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Monetizing Platforms: An Empirical Analysis of Supply and Demand Responses to Entry Costs in Two-Sided Markets

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Abstract. This study investigates the consequences of monetizing a marketplace for product promotion within a digital platform, specifically the Giveaways program on Goodreads.com. Using a natural experiment and fine-grained platform data from 2016 to 2020, we examine how introducing a fixed entry cost for content creators affected both supply and demand in this two-sided market. Our findings reveal significant shifts in marketplace dynamics after monetization: (1) a substantial decrease in overall program participation, particularly among indie publishers and self-published authors, leading to increased market concentration; (2) reduced genre diversity, with popular genres becoming more dominant at the expense of niche categories; and (3) intensified promotional effects, characterized by higher review volume but lower average ratings for participating books. Analysis of review text suggests an increase in consumer-book mismatches as a potential mechanism driving this outcome. Our study advances platform economics by demonstrating how entry costs reshape marketplace composition and affect value creation in two-sided markets. These findings inform platform design and policy, particularly for markets with horizontally differentiated products and heterogeneous consumer preferences.

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Keywords: digital platform • two-sided market • entry cost • monetization • cultural products • Goodreads

1. Introduction

In the digital age, cultural product markets—including books, music, and movies—have undergone radical transformations (Brynjolfsson et al. 2003, Waldfogel 2017). Although digital technologies have dramatically reduced content production costs and lowered barriers to entry, they have also created a paradox: an abundance of new products floods the market, yet content creators face increasingly challenging conditions for gaining visibility. The book market exemplifies this trend. With over 4 million new titles published in the United States in 2021 alone, authors face unprecedented competition, necessitating more sophisticated and strategic approaches to promotion (Nagaraj and Ranganathan 2022). In this crowded marketplace, digital platforms have emerged as crucial intermediaries, significantly influencing how cultural products are discovered, promoted, and consumed.

As digital platforms have become central to product discovery, their decisions about product curation and promotion have taken on increased importance (Constantinides et al. 2018, Aguiar and Waldfogel 2021). Recent studies suggest that consumption patterns are becoming increasingly concentrated and reliant on platform-driven recommendations (Fleder and Hosanagar 2009, Ghose et al. 2014). This growing influence places platforms in a delicate position: they must balance the needs of content creators seeking effective promotion with consumer' desires for relevant product discoveries, while developing sustainable business models (Bhargava et al. 2022, Wu and Zhu 2022). The challenge of monetization—how platforms can capture value from the ecosystems they create—has emerged as a critical and complex issue in platform economics (Parker et al. 2016).

In this paper, we examine the effect of platform monetization by studying a major policy change in a platform-mediated promotional program. Specifically, we analyze the introduction of an entry cost for authors and publishers in a marketplace for book promotion, which provides a natural experiment in how monetization affects both content creators and consumers. By exploring changes in participation patterns, book diversity, and reader engagement, we uncover several key findings. Our results reveal how a seemingly straightforward policy change can reshape the entire ecosystem—from who participates in the market to what books are promoted and how readers respond.

More specifically, our study examines Goodreads.com, the world's largest book-focused social platform, with over 125 million registered users. Besides letting readers track books and share reviews, Goodreads offers a Giveaways program, where authors and publishers distribute free copies to generate reviews and visibility. The program has become a popular promotional tool, especially valuable for independent authors and small publishers who lack marketing resources. Although initially free to use, in January 2018, Goodreads began charging for participation in the program, creating a natural experiment to study the effects of platform monetization.

Using comprehensive data on Giveaways campaigns, book metadata, and user reviews from 2016 to 2020, we employ a variety of econometric and machine learning techniques to analyze the effects of this monetization policy. Our results reveal multifaceted impacts across the platform ecosystem. On the supply side, we find a significant drop in overall program participation, with a disproportionate effect on indie publishers and self-published authors, leading to increased market concentration. This shift in supplier composition contributes to a reduction in book genre diversity, with popular genres becoming more dominant at the expense of niche categories. On the demand side, we observe an intensification of promotional effects post monetization, characterized by higher review volume but lower average rating valence for participating books. Notably, our analysis of review text suggests an increase in consumer-book mismatches as a potential mechanism driving these outcomes. Collectively, these findings highlight the complex and often-overlooked consequences of platform monetization strategies.

Our study contributes to the literature on platform economics and monetization strategies in several ways. We extend network effect frameworks by examining the distributional impacts of entry cost, revealing how monetization alters marketplace composition and product offerings. We provide empirical evidence of how supply-side contraction can diminish demand-side value, potentially destabilizing two-sided markets. Our analysis of genre diversity and book ratings offers insights into monetization's indirect costs, highlighting trade-offs between short-term revenue and long-term ecosystem health. Finally, by demonstrating monetization's exacerbation of promotional effects, we bridge platform monetization literature with research on online reputation.

Moreover, our research on entry costs in two-sided markets touches upon the important trade-off between positive network effects and potential social inefficiencies from free entry, connecting two distinct literatures. Although classical economic models show that free entry can be excessive due to business stealing effect (Spence 1976, Dixit and Stiglitz 1977, Mankiw and Whinston 1986), they do not account for network effects in two-sided markets (Rochet and Tirole 2003, Parker and Van Alstyne 2005, Armstrong 2006). Although we do not formally model these competing forces in a market equilibrium framework, our results suggest that outcomes depend on which force dominates, highlighting the importance of considering both dynamics.

The remainder of this paper is structured as follows: Section 2 reviews the related literature and positions our work within existing research. Section 3 describes our empirical setting and data collection process. Section 4 presents our main empirical results, examining the effects of monetization on supply-side participation, product diversity, and demand-side responses. Section 5 discusses the implications of our findings for platform design, management, and policy, and suggests directions for future research.

2. Related Literature

Our study sits at the intersection of three related areas of research: digitization and platform economics, entry cost in two-sided markets, and the impact of promotions on consumer ratings. This literature review synthesizes key findings from these domains, highlighting the gaps in current understanding and positioning our work within this broader context.

2.1. Digitization and Platform Economy

Digitization and the emergence of online platforms have ushered in "a golden age of music, movies, books, and television" (Waldfogel 2017), presenting both opportunities and challenges for creators. However, as marketplaces have become increasingly crowded, the importance of self-promotion for cultural products has grown significantly (Nagaraj and Ranganathan 2022). In this environment, platforms have emerged as crucial mediators, wielding considerable influence over product success through their promotion and policy decisions. For instance, Aguiar and Waldfogel (2021) demonstrate how Spotify's promotion decisions significantly impact song and artist success. Similarly, Rietveld et al. (2019) argue that platforms strategically choose which complements to promote to effectively manage value creation within their ecosystems.

Building on the crucial importance of platforms in creative markets, our study contributes to the literature on platform monetization strategies, a key aspect of managing value creation (Parker et al. 2016). As platforms evolve from mere intermediaries to active market shapers, they face complex decisions about how to capture value from the ecosystems they foster. These decisions include determining pricing structures (e.g., subscription fees, transaction fees, enhanced access fees) and identifying which market participants to charge (e.g., one or both sides of the market, implementing freemium models, or subsidizing key players) (Farronato 2019). Although existing research has primarily focused on preserving network effects during monetization, we argue that the implications of these strategies extend beyond network dynamics, particularly in creative markets. For instance, Wu and Zhu (2022) demonstrate how different revenue models in a novel-writing platform distinctly influence content creation under competitive pressure, with revenue-sharing models eliciting more robust responses in terms of content quantity and novelty compared with pay-by-the-word models. This example highlights the complex interplay between monetization strategies and creative output, demonstrating the multifaceted nature of platform decisions in cultural markets.

2.2. Entry Costs in Two-Sided Markets

Our study contributes to the understanding of entry costs in two-sided markets by examining the critical trade-off between network effects and social inefficiencies arising from free entry. The literature on two-sided markets has extensively documented how network externalities shape platform competition and market outcomes (Rochet and Tirole 2003, Parker and Van Alstyne 2005, Armstrong 2006). These studies highlight how the value of platform participation for one side depends on participation from the other side, creating feedback loops that can lead to market expansion. Platform pricing strategies must therefore carefully balance these cross-side externalities to maximize overall platform value (Hagiu 2009, Weyl 2010). However, the welfare implications of entry costs in such markets remain underexplored, particularly in contexts where network effects interact with traditional market forces.

This gap becomes particularly salient when considering the classical economics literature on free entry and social efficiency. In traditional one-sided markets, monopolistic firms facing fixed costs can experience either excessive or insufficient entry from a social planner's perspective (Spence 1976, Dixit and Stiglitz 1977). The classic "business stealing" effect, where new entrants capture market share from incumbents without generating sufficient compensating social benefits, typically leads to overentry (Mankiw and Whinston 1986). However, these models do not account for the dynamics of two-sided markets, where entry costs affect not only direct competition, but also platform network effects. Although we do not formally model these competing forces, our empirical findings suggest that understanding their relative strength is important for platform design and policy.

