How Do Bounce Rates Vary According to Product Sold ?

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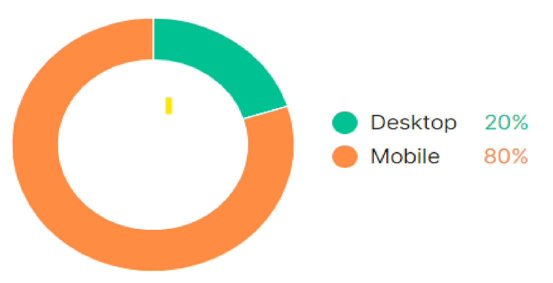
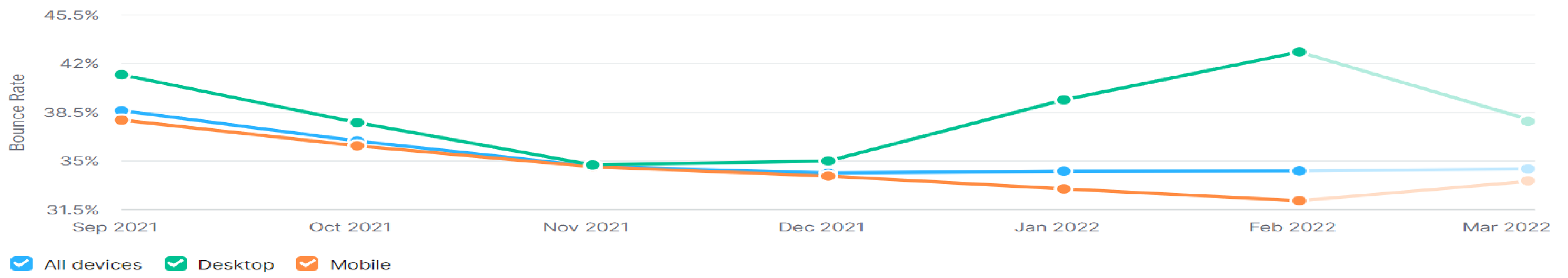
Introduction

There has been an increase in the Mobile traffic share compared to Desktop traffic share. In addition, general trends show that the Mobile bounce rate is increasing. However, some discrepancies show the opposite direction in some e-commerce websites (see example below):





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We believe that the Mobile bounce rate is highly affected by the type of products sold by the e-commerce websites compared to Desktop, and as a result, it affects the relationship between bounce rate and traffic share. Shown below is a Hypothesis:

Ha: In case of Mobile, types of Products sell by the E-commerce websites affects the relationship between Bounce Rate and Traffic Share.

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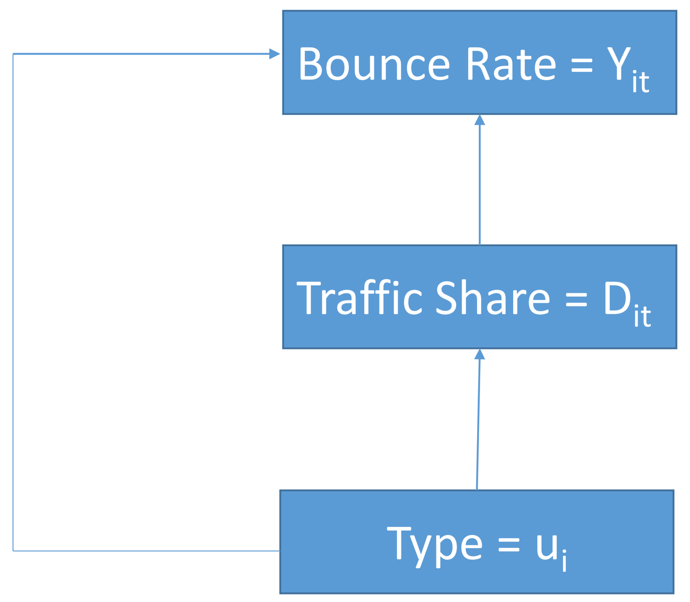
Conceptual Layout

This is a conceptual layout which is in alignment with our hypothesis, the time-invariant variable directly affects the bounce rate and indirectly affects through time-variant variable, i.e. traffic share. The time-invariant variable here is either category of the products or individual websites themselves



Methodology

Based on various e-commerce websites' product types, we created 30 categories with their respective abbreviation. Analyzing their effect on the bounce rate was easier afterward.

