The Impact of AI-generated Review Summaries: Evidence From Indian E-Commerce

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Overview

Introduction

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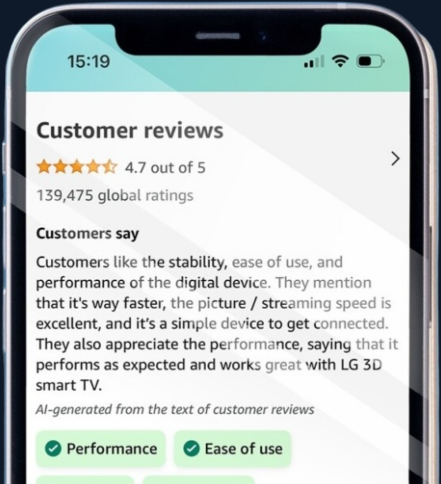
- Product reviews (rvu) influence consumer purchase decisions, hence economic outcomes.
- Consumers face behavioral constraints and search costs—volume of rvu.
- Rapid development of LLMs and AI prompts adoption to provide overviews and summaries.
- Promising effect in mitigating costs and constraints (literature and intuition), but effect not studied.
- Diff-in-Diff approach—identify the effect of AI-generated summaries of rvu on product-level price and sales.

AI-Generated Review Summary

- Source: Amazon.in



Related Work

AI Summarization and Purchasing Behavior

Wang and Wang (2025)

1. AI-generated rvu summaries on consumer purchasing behavior using a staggered diff-in-diff framework—Amazon.com
2. AI-overviews significantly increased product sales
3. Short pre-treatment testing data— parallel trends test
4. Within-platform products correlated platform-wide shocks (such as advertising campaigns), confound estimates.
5. Exogenous treatment assumption questionable

Product Reviews and Consumer Behavior

1. Luca (2016) + Chevalier and Mayzlin (2006): Positive rvu's predict ↑ sales(demand), customers react to written rvu's.
2. Sun (2012): Rvu variance affects sales through signaling niche appeal or distaste—LLM algorithms.
3. Jang et al. (2012): Rvu matters more in consideration than choice.
4. Nosko and Tadelis (2014): Reputation—information from quality.

Search Costs and Cognitive Constraints

1. Search
   1.1 Nelson(1970): Information is costly
   1.2 Seiler (2013): Limited search due to effort and time constraints
   1.3 Wildenbeest et. al (2017): Price EQ depends on distribution.
   1.4 Ariely and Lynch (2000): $\downarrow$ search costs $\implies$ competitive pricing.
2. Information Overload
   2.1 Sweller (1988): Cognitive Load Theory
   2.2 Hu and Krishen (2019): Threshold after which #rvu's $\downarrow$ satisfaction

AI Generated Review Summary

AI gen rvu summaries can $\downarrow$ search costs and overload $\implies$ influence economic/market outcomes

Empirical Strategy

Context

- Two biggest e-commerce platforms in India.

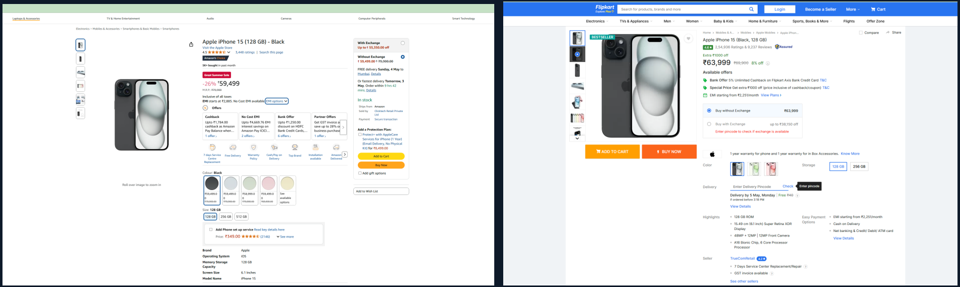
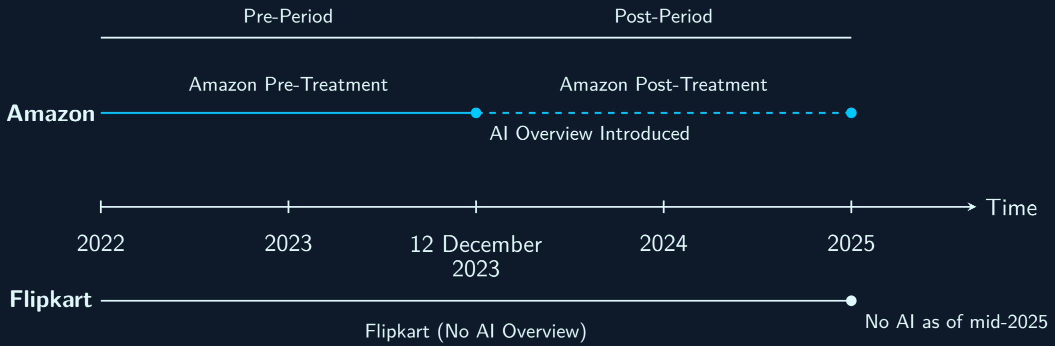


