

The Impact of Winning a Literary Award on the Goodreads Ratings of Novels, 2010-2016*

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In the 2014 paper “The Paradox of Publicity: How Awards Can Negatively Affect the Evaluation of Quality” authors Kovács and Sharkey find that, counterintuitively, winning a prestigious literary award decreased readers’ perception of prizewinning novels’ quality. To test the persistence of their findings, this analysis repeats a portion of the authors’ experiment using Goodreads reviews of prizewinning novels between 2010 and 2016 with a difference-in-differences design. Contrary to previous results, we find no evidence that winning a literary prize affects the post-award Goodreads ratings of prizewinning novels relative to other similar works. While these findings suggest that the ‘paradox of publicity’ may not hold in general, there are also several limitations to this analysis and of online review data in general which are discussed further.

1 Introduction

Several studies have shown the counterintuitive result that awards granted to cultural products have an adverse effect on consumers’ perception of said products’ quality. Kovács and Sharkey (2014) demonstrated that novels which received prestigious literary awards between 2007-2011 were rated lower than other similar novels by reviewers on Goodreads.com, a social book curation and review platform. More recently, Rossi and Schleef (2024) observed that consumer ratings of movies declined after they were nominated for an Academy Award and Rita et al. (2022) found that reviewers expressed fewer positive sentiments of restaurants’ food, service, and ambiance after they received a Michelin star. All papers suggested that an increase in consumer expectations and a broader audience resulting from the reception of an award negatively impacted consumers’ perception of quality.

*Code and data are available at: <https://github.com/EthanSansom/goodreadsratings>.

Such studies, which consider a ‘treated’ sample of award winners, have a necessarily small number of treated subjects compared to a large number of potential control subjects (i.e. cultural products which did not win an award). This can present challenges to inference in common identification strategies, such as a difference-in-differences design, when few treated groups are available or there are discrepancies in the number of observations (e.g. reviews) between subjects (e.g. restaurants, movies, books) (Ferman and Pinto 2019). In this analysis, we repeat portions of the Kovács and Sharkey (2014) experiment to assess the effect of winning a literary award on the Goodreads ratings of prizewinning novels between 2010 and 2016, using a large dataset of Goodreads reviews collected in 2017 (Wan and McAuley 2018; Wan et al. 2019). The purpose is twofold, first to re-test the hypothesis that awards can have a negative impact on consumers’ perception of quality and second to comment on the methodological challenges of this and other experiments which rely on online reviews as a measure of perceived quality.

The estimand of interest is the average effect of winning a literary award on a novel’s Goodreads rating following the award announcement, compared to the counterfactual trend in ratings had the novel not won an award. Given that we cannot observe the counterfactual case (the natural trend of a novel’s ratings over time in the absence of an award shock) we instead compare the change in winning novels’ Goodreads ratings trajectories relative to that of comparable non-prizewinning novels.

Contrary to prior studies, we find no evidence of a negative (or positive) impact of award winning on the Goodreads ratings of prizewinning novels. Further, no evidence is found that prizewinning novels become more popular (receive a greater number of reviews) than other comparable novels, failing to support the hypothesis that awards draw a broader reader base which contributes to lower reviews. Potential sources of this discrepancy and limitations of this analysis are discussed in Section 5.1.

The remainder of this paper proceeds as follows. In the Data Section 2, the sample of novels considered for this analysis is described and an overview of the Goodreads review dataset is provided (Wan and McAuley 2018; Wan et al. 2019). Two difference-in-differences models estimating the effect of award-winning on average Goodreads ratings and review volume are motivated and specified in the Models Section 3, followed by a discussion of the model results in the Results Section 4. Finally, in the Discussion Section 5 we summarize the results and limitations of this analysis.

This paper uses the R statistical software (R Core Team 2023) to load, clean, visualize, and model Goodreads ratings. The package `here` (Müller 2025) is used to construct relative file paths, packages `readr` (Wickham, Hester, and Bryan 2025) and `arrow` (Richardson et al. 2025) are used for reading and writing datasets and models, `testthat` (Wickham 2011) is used for data validation, `dplyr` (Wickham et al. 2023), `purrr` (Wickham and Henry 2025), `stringr` (Wickham 2025), and `lubridate` (Grolemund and Wickham 2011) are used for cleaning data, including character and date variables, `zoo` (Zeileis and Grothendieck 2005) is used for calculating rolling averages, `fixest` (Bergé 2018) is used for fitting the fixed-effects regression models described in Section 3, and finally `modelsummary` (Arel-Bundock 2022),

`tinytable` (Arel-Bundock 2025), `knitr` (Xie 2025, 2014, 2015), `kableExtra` (Zhu 2024), and `ggplot2` (Wickham 2016) are used to generate tables and figures.

