TripAdvisor's Half-Bubble Rounding & Hotel Popularity

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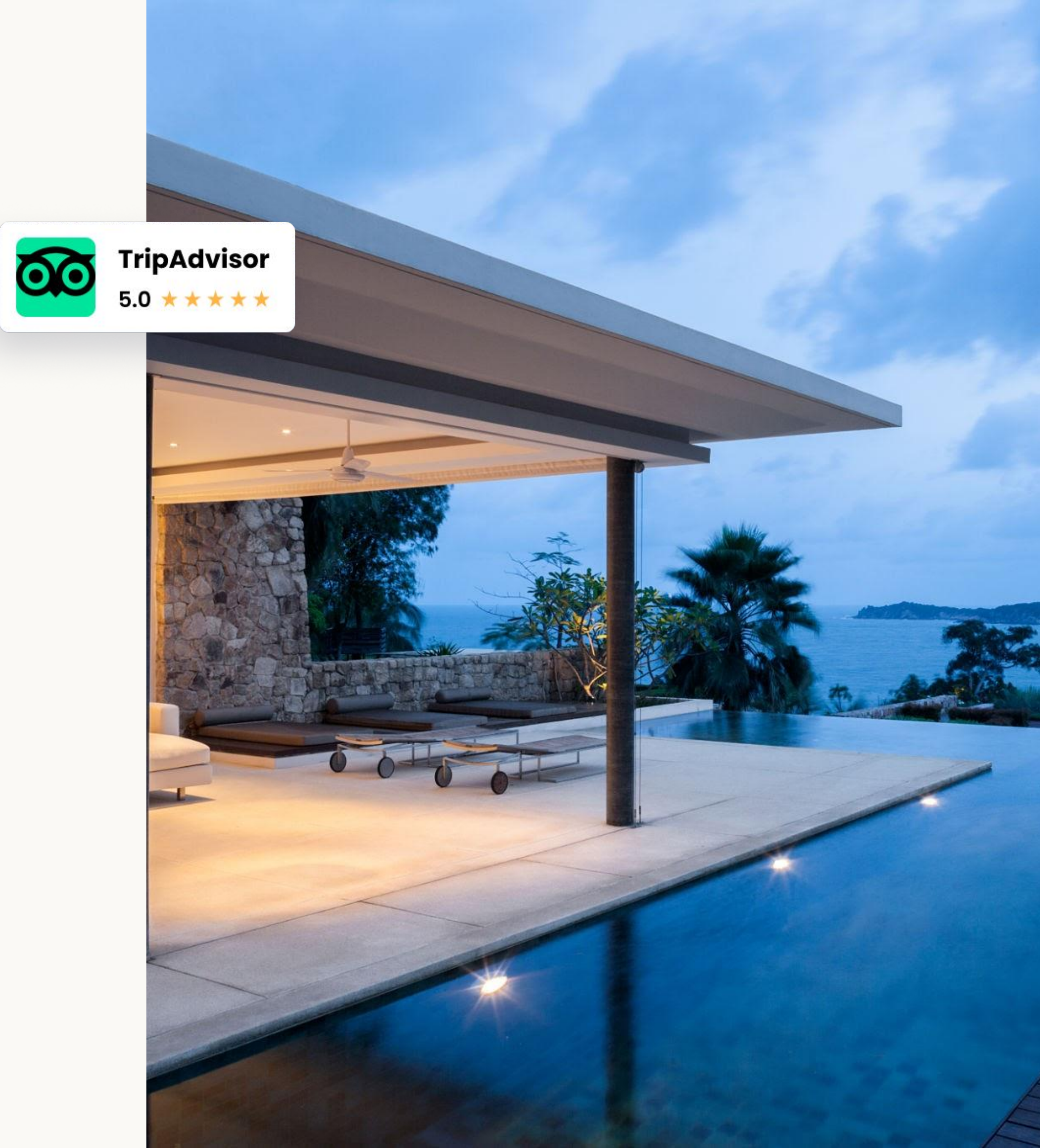


Intro & Objectives

Rating-Rounding Feature
TripAdvisor converts raw averages to the nearest 0.5-bubble (3.5 ★, 4.0 ★)

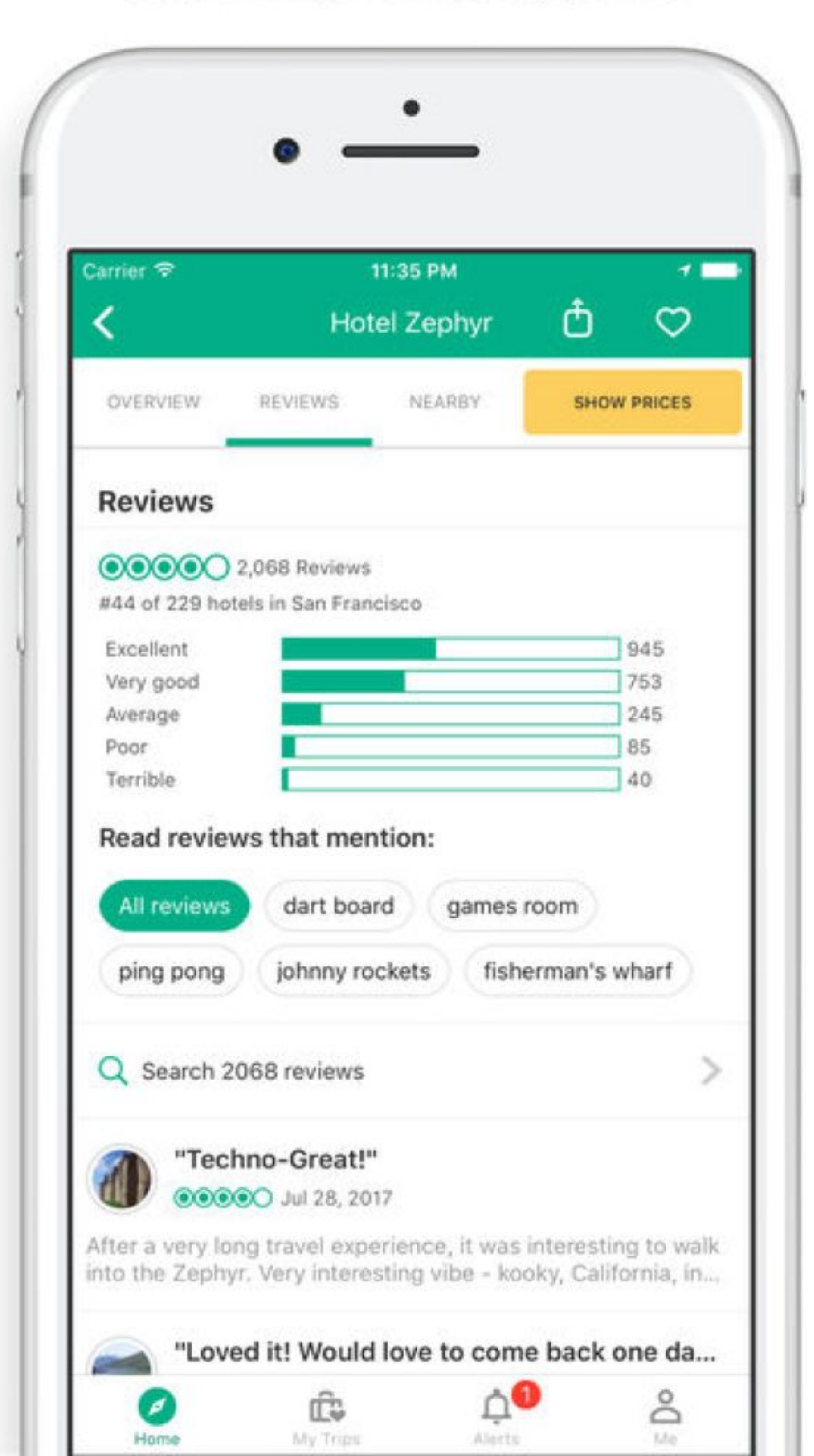
Research Question
Does just crossing a rounding cutoff boost a hotel's popularity (page views)?