Figure 1: Same Product on Amazon and Flipkart

Context


Pre-Period
Post-Period
Amazon Pre-Treatment
Amazon Post-Treatment
Amazon
AI Overview Introduced
Time
2022
2023
12 December 2023
2024
2025
Flipkart
No AI as of mid-2025
Flipkart (No AI Overview)

Model Specification

- Three-way panel with product intersection i, platform j, time t.

$$y_{ijt} = \gamma \cdot (AI_{ijt}) + \beta Z'_{ijt} + \alpha_i + \delta_t + \theta_j + \epsilon_{ijt}$$

Model: Outcome variable y_{ijt}

$$\underbrace{y_{ijt}}_{\text{Outcome}} = \gamma \cdot \mathrm{AI}_{ijt} + \beta Z'_{ijt} + \alpha_i + \delta_t + \theta_j + \epsilon_{ijt}$$

Definition: y_{ijt} is the outcome variable for product i on platform j at time t.

- It captures either:
  - s_{jit}: Sales rank of the product
  - p_{jit}: Price of the product

Model: Treatment Variable AI_{ijt}

$$y_{ijt} = \gamma \cdot \underbrace{\text{AI}_{ijt}}_{\text{AI-overview}} + \beta Z'_{ijt} + \alpha_i + \delta_t + \theta_j + \epsilon_{ijt}$$

Definition: AI_{ijt} is a binary indicator equal to 1 if product i on platform j had the AI-overview at time t.

- Represents our core "treatment" in the DiD design.

Model: Controls Z_{ijt}

$$y_{ijt} = \gamma \cdot AI_{ijt} + \beta \underbrace{Z'_{ijt}}_{\text{Controls}} + \alpha_i + \delta_t + \theta_j + \epsilon_{ijt}$$

Definition: Z_{ijt} is a vector of observed time-varying covariates.

- Could include review counts, average rating, etc.

Model: Product Fixed Effect α_i

$$y_{ijt} = \gamma \cdot AI_{ijt} + \beta Z'_{ijt} + \underbrace{\alpha_i}_{\text{Product FE}} + \delta_t + \theta_j + \epsilon_{ijt}$$

Definition: α_i product-FE, controls for time-invariant characteristics of product i.

- Accounts for inherent popularity, brand identity, or product type.

Model: Time Fixed Effect δ_t

$$y_{ijt} = \gamma \cdot AI_{ijt} + \beta Z'_{ijt} + \alpha_i + \underbrace{\delta_t}_{\text{Time FE}} + \theta_j + \epsilon_{ijt}$$

Definition: δ_t time-FE, controls for common temporal shocks affecting all products.

- Examples: seasonality or promotional events.

Model: Platform Fixed Effect θ_j

$$y_{ijt} = \gamma \cdot AI_{ijt} + \beta Z'_{ijt} + \alpha_i + \delta_t + \underbrace{\theta_j}_{\text{Platform FE}} + \epsilon_{ijt}$$

Definition: θ_j platform-FE, captures platform-level differences.

- Controls for pricing structure, UI, or base-level engagement differences.

Model: Error Term ϵ_{ijt}

$$y_{ijt} = \gamma \cdot AI_{ijt} + \beta Z'_{ijt} + \alpha_i + \delta_t + \theta_j + \underbrace{\epsilon_{ijt}}_{\text{Error Term}}$$

Definition: ϵ_{ijt} idiosyncratic error term.

- Assumed mean-zero and uncorrelated with AI-adoption, conditional on controls and FEs.

Data

Data

- Data is gathered through web-scraping, current and archived, pages from Amazon.in and Flipkart.com
- No readily available pre-existing dataset
- To-fold data collection workflow:
  1. Product intersections are found (identifying products sold on both platforms)
  2. Historical price and rating count data is gathered through web archive pages.

Product Intersections

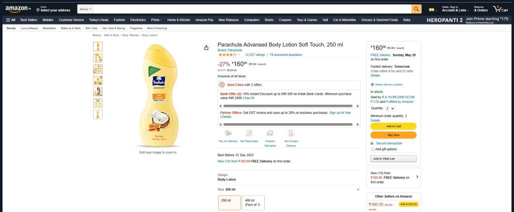
- 5 Umbrellas + (many) Categories: Electronics, Fashion, Home, Office, Toys
- Common categorical queries $\rightarrow$ save title + characteristics output (2 CSVs for each category)
  1. Amazon products: 65,890
  2. Flipkart Products:104,157
- Match based on category-specific score thresholds
  - Score = Brand + Attribute + title fuzzy matching
  - $\approx$ 17000 unique URLs $\approx 8,500$ product intersections

Historical Prices + Co-variates (Organically)