2 Data

2.1 Overview

To promote comparability, we consider the same slate of literary awards studied in Kovács and Sharkey (2014), those being the Man Booker Prize, the National Book Award (fiction and non-fiction categories), the PEN/Faulkner Award, and the National Book Critics Circle Award (fiction, non-fiction, memoir/autobiography, and biography categories). These awards are chosen for their prestige and reach to ensure that they represent a significant shock to the prizewinning novels’ status. As part of the selection process, judges for each of these awards name a shortlist of 3 to 7 novels from which the winner is chosen. Shortlisted novels are announced publicly, several weeks or months prior to the announcement of a winner. A dataset of shortlisted and winning novels, as well as the announcement dates of both the shortlist and winner, was collected manually for each award in the years 2010 to 2016. Shown below in Table 1 are the novels shortlisted for the 2010 Man Booker Prize.

Table 1: 2010 Man Booker Prize Shortlist

Author	Title	Type	Year	Shortlist Date	Winner Date
Howard Jacobson	The Finkler Question	Winner	2010	2010-09-07	2010-10-12
Emma Donoghue	Room	Finalist	2010	2010-09-07	2010-10-12
Tom McCarthy	C	Finalist	2010	2010-09-07	2010-10-12
Andrea Levy	The Long Song	Finalist	2010	2010-09-07	2010-10-12
Peter Carey	Parrot and Olivier in America	Finalist	2010	2010-09-07	2010-10-12
Damon Galgut	In a Strange Room	Finalist	2010	2010-09-07	2010-10-12
Emma Donoghue	Room	Finalist	2010	2010-09-07	2010-10-12

Reviews of these novels from their publication date to late 2017 are sourced from the UCSD Book Graph, a dataset of over 15 million reviews of 2,360,655 books from around 465 thousand users scraped from Goodreads.com (Wan and McAuley 2018; Wan et al. 2019). Prizewinning and shortlisted novels were matched to novels recorded on Goodreads by title and author, with matches later verified manually. Complete book reviews in the dataset include a plain-text review of a novel alongside an integer rating of 1 to 5 stars. In line with Kovács and Sharkey (2014), this analysis considers only ratings which are accompanied by a plain-text review.

2.2 Measurement

Goodreads ratings are user-submitted evaluations of a novel’s quality on an integer scale from 1 to 5 stars. The ratings are collected via a web scrape of publicly available data on the profiles of Goodreads users in late 2017 and may not contain all reviews available on Goodreads, given that information about the web scraping process is not provided (Wan and McAuley 2018; Wan et al. 2019). Further, ratings may be missing due to users deleting their profile or reviews over time. As a proxy for a user’s subjective evaluation of a novel’s quality, online ratings are only partially reliable. Online ratings, for example, are subject to a herding effect wherein customers’ reviews are biased towards the average of previous reviews (Lederrey and West 2018). A substantial portion of Goodreads reviews (around 9%) are estimated to be sponsored reviews, which could bias ratings upwards relative to reviewers’ actual assessment of quality (Hu et al. 2023).

2.3 Sample Selection

A challenge to identifying the effect of winning an award on a novel’s perceived quality over time is distinguishing between trends in ratings attributable to the novel’s inherent features and trends in ratings attributable to winning an award. For instance, prizewinning novels may be true classics, whose relevance and appeal do not deteriorate over time even in the absence of an award. In this case, an observed post-award increase or persistence in ratings, relative to all other books, may reflect the continuation of an existing trend in ratings rather than a causal effect of winning an award. Addressing this concern requires comparing prizewinning novels to other novels with similar pre-award rating trajectories, so that discrepancies in the post-award ratings of prizewinning novels and the comparison group can be plausibly attributed to the award decision.

Kovács and Sharkey (2014) note that the awards process itself provides such a comparison group. Several weeks or months prior to choosing a winning novel, each award’s judges publicly name three to five shortlisted novels from which the winner is selected. These shortlisted books are deemed to be similar to the prizewinning novels in terms of quality by the awards’ judging panels and share a similar publication date (typically within a year of the award being announced), meaning they are more likely than other books on Goodreads to follow ratings trajectories similar to that of their prizewinning competitor.

