“Just One More Clip”: Short Videos, Big Self-Control Problems[*]

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Abstract

I develop a structural model of temptation to examine how short-form social media content triggers repeated present bias and exacerbates self-control problems. Using microdata from a U.S. short drama series, I find viewers consume 23 episodes (82%) more than they initially intend and spend $5.51 (23%) more than necessary. The minute-long format magnifies welfare losses from temptation, whereas mandatory breaks could mitigate these losses by interrupting immediate impulses. Extending the analysis to TikTok, I show short videos triple efficiency losses compared with longer content, reducing U.S. consumer surplus by $10.2 billion per month. These findings highlight the potential for policy interventions.

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1 Introduction

Many of us are familiar with the regret that follows giving in to temptation. We promise to stop after just one more snack, episode, beer, or game, only to find hours slipping away. Despite recognizing the harm, resisting proves difficult. This phenomenon, known as the *self-control problem*, arises from present bias and has been identified in many contexts (e.g., DellaVigna and Malmendier, 2006). Sadly, social media platforms such as TikTok, YouTube and Instagram exploit this vulnerability by delivering endless streams of short, engaging content that intensifies users' temptation to consume more than intended. The American Psychiatric Association classifies this issue as "internet use disorder," linking it to negative effects on mental health and well-being.[1]

The welfare loss resulting from self-control problems in short-form content consumption could be enormous. For example, in the U.S. market alone, over 170 million people use TikTok for an average of 58.4 minutes per day in 2023.[2] When calibrated using the average hourly earnings, the annual usage time is equivalent to 7.8% of U.S. GDP.[3] Given this scale, quantifying how much time is wasted on social media, the magnitude of efficiency loss, and how much of this inefficiency is driven by short-form content design is crucial. More importantly, understanding the magnitude of this mechanism is essential for effective policy design. Current policy discussions range from time-limit tools to outright social media bans, requiring systematic evaluation that accounts for inefficiencies caused by self-control problems.[4] My paper contributes by constructively analyzing self-control problems through a structural approach, providing insights into both the magnitude of welfare loss and potential policy solutions.

I begin by analyzing a stylized model of temptation in the context of short video platforms, demonstrating how self-control problems emerge and how short-form content exacerbates them. Users derive intrinsic utility from each clip of short videos but also experience a short-term, irrational temptation toward these clips for a limited period, the duration of which varies. The central assumption is that preferences exhibit present bias, as temptation continually shifts toward upcoming clips while users keep watching.[5] As a result, self-control problems arise among users with naïve perception, low intrinsic valuations, and prolonged temptation, leading them to consume more content than they would have preferred ex ante. Short-form formats intensify present bias by shrinking each decision window below the duration of temptation, thereby worsening

[1] The APA defines "internet use disorders" as a pattern of behavior characterized by an inability to control use, difficulties with personal and professional responsibilities, and continued use despite negative consequences. See Allcott, Braghieri, Eichmeyer, and Gentzkow (2020); Rosenquist, Morton, and Weinstein (2021); Braghieri, Levy, and Makarin (2022); Allcott, Gentzkow, and Song (2022) for more evidence on these negative consequences.

[2] The number of U.S. users is based on TikTok's public statement during the Senate Judiciary Committee Hearing on the Online Child Sexual Exploitation Crisis on January 31, 2024. The average daily time spent on TikTok is sourced from a 2024 survey by eMarketer.

[3] The average hourly earnings in January, 2025 was $35.87, released by the Bureau of Labor Statistics (BLS).

[4] For instance, on November 21, 2024, Australia introduced a bill in parliament to ban social media use, including TikTok, for children under 16 (Reuters, November 20, 2024, "Australia launches 'landmark' bill to ban social media for children under 16"). In response, TikTok has implemented a time-limit tool featuring "break" videos that prompt users to take regular screen-time breaks after prolonged use.

[5] For example, when a user watches the first video, they feel tempted to watch the second; upon reaching the third, the temptation moves to the fourth, creating an ongoing cycle of impulsive consumption.

self-control problems.[6] By contrast, longer videos are less addictive, because users with temptation durations shorter than the video's length anticipate boredom before completion.[7] Within this stylized model, I show a policy of mandatory ad breaks can effectively mitigate temptation and reduce self-control problems. The underlying economic idea is general: breaking up a tempting good into smaller units (e.g., a small pack of chips or cigarettes) can increase demand by amplifying consumers' self-control problems.

