

A Comparative Analysis of Price Fluctuations in Woodland, Bata and Campus Footwear on Amazon India and Flipkart during the 2026 Festive Sale Period

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Abstract: *Online marketplaces make footwear prices easy to compare, but displayed prices can vary by model, variant, seller, availability, observation date, and promotional eligibility. This study examines available price evidence for selected Woodland, Bata, and Campus footwear listings on Amazon India and Flipkart during the 2026 festive-sale monitoring project. It adopts a quantitative, descriptive and observational design with a longitudinal orientation. The baseline frame includes 11 records, with 10 numeric prices ranging from ₹629 to ₹3,299; the mean is ₹1,339.40, and the median is ₹999. Two dated secondary tracker comparisons show lower later values: Campus Men First Running Shoes declined from ₹1,291 on 4 October 2026 to ₹999 on 11 October 2026, a difference of ₹292 or 22.62%; Woodland men's GC 6340024HS sneaker declined from ₹2,789 on 31 August 2026 to ₹2,138 on 15 October 2026, a difference of ₹651 or 23.34%. These are endpoint comparisons, not complete daily observations or direct checkout records. The available evidence does not establish an exact same-date, same-product-and-variant price pair across Amazon India and Flipkart, a complete daily sale-period panel, or a causal effect of the festive sale. The article emphasizes product matching, consistent price definitions, and transparent reporting of missing evidence.*

Keywords: Online price dispersion; price fluctuation; footwear; festive sale; Amazon India; Flipkart; product matching

1. Introduction

E-commerce marketplaces have changed how consumers discover, evaluate, and purchase products. Listings can display prices, seller information, ratings, delivery conditions, and promotional benefits together, reducing some search costs. Yet the price shown is not necessarily stable or universal: it may depend on model, size, color, seller, stock position, delivery location, and eligibility for bank-linked offers or coupons. A marketplace price should therefore be treated as a time-specific observation tied to an identifiable listing.

Research indicates that online markets can retain price dispersion even when search costs are relatively low (Brynjolfsson & Smith, 2000; Pan et al., 2004). Posted prices can also differ from transaction prices (Ghose & Yao, 2011). Festive campaigns provide a commercially relevant context for price observation, but platform announcements do not prove a particular shoe's price history (Amazon Staff, 2026; Flipkart, 2026). This article examines the available evidence for selected Woodland, Bata, and Campus footwear listings on Amazon India and Flipkart and distinguishes supported calculations from questions the records cannot resolve.

2. Literature Review and Conceptual Foundation

Search-cost theory treats information search as an activity requiring time and resources (Stigler, 1961). Electronic marketplaces can reduce the cost of discovering alternatives (Bakos, 1997), but consumers must still establish whether

listings represent the same product and comparable terms. Price dispersion is variation in prices for an item with the same measured characteristics across sellers or settings. Pan et al. (2004) identify measurement and product comparability as central issues, while Ba et al. (2012) consider retailer differentiation and service attributes as possible explanations for price variation. More recent work has examined the prevalence and determinants of within-retailer dispersion in e-commerce (Fedoseeva & Irek, 2023) and transaction-price dispersion on large online platforms (Wang & Li, 2020).

Dynamic pricing concerns adjustments over time in response to competitive or market conditions. Fisher et al. (2018) examine competition-based dynamic pricing, but a difference between two observed prices does not establish why it occurred. Seller replacement, stock movement, listing revisions, and conditional promotions may affect the displayed offer. Reference-price research likewise distinguishes an advertised comparison value from a verified historical selling price. Jensen et al. (2003) examine how advertised reference prices shape consumer perceptions and search intentions. Accordingly, an MRP or crossed-out value is not automatically a dated pre-sale price.

The study follows four principles: separate temporal fluctuation from cross-platform dispersion; match product and variant before comparison; distinguish unconditional prices from conditional offers; and report missing evidence rather than reconstructing it. These principles matter especially in footwear, where model, color, size, and intended use can materially distinguish listings.