2.3. Price Discount and Consumer Ratings

Our research intersects with literature examining the impact of promotional schemes on consumer evaluations (Li et al. 2019). Previous work has identified two primary effects. The first effect suggests that free or discounted products might elicit positive consumer behavior through two distinct mechanisms: a reciprocity mechanism, where consumers provide higher ratings either as an expression of gratitude for receiving free products or in anticipation of future promotional opportunities (Mo and Li 2018, Lin et al. 2019, Qiao et al. 2020); and an uncertainty reduction mechanism, where experiencing free products enables consumers to make more informed subsequent purchases, leading to greater satisfaction and higher ratings for similar items (Pu et al. 2024).

Conversely, the "Groupon effect" documents that although promotional strategies effectively boost sales, they simultaneously lead to lower ratings (Byers et al. 2012a, b). Recent empirical evidence from book (Zegners 2019) and mobile app markets (Liu et al. 2019) provides support for this effect, particularly pronounced for products offered free of charge. They attribute this phenomenon to misalignment between consumer preferences and product characteristics.

Our study extends this literature by examining how platform monetization strategies influence these promotional effects. Our empirical analysis in book giveaways reveals that the Groupon effect dominates, and, more importantly, platform monetization amplifies this negative effect. Specifically, monetization exacerbates the Groupon effect by altering both the selection of participating books and the composition of participating consumers, resulting in more pronounced preference-product mismatches and consequently even lower ratings.

3. Setting and Natural Experiment

3.1. Empirical Setting

Our empirical setting is Goodreads.com, the world's largest online community for book readers. This platform serves as a comprehensive ecosystem for literary engagement, allowing users to search an extensive database of books, receive personalized reading recommendations, curate reading lists, and share ratings and reviews. Goodreads also incorporates social features, enabling users to connect with others and track their friends' reading activities. As the publishing industry continues to see an annual increase in new titles, Goodreads has become increasingly vital in the book discovery process, assisting digital-age consumers in finding their next read and providing crucial prepurchase information.

Within this ecosystem, our analysis focuses on the Goodreads Giveaways program, a promotional tool that connects authors and publishers with potential readers. In a Giveaways campaign, authors or publishers offer to distribute a specified number of their books (e.g., 100 copies in Figure 1(b)). Users can browse individual campaigns and enter for a chance to win a free copy. Winners are selected through a random drawing at the end of the listing period, typically lasting a few weeks. The campaign also integrates social features—for instance, when a user's friend enters a campaign, it appears on their timeline, increasing the book's visibility. This mechanism allows authors and publishers to distribute their books to readers, who are encouraged to provide reviews, thereby generating early buzz and engagement. Figure 1(a) illustrates the Giveaways landing page for authors and publishers, while Figure 1(b) offers an example of a Giveaways campaign.

Figure 1. (Color online) Illustrating the Giveaways Program

Notes. The figure presents screenshots of the starting page and an example of a Giveaways campaign featuring the book title "Greenwich Park." These images highlight some key features of the program, offering a visual representation of how users can engage with the content and participate in Giveaways campaigns.

A significant change occurred in January 2018 when Goodreads began monetizing the Giveaways program. Previously free for authors and publishers to participate in, Goodreads introduced a fixed participation cost of $119 for a single Giveaways campaign.[1] The policy announcement was made on November 28, 2017, and took effect on January 9, 2018. This sudden change was unanticipated by authors and publishers,[2] and the short time span between announcement and implementation precluded strategic reactions. This exogenous variation creates a natural experiment, allowing us to investigate how platform monetization impacts the supply side, product diversity, and, ultimately, consumer satisfaction.

The Goodreads Giveaways program was created with the value proposition of promoting book discovery. The program is known for its diverse reading selections, spanning various genres, such as science fiction, romance, and biography. Over our observation period (2016–2020), more than 120,000 unique books were listed in the program, underscoring its substantial scale and importance as a promotional scheme on the platform. Its effectiveness was highlighted in Goodreads's 2017 media kit, which reported that 50%–60% of Giveaways winners wrote book reviews, helping titles reach broader audiences. The program also proved operationally efficient, as Goodreads, unlike platforms such as Amazon Vine, did not need to manually select winners or handle book distribution.

Goodreads' primary revenue streams previously involved book discovery packages, including direct advertising with publishers, sponsored mailers, and affiliate links. Our calculations suggest that the Giveaways program generates an estimated $5–8 million in revenue over two years post monetization.[3] It's worth noting that although the Giveaways program is a promotional tool, Goodreads listings themselves are highly inclusive. The platform catalogues nearly all books published in the United States, regardless of their participation in promotional activities. This comprehensive setting, combining a large-scale book discovery platform with an unexpected monetization of a key promotional tool, provides an excellent opportunity to study the multifaceted effects of platform monetization on various stakeholders in a two-sided market. By examining the impact on authors, publishers, and readers, we can gain valuable insights into the complex dynamics of platform economics in cultural goods markets.

3.2. Data

To examine the consequences of this exogenous monetization policy shift, we gather comprehensive data using both the Goodreads Application Programming Interface (API) and a customized web crawler. Our data set comprises: (1) the entire set of Giveaways campaigns hosted on the platform from January 2016 to February 2020 (prior to the COVID pandemic)—approximately two years before and two years after the implementation of the monetization policy in January 2018; (2) metadata for all books involved in these Giveaways campaigns, including information about their authors and publishers; and (3) star ratings and textual reviews associated with each book promoted through the Giveaways program.

In constructing our estimation sample, we apply two filtering criteria to the raw data. First, we exclude books with atypical promotion timing relative to their publication date. The average difference between a book's participation date in Giveaways and its release date is 108 days, indicating that a typical participating book is promoted through the Giveaways program three to four months postrelease. We remove books falling outside a window of five years prepublication to one year postpublication, eliminating approximately 2.5% of books. Second, we exclude books that participated in Giveaways more than three times to maintain consistency in our analysis of promotional effects. This removes an additional 6% of books.[4]

After applying these exclusions, our final sample consists of 101,684 Giveaways events for 82,552 unique books, with nearly 36 million associated ratings. Through these Giveaways campaigns, 1,814,643 free book copies have been distributed to readers. Our analysis primarily focuses on Giveaways involving printed books, which constitute the vast majority (over 94%) of hosted Giveaways. Results remain qualitatively similar when e-books are included.

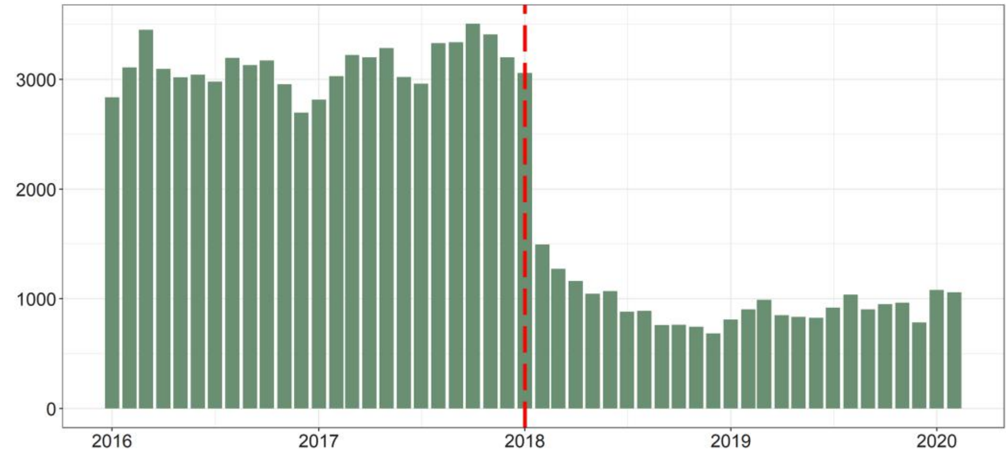
3.3. Model-Free Evidence

Without prior examination of the data, the impact of a few-hundred-dollar cost on Giveaways program participation is not immediately clear. Given the substantial investment in creating a book, authors and publishers might still choose to promote their works, despite this new cost. However, the resources available to major publishing houses like Penguin Random House vastly differ from those of independent authors or small publishers, who often operate under tight budget constraints. For these smaller players, the newly introduced participation cost could present a significant barrier to program engagement.

Our preliminary empirical observations confirm that the January 2018 monetization of the Giveaways program indeed had a substantial impact on author and publisher participation. Figure 2 illustrates an immediate and marked decline in the monthly number of Giveaways campaigns following the policy change. The average number of Giveaways campaigns per month dropped dramatically from approximately 3,000 to around 1,000. This initial evidence suggests that the monetary burden poses a significant obstacle with potential ramifications for program participation and reader engagement.

Although some reduction in participation might be beneficial in filtering out potential misuse—that is, repeatedly listing the same book to take advantage of the free program—our data indicate that such undesirable behavior was relatively rare. Authors or publishers

Figure 2. (Color online) Number of Giveaways Campaigns Over Time: The Impact of Platform Monetization



Notes. A sharp decline in participation is observed following the implementation of monetization. The red vertical dashed line marks January 2018, when the platform began to impose cost for participation in Giveaways campaigns.

engaging in repetitive posting (more than three times) account for only 6% of participating books. Thus, the observed decrease in supply at this scale remains a cause for concern. In subsequent sections, we will delve deeper into the sources of this reduced participation and its implications for the Giveaways book promotion ecosystem.[5]

Given that the Giveaways program serves as a mechanism for building readership and generating early book buzz, we examine potential spillover effects on off-platform promotion to complement our main analysis of platform dynamics. Utilizing Twitter's retired API v2 full-archive tweet counts endpoint, we analyze social media discourse related to the Giveaways program. Figure 3 reveals a substantial decline in Twitter discussions mentioning both ″Goodreads″ and ″Giveaways″ following the policy implementation. The reduction in social media engagement extends to various interaction metrics, including comments and retweets (detailed analysis provided in Web Appendix A.1). Although secondary to our core investigation, these patterns in social media engagement provide supplementary evidence for understanding the broader implications of platform monetization by introducing entry cost.