From 2010 to 2016, there were 55 prizewinning novels¹ and 205 shortlisted finalists from the 4 prizes included in this analysis. For each prize, category, and year, the shortlisted novel with the lowest absolute difference in mean pre-award ratings compared to the prizewinning novel was chosen as the comparison group, resulting in 55 matched pairs of prizewinning and finalist novels. This approach is meant to limit any unobserved differences in the prizewinning novels and their comparison group which could confound the impact of award-winning on the ratings

¹The Sellout by Paul Beatty won both the 2015 Man Booker Prize and the 2016 National Book Critics Circle Award for fiction.

of prizewinning novels (Kovács and Sharkey 2014). These 55 pairs were reduced to a final 45 pairs of novels, after omitting novels with no reviews in either the pre-award or post-award periods and duplicate nominations.

2.4 Variables

Table 2 shows a sample of 5 observations of variables relevant for this analysis. The Goodreads reviews are uniquely identified by a User ID, Review ID, and a Book ID (truncated for width). Each review is accompanied by a rating between 1 and 5 stars and is time-stamped², allowing reviews to be identified as occurring either before or after a particular award’s winner is announced.

Table 2: Sample of Goodreads Reviews

User ID	Book ID	Review ID	Rating	Review	Timestamp
60ae4...	76482...	c0cf3...	2	I will start of...	2012-05-17
7efef...	64337...	1c44b...	5	I love this wom...	2009-11-17
d6aa1...	30555...	8dcaf...	4	It’s not a fun...	2017-05-26
a9392...	11869...	71557...	5	Beautiful and h...	2012-01-09
d775e...	24612...	b88e5...	2	The whole time...	2015-09-28

Among the 90 selected novels, the number of ratings is highly variable, with the least reviewed book having just 4 ratings compared to a maximum of 5,356 ratings (see Table 3).

Table 3: Descriptive Reviews Statistics

	Min	Max	Mean	SD
Reviews per Book	4.00	5356.00	539.03	818.06
Rating	1.00	5.00	4.02	1.01
Timestamp	2004-02-12	2017-11-03	2014-10-19	666.43

The average rating for all considered novels is around 4 stars, with prizewinning novels having slightly higher average ratings in the pre-award period (see Table 4) and around 50 more reviews than finalists on average. From the pre-award to post-award period, prizewinners’ average rating decreases by around 0.21 stars compared to a 0.1 star decrease for finalists (see Table 5). The average volume of reviews increases by over 300 for prizewinning novels and by around 100 reviews for finalists.

²Time stamps are reported to the minute, but have been rounded to the day for presentation.

Table 4: Balance of Ratings for Winners and Finalists Prior to Award Announcement

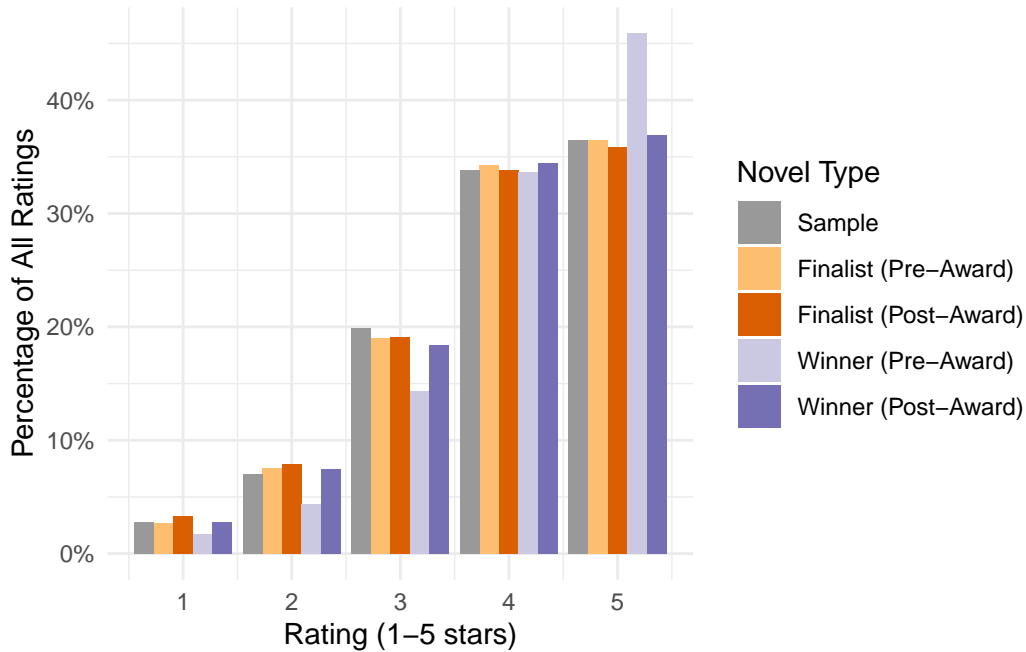
	Finalist Pre-Award (N=7426)		Winner Pre-Award (N=6992)	
	Mean	Std. Dev.	Mean	Std. Dev.
Reviews per Book	165.02	403.48	155.38	213.08
Rating	4.10	0.93	4.17	0.94