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3. Objectives and Research Methodology

The objectives are:

- 1) To document selected footwear prices and availability evidence;
- 2) To calculate absolute and percentage changes where comparable dated observations exist;
- 3) To assess whether the data support matched Amazon India–Flipkart price gaps; and.

The study uses a quantitative, non-experimental, descriptive and observational design, incorporating limited dated price observations. The operational festive-sale window is 8–18 October 2026, ending at 11:59 p.m. IST on 18 October. This is the study-defined analytical cutoff, not a claim that both marketplaces had identical official campaign end dates. The broader project lasted approximately 45 days, but that duration does not establish a complete 45-day daily or hourly price panel.

Purposive sampling identified listings associated with Woodland, Bata, and Campus on both marketplaces. The preferred observation unit is a product–variant–platform–date record, with model, seller, displayed price, reference price, date/time, availability, URL, and offer terms recorded where available. The evidence includes baseline snapshots, dated secondary tracker observations, marketplace snapshots with incomplete temporal comparability, and provisional working values. Only source-supported observations are treated as empirical findings.

Absolute change is later price minus earlier price. Percentage change equals the absolute difference divided by the earlier price, multiplied by 100. A strict platform gap requires the same product and relevant variant on both platforms on the same date, using a consistent price definition. No such pair was verified in the reconciled workbook.

4. Results: Baseline Price Frame

The baseline frame contains 11 records, of which 10 have numeric prices. The numeric values range from ₹629 to ₹3,299; the mean is ₹1,339.40, and the median is ₹999.

Table 1: Descriptive Summary of the Baseline Price Frame

Measure	Result
Number of baseline records	11
Records with numeric prices	10
Mean of numeric prices	₹ 1,339.40
Median	₹ 999
Minimum	₹ 629
Maximum	₹ 3,299
Range	₹ 2,670

These statistics describe the selected heterogeneous listing frame, not market-wide prices. The mean exceeds the median because higher-priced observations raise the average. The brand-group means in the underlying report likewise describe only selected listings and do not control for product type or model mix.

Table 2: Brand-Group Descriptive Summaries for the Selected Baseline Listings

Brand group	Numeric records (n)	Mean listed price	Median listed price
Campus	5	₹931.80	₹999
Woodland	3	₹2,422.33	₹2,789
Bata	2	₹734.00	₹734

5. Dated Tracker Events and Calculations

Two secondary tracker comparisons permit reproducible endpoint calculations. The Campus Men First Running Shoes tracker records ₹1,291 on 4 October 2026 and ₹999 on 11 October 2026. The difference is ₹999 – ₹1,291 = –₹292; percentage change is $(-₹292 / ₹1,291) \times 100 = -22.62\%$.

The Woodland men's GC 6340024HS sneaker tracker records ₹2,789 on 31 August 2026 and ₹2,138 on 15 October 2026. The difference is ₹2,138 – ₹2,789 = –₹651; percentage change is $(-₹651 / ₹2,789) \times 100 = -23.34\%$. Because the earlier Woodland observation predates the 8–18 October study window, this comparison spans a wider period and cannot be described as a reduction occurring wholly within the festive-sale window.

These tracker values are secondary-source endpoints, not continuous daily records or verified transaction prices. Other snapshots lack sufficiently complete timestamps, seller continuity, or variant matching to support reliable timed-change calculations.

Table 3: Dated Secondary Tracker Price Comparisons

Product	Earlier record	Later record	Change	% change
Campus Men First Running Shoes	₹1,291 (4 Oct 2026)	₹999 (11 Oct 2026)	–₹292	–22.62%
Woodland men's GC 6340024HS sneaker	₹2,789 (31 Aug 2026)	₹2,138 (15 Oct 2026)	–₹651	–23.34%

These are secondary-source endpoints, not a continuous daily series or verified transaction prices. The Woodland baseline predates the defined sale window. Other snapshots lack enough timestamp, seller-continuity, or variant evidence for reliable timed-change calculations.