Empirical Setting
Public dataset of hotels: raw rating, displayed score, view counts

Method Preview
RDD around each 0.5-point threshold to isolate the causal effect of rounding

Objectives

Estimate Effect of Rating Rounding Rule	Test RDD validity assumptions	Assess Implications
Estimate the discontinuity in page views when a hotel's score rounds up versus down.	1. Hotels just above and below a cutoff are comparable on unobserved factors. 2. Binning reduces noise and clarifies the jump.	Compare left and right side slopes to see which side of the cutoff gains or loses more.



Regression and Data

Dataset Source

Publicly available TripAdvisor Rating Impact on Hotel Popularity dataset from Kaggle.

Contains records of 4,599 hotels in Rome.

Key Variables

score_adjusted: Average rating from all TripAdvisor users.

bubble_rating: Score rounded to nearest 0.5 by the company.

Data Processing

0.05-point bins were used to average total hotel views.

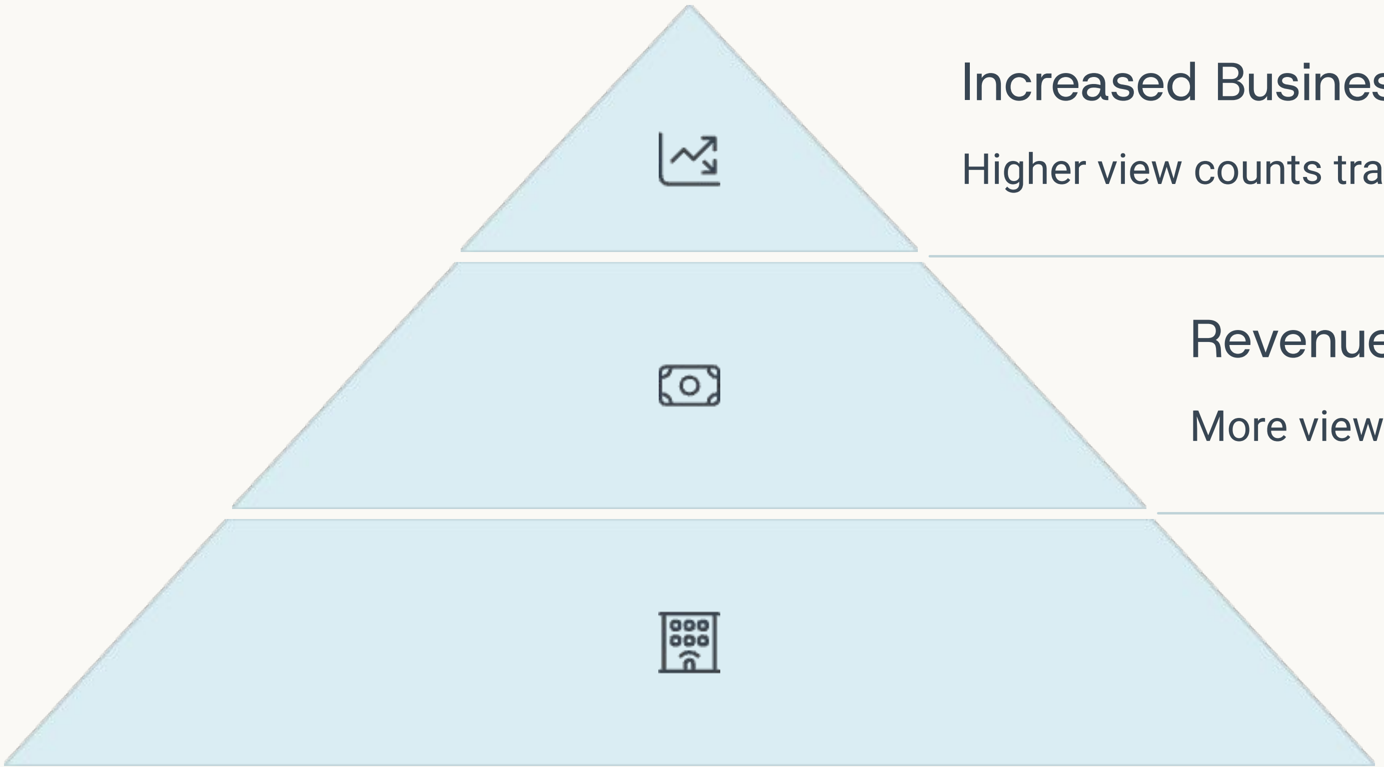
Views were aggregated for each bin to create unique reference points.

Data can be represented in scatter or dot plots.

We are using the publicly available TripAdvisor Rating Impact on Hotel Popularity dataset from Kaggle. This dataset includes 4,599 hotel records from Rome. Each record contains the average user rating (**score_adjusted**) and the company's rounded rating (**bubble_rating**, rounded to the nearest 0.5).

To clean noisy data and distinguish hotels more finely than the `bubble_rating` allows, we binned the raw hotel ratings into 0.05-point increments. For each bin, we aggregated the total number of hotel views, creating unique reference points for our analysis. This allows for clearer representation in scatter or dot plots, supporting the assumptions made in the objectives section.

Application and Expected Implications



Increased Business Opportunities

Higher view counts translate to increased booking opportunities

Revenue Growth

More views lead to advertising revenue and potential network effects

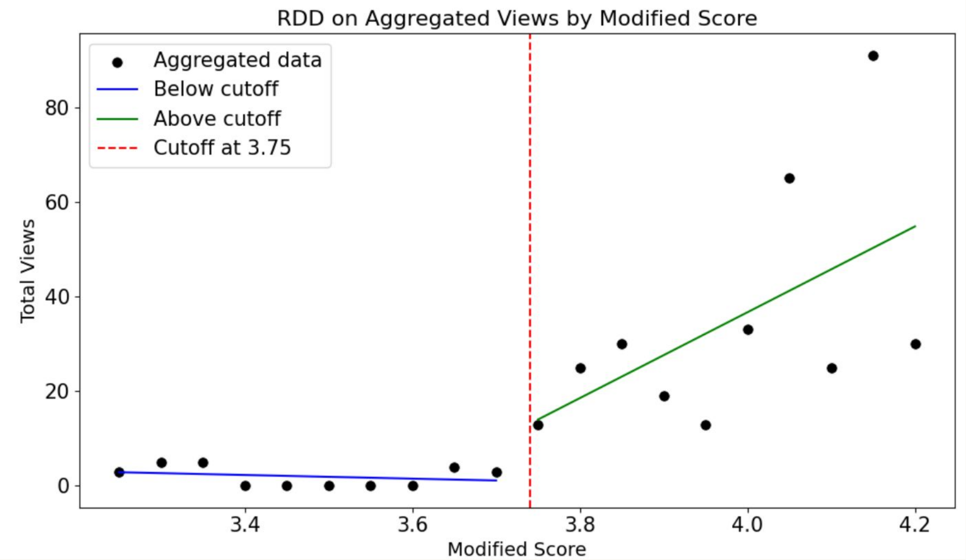
Hotel Rating Incentives

Hotels incentivized to improve ratings to achieve rounded up scores

Our Regression Discontinuity analysis will reveal how TripAdvisor's review rating rounding policy impacts hotel popularity. If hotels just above the rounding cutoff gain significantly higher page views, it will confirm the policy's substantial influence on user attention. Strategically, this incentivizes hotels to marginally improve ratings for a rounded-up score, leading to increased booking opportunities, advertising revenue, and network effects that benefit TripAdvisor's overall business model.

