Engagement-Dependent Utility: Theory and Evidence

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Abstract

A student who expects a college course to be worthwhile may pay close attention and learn a great deal, while a student who expects that course to be a waste of time may scroll through their phone during class and learn nothing. The quality of the lecture is the same for each, but their realized utility is different due to their (belief-induced) engagement level. We develop a model in which consumers choose engagement with a product based on beliefs about product quality and where engagement affects the distribution of realized utility. We then provide evidence on this mechanism in a large-scale experiment with over 500 book readers, recruited from online reader communities and randomly assigned novels to read, with a subset randomly assigned to view reviews before reading. We show that negative reviews reduce both expectations and realized enjoyment: readers shown bad reviews are 15 percentage points less likely to report above-average expectations and 11 percentage points less likely to report above-average enjoyment. This negative effect on enjoyment is driven by a compression of the enjoyment distribution, with lower density of both high ratings and very-low ratings, and sustains over the course of reading, with bad-review exposed readers showing declining trajectories of enjoyment while control readers show increasing trajectories. We estimate a structural model from our experimental data and, through stylized simulations, illustrate how the realized utility and average ratings of products can be shaped by different marketing strategies in this framework.

Keywords: consumer learning, experience goods, engagement, dynamic consumption

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1 Introduction

Consider a student sitting in a classroom on the first day of a new course. If she expects the material to be valuable, she sits up front, takes notes, and engages with the lecture. If she expects it to be a waste of time, she sits in back, checks her phone, and lets her mind wander. At the end of the semester, the engaged student has learned something; the disengaged student has not. Both students may feel vindicated in their initial expectations, even though they experienced the same lectures.

This dynamic is not limited to classrooms. A reader who expects a book to be tedious may read inattentively, missing the rewards that close attention would reveal. A gym member who doubts a program's efficacy may skip sessions or exercise half-heartedly. A viewer who expects a film to be pretentious may watch distractedly, phone in hand. In each case, low expectations induce low engagement, which produces disappointing outcomes, which validate the low expectations. Initial beliefs become self-fulfilling prophecies. But in traditional utility models of consumption, products have fixed final utility, and beliefs generally only shape either purchase decisions or search decisions, overlooking this mechanism.[1]

This paper develops a model of engagement-dependent utility for products requiring sustained consumption; tests it experimentally using a large-scale reading study; estimates structural parameters from these data; and evaluates counterfactuals and implications for marketing strategy.

At core, the theoretical mechanism that we propose is simple. Consumers face

[1]There is also a subset of models wherein expectations may affect the interpretation of experiences that are otherwise fixed in nature, such as reference-dependent utility models, expectancy-disconfirmation models or assimilation models (Kőszegi and Rabin, 2006; Oliver, 1980; Anderson, 1973); as we discuss in detail in the literature review and in the main text below, the mechanism we propose is distinct, where the experience itself is partially determined by the consumer's choice of engagement, which has important differences in both empirical predictions and in implications for marketing strategy.

uncertainty about product quality and choose how intensively to engage based on their beliefs regarding product quality. Engaged consumption is effortful but rewarding when the product is good; disengaged consumption is easier but yields compressed, middling outcomes regardless of quality. Because engagement affects realized utility, and realized utility informs updated beliefs, initial expectations can become self-fulfilling, especially across dynamic consumption of a given product of uncertain quality, such as reading a book over time. A pessimistic consumer disengages, experiences mediocrity, and remains pessimistic and disengaged. An optimistic consumer engages, experiences the product's true character (good or bad), and updates accordingly. We formalize this into a theoretical model and establish that this engagement channel has meaningful implications for marketing strategy: through affecting beliefs and subsequent engagement, marketing efforts can not only determine the purchase of the product but also shape the distribution of realized value itself, through a behavioral channel distinct from previously studied interpretive mechanisms. By convincing students to engage, convincing gym-goers to commit to their workout, or convincing movie watchers to put away their phones, successful marketing campaigns can themselves be instrumental to the actual realized utility of the product being marketed.

We provide evidence on this mechanism in a large-scale experiment with over 500 readers recruited from online reader communities, where we randomly assign books for them to read from a large list of roughly 150 classic and contemporary popular books, and ask these readers to report both their expectations of enjoyment and their enjoyment over the course of their reading. In addition, we randomly assign a subset of readers to view reviews before reading. Our results demonstrate that negative reviews substantially lower pre-reading expectations, reducing the probability that readers expect above-average enjoyment by 15 percentage points. This effect extends

to realized enjoyment: random assignment of negative reviews reduces the probability of above-average enjoyment by 11 percentage points, even though this treatment is randomly assigned among an identical reader population and books are randomly drawn from an identical set of books. We find that bad reviews shift readers from the high end of the enjoyment distribution into the middle, increasing the share reporting middling enjoyment by 15 percentage points, and lowering the respective share of both high and very-low utility; and also that the effect of negative reviews sustains over the course of reading, with a significant negative slope of utility of reading over the course of the book for bad reviews compared to the control condition. This compression of utility and sustained pattern of negative utility is difficult to reconcile with standard models of experience goods, where realized utility depends only on product characteristics and consumer preferences. Our interpretation is that expectations affect engagement, and that readers who expect little read less attentively and experience a lower-variance, lower-average utility distribution from the text, and that this difference can sustain over time as early disengagement generates mediocre experiences that reinforce pessimism.

To formalize these dynamics, we develop a model in which consumers read a book of uncertain quality over multiple periods, choosing in each period between engaged and unengaged reading, and where the probability distribution over enjoyment depends on both true quality and chosen engagement. For high-quality books, engaged reading unlocks value, as high enjoyment becomes more likely and low enjoyment less likely. For low-quality books, engagement may backfire, as close attention exposes flaws that inattentive reading would miss. We develop a set of formal results showing that, in such a framework, reader engagement will depend on their beliefs; engagement (and enjoyment) paths will differ across different initial priors; and that utility from a book can be strictly increasing in prior beliefs about that book's expected

utility.

We then estimate this model using GMM, fitting structural parameters using moment conditions from our experimental data, leveraging both initial enjoyment distributions and trajectory patterns across treatment conditions and book quality levels. The estimated model closely reproduces the qualitative effects of bad reviews in the data, including the compressed enjoyment distribution and declining utility trajectories, confirming that our model is consistent with the observed phenomena.

Lastly, we use this estimated model to evaluate a set of stylized marketing counterfactuals in order to concretely illustrate the implications of this framework. We embed the individual reading model in a market simulation with heterogeneous consumers and review dynamics, where early buyers' experiences generate reviews that shift later buyers' priors, and show that this creates meaningful interdependence as the composition of early adopters affects not just early revenue, but the entire trajectory of the product's reputation. We formalize this by constructing a bottom-up decomposition that adds one mechanism at a time—word-of-mouth transmission, early-adopter selection, and price discrimination—quantifying each channel's contribution to both revenue and product ratings. The central insight is that release strategy has a second-order effect not previously considered, because by selecting which consumers buy early, it also determines the average prior beliefs of initial buyers, and therefore the average engagement levels, and therefore the average review rating early customers generate. With this, we show that product ratings are themselves equilibrium objects that depend on release strategy; the same book generates different long-run ratings (as well as different long-run sales revenue) depending on the initial release strategy and/or price, which affects the sequence of consumer types who encounter it. We offer that this can serve as a novel explanation for common release strategies for books (high-price hardcovers first) that has not been previously considered, and similarly

as a novel motivation for limited "buzz-building" release strategies more generally.

Taken together, our results offer a framework in which consumer beliefs shape consumption outcomes through engagement behavior. For goods requiring sustained attention or additional time investment to be realized, beliefs and the marketing efforts that shape them may not merely affect purchase decisions, but the value that consumers enjoy from the products they have purchased. This creates a channel through which promotional strategy affects welfare, distinct from psychological reference-point or interpretive mechanisms, with considerable implications for optimal marketing tactics. More broadly, our findings suggest that the role of marketing may extend much farther than conventional frameworks allow; when engagement is affected by beliefs and utility is affected by engagement, marketing promotion becomes not merely a tool for selling products, but core to the value of the product itself.

The remainder of the paper proceeds as follows. Section 2 reviews related literature. Section 3 describes our experimental data. Section 4 presents reduced-form results and demonstrates model-free support for engagement-based utility. Section 5 develops the theoretical model. Section 6 describes the structural estimation, including parameter estimates and model fit. Section 7 presents counterfactual simulations and develops broader marketing implications. Section 8 concludes.

2 Related Literature

Our paper primarily relates to three literatures in marketing and economics: work on experience goods and consumer learning; research on reference-dependent preferences; and studies of online reviews and release strategy.

The canonical framework for markets with quality uncertainty begins with Nelson (1970), who distinguished search goods from experience goods based on whether

quality is observable before purchase. In the large literature that followed, consumers learn about fixed product quality through consumption signals, updating beliefs and adjusting future behavior (e.g., Erdem and Keane, 1996; Ackerberg, 2003). Our framework departs from this tradition by allowing realized utility to depend not only on product characteristics but also on how consumers engage with the product. The same book can yield high enjoyment for an engaged reader and mediocre enjoyment for a disengaged one, even holding quality fixed. This creates feedback between beliefs and outcomes that is absent from standard learning models.

Second, several existing literatures model channels through which expectations can shape experienced utility. In reference-dependent utility models (Kőszegi and Rabin, 2006, 2009), expectations form reference points, and outcomes that exceed (or fall short of) the reference generate gain (or loss) utility; recent empirical work documents this pattern in several settings (Carrera et al., 2025; Rossi and Schleef, 2024; Li et al., 2025). Separately, a long tradition in consumer behavior documents "assimilation" effects, whereby expectations bias satisfaction ratings toward the prior through interpretive confirmation bias of ambiguous experiences (Anderson, 1973; Deighton, 1984; Hoch and Ha, 1986). More broadly, Shiv et al. (2005) demonstrate that marketing actions such as pricing can alter actual experienced product efficacy through non-conscious expectancy activation, or a "marketing placebo effect". Our mechanism is distinct from these prior channels. We propose a fourth channel, engagement-dependent utility, in which expectations shape how consumers behaviorally engage with a product, and engagement in turn shapes the distribution of realized utility—even when there is no ambiguity in the (engagement-dependent) experience. In Section 4, we present empirical patterns, namely a compression of the enjoyment distribution toward middling outcomes and a persistent divergence in enjoyment trajectories over the course of reading, that are difficult to reconcile with

reference dependence, assimilation, or placebo effects, but are consistent with this engagement mechanism.

Third, our work relates to the large empirical literature documenting how online reviews affect consumer behavior (Chevalier and Mayzlin, 2006; Godes and Mayzlin, 2004; Liu, 2006), with early buzz particularly important for experience goods. Within this literature, several papers document how ratings are shaped by social dynamics and selection: previously posted ratings influence subsequent rating behavior and sales (Moe and Trusov, 2011; Muchnik et al., 2013); who chooses to post, and what they post, evolves endogenously as ratings accumulate (Moe and Schweidel, 2012); and the composition of the rating population itself can generate biases, as when early adopters with idiosyncratic tastes produce unrepresentative reviews (Li and Hitt, 2008), or when publicity attracts poorly-matched consumers (Kovács and Sharkey, 2014).[2] On the firm side, work has examined how firms strategically manage word-of-mouth (Campbell et al., 2017) and how brand strength shapes review content in equilibrium (Chakraborty et al., 2023). Our work complements this literature by identifying a different mechanism: rather than selection into reviewing, we study selection into engagement, i.e. how intensively consumers attend to the product, which shapes the experiences that generate reviews.[3]‘1

Finally, our paper relates to prior work on dynamic consumption decisions in book reading. Lee et al. (2025) and Zhao et al. (2025) model how consumers dynamically choose whether to continue consuming serialized (chapter-by-chapter purchase

[2]Relatedly, Bondi et al. (2025) show that heterogeneity in rater stringency can compress aggregate ratings and reverse product rankings—a cross-sectional aggregation bias distinct from the within-reader distributional compression we document.

[3]Our work also offers a novel explanation for common hardcover-first release strategies in book publishing, traditionally interpreted through intertemporal price discrimination (Clerides, 2002). We identify a second channel: hardcover release selects for consumers with higher priors who engage more intensively, experience the product more favorably, and write more positive reviews, inducing a potential positive-feedback loop.

decision) content. These papers treat the mapping from product characteristics to experienced utility as fixed. We introduce engagement choice as a mediating variable, creating the feedback loop that is central to our analysis: beliefs affect engagement, engagement affects outcomes, and outcomes affect updated beliefs.