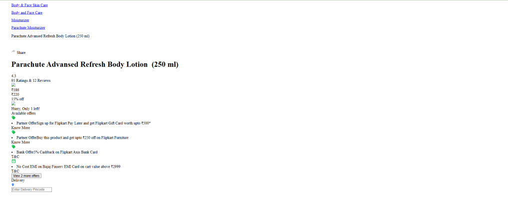
- Archive pages product description pages (PDP) store price and rating count.
  - Tools: Wayback Machine + Memento (fallback)
  - Time frame: **01/01/2022 to 01/01/2025**.
- Attempted granular day data—used first realization in each month.
- Data for **5000** intersections found- unbalanced and discontinuous.
- Panel data: **product (i)** × **platform (j)** × **month (t)**[1]

[1] Comprehensive code script available on request through GitHub

Historical Prices + Co-variates (Snapshots)



(a) Amazon



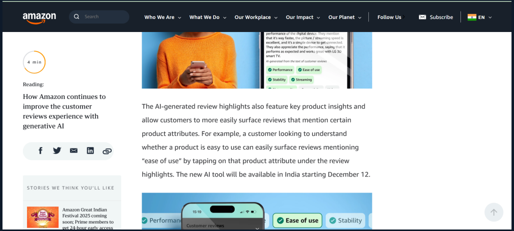
(b) Flipkart

Figure 2: Example of the same product's historical page scraped from platform j

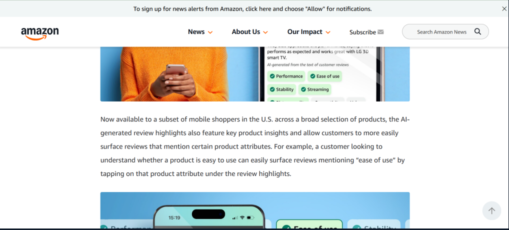
Treatment

- No staggered implementation assumption

Treatment



(a) Amazon India Rollout



(b) Amazon US Rollout

Figure 3: Justification for no stagger roll-out

Treatment

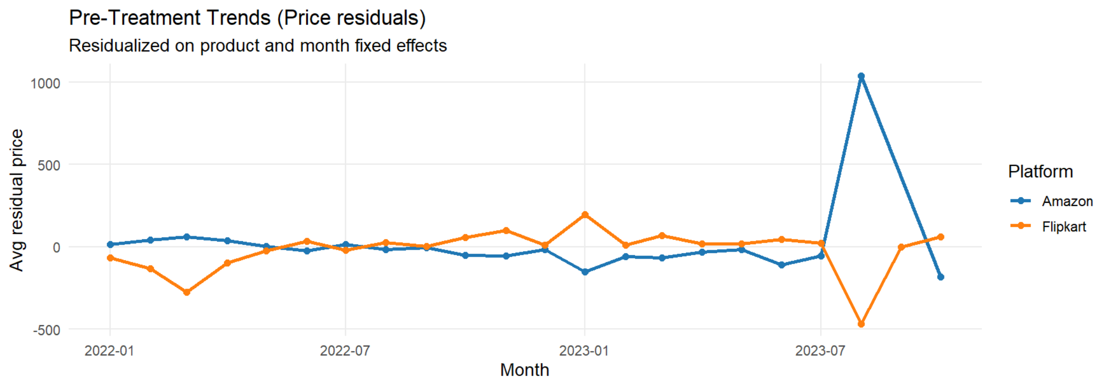
- No staggered implementation assumption[2]
- Add treatment to data

$$(post * treated) = AI = \begin{cases} 1 \text{ if Platform } (j) = \text{Amazon} \wedge \text{Date } (t) \geq 12/12/2023 \\ 0 \text{ otherwise} \end{cases}$$

[2] still working on using snapshots to nail down

Results

Pre-trend Analysis



Regression Analysis

Dependent Variable:	Price	
Model:	(1)	(2)
Variables		
AI	-61.12	-338.3
	(242.2)	(253.1)
ratings_count	-0.0017***	-0.0016***
	(0.0005)	(0.0005)
reviews_count	0.0067	0.0033
	(0.0079)	(0.0083)
Fixed-effects		
unique_product_id	Yes	Yes
platform	Yes	No
month	Yes	Yes
Fit statistics		
Observations	2,102	2,102
R^2	0.99847	0.99842
Within R^2	0.47648	0.46155

Clustered (unique_product_id) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Next Steps

What I have

- AI overview adoption doesn't significantly, **on average, in this sample**[3], explain price variation on Amazon and Flipkart.
- A comprehensive list of product intersections across multiple categories.
- Imminent within product across platform price variation.
- Fairly stable residuals for months with better data (more overlapping product pricing observed)

[3] subject to caveats discussed before

What I hope to have (realistically)

- Access to better data via API keys $\rightarrow$ fill in discontinuity
- Category specific regressions $\rightarrow$ inference about category heterogeneous response to overviews.

Thank You!