Parametric RDD

$$y = \beta_0 + \beta_1 \cdot \text{Treatment} + \beta_2 \cdot (x - c) + \beta_3 \cdot \text{Treatment} \cdot (x - c) + \varepsilon$$

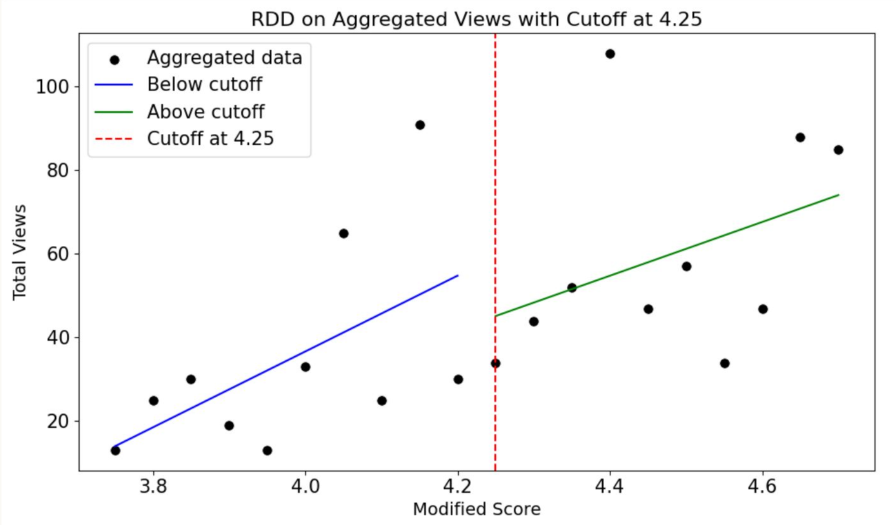


$$\text{Views} = \beta_0 + \beta_1 \cdot \text{Treatment} + \beta_2 \cdot (\text{Score} - 3.75) + \beta_3 \cdot \text{Treatment} \cdot (\text{Score} - 3.75) + \varepsilon$$

Parameter	Estimate
β_0 (Intercept)	0.9333
β_1 (Treatment)	13.0667
β_2 (Score Centered)	-3.8788143
β_3 (Treatment $\times$ Score Centered)	94.5455

Treatment definition: hotels with average rating between 3.25 to 3.74 will be rounded to 3.5, 3.75 to 4.24 will be rounded to 4

The treatment effect of rounding ratings up to 4 versus rounding down to 3.5 has significant impact on hotel viewership



$$\text{Views} = \beta_0 + \beta_1 \cdot \text{Treatment} + \beta_2 \cdot (\text{Score} - 4.25) + \beta_3 \cdot \text{Treatment} \cdot (\text{Score} - 4.25) + \varepsilon$$

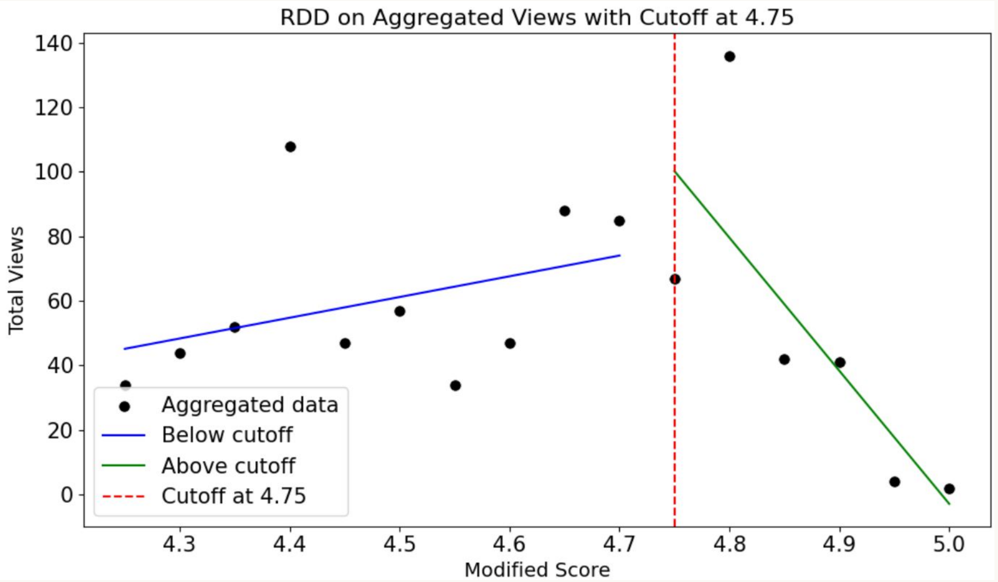
Parameter	Estimate
β_0 (Intercept)	59.3333
β_1 (Treatment)	-14.1879
β_2 (Score Centered)	90.6667
β_3 (Treatment $\times$ Score Centered)	-26.4242

Treatment definition: hotels with average rating between 3.75 to 4.24 will be rounded to 4, 4.25 to 4.74 will be rounded to 4.5

We do not see a similar treatment effect of rounding ratings up to 4.5 versus rounding down to 4

Parametric RDD

$$y = \beta_0 + \beta_1 \cdot \text{Treatment} + \beta_2 \cdot (x - c) + \beta_3 \cdot \text{Treatment} \cdot (x - c) + \varepsilon$$

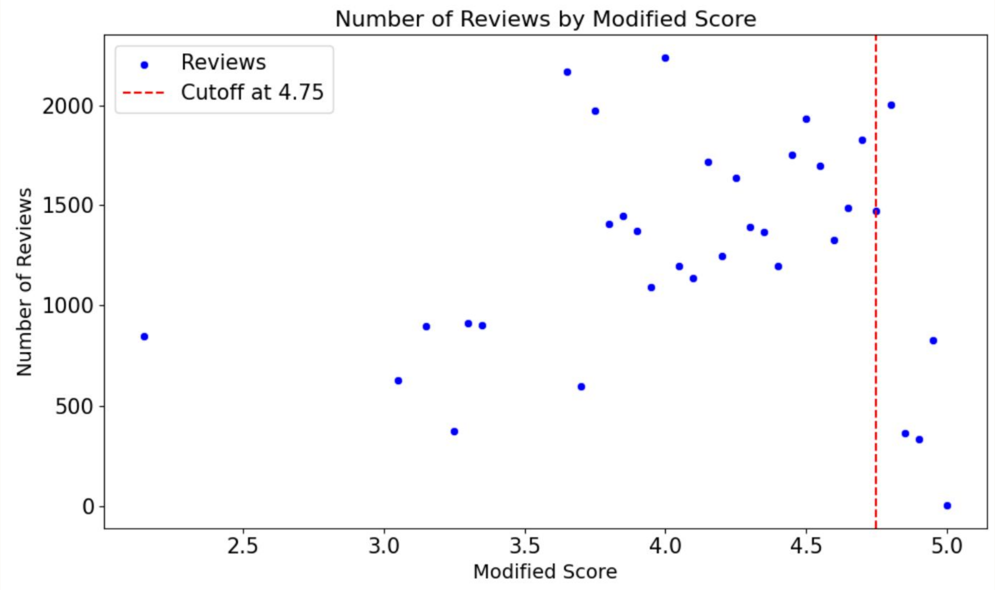


$$\text{Views} = \beta_0 + \beta_1 \cdot \text{Treatment} + \beta_2 \cdot (\text{Score} - 4.75) + \beta_3 \cdot \text{Treatment} \cdot (\text{Score} - 4.75) + \varepsilon$$