6. Cross-Platform Comparability, Availability and Offers

The available price observations do not provide a verified same-date comparison of an identical product and variant across Amazon India and Flipkart. Consequently, we cannot calculate a strict platform price gap from the retained observations. This limitation does not mean both platforms charge the same price; rather, we cannot reliably quantify

the difference without an exact product, variant, and date match.

Brand-level price comparisons require careful interpretation because footwear prices vary by model, intended use, size, color, and seller. For example, comparing a running shoe with a sandal may produce a price difference that reflects product characteristics rather than marketplace pricing. Therefore, interpret the observed brand-level averages as descriptive summaries of the selected listings, not definitive evidence of which brand or platform offers lower prices.

The stock availability register contains seven records: four explicit out-of-stock indicators, one record where checkout was not tested, and two records where availability could not be verified. These observations document the availability status recorded during the audit. However, they do not establish a representative stock-out rate or a complete sequence of stock depletion and subsequent restocking for the same seller and product variant.

The analysis also distinguishes displayed selling prices from conditional promotional benefits. Selected listings included bank offers of ₹120 and ₹100. Although subtracting these amounts illustrates the possible price reduction for eligible customers, the resulting figures do not independently confirm offer eligibility, successful application at checkout, or the final amount paid. Accordingly, the displayed selling price remains distinct from any conditional effective price. Similarly, treat a missing price as unavailable data rather than zero, and an inaccessible listing alone is insufficient to confirm a product is out of stock.

7. Discussion and Implications

The results distinguish a calculable price event from a broad claim about online pricing. Two tracker comparisons show lower later endpoint prices, but the evidence does not support a complete daily price path or establish that either marketplace was consistently cheaper. The baseline statistics describe a heterogeneous purposive frame; they do not measure within-product volatility. Measures such as standard deviation or coefficient of variation are meaningful for price fluctuation only when repeated observations refer to the same product and relevant variant.

The Campus tracker comparison uses two October dates, but two endpoints don't show whether the price fell steadily, changed temporarily, or coincided with seller or offer changes. The Woodland comparison includes an August baseline and must be interpreted as historical context, not a sale-window-only change. Neither comparison establishes that the festive campaign caused the reduction.

For consumers, the findings reinforce the need to verify model and variant, seller, availability and offer conditions, and to review dated price history rather than relying solely on advertised discount percentages. For researchers, the study shows the importance of exact URLs, timestamps, seller identity, and separating source-supported observations from illustrative values. Transparent reporting of these limits improves auditability and reduces unsupported conclusions.

7.1 Reading the Baseline Distribution

The baseline distribution provides a compact description of the selected listings, but it must be interpreted in relation to the sampling frame. The mean price of ₹1,339.40 is higher than the median of ₹999. This pattern is consistent with a right-skewed set of observations in which a small number of higher-priced listings raise the arithmetic mean. It does not, by itself, demonstrate that higher-priced footwear is more volatile or that a particular brand offers better value. The minimum–maximum spread of ₹2,670 is also expected to be sensitive to which footwear categories and price segments are included. Consequently, the range describes heterogeneity across the sampled records rather than temporal price movement.

For price-fluctuation research, distinguishing cross-sectional dispersion from time-series variation is essential. Cross-sectional dispersion asks how prices differ across listings at a particular observation point; temporal fluctuation asks how the price of the same identifiable product changes over time. The baseline frame combines listings that are not established as exact substitutes. Its mean, median, and range provide useful descriptive context, but they should not be interpreted as a brand-level price index, a platform comparison, or a measure of within-product volatility. A future balanced design would report a separate distribution for each exact model and variant and would then calculate temporal measures only for those products with repeated observations.

7.2 Brand-Level Snapshot Interpretation

The underlying baseline records contain five Campus prices, three Woodland prices, and two Bata prices. The corresponding descriptive means are ₹931.80 for Campus, ₹2,422.33 for Woodland, and ₹734.00 for Bata. These values are not a controlled comparison of brand price positioning. The number of records is small and unequal, and the underlying listings do not constitute a matched set of identical product types, intended uses, materials, sizes, or seller conditions. The brand means should therefore be read only as summaries of the listings included in this particular purposive frame.