Panel Data is longitudinal data where specific variables vary according to time, and some are time-invariant. We created a balanced panel data that shows the variation of time-variant Mobile/Desktop share and Mobile/Desktop bounce rate over four years for each category created

Ticker	Category
AAR	Autoparts and Automobile Retailer
ACFR	Arts, Crafts and Fabric Retailers
BPR	Baby Products Retailers
BSR	Bags and Suitcases Retailer
CSJWAR	Clothing, Shoes, Jewelery, Watch and Accessories Retailer
CVPR	Cigarette & Vape Prodcuts Retailer
ESCR	Eyeglasses, Sunglasses and Contacts Retailer
ETR	Electronics and Technology Retailer
FBGR	Foods,Beverages and Groceries Retailer
FSPSR	Fitness & Sports Products and Services Retailer
G	General

Ticker	Year	average_mobile_share	average_mobile_bounce	average_desktop_share	average__desktop_bounce
AAR	2017	0.00	0.00	1.00	0.44
AAR	2018	0.79	0.47	0.21	0.37
AAR	2019	0.80	0.52	0.20	0.28
AAR	2020	0.76	0.53	0.24	0.39
ACFR	2017	0.00	0.00	1.00	0.43
ACFR	2018	0.64	0.48	0.36	0.35
ACFR	2019	0.67	0.52	0.33	0.22
ACFR	2020	0.72	0.53	0.28	0.36

In a panel data set, the Fixed Effects regression model is used to estimate the effect of intrinsic features of individuals. Genetics, intelligence, and cultural variables are examples of inherent qualities. Although such characteristics are not observable or measurable, they must be estimated because leaving them out leads to a poorly trained regression model

$$Y_{it} = \delta D_{it} + u_i + \varepsilon_{it}; \quad t = 1, 2, \ldots, T$$

$$\overline{D}_i \equiv \frac{1}{T}\sum_{t=1}^{T} D_{it}; \overline{Y}_i \equiv \frac{1}{T}\sum_{t=1}^{T} Y_{it}$$

$$Y_{it} = \delta D_{it} + u_i + \varepsilon_{it}$$
$$\overline{Y}_i = \delta \overline{D}_i + u_i + \overline{\varepsilon}_i$$
$$(Y_{it} - \overline{Y}_i) = (\delta D_{it} - \delta \overline{D}) + (u_i - u_i) + (\varepsilon_{it} - \overline{\varepsilon}_i)$$

with time-demeaned variables $\ddot{D}_{it} \equiv D_{it} - \overline{D}, \ddot{Y}_{it} \equiv Y_{it} - \overline{Y}_i$.