Parameter	Estimate
β_0 (Intercept)	77.2667
β_1 (Treatment)	22.9714
β_2 (Score Centered)	64.2424
β_3 (Treatment $\times$ Score Centered)	-476.8139

Treatment definition: hotels with average rating between 4.25 to 4.74 will be rounded to 4.5, 4.75 & above will be rounded to.5

Surprisingly, we see a negative impact of rounding to 5 stars , naturally we thought this could be due to price or credibility



$$Views = \beta_0 + \beta_1 * Rating + \beta_2 * \text{n reviews} + \beta_3 * Ratings * \text{n reviews} + \epsilon$$

Parameter	Estimate
β_0 (Intercept)	67.1731
β_1 (Rating)	-12.4400
β_2 (n_reviews)	-0.1644
β_3 (n_reviews $\times$ Ratings)	0.0438

We ran a regression with interaction terms to see the impact number of number of reviews and rating on views

At high rating (above 4.75) we see that the number of reviews is very low which impacts the trust and credibility of the rating

Interpretation & Implication

Framework

$$y = \beta_0 + \beta_1 \cdot \mathrm{Treatment} + \beta_2 \cdot (x - c) + \beta_3 \cdot \mathrm{Treatment} \cdot (x - c) + \varepsilon$$

$$\beta_L : \beta_2$$

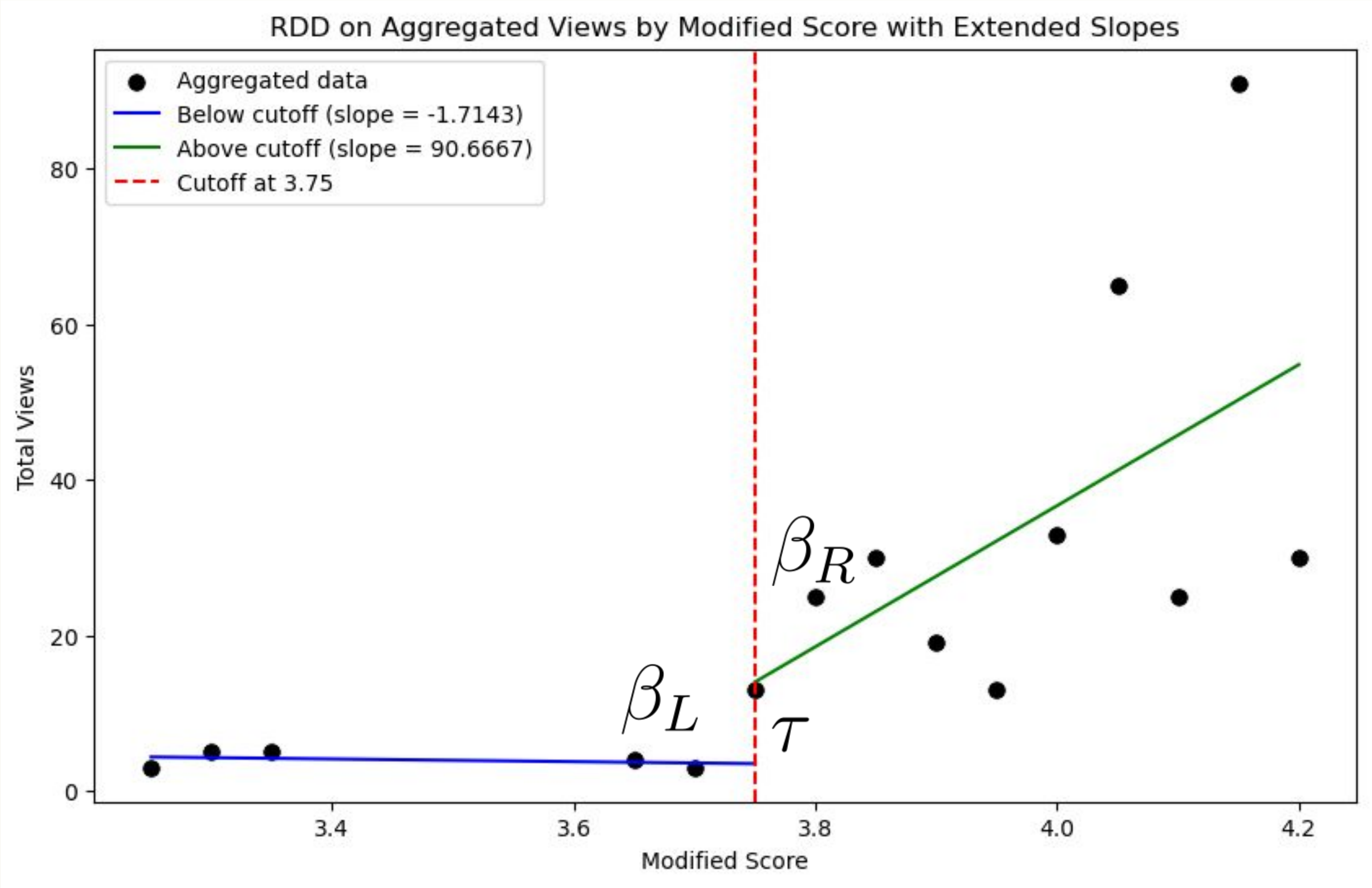
Interpreted as: Impact of rating on views ***before cutoff***