3 Data

To examine how expectations affect consumption experiences of a product, we conducted a large-scale reading study with over 500 readers. This section describes the data and basic experimental design; for full details, see Appendix A.

3.1 Survey Design

We onboarded 584 participants from online reader communities (Reddit book-related subreddits, such as "r/52book", which is an online community for readers who aim to complete one book per week) to read novels and provide both pre-reading expectations data and chapter-by-chapter feedback. These participants may therefore be considered to represent a specific population of "regular" or "habitual" readers. We targeted this community for ease of recruitment into a reading study and to ensure that these were consumers who, at baseline, might derive positive utility from reading books.

Participants were then randomly assigned books from a randomly-selected list of contemporary fiction derived from the library of an anonymous private-sector partner, a book-tracker app company (similar to Goodreads), from which we randomly selected 145 fiction books for our study.[4] This random list of books includes popular novels

[4]Specifically, we randomly selected approximately 200 books, and then excluded roughly 50 because they were determined afterwards to be too short to be considered novels or were nonfiction.

like "The Innocent Man" by John Grisham, award-winning novels like "The Orphan Master's Son", and less-well-known books like "The Best Laid Plans" by Cameron Lund. Participants were told what book they were randomly assigned to read early on in the onboarding process and were asked to inform the research team if they had read the book before, and if so, were randomly assigned a different book to read, to ensure that all reads were comparable "first reads" of a book that had not been previously read by the given study participant. Participants were compensated with a free copy of the book they were randomly assigned and, upon completion of all surveys, $15 for completion of all surveys, which were also reviewed by the research team to ensure reasonable answers and good-faith completion.[5]

Then, prior to reading, participants were randomly assigned to one of three review conditions: bad reviews (two real 1-star reviews gathered from Goodreads for their assigned book), good reviews (two real 5-star reviews), or no reviews.[6] This design allows us to examine how exogenous variation in information exposure affects expectations and, subsequently, how randomly-shifted expectations affects reading experiences. Treatment groups are balanced on observable pre-treatment characteristics, including reading frequency and prior familiarity with the assigned book and author (Appendix Table A1).

[5]Note that this incentive for finishing the assigned book contaminates estimates of the effect of treatment on the choice to finish or not finish the book; as such, we focus our analyses on expectations, enjoyment measures and enjoyment trajectories. When we examine different attrition rates by treatment, we find insignificant differences across review conditions, presented in Appendix Table A2.

[6]Participants saw these reviews (if any) in the same onboarding email that first informed them of the book they'd been assigned, with the framing of "Here are two reviews from previous readers of this book", followed by the reviews. Participants who did not receive a review condition saw the same email without that subsection. See Appendix A for additional details on treatment administration.

3.2 Measurement

Three types of data were gathered. First, before beginning, participants reported their expected enjoyment of the book on a Likert scale ranging from expecting that they "will not enjoy at all" to expecting that they "will enjoy a great deal." Second, participants were asked to take a "chapter-by-chapter" survey of their ongoing enjoyment ("How much are you enjoying the book so far?") on a Likert scale during the course of reading the book, ranging from "not at all enjoying" to "enjoying very much." Third, we collected each book's Goodreads rating in order to classify books independently as either high- or low-quality using large samples of actual online reviews. 2 participants of our 584 did not complete reading surveys and so were not included in the study sample, leading to a final analysis dataset of 582 reader-books.

4 Reduced-Form Results

Prior to introducing our theoretical framework, we present reduced-form evidence from these data on 1) how random exposure to bad (1-star) or good (5-star) reviews alters expectations, and 2) how such random variation in expectations alters reading experiences and enjoyment.

In most standard models of experience goods, realized utility depends on product characteristics and consumer preferences, not on prior beliefs. If this were the case, the review treatment should have no effect on realized enjoyment; the reviews are randomly assigned, the books are drawn from an identical set across conditions, and readers are drawn from the same population. Any observed effect of reviews on expectations should not translate into effects on actual enjoyment. In this section, we examine this assumption empirically.

Table 1: Effect of Randomly-Assigned Reviews on Expectations of Enjoyment

	Positive Expectations
Randomly Shown Two Good (5-star) Reviews	-0.018
	(0.041)
Randomly Shown Two Bad (1-star) Reviews	-0.154**
	(0.049)
N	582
R^2	0.020

Notes: Standard errors clustered at book level in parentheses. *** p<0.001, ** p<0.01, * p<0.05, † p<0.1. Review effects are relative to the omitted category of no review shown. Expectations measured on a scale from 1 to 5 where 5 indicates highest expectation; positive expectations categorized as "expect to enjoy somewhat" or "expect to enjoy a great deal".

4.1 Effect of Reviews on Expectations

We begin by examining the first-order effect of the review treatment on expectations. Given that our data are measured on an ordinal Likert scale, we first analyze this effect by regressing review treatment on the density of responses indicating positive expectations ("expect to enjoy somewhat" or "expect to enjoy a great deal"), presented in Table 1 with standard errors clustered at the book level. We find a null effect of good reviews on positive expectations, but a strongly significant effect of bad reviews, with 15.4% lower density of positive expectations, indicating a sharp negative effect of bad reviews. This pattern is highly consistent with prior research on the superior diagnosticity of negative information, where negative online reviews are generally perceived as more informative and influential than positive cues (Skowronski and Carlston, 1989; Qahri-Saremi and Montazemi, 2023).

Second, for additional transparency and robustness, we present the distributions of expectations ratings for all three conditions (bad reviews; good reviews; and no reviews), shown in Figure 1. Here, we juxtapose each treatment review condition

Figure 1: Distribution of Expectations by Review Treatment



Notes: Side-by-side histograms comparing each treatment to No Review, with chi-squared p-values of the differences between the discrete distributions. Expectations measured on 5-point Likert scale.

against the control (no review) condition in order to demonstrate shifts, and then test the statistical difference between the respective treatment distribution and the control distribution. We find an insignificant positive impact of good reviews (chi-squared test: $p = 0.114$) and a highly significant negative impact of bad reviews (chi-squared test: $p = 0.010$), closely in line with the results of our regression analyses.

4.2 Effect of Expectations on Enjoyment

Given this highly significant effect of the bad review treatment (and the null effect of the good review treatment), we next turn to examining the effect of these randomly-shifted expectations on enjoyment. As noted at the beginning of this section, standard utility models would not predict any effect of expectations on experienced utility, which is generally assumed to be a function of consumer preferences or product characteristics and not of expectations.

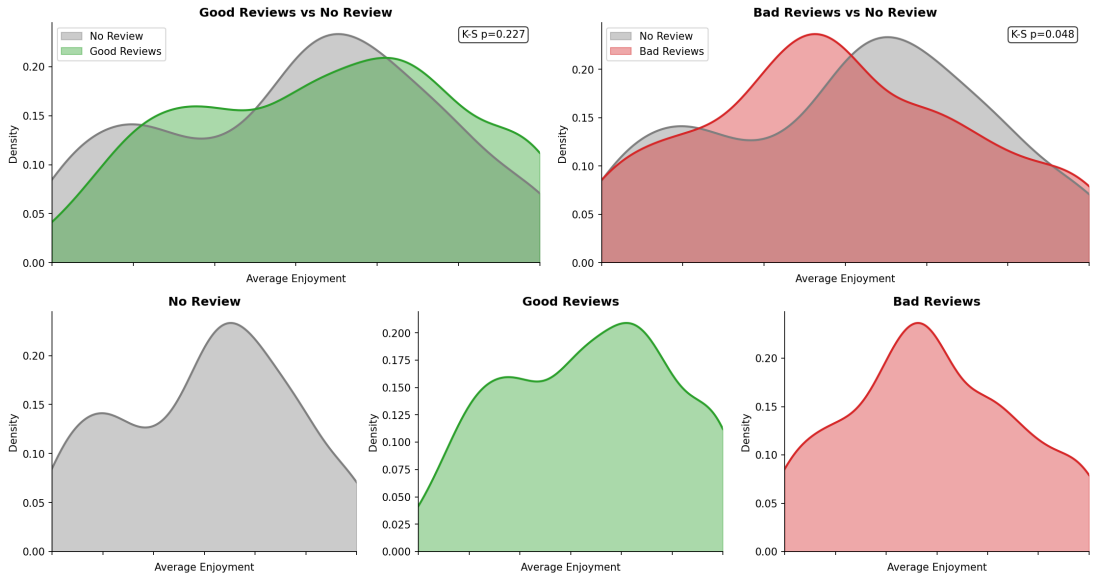
We examine this assumption empirically in Table 2 and Figure 2, where we ex-

Table 2: Reduced-form Effect of Randomly-Assigned Reviews on Enjoyment

	Middling (3-4)	Above-Avg
Randomly Shown Two Good (5-star) Reviews	0.036	0.045
	(0.034)	(0.047)
Randomly Shown Two Bad (1-star) Reviews	0.147***	-0.108*
	(0.040)	(0.051)
N	582	582
R^2	0.024	0.014

Notes: Standard errors clustered at book level in parentheses. *** p<0.001, ** p<0.01, * p<0.05, † p<0.1. Review effects are relative to the omitted category of no review shown. Middling defined as $[3, 4)$ on a 1–7 scale. "Above-Avg" defined as above the mean (4.12).

Figure 2: Distribution of Enjoyment by Review Treatment



Notes: Top row: overlapping kernel density estimates comparing each treatment to No Review, with Kolmogorov-Smirnov test p-values. Bottom row: individual KDEs for each treatment group. Enjoyment averaged at reader level.

amine how randomly assigned reviews shift average enjoyment during reading, measured as the (reader-level) average enjoyment reported during reading. As above, we perform this analysis using simple regression of review treatment against binned ranges, and furthermore present distributions of treated readers against distributions of control readers and testing whether these respective distributions are significantly different from one another.

Our results indicate that bad reviews significantly reduce realized enjoyment. In Table 2, we find that randomly shown negative reviews before reading are 10.8 percentage points less likely to report above-average enjoyment (above 4.12 on the Likert scale), with a particularly large shift in density to the "middling" range (3-4).

Conversely, good reviews have no significant effect on realized enjoyment, consistent with good reviews not moving expectations significantly above baseline, and with changed expectations being the driver of differences in subsequent enjoyment.

This evidence is reproduced in the distributional analysis, presented in Figure 2, where we present kernel density estimation (KDE) plots of the respective treatment distributions compared to the control (no review) distribution of average enjoyment. Here we see that the control distribution is effectively bimodal, with a smaller mode at the low end (1-2 range) of the enjoyment distribution and a larger mode at the middle-to-high range (4-5) of the enjoyment distribution. While good reviews appear to modestly shift this distribution higher while roughly retaining this bimodal shape, the difference between distributions is not statistically significant (Kolmogorov-Smirnov test: $p = 0.227$). Bad reviews, on the other hand, significantly change the distribution (Kolmogorov-Smirnov test: $p = 0.048$), shifting the peak down and compressing the tails, with modestly less mass on the lowest mode leading to a single-peaked distribution centered in the lower-middle (3-4) range.

4.3 Dynamic Enjoyment Effects

The above results demonstrate that expectations significantly moderate subsequent enjoyment, as randomly-assigned bad reviews significantly shift expectations downward, and this subsequently shifts enjoyment downward–in particular, compressing the enjoyment distribution into the middle-lower range.

However, these documented effects could reflect a one-time shift in enjoyment that dissipates as readers form their own impressions. Alternatively, if expectations affect engagement, initial differences could persist or even amplify over time as early disengagement generates mediocre experiences that reinforce pessimism and perpetuate further disengagement.