Table 5: Balance of Ratings for Winners and Finalists Following the Award Announcement

	Finalist Post-Award (N=11982)		Winner Post-Award (N=22113)	
	Mean	Std. Dev.	Mean	Std. Dev.
Reviews per Book	266.27	444.08	491.40	656.95
Rating	4.00	0.99	3.96	1.05

Figure 1 compares the distribution of ratings for prizewinning novels and finalists against that of a random sample of 10,000 novels not included in any of the award shortlists.

Figure 1: Average Distribution of Goodreads Ratings by Award Status

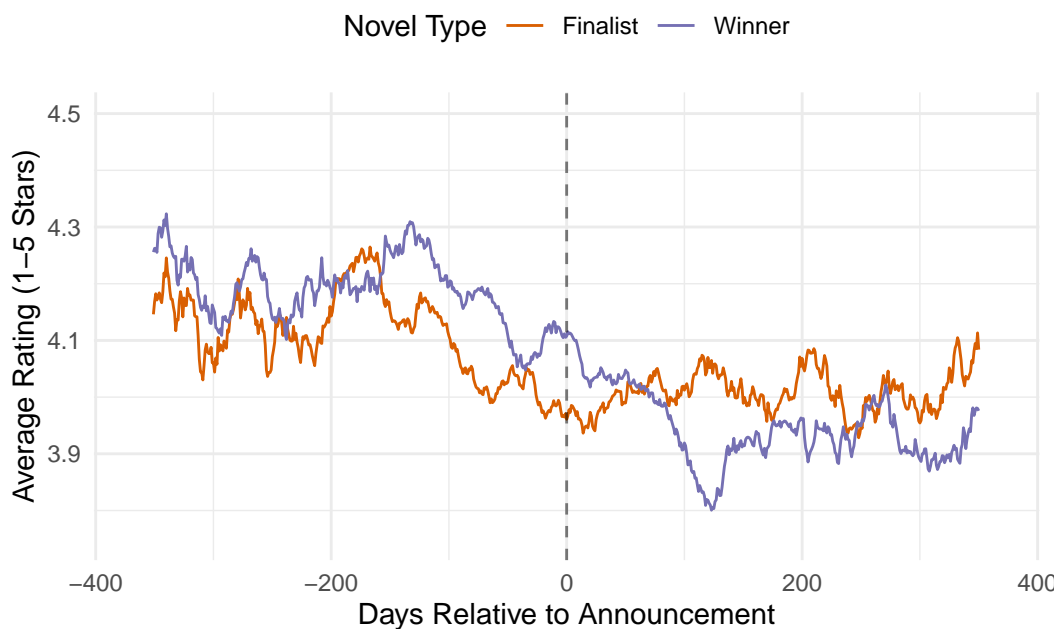


Winners in the pre-award period were much more likely to attain a 5 star rating (around 46%

of ratings) compared to finalists and other novels (around 36%) and are much less likely to have 1, 2, or 3 star ratings. The ratings composition of finalists does not appear to change substantially following award announcements. Prizewinning novels, however, have a steep decline in 5 star reviews to around 37% and have a post-award distribution similar to that of finalists and the random sample of Goodreads novels.

Following the announcement of the award, the average ratings across all prizewinning novels decline from around 4.1 stars at the date of the award announcement to a minimum of 3.8 around 120 days following the award, as shown in Figure 2a. Prior to the announcement, both prizewinning and finalist novels follow a similar awards trajectory, with prizewinning novels consistently having a slightly higher average rating in the year prior to the award announcement. Note that the range of average ratings for both winners and finalists is small, around 0.5 stars across the year prior to and following the award announcement from a maximum of over 4.3 stars and a minimum of 3.8 stars. The full set of ratings for winners and finalists is shown in Appendix Figure 3a.