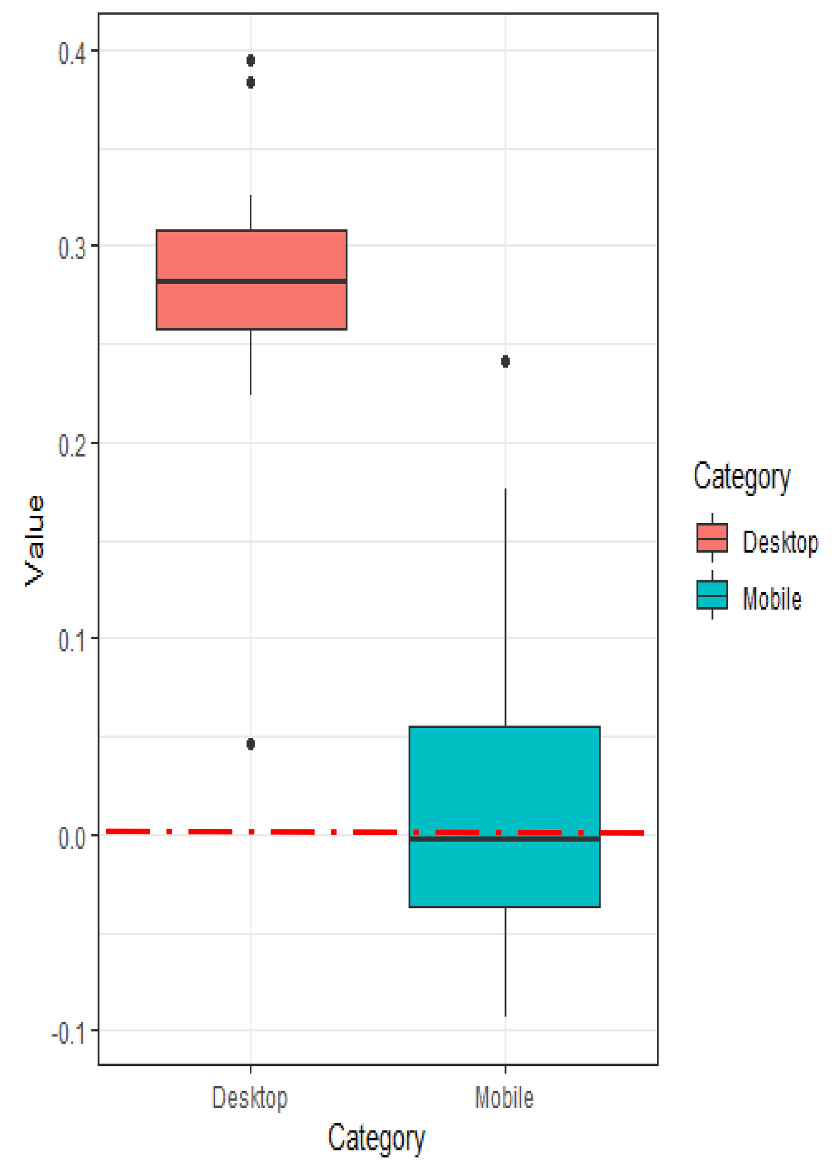
$$\ddot{Y}_{it} = \delta \ddot{D}_{it} + \ddot{\varepsilon}_{it}$$

Mathematical Representation of Fixed effect Model

Result

In case of Mobile, for many categories '-ve' coefficients are obtained indicating greater effect of categories on the Bounce Rate.

In case of desktop, all the categories have same positive signs and approximately same values indicating not much affect of categories on Bounce Rate.



Different Models creates And their Comparison

Models	R-Square value	Conclusion
Category specific Fixed Effect Model For Mobile	0.94	The model is good fit & explained 94% variation in the data
Category specific Fixed Effect Model For Desktop	0.512	The model is not good fit & explained 51.2% variation in the data
Website specific Fixed Effect Model For Mobile	0.825	The model is good fit & explained 82% variation in the data
Website specific Fixed Effect Model For Desktop	0.24	The model is good fit & explained 24% variation in the data

Conclusion

The overall trend confirms that as mobile traffic increases, bounce rate increases but this increase depends on categories of e-commerce websites. The effect of type of e-commerce websites is more in Mobile as compared to Desktop.

Implications for Managers

Bounce Rate through Mobile is low when :

- e-commerce retailers which sells variety of range of products (like general category).
- e-commerce retailers which sells relatively smaller products or those products which require minimum research while buying have lower bounce rate though Mobile

Future Research

- Effect of brand value of different e-commerce websites on the bounce rate.
- How bounce rate varies for tablet based on the type of websites and products sold by these e-commerce websites

References

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- - "FinTech User Behavior Trends: Mobile vs. Desktop." *Semrush Blog*, www.semrush.com, https://www.semrush.com/blog/fintech-user-behavior-trends-mobile-desktop/. Accessed 11 Apr. 2022.