$$\beta_R : \beta_2 + \beta_3$$

Interpreted as: Impact of rating on views ***after cutoff***

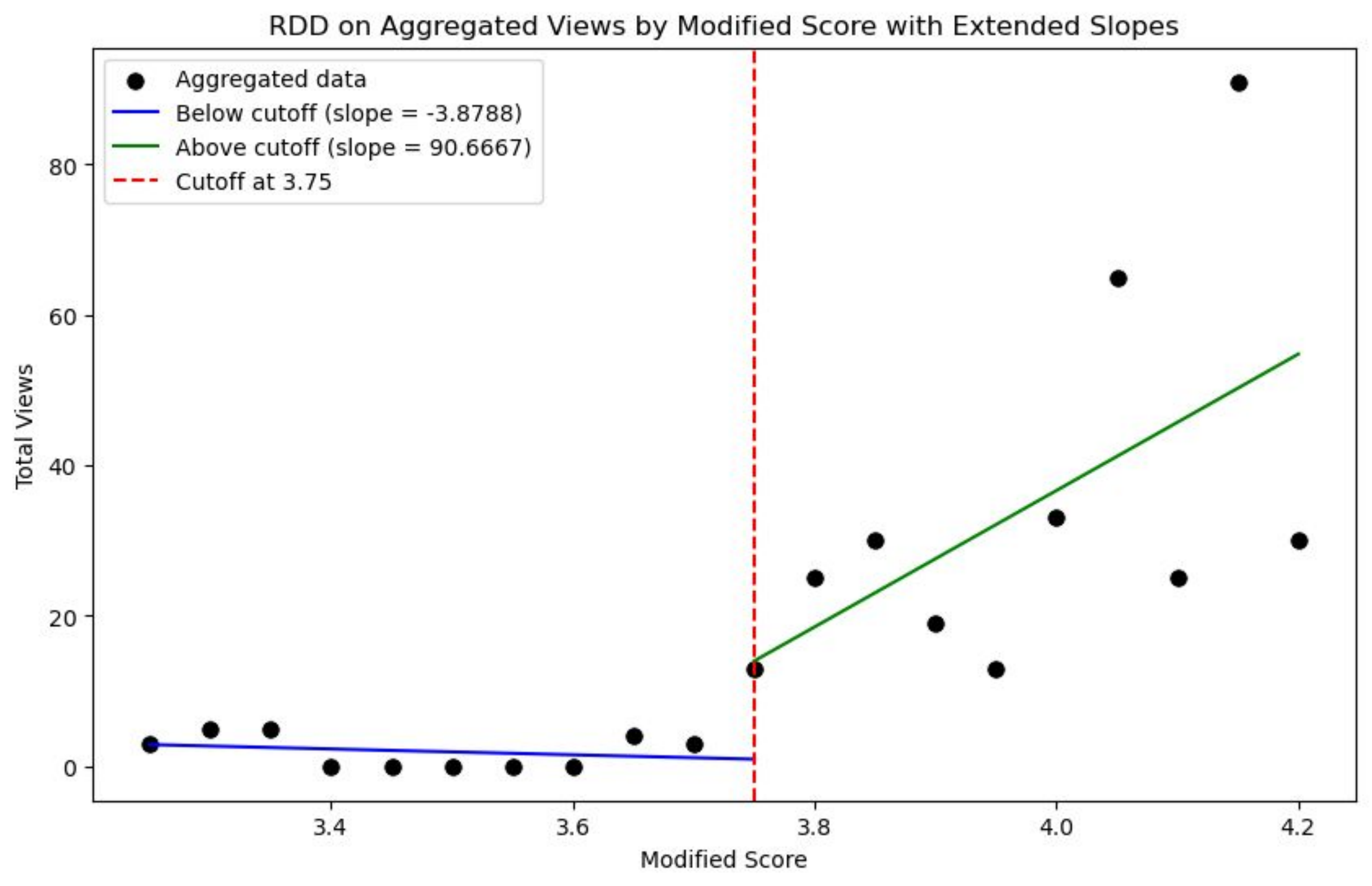
$$\tau(\text{Treatment effect}) : \beta_1$$

Effect of treatment on whe views (clicks)



Different impact on different range of rates.

Most effective on cutoff 3.75 : This might be the range ***in which people might react most sensitively on ratings when clicking.*** Start to perceive as high-quality



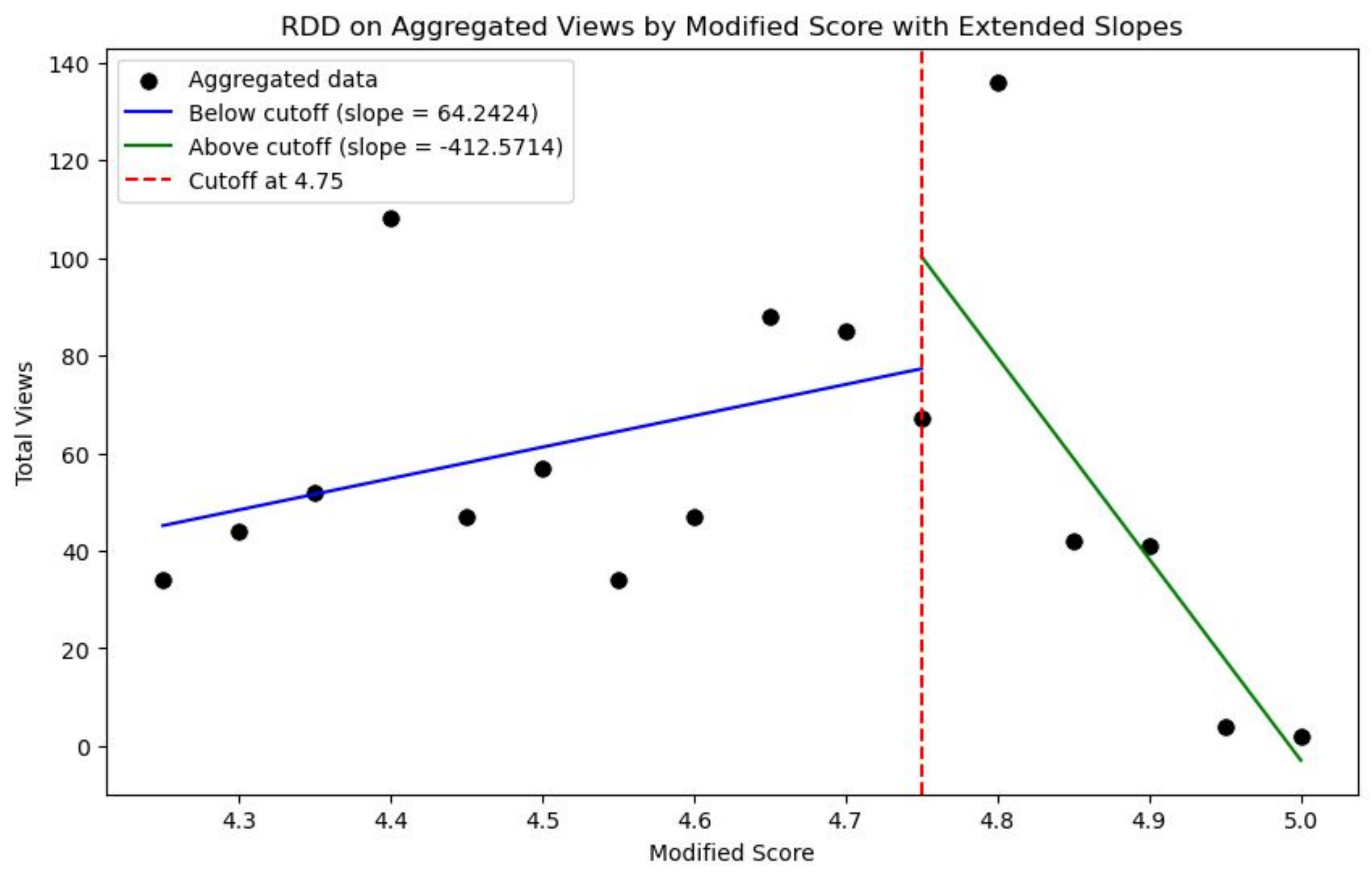
Below cutoff: Flat slope - views are not impacted dynamically when rate increases.

After cutoff: View increase by 90.6 when rating increases by 1.
→ Due to rounding up, users are more ***sensitive reacting to the rating when viewing hotels.***

Impact (Gap): + **13.0667** views increase when rounding up.

Different impact on different range of rates.