Figure 2: Rolling Average of Goodreads Ratings Relative to Award Announcement



(a) Rolling average is a centered 30-day window. The vertical axis is limited to 3.75 to 4.5 stars for visibility.

3 Models

To analyze the dual effects of award winning on valuation and popularity, we specify two models using a matched-pair difference-in-differences design. First, we model impacts to readers' valuation (changes in average ratings) using a linear fixed-effects specification to test the hypothesis that awards negatively impact perceptions of quality. Second, we model popularity (changes in review volume) using a Negative Binomial regression to test the hypothesis that awards increase the number of readers and reviewers of award winning novels. Both models use fixed-effects at the matched-pair level (described in Section 2.3) to control for time and quality differences in shortlisted novels across years and awards. This isolates the impact of winning an award relative to the counterfactual trend in ratings and review volume established by an award winning novel's corresponding finalist.

3.1 Ratings Model

Following Kovács and Sharkey (2014), we use a difference-in-differences design with matched-pair fixed effects to estimate the effect of winning an award on the Goodreads ratings of novels.

$$\text{Rating}_{ijk} = \beta_1 \text{Winner}_i + \beta_2 \text{Post}_k + \beta_3 (\text{Winner}_i \times \text{Post}_k) + \sum_{j=1}^J \alpha_j \text{Pair}_j + \epsilon_{ijk} \quad (1)$$

The outcome Rating_{ijk} is the k th rating of the i th book in the j th matched pair of novels. 45 pairs of novels are considered ($j = 1, \dots, 45$), each containing one prizewinning novel and one shortlisted finalist ($i = 1, 2$). The number of ratings varies by novel, with a mean count of 539.03 (SD 818.06).

Covariates Pair_j are indicators for whether a rating belongs to a book in the j th match pair. The coefficients α_j are the matched-pair fixed effects, which capture the average baseline rating of novels in pair j . These fixed-effects absorb baseline characteristics shared by each pair, such as the overall quality of shortlisted novels in a given year.

Winner_i is an indicator for whether a rating is of a prizewinning novel and Post_k an indicator for whether rating k occurred after the winner of the j th matched-pair's award was announced. The interaction $\text{Winner}_i \times \text{Post}_k$ is equal to 1 for ratings of prizewinning novels submitted in the post-award period and 0 otherwise.

In this specification, β_1 is interpreted as the difference in average ratings between the prizewinning novel and its corresponding finalist in the pre-award period. β_2 estimates the average change in ratings of finalists from the pre-award to post-award period. β_3 is the difference-in-differences estimator, representing the effect of the award on ratings. In particular, β_3 measures

the difference in the change of the prizewinning novel’s average ratings from the pre-award to post-award period relative to the change in the average ratings of the corresponding finalist.

The inclusion of matched-pair fixed effects α_j are important for isolating the effect of winning an award. By absorbing characteristics shared by both novels in each matched pair, these fixed-effects ensure that the difference-in-differences estimator compares each winner with its direct rival, rather than comparing all prizewinning novels to all finalists across different award years with varying baseline qualities.

ϵ_{ijk} is the idiosyncratic error term. Errors are assumed to be independent for ratings in different matched pairs j and j' , but are arbitrarily correlated for ratings of novels within the same matched pair. Correlation is assumed at the matched-pair, rather than the novel, level to account for both autocorrelation of reviews for the same novel over time and the correlation between the winner and finalist within the same award cycle, which share a similar publishing date and are subject to the same time-specific trends in reviews. Accordingly, the standard errors of coefficient estimates are clustered at the matched-pair level.

3.1.1 Parallel Trends Assumption

The validity of the difference-in-differences estimator relies on the parallel trends assumption, which states that, in the absence of an award, the average ratings of prizewinning novels and their finalist counterparts would have followed the same (parallel) trajectory over time. As noted in Section 2.3, we used the matched-pair selection strategy shown by Kovács and Sharkey (2014) to satisfy this assumption. By choosing to limit the comparison of each prizewinning novel to a corresponding finalist which was released in the same award cycle, selected for the same award by a panel of judges, and which has similar average reviews in the pre-award period, we control for time, quality, and prestige related factors which would affect the natural life-cycle of book ratings over time. To empirically assess the parallel trends assumption, we test for the difference of pre-award ratings slopes of winners and finalists (see Appendix Section B). As reported in Table 8, we find no statistically significant difference in the ratings trends of the two groups prior to the award announcement, supporting the assumption that finalists provide a valid counterfactual for the prizewinning novels’ post-awards trajectory.

