The Economics of Free Cash: Understanding Consumer Behavior in Digital Incentive Strategies

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Sincerely,
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Abstract

This study investigates the behavioral effects of free credit incentives on consumer spending within India's rapidly growing instant delivery app ecosystem. Drawing on insights from behavioral economics particularly present bias, habit formation, and loss aversion this study examines whether such incentives have a sustained impact on user engagement or produce only short-lived responses. The analysis is based on primary survey data collected from 100 users of platforms like Zepto. Employing a Difference-in-Differences (DiD) estimation strategy, the study compares spending behavior before and after the withdrawal of free cash offers across treatment and control groups. The results indicate that while these incentives may temporarily increase spending, their removal does not significantly reduce engagement, suggesting a limited long-term effect. The findings contribute to a deeper understanding of digital consumption patterns and the bounded effectiveness of promotional nudges in competitive online marketplaces.

Keywords: Free Credit Cash, Digital Consumption, Instant Delivery App, Present Bias, Habit Formation, Difference-in-Differences

1 Introduction

Incentive driven consumption has become a defining feature of the digital economy, particularly in the context of app-based delivery services. Companies like Zepto routinely offer users free credit cash to shape consumption patterns and retain engagement. These practices have gained traction in a market where users face low switching costs and display high consumer sensitivity to small benefits. The instant delivery platlorms , especially for groceries and essentials, is witnessing intense competition, with platforms vying for user attention through behavioral triggers and interface nudges. While classical economic theory assumes stable preferences and rational behavior, digital platforms increasingly exploit deviations from this ideal leveraging behavioral tendencies such as time-inconsistent preferences, impulse responsiveness, and habitual usage.

Despite the widespread use of incentives in digital markets, there remains limited empirical evidence on their long-term behavioral impact, especially in the Indian context. Do users become loyal customers or is the observed engagement just a reaction to temporary offers? Understanding this distinction has significant implications for platform strategy, user retention, and marketing cost efficiency.

The central aim of this study is to examine how consumers respond to free credit incentives in the context of instant delivery platforms. In particular, it investigates whether such incentives have a lasting effect on engagement or if their impact diminishes once the offers are withdrawn. By linking behavioral theory to empirical evidence, the study adds to a growing body of literature that questions the long-term efficacy of digital nudges. Using a Difference-in-Differences (DiD) framework based on survey data from 100 app users, this research identifies and evaluates the causal impact of free cash offers on consumer spending behavior before and after their withdrawal. In doing so, it offers insights relevant to both platform strategy and consumer policy in rapidly digitizing markets.

2 Literature Review

Digital platforms like Zepto increasingly influence how consumers make decisions by offering upfront free credits, flash deals, and loyalty-based incentives. While classical economic theory assumes that individuals are fully rational and make consistent choices based on stable preferences, actual behavior often deviates from these assumptions. Consumers frequently make decisions under limited attention and imperfect information, relying on mental shortcuts and intuitive judgments. These platforms capitalize on such tendencies by offering instant rewards, framing deals in psychologically appealing ways and nudging users toward more frequent engagement. Behaviors like impulse purchases or repeated app usage in response to small incentives suggest that users are not merely reacting to price changes but to deeper psychological cues. Understanding these patterns requires looking beyond traditional models to account for present bias, habit formation, and the influence of perceived gains and losses.

Free credit offers have become a key marketing tool for delivery apps, often triggering strong behavioral responses. Even small amounts can encourage unplanned purchases or increase order frequency, particularly when framed as exclusive or limited-time benefits. In situations where users make fast, repeated decisions like food delivery these incentives act as effective attention grabbing mechanisms. Research shows that such promotions often yield results far beyond their actual monetary value because users perceive them as gains, anchoring expectations around temporary bonuses rather than base prices (Liu, 2007). One reason for the success of these incentives lies in how consumers evaluate time. Most people tend to prefer immediate rewards even at the cost of long-term benefits , a tendency described as present bias. Loewenstein and Prelec (1992) found that people discount future outcomes more steeply the closer they are to the present, a process known as hyperbolic discounting. Limited-time free credit offers tend to be effective because the appeal of immediate savings can overshadow longer-term spending considerations. Beyond immediate responses, repeated free cash offers can encourage habit formation. Offering such incentives consistently may turn occasional users into regular ones.This is consistent with habit formation models such as Becker and Murphy's (1988) rational addiction theory and Bernheim and Rangel's (2004) model of cue-triggered decisions. In app-based environments, cues like notifications or daily deals can reignite usage even when users have no strong internal motivation, reinforcing habitual behavior over time.