Higher range : After cutoff (rounding up), *views are now negatively impacted by rating*



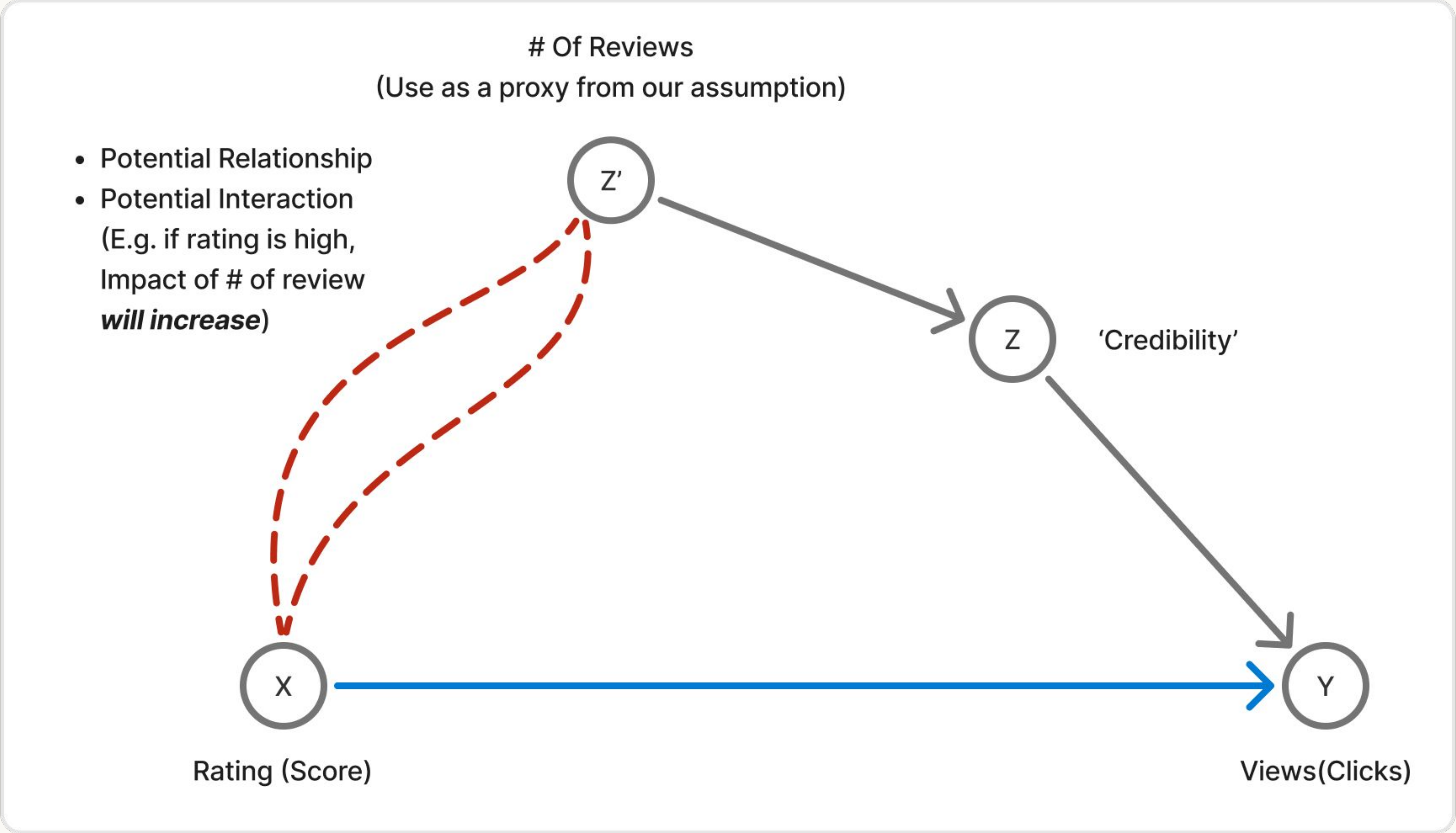
Impact (Gap): + **4.75. At cutoff, treatment have effect of raising view**

Below cutoff: Increase with slope 64.24, rating is positively contributing to views.

After cutoff: Decrease with slop −412.57, rating is ***strongly negatively impacting on views.***

Hypotheses: If rating is too high, especially when rating count aren’t sufficient enough, users might feel it less credible.

$$Views = \beta_0 + \beta_1 * Rating + \beta_2 * \text{n reviews} + \boxed{\beta_3 * Ratings * \text{n reviews}} + \epsilon$$