3.2 Popularity Model

A secondary effect of winning an award on popularity is estimated using a Negative Binomial regression. The model uses the same difference-in-differences covariates described in Section 3.1 but treats the aggregate count of each novels’ reviews as the outcome variable.

Let NumReviews_{ijt} denote the number of reviews of the i th novel in the j th matched-pair in the t th period, where t is either pre-award or post-award. We assume that NumReviews_{ijt} follows a Negative Binomial distribution with a dispersion parameter θ and a conditional expectation $\mu_{ijt} = E[\text{NumReviews}_{ijt} \mid \beta, \alpha]$ modeled as:

$$\mu_{ijt} = \exp \left(\beta_1 \text{Winner}_i + \beta_2 \text{Post}_k + \beta_3 (\text{Winner}_i \times \text{Post}_k) + \sum_{j=1}^J \alpha_j \text{Pair}_j \right) \quad (2)$$

$$= \exp(\beta_1 \text{Winner}_i) \exp(\beta_2 \text{Post}_k) \exp(\beta_3 (\text{Winner}_i \times \text{Post}_k)) \exp \left(\sum_{j=1}^J \alpha_j \text{Pair}_j \right) \quad (3)$$

Note that in this model, coefficients affect the conditional mean multiplicatively rather than additively. A β_3 of 0.40 for example implies that prizewinning novels review volume increased by a factor of $\exp(0.40) \approx 1.5$ times in post-award period, relative to the change in review volume of their corresponding finalists.

A Negative Binomial distribution is chosen over the usual Poisson distribution for counts due to its flexible mean-variance relationship. In particular, the Poisson model imposes the restriction that the conditional variance of NumRatings_{ijt} is equal to the conditional mean μ_{ijt} , while the Negative Binomial variance is a function of μ_{ijt} and the dispersion parameter θ , allowing more flexibility (Hoffmann 2016).

4 Results

Table 6 displays the results of models described in Section 3.1 and Section 3.2.

Table 6: Effect of Winning an Award on Novel Ratings and Popularity

	Ratings	Count of Reviews
Winner	0.072	0.208
	0.035 (0.046)	0.316 (0.513)
Post	−0.099	0.619
	0.026 (<0.001)	0.135 (<0.001)
Winner x Post	−0.028	0.386
	0.028 (0.316)	0.217 (0.082)
Regression Type	Linear	Negative Binomial
N	48 513	180
AIC	134 180.1	2227.8
BIC	134 602.0	2381.1

Matched-pair clustered standard errors are shown below coefficient estimates (p-values in parentheses).
Both models include matched-pair fixed effects.

We do not observe the paradox of publicity noted by Kovács and Sharkey (2014) in the ratings model results. The difference-in-differences estimate of Winner x Post is near 0 ($\beta_3 = -0.028, p > 0.05$) and insignificant at the 5% level, meaning that winning an award is estimated to have no evidence of an effect on the average post-award ratings of prizewinning novels compared to finalist novels. This is in contrast to the large and significant effect size (an estimated 0.171 star decline in average ratings) found by Kovács and Sharkey (2014).

Prizewinning novels are estimated to have a slightly higher average rating ($\beta_1 = 0.072, p < 0.05$) than finalists in the pre-award period, although the difference is less than 0.1 stars. This pre-award difference is mechanically small, due to the matching procedure noted in Section 2.3, which selected finalist novels with similar pre-award average ratings to their corresponding winning novel. The ratings of finalists are estimated to decline ($\beta_2 = -0.099, p < 0.05$) in the post-award period, although the effect on ratings is again less than 0.1 stars.

Similarly, award winning is not shown to significantly affect the number of reviews received by prizewinning novels relative to finalists. Award winning novels are estimated to be slightly more popular than finalists in the pre-award period ($\exp(\beta_1) \approx 1.32, p > 0.05$) and finalists are estimated to receive a higher volume of reviews in the post-award period compared to the pre-award period ($\exp(\beta_2) \approx 1.86, p < 0.05$).

Given that the number of reviews per novel is highly variable, with a minimum review count of 4 and a maximum of 5,356, these findings may be skewed by a small number of volatile low-review novels. To assess the sensitivity of results to the sample composition, we re-estimate the ratings difference-in-difference model restricted to subsamples of matched pairs in which both novels have at least 50, 100, and 200 reviews in the both the pre-award and post-award periods.