In summary, our model-free evidence documents substantial changes in both direct platform participation and complementary social media engagement following monetization. These empirical patterns suggest meaningful changes in this book promotional market. The following sections present an empirical framework to analyze these phenomena and evaluate their implications for market participation, product diversity, and reader engagement.

4. Empirical Results

Our analysis of the Goodreads Giveaways program monetization explores three interconnected dimensions of the marketplace:

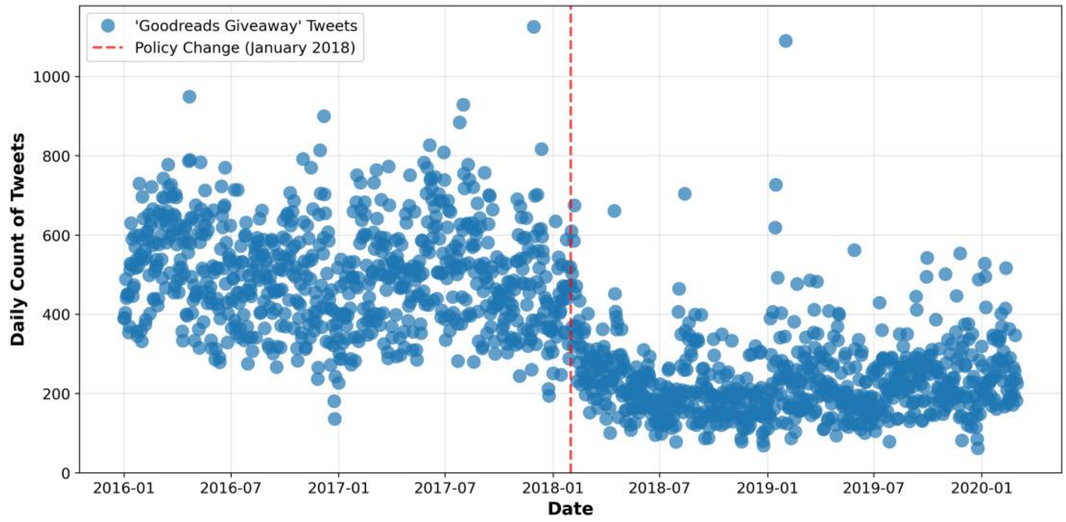
1. **Supply-side dynamics:** We examine how the introduction of a fixed participation cost affects the behavior of authors and publishers, particularly their engagement with and approach to promotional campaigns within the Giveaways program.
2. **Product diversity:** We assess the impact of monetization on the variety and characteristics of books offered through the Giveaways program, with a focus on potential shifts in genre representation.
3. **Demand-side responses:** We analyze readers' reactions to changes in supply and product availability, examining metrics such as review ratings, volume, and the textual content of reviews.

Given our rich data set, we use various levels of aggregations for our analyses, depending on the variable(s) of focus in each analysis. Table 1 highlights the granularity and units of analyses for each section. We further note that our analysis centers on the book promotion marketplace within the Giveaways Program, and not other books listed on Goodreads. This is motivated by the program's significant scale and its key role in user engagement and book promotion. The Giveaways Program serves an ideal microcosm for understanding platform dynamics and impacts of monetization on various stakeholders in the book promotion process.

4.1. Supply-Side Dynamics: Effects on Publishers and Authors

4.1.1. Impact on Publishers. The publishing industry can be divided into three main segments: the Big 5

Figure 3. (Color online) Twitter Mentions of Goodreads and Giveaways: The Impact of Platform Monetization



Notes. This figure illustrates the effect of fixed entry costs on social media engagement with the Giveaways program. The data demonstrate a significant decline in Twitter discussions mentioning both ″Goodreads″ and ″Giveaways″ following monetization implementation.

Table 1. Data Structure and Sample Sizes for Analyses

Analysis focus	Observational units	Sample description
Supply participation (Section 4.1)	Publisher-month	15,323 publishers, 50 months (Jan 2016–Feb 2020)
Book genre diversity (Section 4.2)	Genre-month	50 genres, 50 months (Jan 2016–Feb 2020)
Consumer response (Section 4.3)	Book-month	81,608 books, 24 months (±12 months from Giveaways Participation)

publishers (Penguin Random House, Hachette Livre, HarperCollins, Simon & Schuster, and Macmillan Publishers), who dominate with over 60% of U.S. English-language titles; smaller "indie" publishers; and self-publishing services. Each segment employs distinct publishing processes and promotional strategies. The monetization of the Giveaways program is likely to have varying implications for these groups, making it key to examine their differential responses to the introduction of fixed participation cost.

To analyze these effects, we categorize publishers into the above-mentioned three groups: Big 5, indie, and self-publishing service providers (details provided in Web Appendix B.1). We then collect and associate publishing information for each book featured in the Giveaways campaigns with its specific publisher or service. The introduction of participation cost led to a significant decline in monthly campaigns across all publisher types. Big 5 publishers' average monthly campaigns decreased from 469 to 249, whereas self-publishing services experienced a dramatic drop from 529 to just 22 campaigns per month. Small indie publishers also saw a steep decline, with monthly campaigns falling from 2,083 to 400.

Figure 4 illustrates the shift in publisher composition post monetization. Although the absolute number of campaigns decreased for all publishers, the proportions shifted significantly: the share of Big 5 publishing houses more than doubled from 12% to 30%, whereas indie publishers and self-publishing services saw a decline. This outcome underscores the differential effects of Giveaways monetization across publisher types.

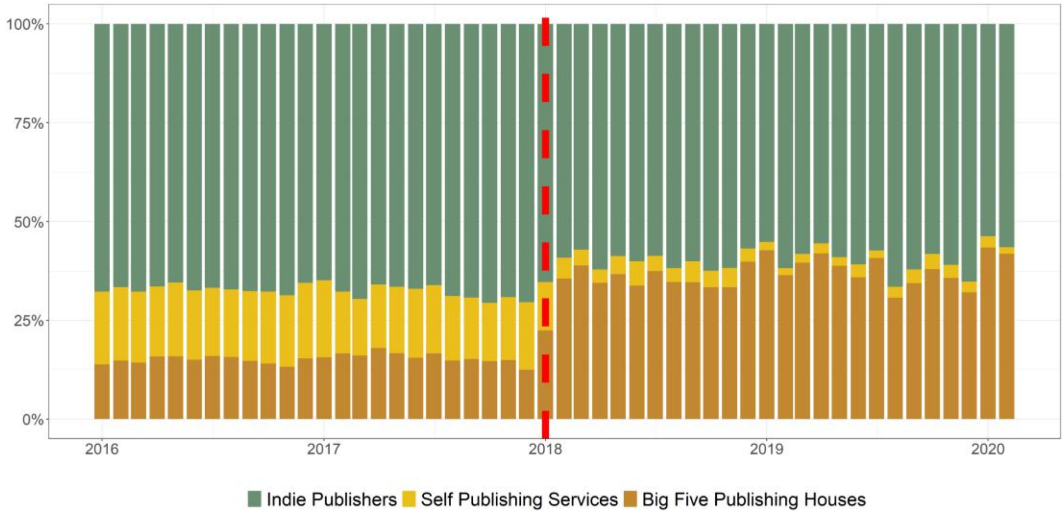
To rigorously examine these heterogeneous effects, we employ a Difference-in-Differences (DiD) framework. Given that the cost change applied to all publishers simultaneously, we use Giveaways data from 2015 to 2018 to create a control group and account for time trends. This approach, previously used in studies by Sim et al. (2022) and Liaukonytė et al. (2023), allows us to leverage historical data as a control group.[6] For this analysis, we group together indie and self-publishers as "non-Big 5" publishers.[7]

As shown in Figure 5, we use Giveaways data from 2017–2018 as the treated group and 2015–2016 as the control group. We estimate the following regression model:

$$y_{it} = \beta_0 + \beta_1 \times \mathit{Treated\ Period}_{it} \times \mathit{After}_t + \beta_2 \times \mathit{Treated\ Period}_{it} \times \mathit{After}_t \times \mathit{Big\ 5\ Publishers}_i + \delta_t + \sigma_i + \epsilon_{it}, \quad (1)$$

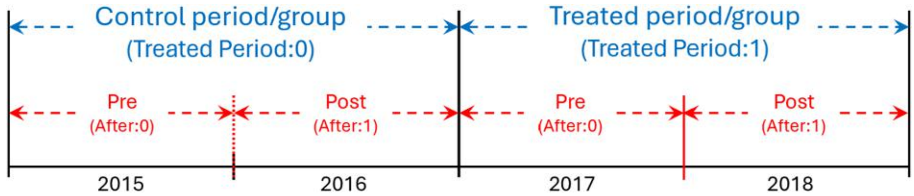
where y_{it} represents either the number of Giveaways campaigns or the proportion of books in the Giveaways

Figure 4. (Color online) Composition of Publishers in Giveaways: Pre- and Post-Monetization



Notes. The figure illustrates the changing composition of publishers participating in the Giveaways program before and after monetization. Despite an overall decrease in campaign numbers across all publisher types, the graph shows a significant increase in the percentage of books from Big 5 publishing houses. Conversely, there is a notable decline in the percentages of books from indie publishers and self-publishing services. The red vertical dashed line marks January 2018, indicating the implementation of the monetization policy.