The ordering of these sample means should not be converted into a conclusion that one brand is generally expensive or inexpensive. For example, comparing a sneaker with a basic slip-on shoe would include product-category differences alongside brand effects. A more defensible comparison would match products by type and intended use, report the size and colour variant, and present both the number of observations and the distribution for each group. If exact models cannot be matched across brands, any cross-brand comparison should be labeled exploratory and should not be presented as a causal or quality-adjusted price ranking.

7.3 Interpretation of Price Changes and Reference Prices

The two tracker events illustrate why arithmetic precision and evidential scope must be reported together. The Campus comparison has two dated observations within October: ₹1,291 on 4 October and ₹999 on 11 October. The later tracker value is ₹292 lower, equivalent to 22.62% of the

earlier value. The calculation is reproducible, but it describes only the difference between two endpoints. It cannot reveal the path between the dates, whether the displayed offer was continuously available, whether seller or variant details remained unchanged, or whether every consumer would have paid the amount at checkout.

The Woodland comparison has a different temporal boundary. Its earlier point, ₹2,789 on 31 August, falls before the operational 8–18 October festive-sale window, while the later point is ₹2,138 on 15 October. The absolute difference is –₹651 and the relative change is –23.34%. This is a longer historical endpoint comparison, not a measure of price movement exclusively during the sale. Combining the two percentages as if they were equivalent estimates of a single campaign effect would be inappropriate because the products, observation intervals, and temporal boundaries differ.

Advertised reference prices require separate treatment. A crossed-out price, maximum retail price, or stated discount can influence how consumers evaluate an offer, but it does not replace a dated historical price record. Research on reference prices highlights the role of comparison information in consumer perceptions (Jensen et al., 2003; Kopalle et al., 1996). For empirical measurement, the earlier price should come from an identifiable dated observation of the same listing or a clearly documented tracker history. A discount percentage calculated from a reference price should be labeled separately from a percentage change calculated from two observed selling-price endpoints.

7.4 Availability and Conditional Offers as Measurement Issues

Availability is not merely a descriptive footnote; it affects what can be observed and what consumers can purchase. In the audit register, four of seven records have an explicit out-of-stock indicator, one has checkout untested, and two have availability not verified. These categories should remain distinct. The four explicit indicators are counts among the retained audit entries and are not a platform-wide stock-out rate. We cannot reclassify the other three records as available or unavailable without further evidence. A listing can remain visible even when the selected size or color is unavailable, and availability can vary by delivery location.

The same principle applies to promotional benefits. A bank-linked offer, coupon, or payment-specific discount may reduce the effective price for an eligible buyer, but it does not necessarily apply to all users or all payment methods. The recorded examples of ₹120 and ₹100 bank offers can support conditional arithmetic scenarios only. Without verified terms and checkout evidence, they cannot be treated as universal price reductions or included in the unconditional listed-price series. The study therefore keeps the displayed-price analysis separate from conditional offer calculations. This separation improves comparability and avoids overstating the economic benefit available to a typical consumer.

7.5 Implications for Consumers, Sellers and Marketplace Researchers

For consumers, a lower displayed price is useful only when the listing matches the required model, size, and color, and when the item can be delivered under acceptable terms. A practical comparison should record the seller, delivery charge (where applicable), payment eligibility, return conditions, and the final checkout amount. Consumers should also distinguish a genuine dated price history from a promotional reference value. The available observations suggest that checking price history can reveal meaningful differences between two points in time, but they do not establish that every advertised discount is genuine or that one marketplace is consistently cheaper.

For sellers and marketplace managers, the study underscores the importance of clear product identifiers and offer presentation. Variant-specific stock information, transparent seller details, and clear eligibility rules reduce the risk that consumers compare unlike offers. A marketplace may host multiple sellers and offers for a product, meaning the price displayed at one moment may not represent a stable platform-level price. Research that ignores seller identity may inadvertently interpret seller substitution as a pricing change. Accordingly, seller continuity should be recorded whenever the research question concerns temporal repricing.