Table 7: Sensitivity Award Effects to Minimum Review Count Thresholds

	Ratings (> 0)	Ratings (> 50)	Ratings (> 100)	Ratings (> 200)
Winner	0.072	0.070	0.108	0.084
	0.035 (0.046)	0.024 (0.003)	0.030 (<0.001)	0.033 (0.011)
Post	-0.099	-0.069	-0.090	-0.080
	0.026 (<0.001)	0.021 (0.001)	0.028 (0.001)	0.031 (0.009)
Winner x Post	-0.028	-0.047	-0.050	-0.024
	0.028 (0.316)	0.027 (0.086)	0.033 (0.136)	0.037 (0.520)
N	48 513	35 558	25 721	21 998
N Matched-Pairs	45	25	18	12
AIC	134 180.1	99 427.3	72 670.1	61 963.6
BIC	134 602.0	99 664.7	72 841.4	62 083.6

Matched-pair clustered standard errors are shown below coefficient estimates (p-values in parentheses).

All models include matched-pair fixed effects.

Table 7 shows the results of the original ratings model compared to the restricted sample models. All estimates of the difference-in-differences coefficient remain near 0 and insignificant, suggesting that the null results observed in Table 6 are not an artifact of influential novels with a low volume of reviews.

5 Discussion

This paper examined the impact of winning a major literary award on the perception of a novel’s quality, using changes in Goodreads ratings over time to identify shifts in readers’ evaluations of quality after a novel publicly receives an award. Following the approach of Kovács and Sharkey (2014), the ratings trajectory of winning novels is compared to that of similar shortlisted novels using a difference-in-differences design with matched-pair fixed effects. This design aims to isolate the effect of award-winning from other ratings trends related to

specific genres or periods. Contrary to prior work assessing the impact of awards on the valuation of cultural products, we found no evidence that awards negatively impacted the ratings of award-winning novels or evidence that award winning novels received substantially more reviews in the post-award period than other finalists (Kovács and Sharkey 2014; Rossi and Schlee 2024; Rita et al. 2022).

These findings suggest that the “paradox of publicity” proposed by Kovács and Sharkey (2014) may rely on the extent of the popularity shock experienced by prizewinning novels. The original theory suggests that awards expand the reach and visibility of prizewinning novels, attracting readers who would not otherwise be drawn to the prizewinning novel, due to their genre preferences or other reading habits. These readers, who differ from the typical audience which gave award winning books high ratings in the pre-award period, have their high expectations (generated by the award) violated and thus tend to rate the prizewinning novel lower, resulting in a negative ratings trend post-award. However, our popularity model showed that prizewinners did not experience a significant increase in readership (as indicated by Goodreads reviews volume) following the award.

The absence of a large influx of new readers provides an explanation for the relative stability of ratings shown in this analysis. If an award fails to expand the readership of a prizewinning novel outside of its usual niche, then the match between readers’ tastes and the prizewinning novel remain strong in the post-award period, resulting in no negative ratings penalty. To differentiate the impact of popularity from other potential effects of awards, future analyses may look at shocks to a novel’s popularity which do not necessarily represent a shock to a work’s prestige, such as the adaptation of a book to a film.