Figure 5. (Color online) Difference-in-Differences Framework for Supply-Side Analysis



Notes. This figure illustrates the Difference-in-Differences framework for supply-side analysis. Giveaways data from 2017–2018 serve as the treated group, with monetization implemented in January 2018 (solid red line). Data from 2015–2016 serve as the control group, with January 2016 (dashed red line) as the reference point for potential policy effects.

program for publisher i in month t. $Treated\ Period_{it}$ indicates the 2017–2018 period, $After_t$ is a dummy for the second year in each period, and $Big\ 5\ Publishers_i$ indicates Big 5 status. We include month (δ_t) and publisher (σ_i) fixed effects and cluster standard errors at the publisher level.

The results in Table 2 reveal nuanced impacts across publisher types.[8] Although Big 5 publishers show a larger per-publisher reduction (43 fewer campaigns monthly), their small number (only five publishers) means their aggregate impact is limited. In contrast, indie publishers and self-publishing houses show a smaller per-publisher decrease (0.129 fewer campaigns monthly), but their large numbers result in a substantial aggregate decline in marketplace participation. This asymmetric response leads to an increased proportion of Big 5 publishers in the Giveaways program, suggesting that smaller publishers—who often lack alternative marketing resources—are disproportionately affected by the participation cost.[9] These shifts reshape the publishing landscape within the Giveaways marketplace, with important implications for market diversity and accessibility.

Our analysis reveals that Big 5 publishers are expanding their share in the Giveaways marketplace, whereas indie publishers and self-publishing service providers are losing ground. To quantify this shift in market concentration over time, we employ the Herfindahl-Hirschman Index (HHI), a widely used measure of market concentration. The HHI is calculated as $HHI_t = \sum_{i=1}^{n} s_{it}^2$, where s_{it} denotes the market share of firm i in time t. Higher HHI values indicate greater publisher concentration, whereas lower values reflect a more competitive industry (Hirshman 1964).

It's important to note that several factors can influence the absolute value of HHI, including market definition, treatment of product lines or business segments, and data availability for smaller companies. Given these considerations, we focus on the percentage change in HHI before and after monetization rather than its absolute value.

In our context, we calculate the HHI with s_{it} representing each publisher's market share in month t. We observe a substantial increase in market concentration following the monetization policy: the average HHI rose from 0.01 pre-monetization to 0.03 post-monetization. This 200% increase in HHI indicates a significant rise in market concentration, suggesting that the Giveaways marketplace has become more concentrated, with fewer publishers capturing larger market shares. (For detailed HHI trends and alternative concentration measures, please refer to Web Appendix B.6.)

Table 2. Impact on Books Published by Different Types of Publishers

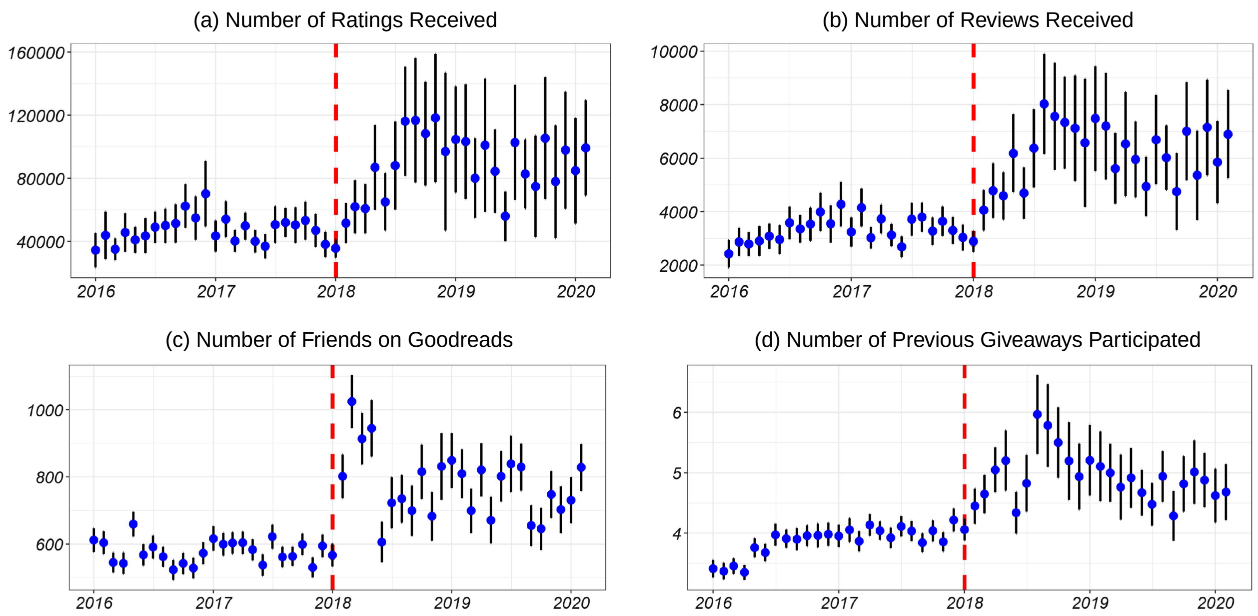
	Dependent variable	
	No. of Giveaways (1)	*Proportion* (2)
Treated Period × After	−0.129***	−0.031***
	(0.023)	(0.0004)
Treated Period × After × Big 5 Publishers	−43.354***	0.016***
	(6.561)	(0.002)
Month fixed effect	Yes	Yes
Publisher fixed effect	Yes	Yes
Clustered standard errors	Yes	Yes
Observations	678,288	611,376
R^2	0.883	0.038

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

4.1.2. Impact on Authors.

To complement our publisher-level analysis, we examine the effects of Giveaways monetization on individual authors by analyzing the characteristics of participants before and after January 2018. Figure 6 reveals significant changes in the profile of participating authors post monetization. First, authors continuing to participate tend to be more popular and recognized, as evidenced by higher numbers of ratings and reviews for their books (panels (a) and (b)). Second, these authors maintain larger networks on Goodreads, demonstrated by higher friend counts (panel (c)). Third, they show greater familiarity with the Giveaways program, participating in more campaigns over the same timeframe (panel (d)). These findings suggest that established authors with a prominent Goodreads presence are more likely to continue using the Giveaways program after monetization, whereas less experienced authors with weaker track records may discontinue participation.

Figure 6. (Color online) Author Characteristics on Giveaways Over Time: The Impact of Giveaways Monetization



Notes. The four graphs display the average monthly ratings and reviews received by authors, the average number of Giveaways campaigns they participate in, and the number of friends they have on Goodreads. The red vertical dashed line identifies January 2018, and the black bars indicate the 95% confidence interval.

Our analysis reveals that the Giveaways monetization policy significantly influences both publishers' and authors' utilization of this promotional program, with varying effects across different groups. At the publisher level, self-publishing service providers and indie publishers experience a substantial decline in participation, whereas the proportion of books by Big 5 publishing houses increases. At the author level, established authors with stronger platform presence are more likely to continue participating, whereas less experienced authors may discontinue use.[10]

These results highlight the importance of considering the differential impacts of platform monetization policies on various segments of participants. Such heterogeneous effects may have long-term implications for market diversity and accessibility in the book promotion ecosystem. The disparate outcomes observed across different publisher types and author profiles highlight the complex dynamics at play when platforms introduce monetization strategies.

4.2. Exploring Product Diversity: An Analysis of Book Genres

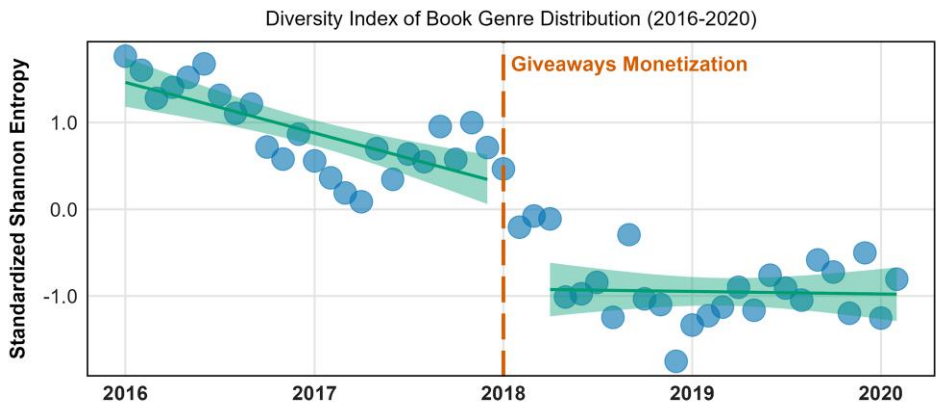
In this section, we investigate the impact of the Giveaways entry cost on books enrolled in the Giveaways program, focusing on product variety in terms of genre diversity. Diversity is particularly relevant for markets of cultural products, such as books, due to the horizontal differentiation arising from consumers' idiosyncratic tastes. As Waldfogel (2003) notes, markets for cultural products often exhibit "preference externalities," where the product offerings available to all consumers are influenced by the tastes of the majority. A diverse book selection serves multiple purposes: it caters to varied reader interests, addresses potential variety-seeking behavior, and enhances cross-side network effects by making the platform more attractive to a broader range of users.

