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Monetizing Serialized Content: How “Wait for Free” Impacts Paid and Free Consumption

Referee Report

This paper examines a relatively novel monetization strategy, "wait for free" (WFF), within a serialized content consumption environment. Utilizing data from a serial fiction platform, the authors investigate whether reducing wait time for a set of series can increase platform revenue. They first develop a conceptual framework that highlights two unique aspects of serialized media consumption: the complementarity between episodes and the time decay of this complementarity value. Based on this framework, the authors explore how the length of waiting time affects both free and paid consumption. Subsequently, using a panel-matching plus stacked Difference-in-Differences (DiD) method, the authors empirically demonstrate that reducing wait time leads to an increase in paid consumption and market expansion.

The adoption of WFF monetization strategies for serialized content platforms is increasingly prevalent in the industry, making this research timely and valuable. The authors link a theoretical model with empirical testing to provide an in-depth analysis of how waiting time impacts platform revenue. I appreciate these aspects of the paper. However, there are concerns regarding the contribution, identification, and model estimation, which I will discuss in detail below to help the authors improve the manuscript further.

Major Comments

1. Contribution/Generalizability

1.1 The abstract and the introduction seem to suggest that the paper provides a definite answer to the research question of whether allowing quicker free consumption increase revenues, positing that a reduction in wait time positively impact both existing and new customers. However, the empirical findings are based on a single intervention on one platform, raising concerns about generalizability. For example, if the wait time were reduced from one hour to one minute, users might be less inclined to pay, leading to a revenue decrease. To clarify the main message, the paper could be strengthened by discussing boundary conditions, highlighting ambiguous theoretical predictions, and clearly discussing countervailing forces in both the theoretical and empirical parts to provide a more comprehensive answer to the posed research question.

1.2 As noted in Choi et al. (2022), the WFF strategy encompasses various aspects a company could optimize, such as the selection of WFF series, the number of initial free episodes, the number of pay-to-access-only episodes at the end, and the length of wait time. The current paper focuses solely on one aspect from the above list -- the length of wait time. It would be beneficial for the authors to discuss this aspect in comparison with other aspects of the WFF strategy. The authors could potentially leverage the richness of the data to explore interaction effects to provide a comprehensive understanding of the various dimensions of the WFF strategy for platforms considering its adoption.

1.3 While the conceptual framework introduces new insights, where countervailing forces lead to ambiguous predictions, the empirical findings, limited to showing effects from one intervention, do not seem to provide much additional insights for other platforms. This may leave readers wondering about the added value of the empirical findings. Additionally, since the complementarity between episodes and the time decay of this complementarity (the two unique features of serialized consumption emphasized by the authors) are not empirically estimated, there appears to be a disconnect between the conceptual framework and the empirical findings. The authors could benefit from making a stronger connection between the two. One way to achieve this is by using a structural model to embed the conceptual framework into the data, followed by conducting counterfactual analyses to determine the optimal wait time strategy or conduct simulations to provide some practical guidance for the platform, similar as in Choi et al. (2022).

2. Identification

2.1 SUTVA Assumption: The authors argue that with over 10,000 series on the platform and the treated group accounting for a tiny proportion, it is unlikely that spillover effects exist. However, as documented in Choi et al. (2022), spillover effects can occur even with a small proportion of treated series due users' concentrated consideration set, potentially leading to biased estimates. Could the authors comment on and address this issue?

2.2 Exclusion of Premium Series in the Sample: The authors focus only on WFF series in the analysis, arguing that WFF accounts for more than 85% of episode consumption, as shown in Figure 1. However, considering the platform's revenue, the proportion from premium series might be significant, and users who purchase premium series could be more valuable from the platform's perspective. How does the reduction of wait time for some WFF series affect the consumption of premium series? Any potential spillover effects to premium series?

2.3 Unobservables: Given that the reduction in wait time appears to be a major intervention by the platform, did the platform undergo other interventions around the same time? For example, did the platform change the ranking or display format to give more attention to the selected series? Addressing whether there were concurrent interventions could help clarify potential biases in the findings.

2.4 Potential Missing Variables for Matching: As shown in Choi et al. (2022), there is substantial heterogeneity in the effectiveness of WFF across genres. Could the authors include genre as part of the matching criteria? Similarly, popularity or the number of past views seems to be another reasonable variable to include in the matching criteria.

2.5 User-Level Self-Selection: Regarding the analysis on the pace of series consumption, since the analysis unit is at the episode-user level, should we be concerned about self-selection by users into specific series or episodes? Lu et al. (2019) demonstrate that a user's previous consumption pattern could influence their future consumption pattern. If there is a systematic difference between users selecting into treated versus non-treated series, the estimated results could be driven by the selection bias.

3. Model Specification

3.1 Initial Free Episodes: Figure 2 suggests that several initial episodes may be offered for free for WFF series. However, it does not seem that the number of initial free episodes is controlled for in the empirical analysis. Furthermore, how would the number of initial free episodes affect the complementary value in the theoretical framework?

3.2 Pricing Information: Are the prices the same for different episodes within a series? Are the prices the same across different series? Did prices change as a result of the intervention? Currently, detailed information about prices or coins needed for paid episodes seems to be missing.

3.3 Handling Unconsumed Follow-up Episodes: How are follow-up (the very next) episodes that have never been consumed handled in the pace of series consumption analysis? Treating them as missing could bias the results.

Minor comments

4. According to Godinho de Matos et al. (2023), similar strategies like WFF could be effective because additional search moments trigger more content use. Could this be part of the reason for the estimated effect? If so, how could this be incorporated into the conceptual framework?

5. It is unclear why the pattern in Table 2 supports the notion of direct complementarity that diminishes over time. This notion should relate to the time gap between episode consumptions, which is not evident in the summary statistics. Could the authors clarify this?

6. What is the exact calculation of the *magnitude* variable? Specifying this would be useful, as the results in online Appendix A2 show opposite signs.

7. Could the authors translate the findings into revenue terms for the platform or use the number of coins to give a more intuitive sense of the scale of the impact?