The impact of these incentives depends not only on their value, but also on how they are structured and presented. A study by Heidhues and Kőszegi (2018) shows how firms carefully craft incentives based on consumers predictable biases and tendencies such as reference dependence or inattention. Rather than reducing prices permanently, apps offer rotating, temporary bonuses that feel exciting and urgent. By repeating these promotions, platforms train users to anticipate rewards, which in turn deepens engagement and loyalty. Once users begin to expect incentives, removing them can backfire. According to Prospect Theory, developed by Kahneman and Tversky (1979) , people are more sensitive to losses than to gains of equivalent size. When a platform stops offering these incentives or reduces its value, users perceive it as a loss even if they are still receiving value. This can lead to lower engagement or even app switching. As a result, platforms manage user expectations carefully, often replacing one offer with another rather than removing rewards entirely. In some cases, users consciously use free cash as a budgeting tool or to guide their own consumption. Gul and Pesendorfer (2001) describes how individuals sometimes impose external rules or rely on environmental cues to manage internal self-control challenges. For example, a consumer might decide to only order food when they get free cash, thus aligning spending with perceived value. This shows that incentives may not only drive impulse but also serve as tools for planned behavior.

Real-world examples support these findings.Hall, Horton, and Knoepfle (2015) studied Uber's incentive programs and found that even modest financial nudges significantly altered behavior. In the Indian context platforms like Zepto routinely use personalized offers, push notifications and flash sales to trigger engagement. While systematic academic studies on these platforms are still emerging, both industry data and user behavior point toward a strong influence of strategic incentives on digital consumption. The literature shows that free cash incentives are more than simple price adjustments — they are powerful behavioral tools that shape consumer decisions in both the short and long term. These rewards tap into well-documented patterns like present bias, habit formation, and loss aversion, influencing how users interact with platforms and how often they return. By offering targeted, timely, and psychologically appealing incentives, apps are able to guide user behavior in ways that standard economic theory cannot fully explain. These theoretical insights provide the foundation for examining how consumers perceive and respond to such incentives in practice.

3 Data Sources

The study is based on primary data collected through a structured online survey administered to users of instant delivery applications such as Swiggy Instamart, Zepto, Blinkit, and Dunzo. The survey was designed to assess consumer behavior before and after the introduction or withdrawal of free cash incentives, including cashback offers, referral bonuses, and instant discounts.

A total of 95 respondents participated in the survey. The questionnaire included both multiple-choice and Likert-scale questions focused on the following aspects:

- Frequency of app usage
- Spending behavior on the platform

- Awareness and receipt of free cash offers
- Changes in engagement following the withdrawal of offers
- Demographic information such as age, gender, and income group

Responses were collected anonymously and compiled into a structured dataset for analysis. The data were cleaned to remove missing values and inconsistencies before proceeding to the econometric analysis.

4 Methodology

To identify the causal effect of free cash incentives on consumer behavior, we employ a *Difference-in-Differences* (DiD) estimation strategy. This quasi-experimental design compares changes in consumer behavior over time between two groups: those exposed to free cash incentives (treatment group) and those not exposed (control group).

4.1 Variable Construction

The key variables used in the analysis are defined as follows:

- **Treatment Group (*treat*)**: A binary variable equal to 1 if the respondent received free cash incentives, and 0 otherwise.
- **Post-Treatment Period (*post*)**: A binary variable equal to 1 if the respondent reported behavioral changes after the withdrawal of offers, and 0 otherwise.
- **Interaction Term (*did*)**: The product of $treat \times post$, representing the DiD estimator.
- **Outcome Variable (*outcome*)**: A binary variable equal to 1 if the respondent reported spending more on the app due to free cash offers, and 0 otherwise.