To assess whether and how the monetization of the Giveaways program affects genre diversity, we first deduce genres for each book by examining the most frequent shelves they were added to on Goodreads.[11] Following this, we adopt Shannon entropy as our diversity metric for genre distribution. Stemming from Shannon's information theory (Shannon 1948), entropy has been widely utilized as a diversity measure across various disciplines, also known as the Shannon diversity index. This quantitative measure reflects both the number of distinct types present and the distribution of individuals among those types.

To assess the impact of monetization on genre diversity, we first categorize books by genre using Goodreads' user-generated bookshelves.[12] We then employ Shannon entropy as our diversity metric, a widely used measure in information theory that captures both the number of distinct categories and their relative proportions (Shannon 1948).

Figure 7 illustrates the monthly entropy-based diversity index before and after the monetization of the Giveaways program. We observe a clear and significant

Figure 7. (Color online) Decline in Book Genre Diversity Following Giveaways Monetization



Notes. The analysis reveals a decrease in entropy during the post monetization period, indicating reduced genre diversity following the implementation of the monetization policy. The red vertical dashed line identifies January 2018, and the gray band indicates the 95% confidence interval.

drop in genre diversity following January 2018. To ensure robustness, we conduct additional analyses controlling for temporal dynamics and using alternative concentration measures such as the Gini coefficient and the Herfindahl-Hirschman Index. These complementary approaches corroborate our main finding of decreased genre diversity post monetization (detailed results are reported in Web Appendix C).

To investigate the mechanism driving this decrease in diversity, we examine changes in the proportions of specific book genres. Figure 8 presents examples of genre proportion changes before and after monetization for three popular and three niche genres.

The analysis reveals a ″rich-get-richer″ effect: popular genres (e.g., thriller, mystery, historical fiction) become more dominant post monetization, whereas niche genres (e.g., science, psychology, poetry) experience further decline. To rigorously test this observation, we estimate the following regression model:

$$\begin{aligned} &\textit{Genre Proportion}_{gt} \\ &= \beta_1 \times \textit{Post Monetization}_{gt} \times \textit{Top 25\% Genre}_g + \beta_2 \\ &\quad \times \textit{Post Monetization}_{gt} \times \textit{Bottom 25\% Genre}_g \\ &\quad + \gamma_m + \epsilon_{gt}, \end{aligned} \tag{2}$$

where the dependent variable is the genre proportion of genre g at giveaway month t. We categorize genres into three groups based on their quartiles in the distribution of genre proportions during the pre-monetization period and create binary indicators for them accordingly: top quartile (i.e., top 25% genre-popular group), bottom quartile (i.e., bottom 25% genre-niche group), and anything in between (i.e., quartile of the genre falls between 25% and 75%—middle group).

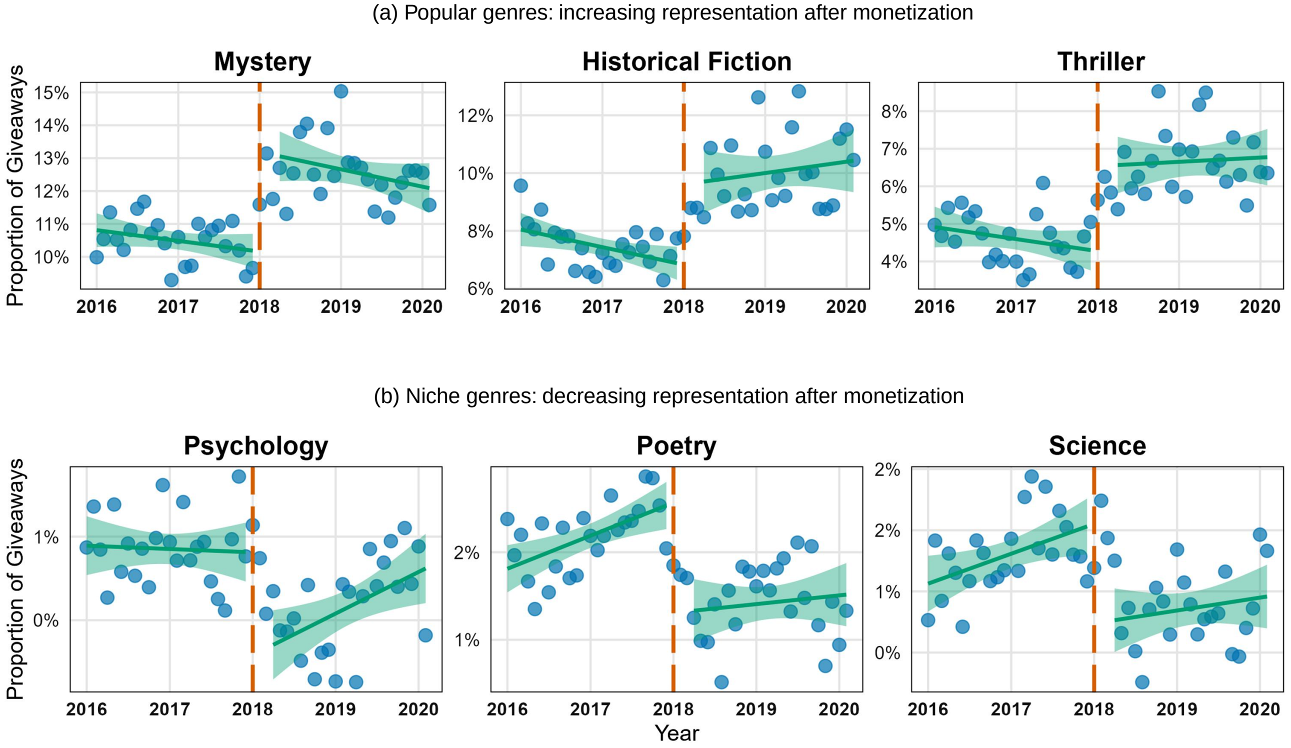
Table 3 presents the results, which are consistent with the visual examples in Figure 8 and support the bipolar effect on book genres. Column (1) reveals that post monetization, the proportions of popular genres rise by 1.2%, on average, whereas those of niche genres decline by 0.1%, on average. Although the decline in niche genres seems small in absolute terms, it could have a substantial impact, given their low baseline. To assess the relative importance of these changes, we calculate the percentage change in proportion for each genre and use this as an alternative dependent variable.[13] Column (2) demonstrates that the proportion of niche genres decreases by as much as 26% relative to their own baseline. In contrast, for popular genres, the 1.2% increase in raw proportion translates to an 11% increase relative to their baseline.

In summary, our findings provide strong evidence that monetizing the Giveaways program leads to a substantial decline in book genre diversity. This decrease can be attributed to a ″rich-get-richer, poor-get-poorer″ dynamic, where popular genres gain market share at the expense of niche categories. The policy appears to exacerbate existing disparities in genre representation, potentially narrowing the range of books promoted through the Giveaways program and impacting the overall diversity of the literary marketplace. These results echo the preference externality idea (Waldfogel 2003), where market mechanisms can systematically underserve minority tastes when fixed costs are present, leading to welfare losses for consumers with nonmainstream preferences as diversity diminishes in favor of mass-market appeal.

4.3. Demand-Side Responses: Consumer Ratings and Book Reviews

In this section, we investigate whether the supply-side changes and book genre shifts resulting from Giveaways monetization extend to the demand side of the market, influencing consumer ratings and book reviews. This analysis provides insights into how the

Figure 8. (Color online) Monetization Widened the Gap Between Popular and Niche Book Genres



Notes. We observe a growing disparity between popular and niche book genres as a result of the platform's monetization policy. The red vertical dashed line identifies January 2018, and the gray band indicates the 95% confidence interval.

observed effects impact consumers and offers valuable managerial implications for digital platforms.

First, we observe a marked decline in reader requests for books (Figure 9) following monetization, paralleling the decrease in campaign participation (Figure 2) from authors and publishers. This pattern aligns with basic economic intuition—fewer available campaigns naturally lead to reduced reader participation opportunities. However, from a platform design perspective, this substantial reduction in reader engagement (approximately 50%) represents an unintended consequence of the monetization policy. Although the platform's objective in implementing entry costs might have been to generate revenue, the resulting decrease in reader participation could undermine the program's role in facilitating book discovery and community engagement.