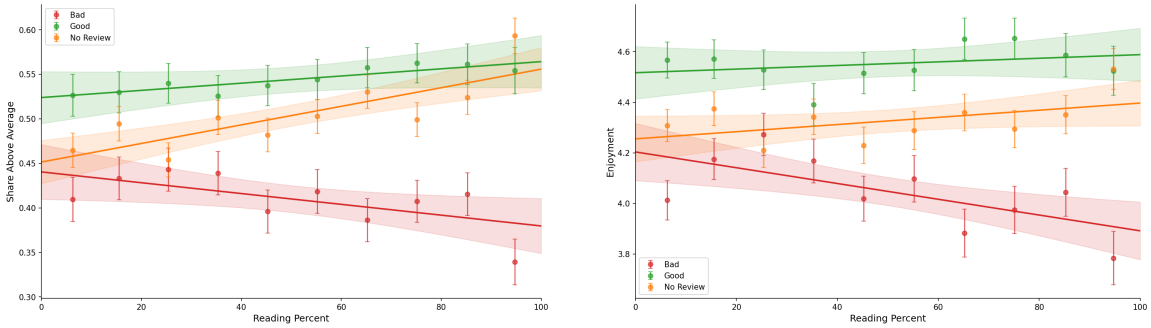
We therefore examine the trajectories of engagement in order to parse these potential explanations more clearly. Figure 3 plots enjoyment trajectories across reading progress, separately by review treatment, using both the density of above-average ratings and averages of the reported Likert ratings over the course of reading the book.[7]

In this figure, we see that the previously-measured gap between treatment groups persists throughout the book, as readers who saw bad reviews do not "catch up" as they gain their own experience with the text. Instead, the trajectories diverge over time. The "good review" and "no review" groups both show modestly increasing enjoyment over the course of reading, consistent with readers becoming more absorbed in books as narratives develop; while in contrast, the "bad review" group shows a declining trajectory. Readers who began with low expectations report progressively lower enjoyment as reading continues.

We examine this divergence statistically using an interaction model that regresses

[7]For this analysis, we restrict to a balanced sample of 417 reader-books with observations in all three thirds of reading progress.

Figure 3: Enjoyment Trajectories by Review Treatment



(a) Above-Average Enjoyment

(b) Likert Average

Notes: Figure shows binned means (with standard error bars) and OLS regression lines (with 95% confidence bands) by reading progress. Panel (a): share of observations with above-average enjoyment. Panel (b): average enjoyment on 1–7 Likert scale. Sample restricted to reader-books with observations in all three thirds of reading progress (417 reader-books).

above-average enjoyment on treatment indicators, reading progress (measured as percent of book completed), and their interaction. The coefficient on Bad Reviews × Progress is −0.165 per 100 percentage points of progress ($p = 0.024$; see Appendix B.7 for full results). The interaction for Good Reviews is small and statistically insignificant, indicating that good review readers follow essentially the same trajectory as no-review readers.

These trajectory differences are consistent with a model in which initial pessimism induces disengaged reading, which generates mediocre experiences, which reinforce pessimism, creating a self-fulfilling cycle that sustains over time. For example, a reader who expects the book to be worthless may read the early chapters less devotedly, fail to connect with the characters or narrative, and find her expectations confirmed. Having learned nothing to change her mind, she continues reading without putting her heart into the task, falls further out of love with the narrative, and enjoys subsequent chapters even less. Meanwhile, a reader without negative priming may be more likely to engage earnestly, connect with the story and characters, and

enjoy it progressively more as the narrative develops.

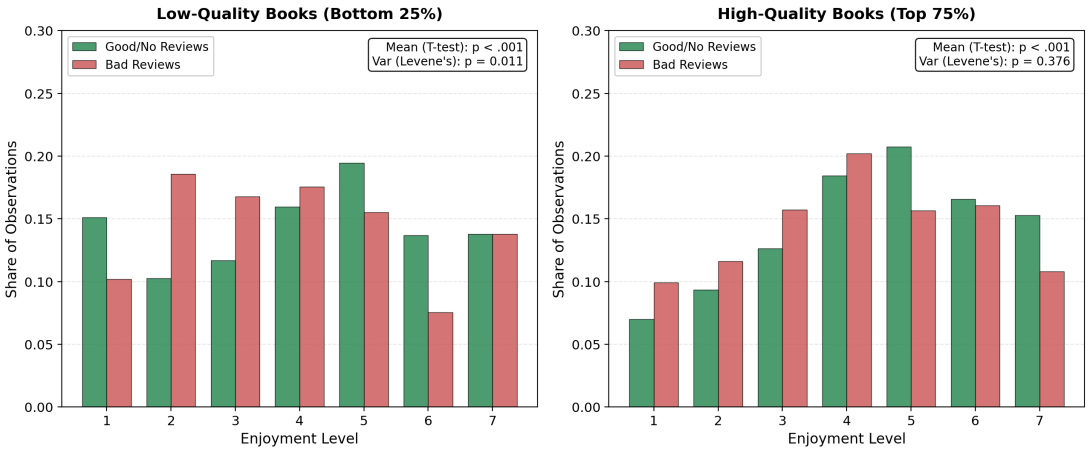
4.4 Enjoyment Effects Across Book Type

Lastly, we examine how enjoyment effects differ across different book quality levels. In a model where Bayesian priors about book type lead to differential engagement patterns, one might expect that engaging with a bad book is suboptimal to disengaging, while engaging with a good book is superior to disengaging, leading to genuine uncertainty about whether to engage or unengage with an unknown book—and a clear path for priors to affect both engagement levels and, through engagement, realized enjoyment.

To measure book quality, we merge our data to review data from Goodreads.com, a large-scale online book reader review platform owned by Amazon, containing thousands of reviews from previous readers of these books; we then map books to either "low-quality" or "high-quality" based on their average Goodreads review rating. We define the quality type cutoff to rationalize the observed density of positive expectations in our data, which is roughly 75% at baseline, and so classify any book below the 25th percentile of Goodreads rating as "low-quality" and any book above the 25th percentile of Goodreads rating as "high-quality". We then graph the distribution of ratings by both book type and review treatment, to examine how the effect of shifted expectations differs across book types.

The distributions of reported ratings are presented in Figure 4. (As good reviews have minimal, insignificant effects, we combine good reviews and no reviews into a single distribution in this analysis to focus on the effects of bad reviews.) Between book types, we find a clear difference in the pattern of bad review treatment effects, highly consistent with an engagement-based utility framework: for high-quality

Figure 4: Enjoyment by Review Treatment X Book Type



Notes: Figure shows distribution of reader ratings across rating levels for different review treatments, stratified by book type. "Low-quality" defined as books below 25th percentile of Goodreads rating, "high-quality" defined as books above 25th percentile of Goodreads rating.

books, we find that bad reviews simply shift the distribution down, with a significant difference in means in a two-sample T-test ($p < 0.001$) but insignificant difference in variances by Levene's test ($p = 0.376$), suggesting that disengagement is simply broadly suboptimal. But for low-quality books, we find that bad reviews compress the distribution (Levene's test: $p = 0.011$) in addition to shifting the mean down, reducing the probability of a high 5 or 6 rating and also reducing the probability of a worst-case 1 rating. This suggests that the bad review treatment, which one might interpret as inducing disengagement, may have had a protective effect, in terms of the likelihood of the worst-case rating, for bad books specifically.

4.5 Candidate Explanations

With these patterns established, we briefly discuss how these results may or may not be reconciled with different models of dynamic or expectations-related utility.

First, reference-dependent utility models (Kőszegi and Rabin, 2006, 2009) predict

the opposite pattern to what we observe. In these frameworks, expectations form a reference point against which outcomes are evaluated, and lower expectations should generate more frequent "pleasant surprises," leading to *higher* reported satisfaction (Carrera et al., 2025; Rossi and Schleef, 2024; Li et al., 2025). Our findings point in precisely the opposite direction: lower expectations cause lower, not higher, experienced enjoyment.

Second, assimilation or confirmation bias (Anderson, 1973; Deighton, 1984; Hoch and Ha, 1986) could shift ratings toward prior expectations through interpretive channels, if readers interpret ambiguous textual experiences more negatively when primed with bad reviews. However, this mechanism operates predominantly on ambiguous experiences (Hoch and Ha, 1986; Yi, 1993), and so should attenuate as readers accumulate direct experience with the text. We observe the opposite: the treatment effect persists and widens over the course of reading. Moreover, assimilation predicts a leftward shift of the enjoyment distribution but not the compression toward middling outcomes that we document, particularly for low-quality books.

Third, placebo-like expectancy channels (Shiv et al., 2005) may alter experienced product efficacy through "marketing placebo effects", but like assimilation, such perceptual effects should be strongest when the expectancy prime is fresh and would attenuate as consumers accumulate direct experience, and would predict a level shift in experienced utility rather than the variance compression we observe. Similarly, mood or affect spillovers from reading negative reviews would be expected to decay over time (Forgas, 1995), and would not predict distributional compression.

The preponderance of empirical evidence we observe is instead, we argue, most consistent with a model wherein expectations affect engagement, and the quality of attention that readers bring to the text affects the utility they actually extract from the experience. While we acknowledge that we are not able to directly observe engage-

ment in this context, and while the above explanations may be a partial explanation for some of the patterns we observe, the complete set of evidence fits best with the engagement-dependent utility model of consumption that we propose in this work. A reader who expects disappointment may check her phone intermittently rather than immerse, and thereby fulfill her own prophecy, similar to a student "checking out" on a class that they have low expectations for, compressing their realized utility distribution and plausibly sustaining over time.

5 Theoretical Model

We here present a formal dynamic model of consumption for multi-period experience goods with unknown quality. The model captures how consumers update their beliefs about product quality based on period-by-period consumption signals, and how these beliefs influence their consumption intensity over time, which in turn determines their distribution of realized utility.

5.1 Setup

Consider a book with T chapters indexed by $t \in \{1, 2, \ldots, T\}$. A reader plans to read all chapters but decides for each chapter whether to read it in an engaged manner (e) or an unengaged manner (u). We normalize the utility from not reading the book to zero.

The overall quality of the book is $Q \in \{G, B\}$, representing good and bad quality respectively. Upon reading chapter t, the reader receives utility $u_t \in \{u_H, u_M, u_L\}$ with $u_H > u_M \geq 0 > u_L$.[8] If the quality of the book is Q and reading level is I, the

[8]N.B. that the precise scaling is arbitrary and all results depend on utility differences; the ordering is invariant to additive transformations.

probability of receiving utility u_j for $j \in \{H, M, L\}$ is p_j^{QI}, where $\sum_j p_j^{QI} = 1$.

We assume that the likelihood of receiving high utility is strictly higher when $Q = G$ than when $Q = B$ for engaged reading, and weakly higher for unengaged reading: $p_H^{Ge} > p_H^{Be}$ and $p_H^{Gu} \geq p_H^{Bu}$. This ensures that high enjoyment is a positive signal of quality, and allows for the limiting case where unengaged reading is relatively uninformative.

Let expected utility when quality is Q and reading level is I be $EU^{QI} = \sum_j p_j^{QI} u_j$. We assume that engaged reading of a good book yields the highest expected utility, that unengaged reading yields weakly positive expected utility regardless of quality, and that engaged reading of a bad book yields strictly negative expected utility:

$$EU^{Ge} > EU^{Qu} \geq 0 > EU^{Be} \quad \text{for } Q \in \{G, B\}.$$

Engagement thus amplifies both rewards and risks. For a good book, engaged reading unlocks value that passive reading misses; for a bad book, it exposes flaws that passive reading would overlook. Unengaged reading is "safe" in the sense that it yields weakly non-negative expected utility regardless of quality, but foregoes the upside of engagement when the book is good.[9]

[9]Note that we do not consider the choice to stop reading the book in this simple model, as in our data, readers were incentivized to finish their assigned book and so we do not have unconfounded identification of baseline finishing rates, or the effects of review treatments on finishing rates. We leave the addition of a "stopping" choice to this model to future work; we expect that adding this feature would only sharpen the final implications of our model, as lower realized utility could then lead to early, unsatisfied exit from the book, heightening potential negative feedback loops even more.

5.2 Belief Updating and Optimal Reading

The reader's prior belief that $Q = G$ is $\pi_0 \in (0, 1)$. When she chooses reading level I in chapter t and receives utility u_j, her posterior probability that $Q = G$ is

$$\pi_t(\pi_{t-1}, j, I) = \frac{\pi_{t-1}\, p_j^{GI}}{\pi_{t-1}\, p_j^{GI} + (1 - \pi_{t-1})\, p_j^{BI}}. \tag{1}$$

This implies $\pi_t \geq \pi_{t-1}$ if and only if $p_j^{GI} \geq p_j^{BI}$. Given our assumptions, the reader's belief that $Q = G$ strictly increases upon receiving high utility under engaged reading, and weakly increases under unengaged reading.

