Forest, Logistic Regression, and Support Vector Machine (SVM). Following prior machine learning literature (e.g., He, Hollenbeck, Overgoor, Proserpio, & Tosyali, 2022), we split the ground truth dataset into training and testing datasets, allocating 80% for training and 20% for testing. Each model's performance is evaluated based on several key metrics: AUC (Area Under the ROC Curve), Accuracy, True Negative Rate (TN Rate), True Positive Rate (TP Rate), and F1 Score. AUC measures the model's ability to distinguish between products with and without solicited reviews. Higher values indicate better performance. Mathematically, $\mathrm{AUC} = \int_0^1 \mathrm{TPR(FPR)}\ \mathrm{d(FPR)}$, where FPR is the proportion of products with genuine reviews mistakenly identified as products with solicited reviews, False Positives / (False Positives + True Negatives). Accuracy is the ratio of correctly predicted instances (both true positives and true negatives) to the total instances. Specifically, Accuracy = (True Positives + True Negatives) / (True Positives + True Negatives + False Positives + False Negatives). True Negative Rate (TN Rate) is the proportion of products with genuine reviews that are correctly identified. Specifically, TN Rate = True Negatives / (True Negatives + False Positives). True Positive Rate (TP Rate) is the proportion of products with solicited reviews that are correctly identified. Specifically, TP Rate = True Positives / (True Positives + False Negatives). F1 Score is the harmonic mean of precision and recall, which considers both false positives and false negatives. Specifically, F1 Score = 2 * (Precision * Recall) / (Precision + Recall), where Precision = True Positives / (True Positives + False Positives), and Recall = True Positives / (True Positives + False Negatives).

Table A2 summarizes the performance metrics for each model. The Random Forest model demonstrates the highest performance across all metrics, achieving an AUC of 0.866, an Accuracy of 0.807, and an F1 Score of 0.807. This indicates that Random Forest effectively balances the detection of both true positives and true negatives, making it a strong candidate for identifying products involved in review-solicitation campaigns.

Table A1
Review Features

Feature	Description
N_of_Reviews	Number of reviews
Avg_Days_Between_Reviews	Average of time in days between reviews
Min_Days_Between_Reviews	Minimum of time in days between reviews
Max_Days_Between_Reviews	Maximum of time in days between reviews
Stdev_Days_Between_Reviews	Standard deviation of time in days between reviews
Avg_Review_Rating	Average review ratings
Share_Helpful_Reviews	Share of reviews with helpful votes
Share_1Star	Share of reviews with one-star rating
Share_5Star	Share of reviews with five-star rating
TFIDF_Review_Body	Avg similarity of TF–IDF features between reviews of a product
Std_Review_Len	Variation of review lengths of a product
Share_Photo	Share of reviews with review photos

Note: This table presents the key features used in the detection of products with solicited reviews on Amazon. These features are derived from user reviews and item metadata, which were based on the methodologies of Clarke et al. (2020) and He, Hollenbeck, Overgoor, Proserpio, & Tosyali (2022). The features capture various aspects of review patterns. These metrics are specifically designed to detect and analyze review solicitation.

Table A2
Machine Learning Model Performance

Model	AUC	Accuracy	TN Rate	TP Rate	F1 Score
Random Forest	0.866	0.807	0.826	0.782	0.807
Logistic Regression	0.844	0.724	0.617	0.864	0.723
SVM	0.865	0.804	0.872	0.713	0.802

Note: This table presents the performance metrics of three machine learning models, Random Forest, Logistic Regression, and Support Vector Machine (SVM), used to detect products involved in review solicitation. The metrics include Area Under the ROC Curve (AUC), Accuracy, True Negative Rate (TN Rate), True Positive Rate (TP Rate), and F1 Score. The ground truth dataset was split into training (80%) and testing (20%) sets following the methodology of He, Hollenbeck, Overgoor, Proserpio, & Tosyali (2022). Random Forest demonstrates the highest performance across most metrics, making it the primary machine learning model for detecting products having solicited reviews in our study.

Appendix B
Variable Definitions

Variable	Definition	Data sources
Interest: Review Manipulation		
Solicited_Ratio	The proportion of products with solicited reviews divided by the total number of products per year.	Amazon
Suspect	An indicator variable that equals one if firm-years in which the actual Earnings Per Share (EPS) equals or exceeds the median forecasted EPS by just one cent and 0 otherwise.	IBES
Suspect_ 1%	An indicator variable that equals one if firm-years in which the actual reported sales equal or exceed the median forecasted sales by no more than 1% of actual sales and 0 otherwise.	IBES
SALE	Firm sales scaled by lagged total assets, calculated as total sales in year *t* divided by total assets in year $t-1$.	Compustat
Main Test: Control Variables		
SIZE	The natural logarithm of the market value of equity (mkvalt).	Compustat
HasDebt	An indicator variable that equals 1 if there is long-term debt (dltt) outstanding during the year, and 0 otherwise.	Compustat
MTB	A firm's market value of equity to book value of equity ratio in a given year.	Compustat
ROA	Net income before extraordinary items scaled by book value of total assets.	Compustat
InstOwn	The proportion of shares owned by institutional investors in a given year.	Thomson/Refinitiv/Institutional (13f) Holdings
SGA	The ratio of Selling, General, and Administrative expenses (xsga) to total sales in a given year.	Compustat
AD	The natural logarithm of advertising expenses (xad) in a given year.	Compustat
Count	The natural logarithm of the number of products on Amazon in a given year (total_count).	Amazon
Cross-Sectional Tests: Firm-Level Characteristics		
Rating	An indicator variable that equals 1 if a firm contains a credit rating in a given year, and 0 otherwise.	Capital IQ
Analyst	Natural logarithm of the number of analyst estimates (NUMEST) for a given firm in a given year.	IBES

Cashflow	Operating cash flows in a given year.	Compustat
CL	Current liabilities in a given year, calculated by dividing current liabilities (lct) by total assets (at).	Compustat
Altman_Z	The higher the Altman_Z, the company is more likely to be in good financial health. Altman_Z=3.3*(ebit/at) +0.99*(sale/at) +0.6*(ceq/at) +1.2*(act/at) +1.4*(re/at)	Compustat
Cross-Sectional Tests: Product-Level Characteristics		
Solicited_Dummy	An indicator variable that equals 1 if a product has solicited reviews in a given year, and 0 otherwise.	Amazon
Reviews_Lag	An indicator variable that equals 1 if the number of reviews for a product in a given year is greater than or equal to the median number of reviews, and 0 otherwise.	Amazon
ASIN_Age	An indicator variable that equals 1 if the age of the product is greater than or equal to the median age of products, and 0 otherwise	Amazon
Price	An indicator variable that equals 1 if the price of the product is greater than or equal to the median price of products, and 0 otherwise	Amazon
HHI_Product	An indicator variable that equals 1 if the Herfindahl-Hirschman Index (HHI) for a product’s category in a given year is above the median HHI of all product categories within that year. Since product sales on Amazon are not available, we use the number of reviews to infer a product’s sales. Prior research also shows that the number of reviews is positively associated with sales (Park et al., 2019; Zhang et al., 2013). Specifically, the market share of a product is defined as the number of reviews for the product divided by the total number of reviews in its product category for the year. A higher HHI indicates a more concentrated market.	Amazon