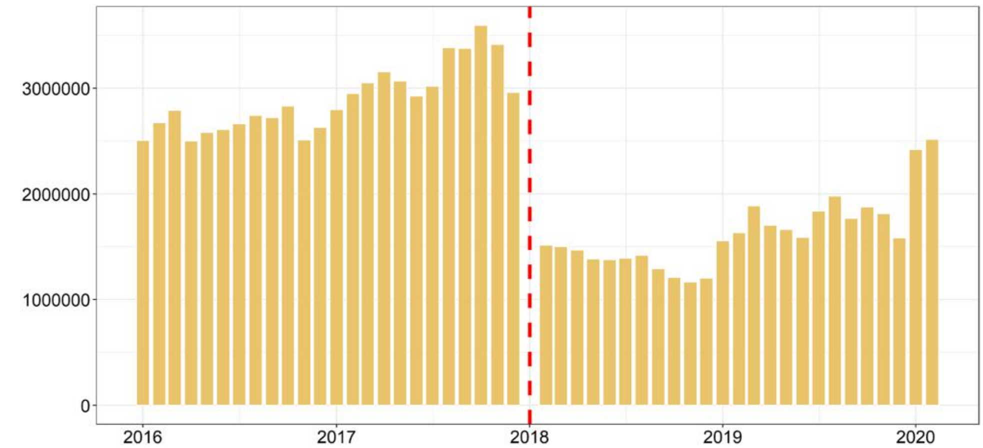
These aggregate patterns are informative, but they do not reveal the policy's effect on individual book performance. Although overall reader participation decreased, this coincided with a reduction in participating books, making the net impact on ratings and reviews theoretically ambiguous. A book-level

Table 3. Effects of Giveaways Monetization on Popular and Niche Book Genre

	Dependent variable	
	Raw Proportion (1)	*Percentage Change* (2)
Post-Monetization × Top 25% Genre	0.012***	0.110***
	(0.001)	(0.010)
Post-Monetization × Bottom 25% Genre	−0.001***	−0.262***
	(0.0001)	(0.039)
Month fixed effects	Yes	Yes
Genre fixed effects	Yes	Yes
Observations	2,350	2,350
R^2	0.969	0.188

$^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Figure 9. (Color online) Number of Requests from Users for Giveaways Books



Note. This figure shows a nearly 50% decline in readers' engagement with the Giveaways program, as indicated by the number of requests submitted for giveaway books, following January 2018.

analysis is necessary to understand how monetization influenced reader evaluations. To systematically examine these effects, we aggregate ratings data at the book-month level and estimate the following fixed-effects regression model:

$$r_{jt} = \alpha_j + \gamma_t + \beta_1 \times Post\ Giveaway_{jt} + \beta_2 \times Post\ Giveaway_{jt} \times Post\ Monetization_j + \epsilon_{jt}, \quad (3)$$

where r_{jt} represents our dependent variable (either the average rating score or the number of ratings) for book j in month t. *PostGiveaway* is an indicator variable equal to one if month t occurs after the conclusion of the Giveaways campaign for book j, whereas *PostMonetization* is an indicator variable equal to one if Giveaways campaign j follows the implementation of the monetization policy in January 2018. We include book fixed effects to control for time-invariant book characteristics and year-month fixed effects to account for common temporal trends in demand across books. Standard errors are clustered at the book level.

The parameter of interest, β_2, captures the impact of the Giveaways program monetization on the volume and valence of ratings for promoted books. Specifically, β_2 estimates the difference in promotional effects between books participating in Giveaways post-monetization and those participating pre-monetization. This can be interpreted as a difference-in-differences estimator, with pre-monetization Giveaways books serving as the control group for counterfactual estimation.

To mitigate the influence of non-Giveaways-induced ratings and long-term trend effects, our primary analysis focuses on a two-year window surrounding the Giveaways participation date (one year before and one year after). For the rating volume outcome, book-month combinations with no ratings are set to zero, whereas for the average rating outcome, these observations are excluded as undefined.[14]

Our findings reveal that the monetization policy amplifies the existing promotional effects of Giveaways campaigns, resulting in both a further increase in rating volume and lower rating scores. Table 4 presents the model estimates. Consistent with the Groupon effect described earlier, we observe that Giveaways participation increases the rating volume of promoted books, while lowering their average ratings (see β_1 in columns (1) and (3)). More importantly, the coefficient β_2 demonstrates the moderating effect of monetization: the average rating declines by an additional 0.05 stars post-monetization (column (2)), whereas the number of ratings increases by 14.5 reviews per month (column (4)). These results suggest that although book adoption (proxied by number of ratings) increases, the participation cost on the supply-side does not lead to improved consumer ratings.

To further examine the selection on observables assumption and the dynamic effects of monetization on ratings and rating volume, we estimate an event study model:

$$y_{jt} = Post\ Monetization_j + \sum_{\substack{k=-12 \\ k\neq-1}}^{12} \beta_m \times \mathbf{I}\{D_{jt} = k\} + \sum_{\substack{k=-12 \\ k\neq-1}}^{12} \beta_k \times \mathbf{I}\{D_{jt} = k\} \times Post\ Monetization_j + \delta_t + \epsilon_{jt}, \quad (4)$$

where y_{jt} is either the average rating or the number of ratings, and $\mathbf{I}\{D_{jt} = k\}$ is an indicator for month $k \in -12, 12$ for each book j relative to its participation in Giveaways, with month -1 as the reference level.

Figure 10 plots the β_k coefficients from these regressions. The results are consistent with those presented in Table 4, offering detailed insights into the dynamic effects on rating volume and valence. In this analysis,

Table 4. Effects of Giveaway Monetization on Average Book Ratings and Number of Reviews

	Dependent variable			
	Average Rating		*Number of Ratings*	
Post-Giveaway	−0.201***	−0.184***	11.008***	6.841***
	(0.003)	(0.004)	(0.182)	(0.176)
Post-Giveaway × *Post-Monetization*		−0.050***		14.454***
		(0.008)		(0.372)
Number of books	80,498	80,498	81,608	81,608
Overall mean rating	3.73	3.73	9.37	9.37
Book fixed effects	Yes	Yes	Yes	Yes
Year-month fixed effects	Yes	Yes	Yes	Yes
Observations	961,426	961,426	2,036,383	2,036,383
Adjusted R^2	0.512	0.512	0.131	0.134

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

we use books that participated in Giveaways before monetization as the control group. As a further robustness check, presented in Section 4.5.1, we gather additional data to explicitly create a control group comprising books that never participated in the Giveaways program. This alternative approach yields similar effects, reinforcing our findings.

In summary, our analysis reveals that the monetization of the Giveaways program exacerbates the existing promotional effects, leading to even lower ratings, despite increased engagement. To better understand these effects, we explore potential mechanisms in the next section.

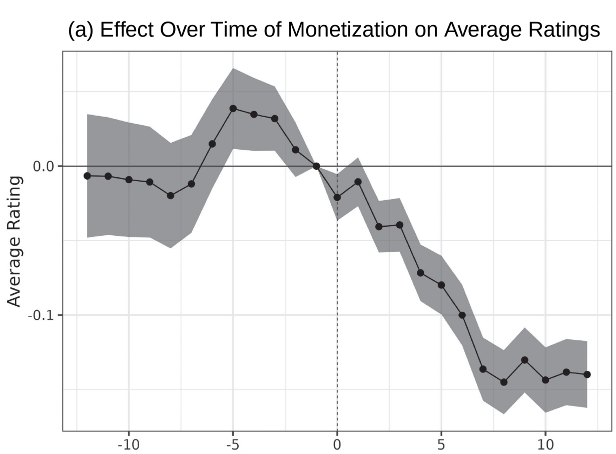
4.4. Mechanism: Increase in Consumer-Book Mismatch

To quantify fit and assess whether negative reviews stemming from ″horizontal″ fit mismatch increase after monetization, we analyze review text using a Bidirectional encoder representations from transformers (BERT) fine-tuned classification model (Devlin et al. 2018). We develop a classification approach to identify negative reviews arising from mismatches between product characteristics and customer expectations, rather than objective quality issues, following Banerjee et al. (2021).

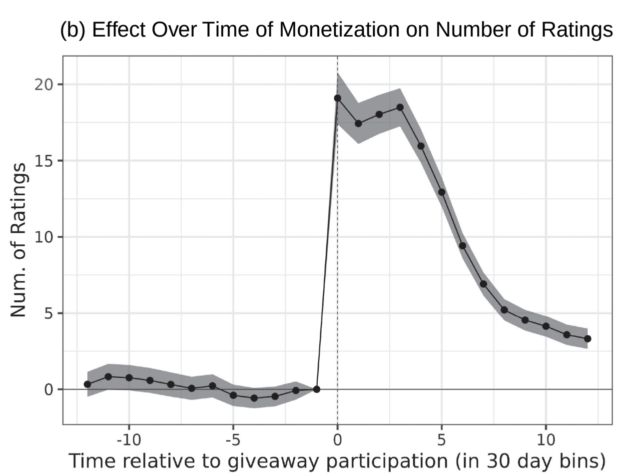
Our process involves creating a carefully labeled training data set through the following steps:

1. Sampling a subset of 3,000 negative reviews and enlisting two independent workers on Amazon Mechanical Turk (MTurk) to assign each review a discrete score between 1 (fully objective) and 5 (fully fit related).
2. Consulting a third worker in instances of tied scores.
3. Aggregating these scores into a binary classification for our classifier, excluding neutral scores of 3 (representing only 3% of the data points).