For the final chapter T, the expected utility from reading level I for a reader with prior probability π_{T-1} is

$$EU_T^I(\pi_{T-1}) = \pi_{T-1} \cdot EU^{GI} + (1 - \pi_{T-1}) \cdot EU^{BI}.$$

The gain from engagement is, therefore,

$$EU_T^e(\pi_{T-1}) - EU_T^u(\pi_{T-1}) = \pi_{T-1}(EU^{Ge} - EU^{Gu}) + (1 - \pi_{T-1})(EU^{Be} - EU^{Bu}). \tag{2}$$

Since $EU^{Ge} - EU^{Gu} > 0$ (engagement helps for good books) and $EU^{Be} - EU^{Bu} < 0$ (engagement hurts for bad books), both of which follow from our assumption on EU^{QI}, this expression is strictly increasing in π_{T-1}. It is positive when $\pi_{T-1} = 1$ and negative when $\pi_{T-1} = 0$, so there exists a unique threshold $\pi_{T-1}^* \in (0, 1)$ such that the reader engages if and only if $\pi_{T-1} \geq \pi_{T-1}^*$.

For earlier chapters $t \in \{1, 2, \ldots, T-1\}$, the reader accounts for how current reading choices affect future beliefs and decisions. The expected utility from reading

level I in chapter t is

$$EU_t^I(\pi_{t-1}) = \pi_{t-1}\left(EU^{GI} + \sum_j p_j^{GI} \max_k EU_{t+1}^k(\pi_t(\pi_{t-1}, j, I))\right) + (1-\pi_{t-1})\left(EU^{BI} + \sum_j p_j^{BI} \max_k EU_{t+1}^k(\pi_t(\pi_{t-1}, j, I))\right). \quad (3)$$

The reader compares $EU_t^e(\pi_{t-1})$ and $EU_t^u(\pi_{t-1})$ and chooses accordingly. To eliminate trivial multiplicity, we assume that ties are broken in favor of engagement. This framework yields several properties, which we state informally here and formalize with proofs in Appendix C.1:

Threshold policy. For each period t, there exists a belief cutoff π_t^* such that the reader engages if and only if her current belief exceeds π_t^*.

Uniqueness. Given the model parameters, the optimal reading plan is unique, in the sense that for any history of prior engagement and realized utilities, there is a single optimal engagement choice.

Monotonicity. The expected value of engagement is increasing in the reader's belief, so readers who are more optimistic about book quality always find engagement weakly more attractive.

Belief divergence. Two readers with sufficiently different initial priors reading the same book will follow different stochastic belief processes and arrive at different expected final beliefs—even though they face the same underlying quality.

Self-fulfilling beliefs. For a good book, an optimistic reader who engages throughout can experience substantially higher expected utility than a pessimistic reader who never engages, despite both reading the same book. Initial beliefs shape engagement, engagement shapes outcomes, and outcomes validate the initial beliefs.

6 Structural Model

To demonstrate that this model is indeed consistent with our data, and to fit parameters for later counterfactual exercises, we estimate a structural version of our theory model presented above using Generalized Method of Moments (GMM).

6.1 Calibration and Moment Conditions

To estimate this model, we directly leverage the exogenous random variation in expectations and in downstream enjoyment from our study. The model has 8 free probability parameters: $\{p_H^{Ge}, p_M^{Ge}, p_H^{Gu}, p_M^{Gu}, p_H^{Be}, p_M^{Be}, p_H^{Bu}, p_M^{Bu}\}$.[10] We calibrate the baseline prior under the control condition (and under the "good review" condition, which did not significantly shift expectations) to be the rational-expectations prior of $\pi_0 = 0.75$, but allow the magnitude of the shift in the prior from the "bad review" treatment to be estimated from data, with the constraint that it is bounded above by 0.75. We designate this reader prior under the bad review treatment as $\pi_{0,bad}$. In total, this leads to 9 parameters that we aim to estimate from the data.

Initial Utility Moments

As our measure of enjoyment over the course of the book is based on a cumulative question of how much the reader is enjoying the book so far, we model these reported data points as corresponding to a simple functional form of $U_{it'} = \sum_{t \leq t'} u_{it}$ for $t' \leq T$ where u_{it} is the utility from reading session $t \in \{1, 2, ..., T\}$. With this, in period 1, $U_{1t} = u_{1t}$, and we can treat initial utility reports as measures of realized per-period utility. We model each book as consisting of three periods, broken into three thirds of the reading progress, and so $U_{1t} = u_{1t}$ corresponds to ratings during the first third

[10] Note that p_L^{QI} is defined by $1 - p_H^{QI} - p_M^{QI}$.

of reading a book.[11]

Following our model and our bucketed-range evidence from our reduced-form data, we model $u_{it} \in \{u_H, u_M, u_L\}$ and map observed ratings in the $(4, 7]$ range to u_H, observed ratings in the $(2, 4]$ range to u_M, and observed ratings in the $(1, 2]$ range to u_L. This captures the salient ranges that shift in density under the observed reduced-form bad review treatment in Table 2 and Figures 2 and 4 in a simplified three-tier system.

We then measure the respective density of u_H, u_M and u_L in each of the 2x2 conditions of {High / Low} Quality Book $\times$ {Bad Review Treatment / No Bad Review Treatment}, bucketing the "no review" and "good review" groups together since we see no significant effect from the good review treatment. As above, we categorize books into two quality types based on Goodreads rating, where low-quality corresponds to books below the 25th percentile of rating in our sample and high-quality corresponds to books above.[12]

These densities serve as our first type of moment condition. While engagement itself is not directly observed, the respective observed distributions of utility for bad books and the observed distributions of utility for good books allows us to identify the probability of high, medium or low utility for either quality type, and similarly the observed distributions under the control versus bad review treatment allows us to identify engaged versus unengaged distributions for each respective level of book quality.

[11] For this estimation, we use the balanced sample of 417 reader-books for which we observe at least one rating in each third of the reading progress.

[12] As noted above, this 25th percentile cutoff is chosen to rationalize the no-review expectations data, which reports expectations of positive utility for roughly 75% of books.

Utility Trajectory Moments

Next, in order to pin down $\pi_{0,bad}$, we add an additional type of moment condition based on the slope of the utility trajectory over the course of the book. Here, we exploit the reduced form evidence of differential trajectories presented in Figure 3 in order to identify not only how much utility distributions shift but also how they change over the course of reading, which will allow us to identify $\pi_{0,bad}$ from the data: if differences quickly dissipate, the shift in prior is likely modest and soon negligible relative to the information gleaned from reading, whereas if differences endure or strengthen, the shift in prior is implied to be stronger.

To measure trajectories, we calibrate model utility to $u_H = 1$, $u_M = -0.5$, and $u_L = -2$ to approximately correspond to the center of the given ranges, where the high range implies strictly positive utility, the medium range implies modestly negative utility, and the low range implies starkly negative utility.[13] We then calculate, for any given set of model parameters, the implied slope of U_{it} across the thirds of the book, and fit this to the empirical slopes of utility across thirds of the book.

Model Restrictions

Finally, in addition to the moment conditions above, we adopt several restrictions that strengthen the theoretical assumptions for our empirical context. These assumptions include an assumption that probabilities are strictly between 0 and 1; that the prior under bad reviews is strictly lower than the rational expectations prior without bad review treatment; that high utility draws are informative of book type (more likely

[13] As 4 is the center of the 1-7 Likert range, it corresponds here to neutral or 0 utility. Note as well that the calibrated utility values $u_H = 1$, $u_M = -0.5$, $u_L = -2$ shift the zero point of the utility scale relative to the theory's normalization (in which $u_M \geq 0$); but as noted in that section, since all engagement decisions and belief dynamics depend on utility differences, this additive shift does not affect any behavioral predictions.

from good books); and that engagement is optimal for high-quality books and disengagement is optimal for low-quality books, in order to ensure that readers don't all choose the same mode. For more details, see Appendix E.2.

Estimation Procedure

We estimate the nine parameters $\theta = (p_H^{Ge}, p_M^{Ge}, p_H^{Be}, p_M^{Be}, p_H^{Gu}, p_M^{Gu}, p_H^{Bu}, p_M^{Bu}, \pi_{0,bad})$ by minimizing the GMM criterion:

$$\hat{\theta} = \arg\min_{\theta} \left[m(\theta) - \hat{m}\right]' W \left[m(\theta) - \hat{m}\right] \tag{4}$$

where $\hat{m}$ is the vector of empirical moments, $m(\theta)$ is the vector of model-implied moments (computed via simulation), and W is a weighting matrix.[14] We estimate standard errors using bootstrap across 100 draws.

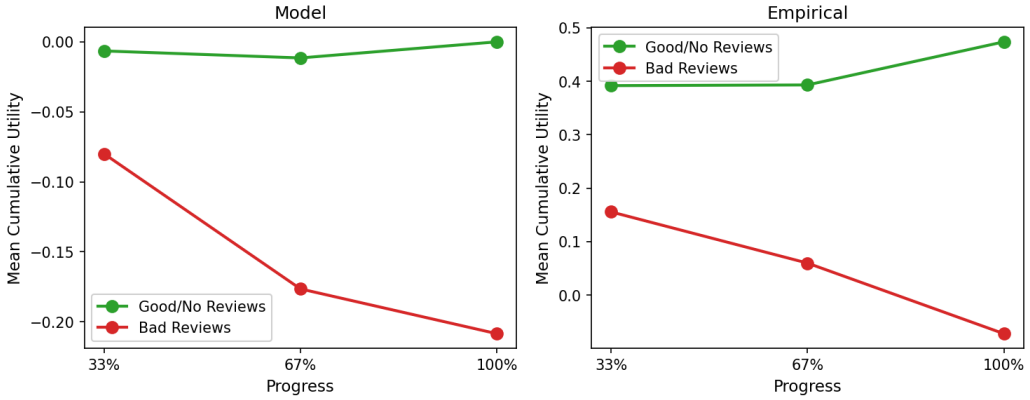
6.2 Model Fit

Parameter estimates are presented in Appendix Table E1. We recover strong effects of both engagement mode and book quality: we estimate 54% probability of high utility from engaged reading of a good book, compared to 34% probability of high utility from unengaged reading of a bad book; as well as roughly 15% probability of low utility from engaged reading of a bad book, versus roughly 10% probability of low utility from disengaged reading of a bad book. All parameters are recovered with tight bootstrapped confidence intervals, with standard errors of roughly 0.005.

With this estimated model, we are able to qualitatively match the empirical moments well. In Figure 5 we show the full trajectory comparison between model pro-

[14] As this is primarily an illustrative exercise for a simple, stylized model, we do basic one-step GMM with an identity weighting matrix across these models.

Figure 5: Model-Projected vs. Empirical Trajectories



Notes: Figure shows trajectories of utility in empirical data compared to fitted model projections. Empirical mean cumulative utility defined as average Likert score minus 4. Based on estimation sample of 417 reader-books with observations in all three thirds of reading progress.

jections and empirical data to further illustrate how the model is able to capture the pattern of utility dynamics, with sustained negative utility in the bad review condition versus flat/slightly-increasing utility in the good review condition. In Appendix Figure E1, we demonstrate that the model is also able to match the patterns of the initial density moments, and in particular reproduces the compressed-enjoyment-distribution effect of bad reviews on low quality books, with induced disengagement leading to higher probability of middling utility and lower probability of low utility.

While this GMM estimation exercise is stylized and based on a simple model, we present this as a simple "existence proof" that our model is fully able to account for the otherwise-puzzling patterns recovered from our experimental data.

7 Counterfactuals: Marketing Implications of Engagement-Dependent Utility Goods

With this estimated model, we turn to illustrating the marketing implications. As above, this is intended as a simple demonstrative exercise to show a set of first-order implications from our model that are novel to this engagement-based utility framework, using a stylized model consistent with our experimental data. We ground our counterfactuals in terms of optimal marketing strategy for books, focusing on how engagement-dependent utility changes our understanding of traditional hardcover-first release strategies.

Rather than comparing static and hardcover pricing directly, we build the hardcover advantage piece by piece, adding one mechanism at a time. This bottom-up decomposition isolates the contribution of three distinct channels of word-of-mouth transmission; early-adopter selection; and price discrimination.

7.1 Simulation Framework

We embed the estimated reading model into a market simulation with $N = 2{,}000$ consumers whose baseline priors are drawn from a Beta(2, 12) distribution (mean ≈ 0.14). The market unfolds over 12 periods; each period, a cohort is exposed to the product and decides whether to purchase based on expected utility. Buyers' realized utilities become public reviews that update subsequent consumers' priors. Full details appear in Appendix A.5. We construct four release strategies of increasing complexity:

1. **Simultaneous Release** (Baseline): All consumers arrive at once at \$10, with no word-of-mouth.