4.2 Model Specification

We estimate the following linear regression model, known as the Linear Probability Model (LPM), which is appropriate for binary dependent variables when coefficients are to be interpreted as marginal effects:

$$outcome_i = \beta_0 + \beta_1 \cdot treat_i + \beta_2 \cdot post_i + \beta_3 \cdot (treat_i \times post_i) + \varepsilon_i \tag{1}$$

- β_0 represents the baseline probability of increased spending for the control group before the intervention.
- β_1 measures the difference in baseline spending behavior between treated and untreated respondents before the treatment change.
- β_2 captures any general shift in reported spending behavior after the reduction in offers, applicable to both groups.

- β_3 is the Difference-in-Differences estimator and reflects the causal effect of offer withdrawal on the probability of increased spending due to incentives.

Although the outcome variable is binary, we use the LPM for simplicity and ease of interpretation. To ensure robustness, results were cross-validated using logistic regression (logit) specifications.

4.3 Estimation and Software

The analysis was conducted using `R Studio`, utilizing packages such as `dplyr` for data wrangling, `readxl` for Excel file import, and `broom` for tidying model outputs. Observations with missing values for key variables were excluded to ensure consistent sample sizes across model estimations.

5 Results

Table 1 presents the output of the Difference-in-Differences regression estimating the impact of free cash incentives on consumer spending behavior on instant delivery apps.

Table 1: Difference-in-Differences Regression Results

Variable	**Estimate**	**Std. Error**	**t value**	**p-value**
Intercept	0.143	0.173	0.827	0.411
Treatment (*treat*)	0.357	0.189	1.890	0.062
Post-treatment (*post*)	0.312	0.221	1.410	0.162
Interaction (*did*)	**-0.0068**	0.244	-0.028	0.978

Notes: The dependent variable is a binary indicator equal to 1 if the respondent reported spending more due to free cash incentives. The key coefficient of interest is the interaction term (*did*), which captures the treatment effect. The standard errors are heteroskedasticity-robust. The model explains 16.6% of the variation in the outcome ($R^2 = 0.1656$).
F-statistic = 6.022 on 3 and 91 DF, p-value = 0.0009

The coefficient on the interaction term (*did*), which captures the causal effect of free cash offers on consumer behavior, is statistically insignificant ($p = 0.978$), indicating that the withdrawal of free cash offers had no significant average treatment effect on reported consumer spending behavior.

However, the treatment group (*treat*) shows a positive and marginally significant effect ($p = 0.062$), suggesting that consumers who received free cash incentives were somewhat more likely to report increased spending. This aligns with behavioral expectations but fails to hold after the withdrawal of incentives.

Interpretation: While there is evidence that free cash incentives initially influenced user engagement, their removal did not lead to a significant drop in spending, suggesting that long-term retention may not rely solely on such offers.

6 Conclusion

This study set out to assess the behavioral impact of free credit incentives on consumer spending patterns in the context of instant delivery platforms. Drawing on insights from behavioral economics and supported by primary survey data, the analysis applied a Difference-in-Differences approach to isolate the effect of such incentives on user behavior. While the results suggest that free cash offers may initially prompt increased engagement and spending, this effect appears short-lived: the withdrawal of these offers did not produce a statistically significant decline in reported consumption.

These findings align with theoretical models that emphasize short-term responsiveness to rewards but caution against overestimating their lasting influence. Users may adapt to incentives quickly, internalize new consumption baselines or shift focus once the stimulus is removed. As platforms continue to rely on promotional tools to shape demand, understanding the limitations of such strategies becomes increasingly important. Future research could explore heterogeneity across user demographics, alternative incentive designs or compare the effects of recurring versus one time offers. For now, this study highlights that while behavioral nudges can trigger action, sustaining behavior requires more than intermittent incentives.

7 References

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A Appendix A: Regression Output

	(1)
(Intercept)	0.143
	(0.173)
	(0.411)
treat	0.357+
	(0.189)
	(0.062)
post	0.312
	(0.221)
	(0.162)
did	-0.007
	(0.244)
	(0.978)
Num.Obs.	95
R2	0.166
R2 Adj.	0.138
AIC	126.8
BIC	139.6
Log.Lik.	-58.409
F	6.022
RMSE	0.45

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Figure 1: Difference-in-Differences Regression Output