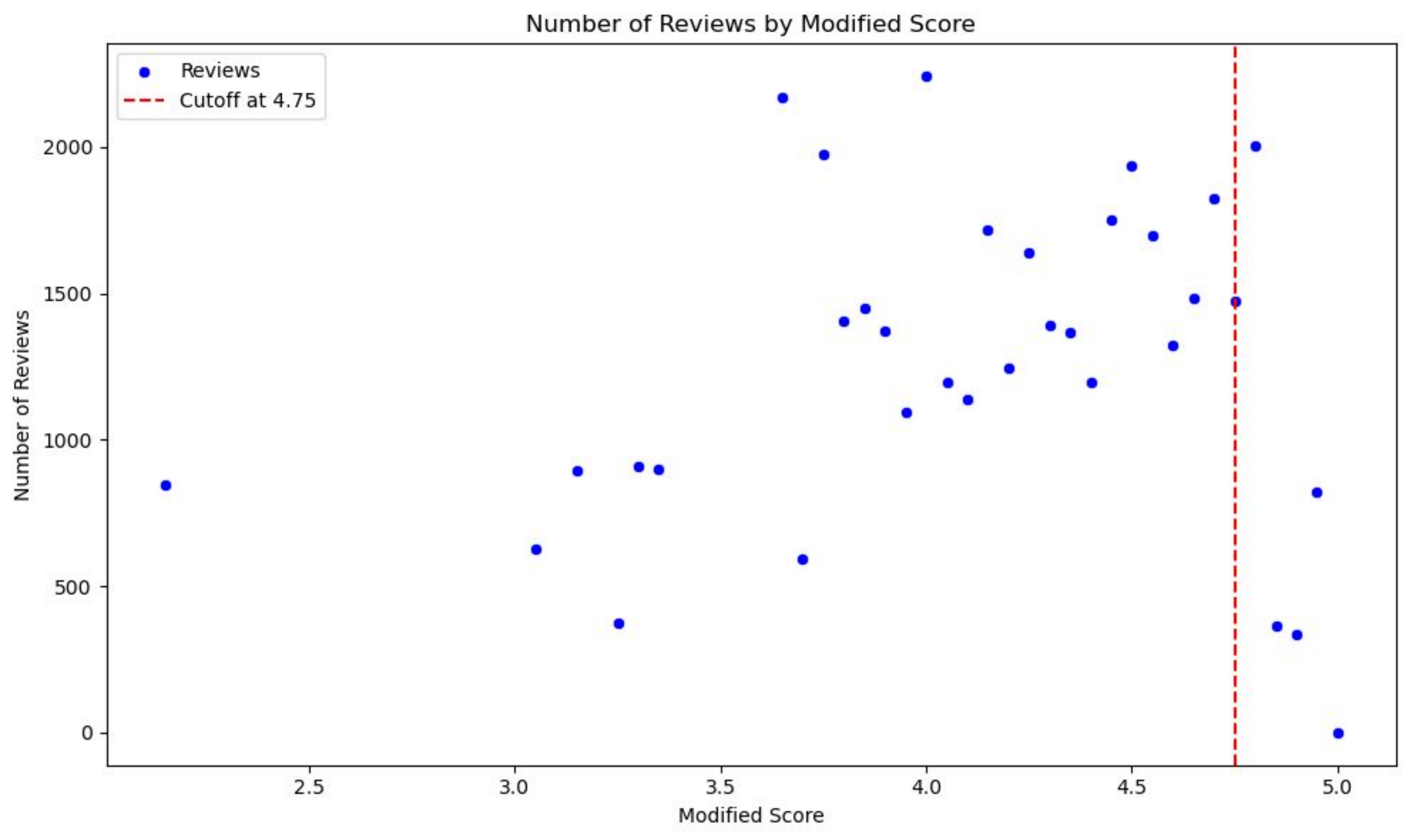


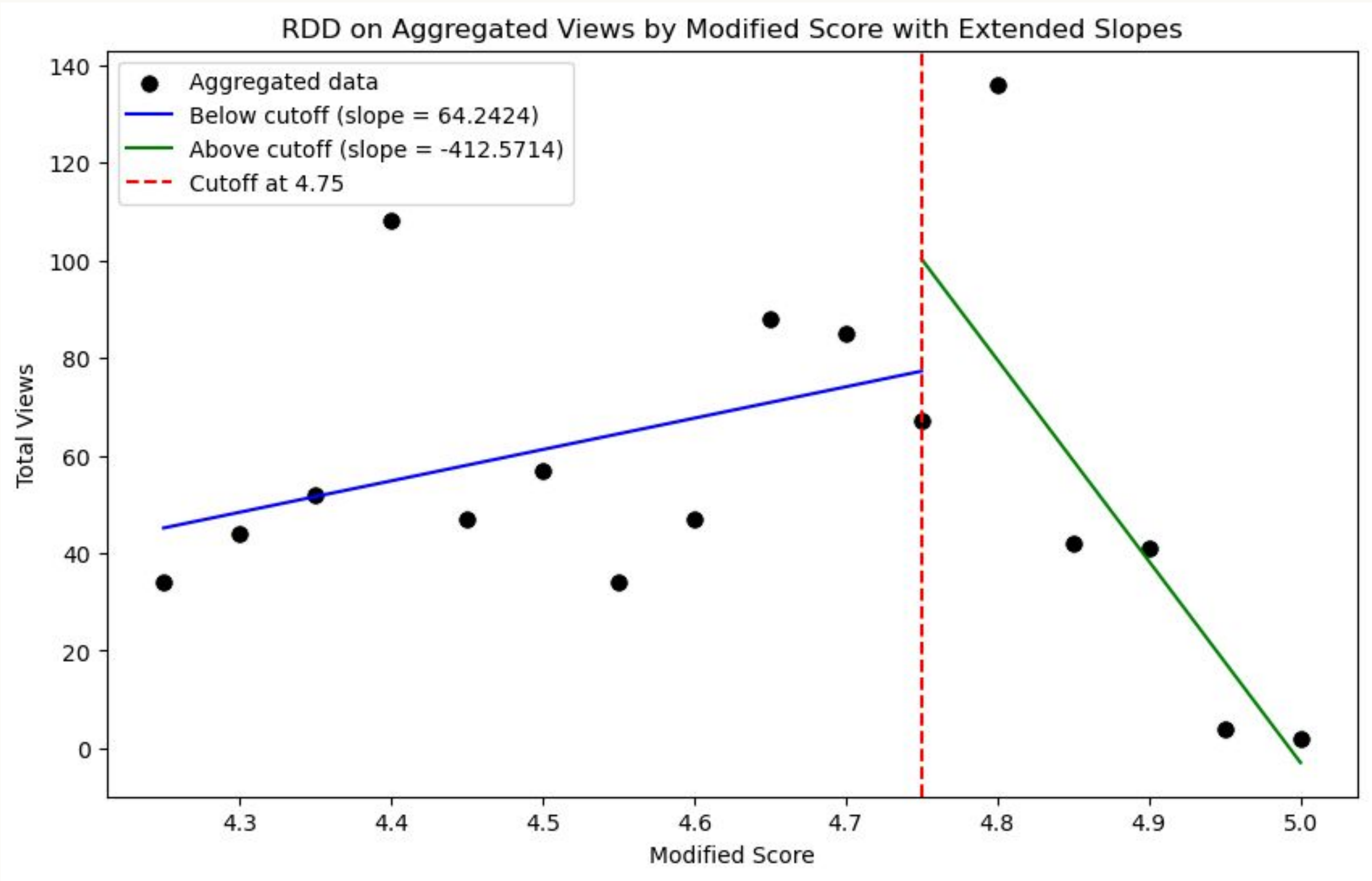
$\beta_3 > 0$:

Impact of # of review increases when rating is higher

→ If we have ***less amount of review for higher rating range***, it could be reason for ***the negative slope.***

Coefficient of interaction term (β_3) : +0.0438





- Comparing impact of n_reviews when rating is 3 VS 5:

$$\beta_3 * 3 * n_{reviews} = n_{reviews} * 0.1314$$

$$\beta_3 * 5 * n_{reviews} = n_{reviews} * 0.219$$

→ However, treatment effect itself is still positive.

→ Also, this never means 'pure impact of rating' on view in this range is negative.

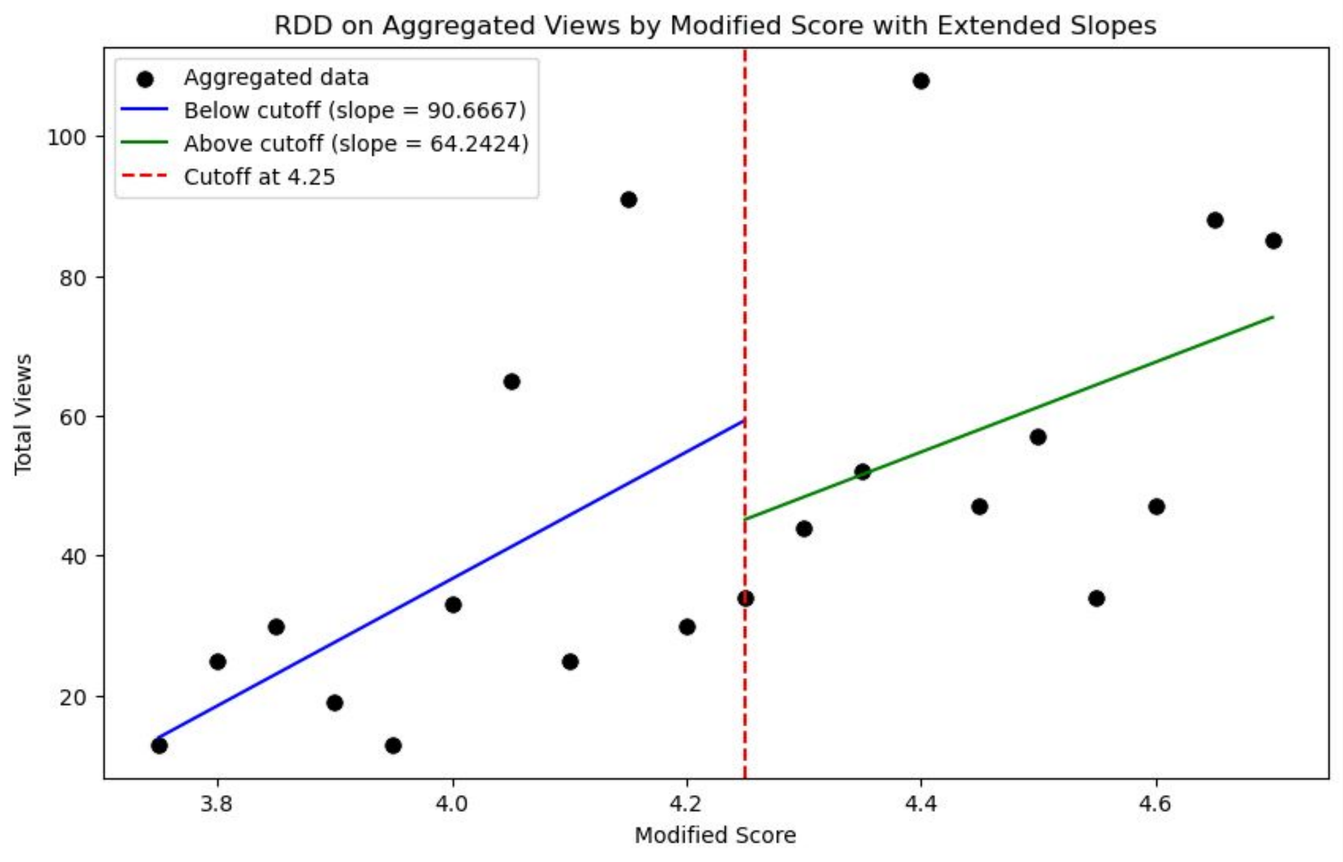
(To measure this and extend slopes further, we need to control for # of reviews)