2. **Sequential Release**: Consumers arrive over 12 periods at \$10. Early buyers'

reviews update later buyers' priors, adding word-of-mouth dynamics.

3. **Limited Release**: Same $10 price, but for the first 3 periods only high-prior consumers can purchase—analogous to advance reader copies (ARCs) or invite-only early access. This adds early-adopter selection without any price premium.

4. **Hardcover Pricing**: $20 for the first 3 periods, then $10. Same selection as Strategy 3, plus a revenue premium.

The total hardcover advantage decomposes as: word-of-mouth (Strategy 2 minus 1) + selection (Strategy 3 minus 2) + price discrimination (Strategy 4 minus 3).

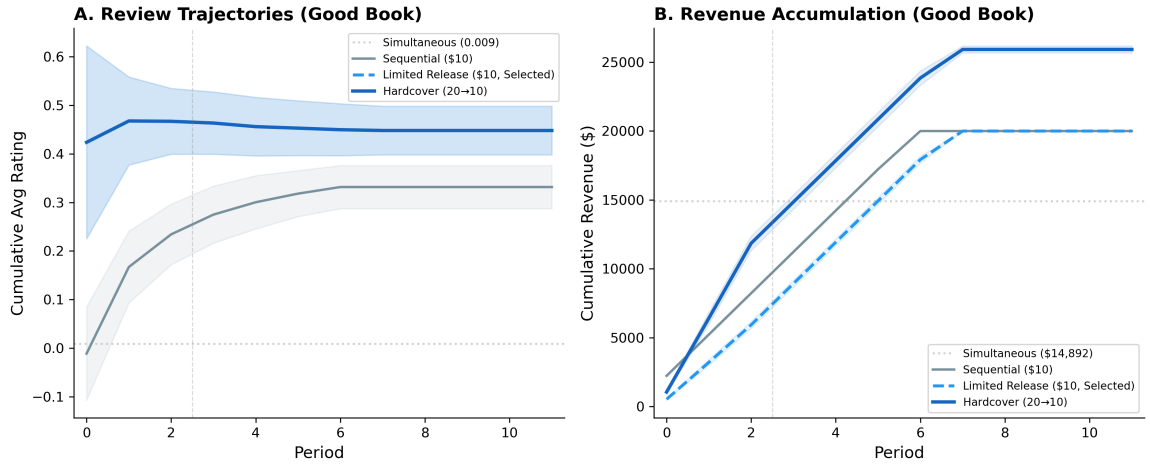
7.2 Results

Figure 6 presents review trajectories and cumulative revenue for a high-quality book.[15] Under simultaneous release, the average rating is essentially zero (0.009), as the pessimistic prior distribution means most readers are disengaged, producing middling reviews even for a good book. Sequential release with word-of-mouth substantially improves ratings to 0.332, as early buyers' positive experiences propagate through reviews and lifts later consumers' engagement. The limited release strategy further improves ratings to 0.448 by ensuring that the first reviews come from high-prior, engaged readers and generating a "review snowball" that subsequently elevates the entire market's engagement trajectory. Note that the limited release and hardcover strategies produce identical rating trajectories, since they select the same early adopters, who induce the same reputation/ratings paths.

In terms of revenue, sequential and limited release converge to $20,000 (the market saturates at $10 regardless of who reads first), while hardcover pricing generates

[15]For low-quality books, the detailed review trajectories are presented in Appendix B.6.

Figure 6: Review Trajectories and Revenue Under Alternative Release Strategies (Good Book)

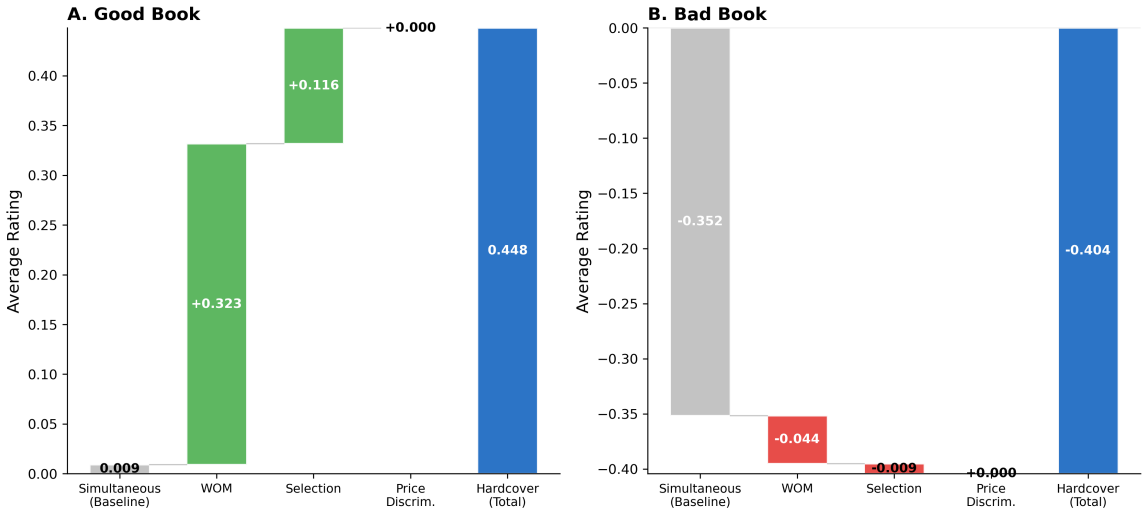


Panel A shows cumulative average review ratings over 12 market periods under four release strategies: simultaneous release (dotted horizontal line), sequential release (gray), limited release (dashed blue; same $10 price but only high-prior consumers can purchase in periods 1–3), and hardcover pricing (solid dark blue; $20 in periods 1–3, then $10). The dashed vertical line marks the end of the restricted-access/hardcover window. Panel B shows cumulative revenue. 50 bootstrap simulations; shaded regions show ±1 s.d.

$25,926 through price discrimination on early high-prior buyers. That said, we highlight that these revenue differences may plausibly understate revenue implications in a richer environment; we keep our simulated environment exceedingly simple, but if e.g. higher ratings also expand the total market for a book, which may be quite likely, these revenue implications may be much larger in practice.

Figure 7 decomposes the rating advantage into channel contributions, for both good and bad books. For the good book, word-of-mouth contributes +0.323 (lifting engagement from 15% to 51% of readers), early-adopter selection contributes +0.116 (raising engagement to 67%); price discrimination does not change ratings. For the bad book, the mechanism reverses: word-of-mouth worsens ratings by −0.044 and selection by a further −0.009, as engaged early adopters discover flaws that inattentive readers would overlook. The total rating under hardcover pricing is 0.448 for good

Figure 7: Rating Decomposition: Good Book vs. Bad Book



Waterfall decomposition of average ratings from the simultaneous baseline to the hardcover total, for good books (Panel A) and bad books (Panel B). Green bars show positive contributions; red bars show negative contributions. Blue bar shows the total under hardcover pricing. 50 bootstrap simulations.

books versus −0.404 for bad books—a gap driven almost entirely by the engagement channel rather than by any difference in the simulation mechanics. The full decomposition with confidence intervals is presented in Appendix Table B2; engagement rates by strategy and quality are presented in Appendix Figure B2.

This asymmetry accords well with industry practice and offers a novel explanation for it. It is not merely that high-quality books can sustain a higher price—it is that the hardcover release mechanism actively improves a good book's reputation by selecting engaged early readers, while the same mechanism actively damages a bad book's reputation. The decision between hardcover and paperback release is therefore not only a pricing decision but a reputation management decision, and the engagement channel identified in our model is what makes early-adopter composition consequential for long-run product ratings.

8 Conclusion

How much utility a consumer derives from a product may depend, in part, on how she chooses to consume it. This observation is intuitive for products requiring sustained engagement: a book read attentively yields different rewards than one read inattentively; an exercise program followed faithfully produces different results than one abandoned halfway through. What is less obvious is that this dependency creates feedback between beliefs and outcomes. If consumers who expect little disengage, and disengagement yields disappointing experiences, then pessimistic expectations can become self-fulfilling prophecies. This paper formalizes this mechanism, documents it experimentally, and explores its implications for marketing strategy.

Our experimental evidence demonstrates that randomly assigned negative reviews causally reduce realized enjoyment, not just expectations. Bad reviews reduce the probability of above-average enjoyment by 11 percentage points and increase the probability of middling enjoyment by 15 percentage points, even though the book distribution and reader distribution are identical across conditions. The effect is also not a one-time shift that fades as readers form their own impressions, but sustains over the course of reading, as bad-review readers show declining enjoyment trajectories while control readers show increasing trajectories. The enjoyment distribution also compresses toward mid-to-low enjoyment under bad reviews, particularly for low-quality books, further supporting an engagement-based interpretation in which inattentive reading yields middling outcomes.

We then build on this evidence to develop a formal model of engagement-based utility, where consumers of uncertain-quality products choose between engaged and unengaged consumption in each period, and engagement amplifies both the rewards of good products and the costs of bad ones. We estimate a structural version of this

model using GMM, leveraging the exogenous variation from our experiment to identify the utility distributions under engaged and unengaged reading for both high- and low-quality books. The estimates indicate a large gap between engaged and unengaged reading, and the estimated model closely reproduces the qualitative patterns of compressed enjoyment under bad reviews and the divergent trajectories across review conditions.

Lastly, we use this estimated model to evaluate counterfactual marketing strategies in a set of stylized simulations, embedding the individual reading model in a market simulation with heterogeneous consumers and endogenous review dynamics. We decompose the hardcover pricing advantage into three channels: word-of-mouth transmission, early-adopter selection, and price discrimination. We show that selecting engaged early adopters generates a meaningful improvement in product ratings (+0.116, a 35% improvement over the sequential baseline) for high-quality books, even at the same price as a standard release—its value is entirely reputational. For low-quality books, the mechanism reverses, as engaged early adopters generate harsher reviews. Hardcover pricing then monetizes the selection advantage through standard price discrimination, while the rating asymmetry rationalizes why mass-market paperback strategies are often pursued for lower-quality titles.

Our findings have clear practical implications for managers launching experience goods. The conventional wisdom is to maximize early sales to build momentum. Our analysis suggests a more nuanced view. The quality of early adopters matters as much as the quantity, and a broad launch that attracts skeptical marginal consumers may generate lukewarm reviews that depress subsequent demand; alternatively, a targeted launch that attracts enthusiasts may generate positive reviews that expand the market. The optimal strategy depends on how early reviews shape later consumers' engagement, not just their purchase decisions. Our decomposition shows that con-

trolling early-adopter composition generates a 35% improvement in ratings for good books even at the same price as a standard release, suggesting that the reputational value of targeted launches may be achievable through mechanisms other than price discrimination—such as advance reader copies, invite-only access, or curated early distribution. These findings also have implications for platforms that intermediate between products and consumers. Review systems that weight early reviews heavily, or that display reviews chronologically, amplify the dynamics we identify. A product that happens to attract engaged early reviewers may enjoy persistent advantages over an identical product that attracts disengaged early reviewers. Platform designers might consider whether such path dependence is desirable, and if not, how to mitigate it.

At the same time, several limitations remain. Our evidence comes from book reading, a context where engagement is particularly salient and where the distinction between attentive and inattentive consumption is intuitive. Whether similar dynamics operate for other experience goods—such as online courses, video games, exercise programs, or subscription services—remains an empirical question, and the magnitude of the engagement channel likely varies across product categories depending on how much utility depends on active consumer participation. Our sample is drawn from Reddit book communities, a population of relatively avid readers who may differ from the general consumer population in their baseline engagement levels and sensitivity to reviews. The treatment itself—showing two extreme reviews before reading—is a stylized intervention, and the mapping to real-world review exposure, where consumers encounter a mix of review valences and may selectively attend to different information, is imperfect. We also do not directly observe engagement; we infer it from the pattern of enjoyment outcomes across treatment conditions and book quality levels, rather than measuring reading behavior (such as eye tracking)

directly. Lastly, the relative importance of the engagement channel versus interpretive or perceptual channels likely varies across product categories: for short-duration consumption experiences such as restaurant meals, expectation-based perceptual effects may dominate (Li et al., 2025), while for goods requiring sustained attention, the engagement channel we identify may be comparatively more important. Mapping the boundary conditions between these channels across product types is a natural direction for future research.