Figure 10. Event Study Plot Comparing Giveaways Effects Pre- vs. Post-Monetization



Effect over time of monetization on average ratings: the points plot the β_k coefficient estimates from Equation (4), and the ribbon indicates the 95% confidence interval. Given imperfect parallel trends, Figure 14 in the Web Appendix replicates this analysis on a smaller matched sample.



Effect over time of monetization on number of ratings: the points plot the β_k coefficient estimates from Equation (4), and the ribbon indicates the 95% confidence interval.

Notes. The points plot the β_k coefficient estimates from Equation 4, and the ribbon indicates the 95% confidence interval. Given imperfect parallel trends in figure (a), Figure 14 in the Web Appendix replicates this analysis on a smaller matched sample.

Our analysis indicates that approximately 65% of negative reviews were attributable to poor fit. The labeling prompt we used on MTurk, as well as other estimation details, can be found in Web Appendix D.1. We subsequently utilize these labeled data to fine-tune a pretrained BERT model (Devlin et al. 2018), achieving an F-1 score of 0.78 on the validation sample.[15] To evaluate the face validity of our classifier, we extract the predicted probabilities of each classified review belonging to the "fit" category and find the highest probability fit reviews to be more subjective in nature, with phrases like "it just didn't work for me," whereas those that are less likely to be fit related dealing with the plot and the writing (details in Web Appendix D.1.1).

Using this classifier, we label all negative reviews in our data set and estimate a similar specification as before:

$$Fit_{jt} = \alpha_j + \gamma_t + \beta_1 \times Post\ Giveaway_{jt} + \beta_2 \times Post\ Giveaway_{jt} \times Post\ Monetization_j + \epsilon_{jt}, \quad (5)$$

where Fit_{jt} is the proportion of reviews related to fit in a given month.

Table 5 shows that the proportion of fit-related negative reviews grows by 15% post-Giveaways, increasing by a further 12.5% postmonetization. These findings reveal that negative reviews due to horizontal fit mismatch increase following monetization, indicating that Giveaways monetization can influence the efficiency of consumer-book matching by shrinking the "long tail" of product offerings.

To further corroborate our findings, we employ an alternative measure of fit mismatch based on rating dispersion (Zegners 2019). Rating dispersion is a useful metric, as it captures the spread of opinions about a book, with higher dispersion potentially indicating a greater diversity of reader reactions and, consequently,

Table 5. Effects of Giveaways Monetization on Proportion of Fit-Related Negative Reviews

	Dependent variable	
	Proportion of Fit-Related Negative Reviews	
	(1)	(2)
Post-Giveaway	0.008***	0.006***
	(0.0005)	(0.001)
Post-Giveaway × *Post-Monetization*		0.005***
		(0.001)
Number of books	80,498	80,498
Overall mean fit proportion	0.04	0.04
Book fixed effects	Yes	Yes
Year-month fixed effects	Yes	Yes
Observations	961,426	961,426
Adjusted R^2	0.125	0.125

$^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

a higher likelihood of mismatch for some readers. We calculate this measure as follows:

$$Dispersion_{jt} = \frac{1}{N_{jt}} \sum_{i=1}^{N_{jt}} |r_{ijt} - \bar{r}_{jt}|, \quad (6)$$

where r_{ijt} is the rating of review i for book j at time t, $\bar{r}_{jt}$ is the average rating for book j at time t, and N_{jt} is the total number of ratings for book j at time t. We then estimate a similar regression model as before, using this dispersion measure as the dependent variable. The results, presented in Web Appendix D.2, show a significant increase in rating dispersion postmonetization, providing additional evidence consistent with the mismatch hypothesis.

4.5. Robustness and Alternative Explanations

This section addresses potential threats to validity arising from strategic reactions by publishers, authors, and consumers. We employ alternative empirical strategies and investigate several hypotheses to strengthen the validity of our main results and rule out alternative explanations for the observed effects of Giveaways monetization.

4.5.1. Alternative Control Group for Demand Effects Estimation. The difference-in-differences analysis of the demand side in Section 4.3 implicitly forms a control group using books involved in the Giveaways program during the pre monetization period. As a robustness check, we gather additional data to explicitly create a control group comprising books that never participated in the Giveaways program. To do so, we first identify books that participated in Giveaways, which we refer to as "focal books." For each focal book, we collect information on the set of books displayed under the "Readers Also Enjoyed" banner (shown in Figure 12 in the Web Appendix). This method enables us to estimate a different, yet equally relevant, estimand, which allows for a more robust construction of counterfactual outcomes for comparison.[16]

We employ an alternative empirical strategy utilizing recent advanced modeling techniques from the staggered difference-in-differences literature (Callaway and Sant'Anna 2021). The key parameters derived from this method are group-time average treatment effects, denoted as $ATT(g,t)$. For estimation details, please refer to Web Appendix D.3. Employing this estimation strategy, we replicate our previous findings: monetization of the Giveaways program moderates and amplifies its promotional effects. The overall treatment effect of Giveaway participation on number of ratings is 5.75 for the pre-monetization sample, compared with 15.53 for the postmonetization sample—an increase of approximately 10 reviews. Similarly, for star ratings, there is a difference of −0.08 stars between the pre- and post-monetization samples (Table 12 in the Web Appendix).

To gain deeper insights, we disaggregate the estimates and examine dynamic effects over time. We calculate the aggregated treatment effect by length of exposure, which can be interpreted as an event-study style estimator. Figure 11 illustrates these dynamic effects, with 95% confidence intervals adjusted for multiple hypothesis testing. For both outcome variables, the figure reveals systematic differences in effects for books participating in the Giveaways program before and after its monetization. These differences in effect estimates are statistically significant and corroborate our previous analysis.

Across both our two-way fixed effects and staggered difference-in-differences specifications, we find that beyond the baseline rating decline following Giveaways, monetization leads to an additional 0.05- to 0.08-star decrease, while also generating an extra 10–14 ratings above the typical Giveaways-induced volume increase. These results strongly suggest that monetization amplifies the promotional effects of Giveaways. In an alternative estimation strategy, we calculate treatment effects by calendar month. This approach allows us to identify heterogeneity based on when a book participates in Giveaways (i.e., before or after January 2018). The results of this model, which are qualitatively similar, can be found in Web Appendix D.5. Finally, to further alleviate concerns about imperfect parallel trends, we report results from a triple-difference estimator using matched-book fixed effects in Web Appendix D.6.

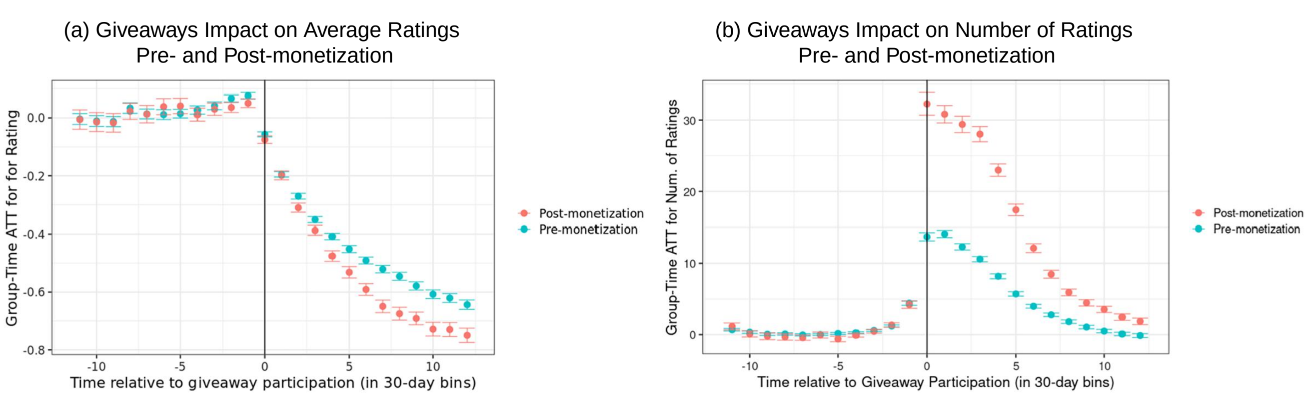
4.5.2. Quality of Giveaway Participants. A potential concern is that books participating in Giveaways post-monetization might be of systematically higher quality, which would suggest that the monetization policy is pricing out lower-quality participants, on average, which may actually benefit Goodreads. To address this, we conduct multiple analyses: First, although authors participating after monetization are more popular or experienced (Figure 6), their overall ratings are not higher (Figure 15 in the Web Appendix); Second, we analyze preparticipation average ratings for books in Giveaways between 2017 and 2019, controlling for participation month and publisher fixed effects. We find no evidence of differential preparticipation means (Table 19 in the Web Appendix).

These findings suggest that there is no stark difference in the quality of books participating in Giveaways after monetization, at least based on Goodreads ratings. This counters the explanation that monetization is raising the overall quality of participants who choose to list their books after the policy change. However, we acknowledge that measuring book quality is subjective and challenging, and our analysis is limited to available metrics.

4.5.3. Strategic Promotion of Books. Another potential source of bias could arise if publishers strategically choose which books to promote through Giveaways based on market performance. For instance, publishers might list their least circulating books when participation is free but opt for more popular titles when required to pay a fee. To examine this possibility, we collect auxiliary data from Keepa.com on the sales ranks of a subset of participating books. We focus on books from the Big 5 publishers, given their continued participation postmonetization, allowing us to understand the strategic behavior of publishers who are not "priced out" by monetization but still reduce their participation.