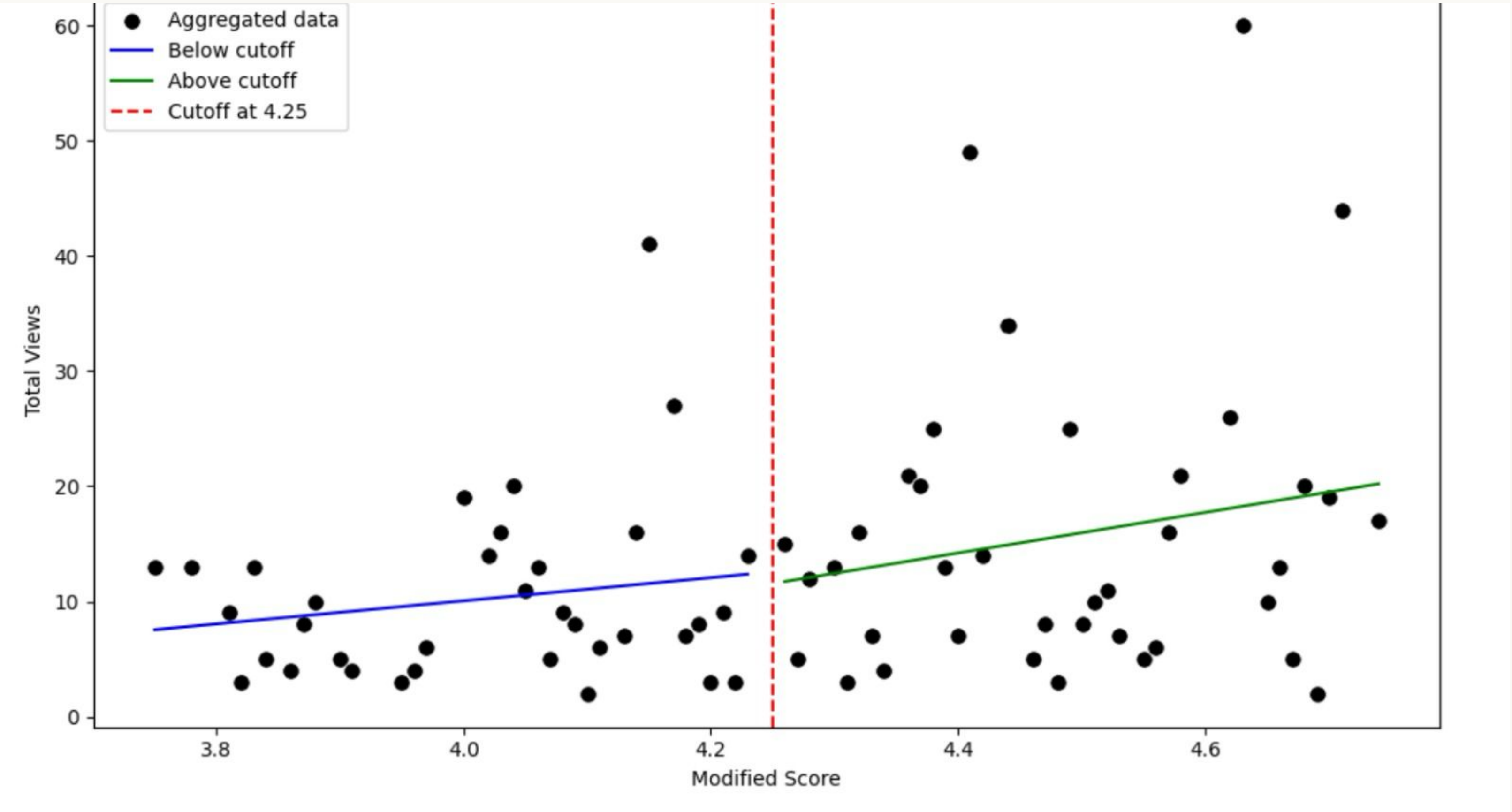
- # Of ratings significantly dropped after 4.75 cutoff

  → We see ***negative slope because of significant drop on the view***

Different impact on different range of rates.

No significant change in 4.25 cutoff: We see discontinuity and slight drop here, but unlike other ranges, discontinuity & before / after trend does not seem significant. We looked into further analysis to clarify





Below cutoff: 64.24
After cutoff: 90.66
Impact (Gap): −14.18

With higher granularity of data (reducing variance by using smaller aggregation bins)

Business Implications of analysis

Summary of observations:

	Rounding down 3.5 vs rounding up 4.0	Rounding down 4.0 vs rounding up 4.5	Rounding up 5.0
Treatment Effect	High and Positive	Small and Positive	High and Positive
Slope	Positive Slope	Similar Slope	Negative Slope

Recommendations for the business:

- For the goal of increasing viewership
  - Not to change the round-up currently presented
    - Maximizes results for the rating bellow 4.75
  - Generate campaign to incentivize ratings in highly reviewed hotels
  - Generate campaign to incentivize Hotels to get a rating higher than 3.75

Network effect of modifications

Network effect :

- Increase the hotels reviewed higher than 4
  - Increase the partial derivate with respect to revenue
  - Increase the partial derivate with respect to quality

Future Research Directions

1. **Control Variables**

   Consider the number of reviews to control the variables

2. **Conversion Analysis**

   Link rounded ratings to booking conversion outcomes

3. **Heterogeneity Studies**

   Analyze segments most sensitive to visual rounding by hotel class or review volume

While our current data do not include bookings or revenue, future work could link the rounded rating to conversion outcomes, enabling a full welfare analysis for both hotels and TripAdvisor. Additionally, heterogeneity analyses by hotel class or review volume could reveal segments most sensitive to visual rounding.

Strategic Implications

Platform Strategy

A significant impact would confirm TripAdvisor's coarse scale effectively influences user attention.

Hotel Behavior

Large gains at thresholds would incentivize hotels to focus on marginal rating improvements.

Policy Refinement

If round-down penalties are disproportionate, finer increments (e.g., 0.1-step ratings) could reduce distortions.

RDD with mean of views instead sum (same results)