5.1 Weaknesses and next steps

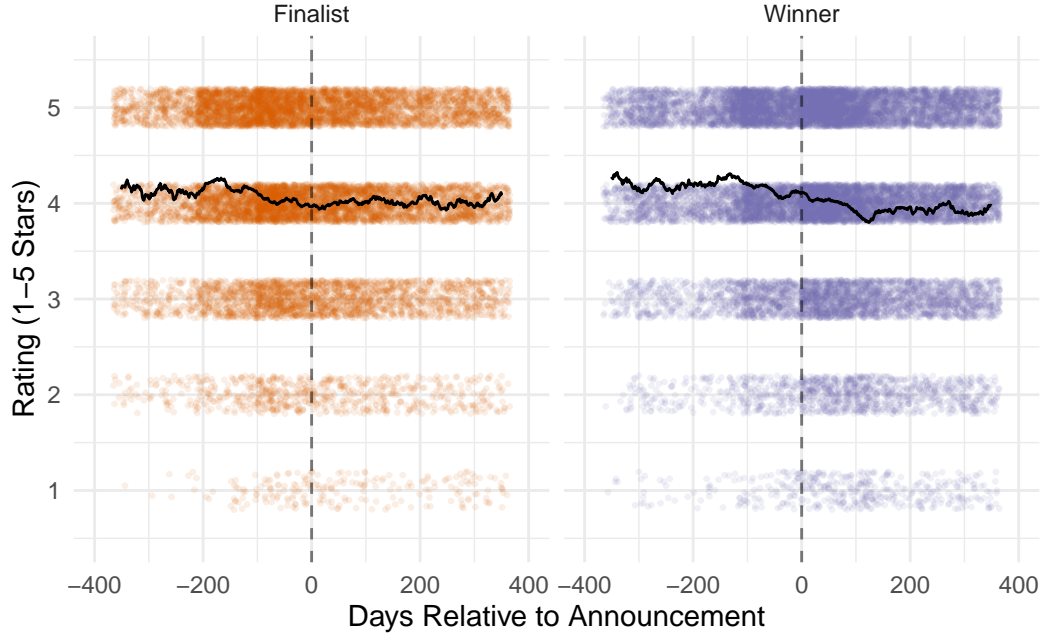
Several limitations remain in this analysis. Unlike in the analysis by Kovács and Sharkey (2014), the matched-pair design failed to eliminate statistically significant differences in the pre-award ratings of award-winning novels, suggesting that the matched-pair design may not have fully eliminated differences in the ratings trends of prizewinners and their corresponding finalists. Goodreads ratings as a measure of readers’ perception of quality also face a number of shortcomings. For example, ratings are voluntary and asynchronous, meaning that changes in ratings may be attributable to changes in reviewer composition (e.g. readers who were gifted a prizewinning or shortlisted novel) rather than changes in the perception of individual readers. As noted in Section 2.2, Goodreads ratings are also predisposed to tend towards the average or early ratings and contain a large proportion of sponsored reviews which may be biased (Lederrey and West 2018; Hu et al. 2023). Consequently, our estimates of the negative effect of awards on readers’ perceptions of quality are likely conservative, as social pressure may dampen the expression of negative sentiments in Goodreads reviews.

Appendix

A Data Visualization

Figure 3a plots every rating provided to prizewinning and finalist novels in the 365 prior to and following the announcement of award winners.

Figure 3: Distribution of Goodreads Ratings Relative to Award Announcement



(a) Each rating is a point. A 30-day centered rolling average of ratings is shown in black.

B Parallel Trends Model

Here, we specify a linear model to check that prizewinning novels and their corresponding finalists follow a parallel ratings trend in the pre-award period.

$$\text{Rating}_{ijk} = \beta_1 \text{Winner}_i + \beta_2 \text{Months}_k + \beta_3 (\text{Winner}_i \times \text{Months}_k) + \sum_{j=1}^J \alpha_j \text{Pair}_j + \epsilon_{ijk} \quad (4)$$

The outcome Rating_{ijk} , covariate Winner_{ijk} , and matched-pair fixed effects α_j are defined as in Section 3.1. Months_k is the number of months prior to the award announcement that the k th rating was submitted. The term of interest is the interaction $\text{Winner}_i \times \text{Months}_k$, which is 0 for finalists and equal to Months_k for prizewinning novels.

The slope (trend) of pre-award ratings for finalists is $\delta_{\text{Finalist}} = \beta_2$, while that of prizewinning novels is $\delta_{\text{Winner}} = \beta_2 + \beta_3$. If β_3 is 0, then $\delta_{\text{Winner}} = \delta_{\text{Finalist}}$ and finalists and winners share the same (parallel) trend in ratings in the pre-award period.

Table 8 shows the results of the parallel trends model. Note that the ratings of all novels are estimated to have a statistically significant decline over time ($\beta_2 = -0.015, p < 0.05$), while $\beta_3 = -0.001$ ($p > 0.05$) is not significantly different from 0, suggesting that $\delta_{\text{Finalist}} \approx \delta_{\text{Winner}}$ and that the parallel trends assumption is satisfied.

Table 8: Difference in Pre-Award Ratings Trends for Winners and Finalists

	Pre-Award Trend
Winner	0.051
	0.046 (0.278)
Months	-0.015
	0.005 (0.006)
Winner x Months	-0.001
	0.007 (0.836)
N	14 418
AIC	38 281.6
BIC	38 645.2

Matched-pair clustered standard errors are shown below coefficient estimates (p-values in parentheses).

Model includes matched-pair fixed effects.

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