The formal model introduces additional simplifications. The model assumes binary engagement choice (engaged or unengaged), whereas real reading likely involves a continuum of attention levels. Consumers are modeled as myopic, choosing engagement period by period without considering how current engagement affects future beliefs and enjoyment; a forward-looking model might generate different dynamics, particularly for readers who strategically invest in early engagement to resolve uncertainty. Conversely, products (books) may have differential utility distributions at different points (at different chapters), and the utility or disutility of engaged or unengaged consumption may vary dynamically along with engagement levels—later work may consider optimal dynamic product design to induce engagement early through clear quality signaling early on, for example with a "catchy opening" or other design choices.

More broadly, our findings speak to a fundamental question about where value resides in consumption. The standard economic view treats utility as arising from the match between product attributes and consumer preferences, a transaction in which the consumer is essentially passive. The mechanism we identify suggests a more active picture: consumers co-create their experiences through the intensity and quality of their engagement. A great book unread is worth nothing; a good book read with care may be worth more than a great book read inattentively. If expectations shape

engagement, and engagement shapes outcomes, then beliefs about products are not merely forecasts of value but partial determinants of it. The line between marketing and product design blurs when how a product is perceived affects how it is consumed, and how it is consumed affects what it delivers.

References

Ackerberg, D. A. (2003). Advertising, learning, and consumer choice in experience good markets: An empirical examination. *International Economic Review*, 44(3):1007–1040.

Anderson, R. E. (1973). Consumer dissatisfaction: The effect of disconfirmed expectancy on perceived product performance. *Journal of Marketing Research*, 10(1):38–44.

Bondi, T., Rossi, M., and Stevens, R. L. (2025). The good, the bad and the picky: Consumer heterogeneity and the reversal of product ratings. *Management Science*, 71(8):7200–7222.

Campbell, A., Mayzlin, D., and Shin, J. (2017). Managing buzz. *The RAND Journal of Economics*, 48(1):203–229.

Carrera, C., Martínez-de Albéniz, V., and Sosa, M. E. (2025). The bright side of lower quality: Evidence from restaurant exploration. *Management Science*. Forthcoming.

Chakraborty, I., Deb, J., and Öry, A. (2023). When do consumers talk? Cowles Foundation Discussion Paper No. 2254R3, Yale University.

Chevalier, J. A. and Mayzlin, D. (2006). The effect of word of mouth on sales: Online book reviews. *Journal of Marketing Research*, 43(3):345–354.

Clerides, S. K. (2002). Book value: Intertemporal pricing and quality discrimination in the us market for books. *International Journal of Industrial Organization*, 20(10):1385–1408.

Deighton, J. (1984). The interaction of advertising and evidence. *Journal of Consumer Research*, 11(3):763–770.

Erdem, T. and Keane, M. P. (1996). Decision-making under uncertainty: Capturing dynamic brand choice processes in turbulent consumer goods markets. *Marketing Science*, 15(1):1–20.

Forgas, J. P. (1995). Mood and judgment: The affect infusion model (AIM). *Psychological Bulletin*, 117(1):39–66.

Godes, D. and Mayzlin, D. (2004). Using online conversations to study word-of-mouth communication. *Marketing Science*, 23(4):545–560.

Hoch, S. J. and Ha, Y.-W. (1986). Consumer learning: Advertising and the ambiguity of product experience. *Journal of Consumer Research*, 13(2):221–233.

Kőszegi, B. and Rabin, M. (2006). A model of reference-dependent preferences. *The Quarterly Journal of Economics*, 121(4):1133–1165.

Kőszegi, B. and Rabin, M. (2009). Reference-dependent consumption plans. *American Economic Review*, 99(3):909–936.

Kovács, B. and Sharkey, A. J. (2014). The paradox of publicity: How awards can negatively affect the evaluation of quality. *Administrative Science Quarterly*, 59(1):1–33.

Lee, P. S., Kumar, V., and Sudhir, K. (2025). Pay now or wait to unlock? cliffhangers and monetization of serialized media. Technical report, Yale School of Management. Posted: June 25, 2025; Date Written: April 12, 2025.

Li, X., Deng, Y., Manchanda, P., and De Reyck, B. (2025). Can lower(ed) expert opinions lead to better consumer ratings?: The case of michelin stars. *Management Science*. Also circulated as an SSRN working paper.

Li, X. and Hitt, L. M. (2008). Self-selection and information role of online product reviews. *Information Systems Research*, 19(4):456–474.

Liu, Y. (2006). Word of mouth for movies: Its dynamics and impact on box office revenue. *Journal of Marketing*, 70(3):74–89.

Moe, W. W. and Schweidel, D. A. (2012). Online product opinions: Incidence, evaluation, and evolution. *Marketing Science*, 31(3):372–386.

Moe, W. W. and Trusov, M. (2011). Measuring the value of social dynamics in online product ratings forums. *Journal of Marketing Research*, 48(3):444–456.

Muchnik, L., Aral, S., and Taylor, S. J. (2013). Social influence bias: A randomized experiment. *Science*, 341(6146):647–651.

Nelson, P. (1970). Information and consumer behavior. *Journal of Political Economy*, 78(2):311–329.

Oliver, R. L. (1980). A cognitive model of the antec:contentreference[oaicite:5]index=5tisfaction decisions. *Journal of Marketing Research*, 17(4):460–469.

Qahri-Saremi, H. and Montazemi, A. R. (2023). Negativity bias in the diagnosticity of online review content: The effects of consumers' prior experience and need for cognition. *European Journal of Information Systems*, 32(4):611–630.

Rossi, M. and Schleef, F. (2024). Quality disclosures and disappointment: Evidence from the academy nominations. Technical Report 11573, CESifo Working Paper Series. Date Written: December 16, 2024.

Shiv, B., Carmon, Z., and Ariely, D. (2005). Placebo effects of marketing actions: Consumers may get what they pay for. *Journal of Marketing Research*, 42(4):383–393.

Skowronski, J. J. and Carlston, D. E. (1989). Negativity and extremity biases in impression formation: A review of explanations. *Psychological Bulletin*, 105(1):131–142.

Yi, Y. (1993). The determinants of consumer satisfaction: The moderating role of ambiguity. *Advances in Consumer Research*, 20:502–506.

Zhao, C., Mehta, N., and Shi, M. (2025). An empirical investigation of a digital platform's release strategy for serialized content. Technical Report 2023-123, HKUST Business School Research Paper. First posted: July 4, 2023; Last revised: July 2, 2025.

A Data Appendix

This appendix provides additional details on the experimental design, sample characteristics, and data collection procedures.

A.1 Recruitment and Sample

Participants were recruited from book-related subreddits on Reddit, including r/books, r/suggestmeabook, r/52book, and r/bookclub. Recruitment posts described the study as a "book reading research project" and offered compensation of $15 for completing the full study (reading an assigned book and completing all surveys). A total of 584 participants completed onboarding and were randomly assigned to treatment conditions: 228 to no review, 207 to good reviews, and 149 to bad reviews. Our analysis sample consists of all onboarded participants completed both the onboarding survey and chapter-level enjoyment survey data, comprising 582 participants (99.7% of the onboarded sample). Retention does not differ significantly across conditions (χ^2 $p = 0.537$).

A.2 Book Selection

Books were randomly selected from the library of an anonymous private-sector partner, a book-tracker app company (similar to Goodreads). We randomly selected approximately 200 contemporary fiction titles and excluded roughly 50 that were determined to be too short to be considered novels or were nonfiction, yielding a final list of 145 books. This list includes popular novels like "The Innocent Man" by John Grisham, award-winning novels like "The Orphan Master's Son", and less-well-known books like "The Best Laid Plans" by Cameron Lund. Participants were randomly assigned books from this list and were told what book they were assigned early in the

onboarding process. Participants who had previously read their assigned book were randomly assigned a different book, to ensure that all reads were comparable first reads.

A.3 Treatment Administration

Prior to beginning their assigned book, participants in the bad review condition were shown two 1-star reviews randomly sampled from the book's Goodreads page. Participants in the good review condition were shown two 5-star reviews. The no-review control group proceeded directly to the pre-reading expectations survey.

Table A1 confirms that treatment groups do not differ significantly on the observable characteristics that we surveyed during onboarding, including reading frequency and familiarity with the assigned book or author.

Table A1: Balance Across Treatment Conditions (Analysis Sample)

	Books Read Per Year	Typical Finisher	Familiar w/ Author	Familiar w/ Book
Good Reviews	-7.529	0.079	-0.046	0.030
	(4.617)	(0.055)	(0.048)	(0.030)
Bad Reviews	-6.686	-0.026	-0.063	-0.022
	(5.089)	(0.060)	(0.053)	(0.034)
N	577	582	582	582
R^2	0.005	0.006	0.003	0.004

Notes: Each column reports coefficients from a separate OLS regression of the pre-treatment variable on treatment indicators. Standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05.

In analyses that involve statistics of trajectories, we restrict to readers that we observe in all three thirds of reading progress in order to ensure a balanced sample across thirds. This drops roughly 30% of readers, some of whom may have read books

with coarser section breaks and some of whom may be inferred to have attrited or provided incomplete data to the study. We here examine whether such potential attrition differed systematically across review treatment conditions.

Results are presented in A2. We find null differences in attrition across treatment conditions.

Table A2: Attrition by Review Treatment

	P(Remain in Sample)
Good Reviews	-0.053
	(0.044)
Bad Reviews	0.056
	(0.049)
N	582
R^2	0.0085

Notes: Linear regression of review treatment on indicator variable of remaining in balanced (present in all thirds of reading progress) sample. Robust standard errors in parentheses.

A.4 Survey Instruments

The pre-reading survey asked participants to report their expected enjoyment ("How much do you expect to enjoy this book?") on a Likert scale ranging from "will not enjoy at all" to "will enjoy a great deal." Participants also reported their familiarity with the book and author and prior reading of reviews.

After each chapter, participants completed a brief survey asking: "How much are you enjoying the book so far?" (1–7 scale). The surveys were administered via Qualtrics.

A.5 Quality Classification

We classify books as "low quality" if their Goodreads rating falls below the 25th percentile of sample ratings, and "high quality" otherwise. This threshold is chosen to rationalize the observed baseline density of positive expectations in our data (approximately 75%), and maps to the model's binary quality type ($Q \in \{G, B\}$) with prior $\pi_0 = 0.75$.

B Counterfactual Simulation Details

This appendix provides technical details on the counterfactual simulations reported in Section 7.

B.1 Simulation Parameters

Table B1 summarizes the key simulation parameters.

Table B1: Counterfactual Simulation Parameters

Parameter	Value	Description
N	2,000	Number of consumers
Prior distribution	Beta(2, 12)	Baseline prior beliefs (mean ≈ 0.14)
T_{market}	12	Number of market periods
T_{read}	3	Reading periods per consumer
Cohort fraction	15%	Share of remaining market exposed per period
ω	0.35	Review weight in prior updating
Threshold base	-0.075	Intercept in threshold calibration
Threshold slope	0.015	Slope in threshold calibration
HC price	\$20	Hardcover price
PB price	\$10	Paperback price
HC periods	3	Periods at hardcover price
Bootstrap seeds	50	Number of simulation replications

B.2 Purchase Decision

Consumer i purchases if expected cumulative utility exceeds a price-dependent threshold:

$$V(p_i^{\text{eff}}) \geq \bar{u}(P) \tag{5}$$

where $V(p) = \sum_{t=1}^{T} \max\{EU(e,p), EU(u,p)\}$ is expected cumulative utility under optimal engagement. The threshold $\bar{u}(P)$ is calibrated so that a consumer with prior

equal to cutoff(P) is indifferent:

$$\text{cutoff}(P) = -0.075 + 0.015 \times P \tag{6}$$

This yields cutoffs of 0.225 at \$20 (hardcover) and 0.075 at \$10 (paperback).

B.3 Review Dynamics

After each period, consumers update their effective priors based on accumulated reviews:

$$p_i^{\text{eff}} = (1 - \omega) \cdot p_i^{\text{base}} + \omega \cdot s(\bar{U}) \tag{7}$$

where $\bar{U}$ is the average cumulative utility across all prior buyers and $s(\cdot)$ is a sigmoid transformation:

$$s(\bar{U}) = \frac{1}{1 + e^{-\bar{U}/1.5}} \tag{8}$$

The scaling parameter 1.5 ensures that the typical range of cumulative utilities (-3 to $+3$) maps to belief signals roughly in $(0.12, 0.88)$.