We collect daily sales rank information for 6,923 books from 2016 to 2020, creating a time series of sales rank observations. We analyze observations up to the Giveaways participation date for each book to

Figure 11. (Color online) Dynamic Effects Analysis with "Similar Books" as a Control



Notes. For both rating valence and volume outcome variables, the figure reveals systematic differences in effects for books that participate in the Giveaways program before and after its monetization. The black vertical line identifies January 2018, and the bars indicate the 95% confidence interval.

determine whether pre-Giveaways sales ranks differ for books entering Giveaways before 2018 compared with after. Our analysis reveals no systematic differences in the pre-Giveaways sales ranks of participating books premonetization versus postmonetization (Table 20 in the Web Appendix).

In addition, this aligns with research by Aguiar and Waldfogel (2018), which shows that predicting book success is challenging for publishers. Given this uncertainty, it's unlikely that publishers could consistently select books for Giveaways based on anticipated market performance.

4.5.4. Change in Reviewer Composition. A potential concern is that changes in reviewer characteristics post monetization, rather than fit mismatch, may explain the lower ratings. With fewer Giveaways campaigns but more copies per campaign (Figure 3 in Web Appendix A.2), a larger, more diverse reader base may be rating each book, potentially affecting ratings negatively (Kovács and Sharkey 2014).

However, this change in reviewer composition aligns with our consumer-book mismatch hypothesis. We posit that: (1) increased supply concentration and decreased genre diversity (Section 4.2) make it harder for readers to find books matching their tastes; and (2) readers enter Giveaways for books misaligned with their interests, resulting in lower ratings. Our analysis in Section 4.4 supports this, showing an increase in negative reviews related to book-reader mismatch rather than book quality.

Moreover, as seen in Figure 3 in Web Appendix A.2, although the number of copies offered per Giveaways campaign increased, the number of requests decreased postmonetization. This could have led to positive selection if only highly interested readers continued participating, which would result in higher ratings. However, our results in Section 4.3 show decreased average ratings, supporting the mismatch hypothesis.

Our findings extend the "paradox of publicity" argument (Kovács and Sharkey 2014) by demonstrating how monetization of a promotional program can reduce offering variety, creating more opportunities for taste mismatch compared with premonetization Giveaways. This contributes to understanding how monetization affects marketplace dynamics and platform ecosystems.

4.5.5. Reciprocal Behavior of Consumers. Finally, we consider the possibility that the negative effect observed for average ratings in Section 4.3 might mask publisher-level heterogeneity. Specifically, consumers might exhibit reciprocal behavior toward independent publishers, rating them favorably, while being more critical toward Big 5 publishers. If true, the increased proportion of Big 5 publishers postmonetization could explain the decrease in ratings.

To examine this possibility, we conduct a moderation analysis by adding publisher type (Big 5 versus non-Big 5) as a binary interaction term to Equation (5). Our results show that the coefficients are negative and significant for both groups. If reciprocity was driving the results, we would expect to see a positive effect on ratings for the non-Big 5 group.

The fact that all participating books attract lower ratings after Giveaways, with this negative effect amplified further postmonetization, suggests that the overall negative effect is not solely driven by Big 5 books. Therefore, we do not find strong evidence of consumer reciprocity in our setting (Table 21 in the Web Appendix).

5. Conclusion and Discussions

This study examines how Goodreads' monetization of its Giveaways program affected various stakeholders within the book promotion ecosystem. Our analysis reveals substantial changes in marketplace dynamics following the introduction of entry cost. We document three main effects. First, we observe a significant decrease in overall participation, with the impact being particularly pronounced among indie publishers and self-published authors. This shift leads to increased market concentration favoring established publishers. Second, this consolidation contributes to reduced genre diversity, with popular genres gaining market share at the expense of niche categories. Third, on the demand side, we find that the program's promotional effects intensify after monetization—books receive more reviews but lower average ratings. Our analysis of review text suggests that increased consumer-book mismatches drive these outcomes.

Our research advances the understanding of platform monetization in several ways. We demonstrate that introducing entry costs affects not only the volume of participation, but also alters marketplace composition and product offerings. Our findings show how supply-side contraction can diminish value for readers, potentially destabilizing the two-sided market dynamics. By analyzing changes in genre diversity and book ratings, we reveal indirect costs of monetization that highlight important trade-offs between short-term revenue generation and long-term ecosystem health. Through demonstrating how monetization amplifies promotional effects, we bridge platform monetization literature with research on online reputation.

Moreover, our study addresses an important tension in two-sided markets: the balance between positive network effects and potential inefficiencies from free entry. Although classical economic models suggest that free entry can be excessive due to business stealing effects, these models do not account for network effects in two-sided markets. Although we do not formally model these competing forces in a market equilibrium framework, our empirical results indicate that outcomes depend critically on which force dominates. This finding emphasizes the importance of considering both dynamics when designing platform policies.

Our findings have implications for digital marketplaces, particularly those dealing with cultural goods and content creation. As platforms transition from free to monetized models, managers should carefully consider the distributional impacts of entry costs. The effects we document on indie publishers and genre diversity suggest that certain monetization schemes can inadvertently marginalize smaller creators and reduce content variety. These insights extend beyond book promotion to other cultural goods platforms considering similar transitions.

Although our study provides valuable insights, we acknowledge certain limitations. Our focus on a single monetization strategy—fixed entry costs—does not capture the full spectrum of potential effects under alternative pricing models that future research could explore, such as multitiered pricing or subsidies for resource-constrained participants, which might mitigate the negative effects we observed. Additionally, our analysis does not include a market-level equilibrium analysis or investigation of related platforms, where authors and publishers may shift their promotional efforts to other online communities—a substitution effect that paradoxically supports our argument about the potential counterproductivity of the Giveaways program monetization. Finally, although our data provide rich information about reviews and ratings, we cannot directly observe individual reading behavior or book adoption patterns, which limits our demand-side analysis to these observable metrics.

Acknowledgments

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Endnotes

[1] For more information, see the archived Goodreads blog announcement [accessed July 2nd, 2025]: https://web.archive.org/web/20171215071901/https:/www.goodreads.com/blog/show/1108-goodreads-introduces-new-u-s-giveaways-program-a-more-powerful-book-mar.

[2] This is further supported by tweets, Reddit posts, and news articles where authors discuss their surprise and reactions to this change; see [accessed July 2nd, 2025]: https://www.reddit.com/r/Fantasy/comments/7yym6y/authors_opinions_on_new_goodreads_giveaway_fees/.

[3] This revenue estimate is based on the following calculation: Publishers choose between a $119 basic package or a $599 premium package for each campaign. With an average of 1,000 campaigns per month over 26 months, and assuming 20%–40% of campaigns use the premium package, the total revenue ranges from $5.59 million (20% premium) to $8.09 million (40% premium).

[4] Our results remain robust across different data subsets.

[5] Additionally, we examine whether the quality of books (as measured by star ratings) significantly differs for those participating pre-monetization versus post-monetization. Our analysis finds no evidence to support such quality differences.

[6] See Web Appendix B.2 and Web Appendix B.3 for parallel trends and other identifying assumptions.

[7] A comparison between self-publishers and Big 5 publishers is provided in Web Appendix B.7.

[8] Results remain robust when using a one-year window for treatment and control periods (Web Appendix B.4) and when examining only publishers present in both periods (Web Appendix B.5).

[9] Book-level analysis confirms this shift: the likelihood of Giveaways participation increases by 11% for Big 5 books, while decreasing by 5% for self-published books postmonetization (Web Appendix B.7).

[10] We also find suggestive evidence that female authors tend to use Giveaways more frequently for self-promotion compared to male authors; however, their books are more adversely affected by the monetization policy. Please find more details of the analysis in Web Appendix B.8.

[11] We took up to the top two bookshelves for each book as its genres after some manual processing of the raw bookshelves data. This included removing irrelevant shelves (currently reading, Kindle), merging similar shelves ("historical" and "history"; "sci-fi" and "science-fiction"), and, finally, taking the top 50 bookshelves across all books as the genre categories we used.

[12] We identified genres based on the two most frequent bookshelves for each book, after preprocessing to merge similar categories and remove irrelevant shelves. The top 50 resulting categories were used as our genre classifications.

[13] For example, if romance has a genre proportion of 33% in November 2019 and its average pre-period proportion is 30%, the percentage change data point for November 2019 would be $33\%/30\% = 110\%$, indicating a 10% increase relative to its preperiod baseline.

[14] Because we do not directly observe which reviewers receive a free copy of a book from the Giveaways campaign or which reviews are prompted by the Giveaways program, we interpret the effects on reviews and ratings as intent-to-treat (ITT) effects, i.e., the average impact of paid giveaways on consumer reviews. This approach provides a lower bound on the magnitude of effects, as it incorporates the "noise" from all non-giveaway ratings submitted.

[15] We also test other classification models like the C-SVM (convolutional support vector machine, results reported in Web Appendix D.1.1), but we ultimately select BERT for our main results due to its superior predictive performance in our context.

[16] We check for stable unit treatment value assumption violations, i.e., spillovers in Web Appendix D.4, finding them to be negligible.

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