For researchers, the principal implication is methodological. A robust comparison requires a prespecified observation schedule, an explicit matching protocol and an auditable record of each capture. A source URL should be retained with each price, together with timestamp, platform, product code, size, color, seller, availability, listed price and promotion details. Data-quality checks should identify duplicates, missing timestamps, mismatched variants, and observations from secondary trackers only. These steps do not guarantee a complete dataset, but they make it possible to distinguish a valid comparison from an unsupported one.

7.6 Proposed Analytical Protocol for a Follow-Up Study

A follow-up study should define a fixed sample of exact footwear models before data collection begins. Each selected model should be searched on Amazon India and Flipkart using a documented product-matching rule. The study should record observations at the same scheduled times each day before, during, and after the campaign. Where the exact size or color is unavailable, the record should retain the unavailability status rather than substitute a different variant. Each capture should include a timestamp, screenshot or other auditable evidence, product URL, seller name, listed price, delivery charge, reference price, offer terms and stock status. Changes to a listing identifier or seller should be flagged rather than silently treated as continuity.

The primary analysis could then report absolute and percentage change for each product–variant–platform sequence. A platform difference should be calculated only for exact matched pairs observed on the same date and under the same price definition. Summary measures such as median change and interquartile range may be useful where multiple comparable products are observed, while standard

deviation and coefficient of variation should be applied only when the observations represent a meaningful common construct. If the objective is to estimate the causal effect of a festive campaign, the design would also need to account for general price changes, seller turnover, availability, product demand, and other time-varying influences. A simple before-and-after comparison is descriptive and cannot isolate the campaign effect.

7.7 Evidence Classification and Reproducibility

The study uses an evidence hierarchy to avoid treating all price-like values as equivalent. Dated direct marketplace captures with identifiable product and seller details provide the strongest basis for a listing-level observation. Dated secondary tracker values can support endpoint calculations when the tracker identifies the product and dates, but should be described as tracker-reported values. Marketplace snapshots without timestamps can document a displayed amount at an uncertain point but cannot establish temporal direction. Conditional offer amounts can support a separate scenario calculation only when the conditions are stated. Illustrative or manually constructed values are not empirical observations and should not enter the main results. Keeping these categories separate is essential for reproducibility and protects the findings from overstating the completeness of the source record.

8. Limitations, Recommendations and Conclusion

The principal limitation is incomplete observation coverage. Complete task-run logs and a fully populated daily record were not available for the whole monitoring period, so the project duration cannot be described as a complete 45-day price panel. Some records lack exact capture timestamps, seller details, URLs, or variant attributes. Historical trackers are secondary sources and do not necessarily represent direct marketplace or checkout prices. No exact same-date Amazon India–Flipkart product–variant pair was verified. The purposive sample is small and cannot represent all footwear listings or the wider Indian market.

Future monitoring should use one row per product–variant–platform–seller–timestamp. Researchers should preserve the exact URL, size and colour, seller, unconditional price, reference price, offer terms, availability status and evidence capture. Observe both platforms within a consistent time window. Missing observations should remain missing and should not be interpolated or reconstructed. Illustrative series should be stored separately from source-verified observations. A follow-up study should select a balanced set of exact models and collect repeated observations before, during, and after the sale. A complete matched panel could support within-product changes and cross-platform gaps; causal claims would require a design that addresses alternative explanations such as seller changes, general repricing and product-specific demand.

In conclusion, the available evidence supports two endpoint reductions reported by secondary trackers: 22.62% for Campus Men First Running Shoes between 4 and 11 October 2026, and 23.34% for the Woodland sneaker

between 31 August and 15 October 2026. These calculations do not prove continuous sale-period volatility or a causal festive-sale effect. The baseline statistics describe only the selected listing sample. We cannot identify a definitive platform winner because strict matched observations are absent. The study's main contribution is a transparent, evidence-limited account that identifies what the data establish and what additional observations are required.

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