B.4 Reading Simulation

When a consumer purchases, we simulate their $T = 3$ period reading experience using the estimated structural model. In each period, the consumer chooses engagement optimally given current beliefs, then realizes utility drawn from the quality- and engagement-dependent distribution with estimated parameters. Beliefs update via Bayes' rule after each period. The consumer's cumulative utility across all periods constitutes their review.

B.5 Decomposition Methodology

Rather than comparing hardcover and static pricing directly, we build the hardcover advantage incrementally through four release strategies. Each strategy adds exactly one mechanism to the previous:

1. **Simultaneous Release**: All consumers arrive in a single period at \$10, with no review dynamics. This baseline captures independent purchase decisions based on prior beliefs alone.

2. **Sequential Release**: Consumers arrive over 12 periods at \$10. Each period, a randomly selected cohort of 15% of remaining consumers is exposed. Buyers' realized utilities accumulate as public reviews that update subsequent consumers' effective priors. This adds word-of-mouth transmission.

3. **Limited Release**: Same \$10 price throughout, but for the first 3 periods, the utility threshold is elevated to the hardcover level (prior cutoff of 0.225 rather than 0.075), restricting early purchases to high-prior consumers. After period 3, the threshold returns to the standard level. This adds early-adopter selection while holding price constant.

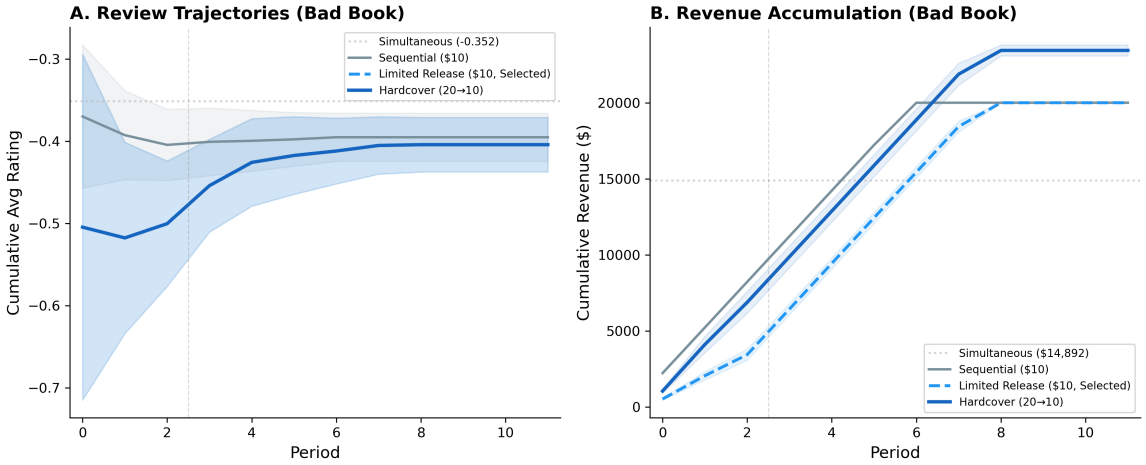
4. **Hardcover Pricing**: \$20 for the first 3 periods with the elevated threshold, then \$10 with the standard threshold. This adds price discrimination on top of the selection mechanism.

The incremental contribution of each channel is computed as paired differences across 50 bootstrap seeds: WOM = Strategy 2 − Strategy 1; Selection = Strategy 3 − Strategy 2; Price Discrimination = Strategy 4 − Strategy 3.

B.6 Low-Quality Books

For low-quality books, the engagement channel reverses. Figure B1 presents the review trajectories and cumulative revenue under the four release strategies. The limited release and hardcover strategies now generate lower ratings than sequential release, because engaged early adopters discover the book's flaws that inattentive readers would overlook. The total rating under hardcover pricing (−0.404) is worse than under simultaneous release (−0.352). The price discrimination effect is also smaller ($3,439 vs. $5,926 for good books), because negative early reviews push marginal consumers below the hardcover purchase threshold.

Figure B1: Review Trajectories and Revenue: Low-Quality Book



Panel A shows cumulative average review ratings under four release strategies for a low-quality book: simultaneous release (dotted horizontal line), sequential release (gray), limited release (dashed blue; high-prior consumers only in periods 1–3 at the same $10 price), and hardcover pricing (solid dark blue; $20 in periods 1–3, then $10). The dashed vertical line marks the end of the restricted-access/hardcover pricing window. Panel B shows cumulative revenue. The limited release and hardcover strategies produce lower early ratings than sequential release because engaged early readers are fully exposed to the book's flaws. 50 bootstrap simulations; shaded regions show ±1 standard deviation.

B.7 Detailed Decomposition Results

Table B2 presents the full revenue and rating decomposition with confidence intervals. For high-quality books, the selection channel contributes zero incremental revenue (the fixed market saturates at $10 regardless of early-adopter composition) but improves ratings by +0.116, a 35% improvement over the sequential baseline. For bad books, the price discrimination effect is smaller ($3,439 vs. $5,926) because negative early reviews push marginal consumers below the hardcover purchase threshold.

Table B2: Decomposition of the Hardcover Advantage

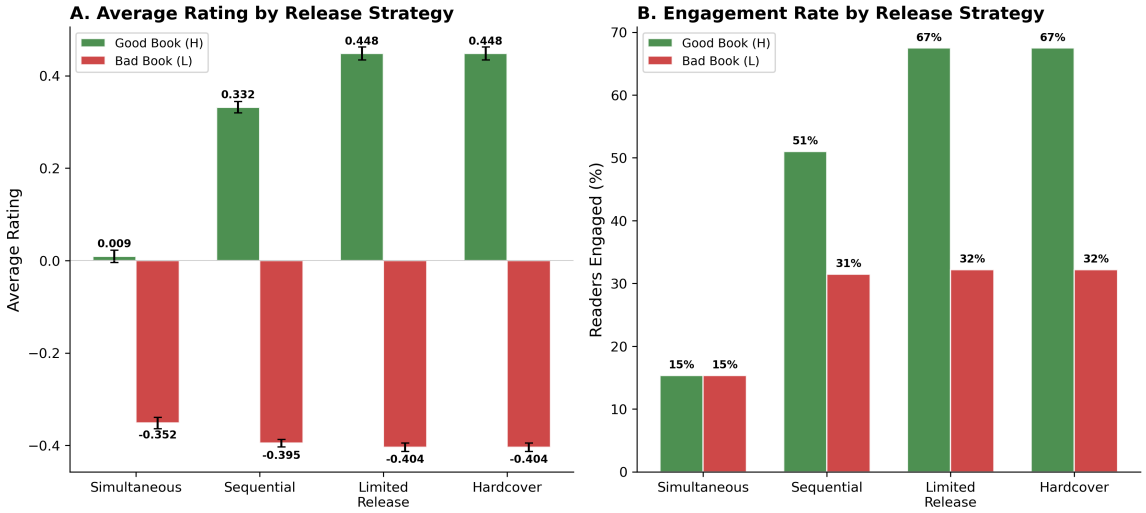
Quality	Channel	Revenue Effect	Rating Effect
Good	WOM (Sequential − Simultaneous)	$+5,108	+0.323
		[$+5,058, $+5,158]	[+0.311, +0.334]
Good	Selection (Limited − Sequential)	$0	+0.116
			[+0.104, +0.129]
Good	Price Discrim. (HC − Limited)	$+5,926	+0.000
		[$+5,854, $+5,998]	
Good	**Total (HC − Simultaneous)**	**$+11,034**	**+0.439**
		[$+10,949, $+11,119]	[+0.426, +0.452]
Bad	WOM (Sequential − Simultaneous)	$+5,108	−0.044
		[$+5,058, $+5,158]	[−0.053, −0.034]
Bad	Selection (Limited − Sequential)	$0	−0.009
			[−0.018, −0.000]
Bad	Price Discrim. (HC − Limited)	$+3,439	+0.000
		[$+3,339, $+3,539]	
Bad	**Total (HC − Simultaneous)**	**$+8,547**	**−0.053**
		[$+8,442, $+8,652]	[−0.063, −0.042]

Notes: Decomposition of the hardcover pricing advantage into three channels. Revenue effects and rating effects are paired differences across 50 bootstrap simulations; 95% confidence intervals in brackets. The selection channel generates zero revenue effect because the fixed market of 2,000 consumers saturates at the $10 price regardless of early-adopter composition.

Figure B2 illustrates the engagement mechanism underlying the decomposition. For good books, the engagement rate rises from 15% (simultaneous) to 51% (se-

quential) to 67% (limited release and hardcover). For bad books, engagement rises more modestly (15% to 31–32%), because negative early reviews depress subsequent consumers' priors.

Figure B2: Average Rating and Engagement Rate by Release Strategy



Panel A shows average review ratings across four release strategies for good books (green) and bad books (red). Panel B shows the percentage of readers who choose engaged reading under each strategy and book quality. 50 bootstrap simulations; error bars show 95% confidence intervals.

C Extended Empirical Analyses

This appendix presents additional analyses of enjoyment trajectories over reading progress, including an interaction model that formally tests whether the bad review effect increases or decreases over the course of reading.

C.1 Interaction Model

Table C1 presents results from a regression of above-average enjoyment on treatment indicators, reading progress (measured as percent of book completed from 0 to 100), and the interaction between treatment and progress. This specification tests whether the effect of bad reviews changes as readers progress through the book.

The significant negative interaction between Bad Reviews and Progress (coefficient of -0.165, $p = 0.024$) indicates that the negative effect of bad reviews on above-average enjoyment grows as readers progress through the book, consistent with a feedback loop in which early disengagement leads to mediocre experiences that reinforce pessimism and sustain over time.

The interaction for Good Reviews is small and not statistically significant (-0.064, $p > 0.10$), indicating that good review readers follow essentially the same trajectory as no-review readers. This asymmetry is consistent with good reviews having little effect on expectations or engagement in the first place.

Table C1: Effect of Reviews on Enjoyment Over Reading Progress

	Above-Average Enjoyment
Bad Reviews	-0.011
	(0.066)
Good Reviews	0.072
	(0.064)
Bad Reviews × Progress (per 100%)	-0.165*
	(0.073)
Good Reviews × Progress (per 100%)	-0.064
	(0.080)
N	15,517
R^2	0.013

Notes: Standard errors clustered at book level in parentheses. *** p<0.001, ** p<0.01, * p<0.05, † p<0.1. Model includes reading progress (percent), treatment dummies, and treatment × progress interactions. Review effects are relative to the omitted category of no review shown. Sample restricted to reader-books with observations in all three thirds of reading progress.

D Theoretical Propositions

This appendix formalizes properties of the optimal reading plan described in Section 5.

Proposition 1 (Uniqueness)**.** *Given parameters* $\{\pi_0, p_j^{QI}, u_j\}$ *and the tie-breaking rule that ties are resolved in favor of engagement, the optimal reading plan provides a unique mapping* $r_t : h_t \to I$*, where* h_t *is the history of engagement levels and realized utilities from all previous periods, with* $h_1 = \emptyset$*.*

Proof. The optimal plan is determined by backward induction. In the final period T, for each belief π_{T-1}, the reader chooses I to maximize $EU_T^I(\pi_{T-1})$. This choice is unique for all $\pi_{T-1} \neq \pi_{T-1}^*$ by the strict monotonicity of $EU_T^e(\pi) - EU_T^u(\pi)$ in π, and unique at π_{T-1}^* by the tie-breaking rule. The continuation value $V_{T-1}(\pi_{T-1})$ is therefore uniquely determined, and by induction, the optimal choice in each earlier period is unique for each history. □

Proposition 2 (Monotonicity)**.** *For each period* t*, the net value of engagement* $EU_t^e(\pi_{t-1}) - EU_t^u(\pi_{t-1})$ *is increasing in* π_{t-1}*.*

Proof. For the final period, $EU_T^e(\pi) - EU_T^u(\pi) = \pi(EU^{Ge} - EU^{Gu}) + (1-\pi)(EU^{Be} - EU^{Bu})$ is linear and strictly increasing in π, since $EU^{Ge} - EU^{Gu} > 0 > EU^{Be} - EU^{Bu}$. For earlier periods, the result follows by induction: higher beliefs make it more likely that the book is good, which raises both the immediate expected utility from engagement and the continuation value (since good-book signals under engagement tend to push beliefs further above future thresholds). □

Proposition 3 (Threshold Policy)**.** *For each period* t*, there exists a threshold* $\pi_t^* \in (0, 1)$ *such that the reader chooses engaged reading in period* t *if and only if* $\pi_{t-1} \geq \pi_t^*$*.*

Proof. For the final period T, the reader engages if and only if $EU_T^e(\pi_{T-1}) \geq EU_T^u(\pi_{T-1})$. Since $EU_T^I(\pi) = \pi \cdot EU^{GI} + (1-\pi) \cdot EU^{BI}$ is linear in π for each I, the difference $EU_T^e(\pi) - EU_T^u(\pi)$ is also linear in π. By assumption, $EU^{Ge} - EU^{Gu} > 0$ and $EU^{Be} - EU^{Bu} < 0$, so this difference is strictly increasing in π. Since $EU_T^e(0) - EU_T^u(0) = EU^{Be} - EU^{Bu} < 0$ and $EU_T^e(1) - EU_T^u(1) = EU^{Ge} - EU^{Gu} > 0$, there exists a unique $\pi_{T-1}^* \in (0,1)$ where the difference equals zero.

For earlier periods, the result follows by backward induction. At each period t, the continuation value $\max_k EU_{t+1}^k(\pi_t(\pi_{t-1}, j, I))$ is determined by the threshold policy in period $t+1$. The expected utility $EU_t^I(\pi_{t-1})$ inherits continuity and monotonicity properties that ensure a unique threshold exists. □

Proposition 4 (Belief Divergence)**.** *Consider two readers with initial priors $\pi_0^H > \pi_0^L$ reading the same book. If $\pi_0^H \geq \pi_1^*$ and $\pi_0^L < \pi_1^*$, then the readers' beliefs evolve according to different stochastic processes, and their expected final beliefs satisfy $\mathbb{E}[\pi_T \mid \pi_0^H] \neq \mathbb{E}[\pi_T \mid \pi_0^L]$ generically.*

Proof. The high-prior reader engages in period 1 and observes a utility draw from the distribution $(p_H^{Qe}, p_M^{Qe}, p_L^{Qe})$. The low-prior reader does not engage and observes a draw from $(p_H^{Qu}, p_M^{Qu}, p_L^{Qu})$. Since these distributions differ by assumption, the readers' posteriors π_1 are drawn from different distributions even conditional on the same true quality Q. This difference propagates forward: different beliefs in period 1 lead to potentially different engagement decisions in period 2, generating further divergence. The expected final beliefs differ unless the utility distributions happen to generate identical expected posteriors, which occurs only for knife-edge parameter values. □

Proposition 5 (Self-Fulfilling Beliefs)**.** *There exist parameter values such that for a good-quality book ($Q = G$):*

(i) A reader with $\pi_0 \geq \pi_1^*$ engages in all periods and experiences expected total utility $\mathbb{E}\left[\sum_{t=1}^{T} u_t \mid \pi_0, Q = G, \text{engage all}\right] = T \cdot EU^{Ge}$.

(ii) A reader with $\pi_0 < \pi_1^*$ who never receives a sufficiently positive signal to cross the engagement threshold experiences expected total utility $\mathbb{E}\left[\sum_{t=1}^{T} u_t \mid \pi_0, Q = G, \text{never engage}\right] = T \cdot EU^{Gu}$.

(iii) If $EU^{Ge} \gg EU^{Gu}$, the high-prior reader's expected utility substantially exceeds the low-prior reader's, despite both reading the same good book.

Proof. Part (i): If $\pi_0 \geq \pi_1^*$ and signals under engaged reading are sufficiently favorable for good books (i.e., p_H^{Ge} is large), then with high probability the reader's beliefs remain above all future thresholds π_t^*, and she engages throughout. Her per-period expected utility is EU^{Ge}.

Part (ii): If $\pi_0 < \pi_1^*$ and signals under unengaged reading are relatively uninformative (i.e., $p_j^{Gu} \approx p_j^{Bu}$ for all j), then the reader's beliefs update slowly. If the thresholds π_t^* do not decline sufficiently fast, the reader may never cross into the engagement region. Her per-period expected utility is EU^{Gu}.

Part (iii): By assumption $EU^{Ge} > EU^{Gu}$, so $T \cdot EU^{Ge} > T \cdot EU^{Gu}$. The gap can be made arbitrarily large by choosing parameters where engaged reading of good books yields high utility (p_H^{Ge} large) while unengaged reading yields middling utility (p_M^{Gu} large). □

Proposition 5 captures the core economic insight: for the same good-quality product, consumers with different initial beliefs can have substantially different consumption experiences. The high-prior consumer engages, enjoys the product, and would rate it highly. The low-prior consumer does not engage, has a mediocre experience, and would rate it poorly. Both ratings accurately reflect their experiences, yet the

difference stems entirely from initial expectations rather than product quality. In this sense, initial beliefs become self-fulfilling.

E Further Structural Model Details

E.1 Parameter Estimates and Model Fit

We present the full set of parameter estimates in Appendix Table E1.

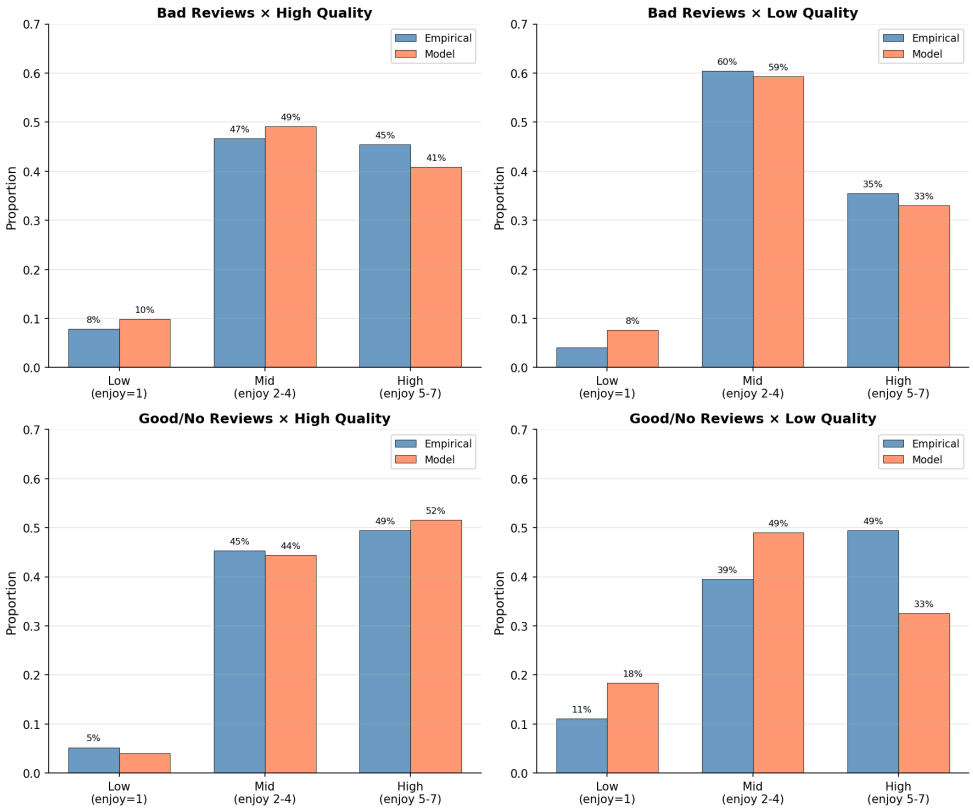
Table E1: Parameter Estimates

Parameter	Estimate	SE
p_H^{Ge}	0.535	(0.007)
p_M^{Ge}	0.425	(0.005)
p_H^{Be}	0.354	(0.004)
p_M^{Be}	0.489	(0.006)
p_H^{Gu}	0.403	(0.005)
p_M^{Gu}	0.495	(0.003)
p_H^{Bu}	0.335	(0.005)
p_M^{Bu}	0.594	(0.005)
$\pi_{0,bad}$	0.193	(0.003)

Notes: Model parameter estimates from GMM. Based on estimation sample of 417 reader-books with observations in all three thirds of reading progress.

We also present the model fit for the initial enjoyment probabilities in Appendix Figure E1. (Fit for trajectory moments are presented in the main text.) While the model does not achieve a perfect fit due to strict constraints (detailed below) and 10 moment conditions for 9 parameters, it is able to qualitatively reproduce the key patterns of the experimental data, including the compression-effect of bad reviews on the utility distribution of low-quality books in particular, with sharply higher probability of middling utility, marginally lower probability of high utility and sharply lower probability of low utility under the induced disengaged consumption.

Figure E1: Model-Projected vs. Empirical Initial Utility Densities



Notes: Figure shows comparison between structural model initial utility moments and empirical initial utility moments. Based on estimation sample of 417 reader-books with observations in all three thirds of reading progress.

E.2 Structural Model Estimation Constraints

The following restrictions strengthen the theoretical assumptions of Section 5 for our empirical estimation. While the theory requires only weak informativeness ($p_H^{Gu} \geq p_H^{Bu}$) and a general expected utility ordering ($EU^{Ge} > EU^{Qu} \geq 0 > EU^{Be}$), estimation benefits from stricter conditions that ensure identification and that all signals are informative. The calibrated utility values $u_H = 1$, $u_M = -0.5$, $u_L = -2$ shift the zero point of the utility scale relative to the theory's normalization (in which $u_M \geq 0$), but since all engagement decisions and belief dynamics depend on utility differences,

this additive shift does not affect any behavioral predictions.

Assumption 1 (Interior Probabilities)**.** *All probability parameters are strictly interior:*

$$p_H^{QI}, p_M^{QI}, p_L^{QI} \in (0,1) \quad \textit{for all } (Q,I) \in \{G,B\} \times \{e,u\} \tag{9}$$

This ensures that all enjoyment levels have positive probability under any quality-mode combination, so that every signal is informative.

Assumption 2 (Pessimistic Prior)**.** *The initial prior under bad review treatment satisfies* $\pi_0 \in (0, \frac{3}{4})$.

This restriction captures our empirical setting where we study consumers who have been exposed to negative reviews, inducing pessimistic beliefs about product quality relative to the rational expectations benchmark of $\pi_0 = \frac{3}{4}$.

Assumption 3 (First-Order Stochastic Dominance Under Engaged Reading)**.** *When reading with engagement, high-quality books yield stochastically dominant enjoyment distributions:*

$$p_H^{Ge} > p_H^{Be} \tag{10}$$

$$p_H^{Ge} + p_M^{Ge} > p_H^{Be} + p_M^{Be} \tag{11}$$

Condition (10) states that good-quality books are more likely to produce high enjoyment when read with engagement. Condition (11) states that good-quality books are more likely to produce at least medium enjoyment. Together, these conditions imply that the enjoyment distribution for good-quality books first-order stochastically dominates that for bad-quality books under engaged reading.

Assumption 4 (High Utility Informativeness)**.** *High utility is more likely from good books regardless of reading mode:*

$$p_H^{GI} > p_H^{BI} \quad \textit{for all } I \in \{e, u\} \tag{12}$$

This ensures that high enjoyment is always a positive signal of quality, consistent with the belief updating analysis in Section 5. This strengthens the theoretical assumption, which requires strict informativeness only under engaged reading ($p_H^{Ge} > p_H^{Be}$) and allows weak informativeness under unengaged reading ($p_H^{Gu} \geq p_H^{Bu}$). The strict version ensures that beliefs update after every signal, even under unengaged reading, which aids estimation.

Assumption 5 (Mode Variation)**.** *Engagement has differential effects by book quality:*

$$\mathbb{E}[u|G, e] > \mathbb{E}[u|G, u] \tag{13}$$

$$\mathbb{E}[u|B, e] < \mathbb{E}[u|B, u] \tag{14}$$

where $\mathbb{E}[u|Q, I] = u_H p_H^{QI} + u_M p_M^{QI} + u_L p_L^{QI}$ *is expected flow utility given quality* Q *and reading mode* I*.*

Condition (13) states that engaged reading unlocks the value of good books: attention and effort allow readers to appreciate narrative complexity, connect with characters, and extract deeper meaning from the text. Condition (14) states that for low-quality books, the benefits of engagement are smaller or even negative, as close attention may expose flaws that cursory reading would overlook. Together, these conditions ensure that beliefs matter for optimal behavior: readers who expect the book to be good prefer engaged reading, while readers who expect disappointment prefer inattentive reading.