Building on these insights, I analyze a popular short drama series on a mobile platform in the U.S. market where self-control problems persist. The series consists of 80 one-minute episodes, closely resembling short videos in both length and vertical mobile optimization. Users must purchase non-refundable platform tokens through a non-linear top-up menu and use them to unlock episodes one by one. This platform design enables the identification of ex-ante preferences and self-control problems, which manifest as users repeatedly purchasing lower-priced token packages.[8] On average, users who purchase at least one package intend to watch for only 28 minutes but ultimately spend 51 minutes on the series. This behavior also results in overpayment, because users could have saved money by purchasing a larger package upfront.[9] Indeed, 39.1% of these users spend more than the rational benchmark, with an average overpayment of $5.51 for the drama series. Moreover, conditional on having previously purchased the smallest package, 69.3% of users deviate from their ex-ante preferences to stop watching and continue purchasing tokens at the next top-up decision—a pattern that remains consistent regardless of how many episodes they have already watched.[10] These findings indicate self-control problems in this setting are widespread, persistent, and economically significant.

I further develop a structural demand model for this short drama by extending the stylized framework to incorporate empirically relevant features. In addition to intrinsic utility and temptation, I introduce rational addiction through habit formation, where consuming the current episode temporarily increases habit stock, thereby enhancing the marginal utility of watching subsequent episodes (Becker and Murphy, 1988). I model drama-watching behavior as a single-agent dynamic discrete-choice problem. Each episode represents a time period in which the user makes two decisions based on their habit stock and token balance. First, if their token balance is insufficient to unlock the current episode, they choose from the menu of token packages. Second, given their updated token balance, they decide whether to unlock the episode. If they choose to un-

[6]Popular social media platforms such as TikTok, Facebook, Instagram, and YouTube Shorts all feature short-form content. Similarly, streaming platforms such as Netflix implement automated features to skip opening and ending sequences, streamlining the viewing experience by eliminating non-essential content.

[7]For example, individuals deliberate more carefully before committing to a two-hour movie versus a one-minute clip. This economic mechanism also extends beyond short videos: it explains why people frequently purchase small beer packages despite the cost savings of larger packs and underpins U.S. laws banning the sale of "loosies" (single cigarettes) as an anti-addiction measure, offering valuable insights for policy discussions.

[8]This setting parallels the discussion on health clubs (e.g., DellaVigna and Malmendier, 2006), where researchers infer exercisers' ex-ante preferences from observed membership purchases.

[9]Users in my sample spend between $29.99 and $69.96 to watch the full 80-minute drama, suggesting a significant level of addiction. For comparison, an adult ticket for a two-hour movie at the Princeton Garden Theatre cost $13.50 in 2024. The much higher willingness to pay for this short drama highlights the strong addictive nature of the content.

[10]The persistence of this pattern suggests users do not become more sophisticated in managing their self-control as the series progresses.

lock, they pay the token price, consume the episode, and proceed to the next period with updated state variables; if they choose not to, they stop watching. I then take the model to the data using the Simulated Method of Moments, targeting moments related to unlocking activity, top-up package purchases, and habit stock dynamics. On average, users derive a negative intrinsic utility of -1.1¢ per one-minute episode relative to their outside option, with heterogeneous tastes exhibiting a standard deviation of 11¢. Temptation effects are substantial, valued at 19¢ per minute and persisting for an average duration of 4.7 minutes. Habit-formation utility ranges from 0 to $1.1 per minute, with each additional episode of habit stock increasing per-episode utility by an average of 1.4¢ in subsequent episodes.

The estimated model reveals a significant loss in user surplus, due to self-control problems, driven in part by the short length of episodes, whereas a policy of a mandatory break could effectively mitigate this inefficiency. On average, users derive a surplus of $0.33 from the drama series, reflecting the combined utility from intrinsic values and habit formation, with 48.3% of them experiencing a negative surplus and the most extreme one losing $32.8. Removing temptation would increase this surplus to $0.78, implying a surplus loss of $0.45 per user due to temptation. Counterfactual simulations show extending the episode length from one to seven minutes raises the average user surplus to $0.40, resulting in a 17.8% reduction in efficiency loss from temptation. A policy mandating an ad break before purchasing tokens proves effective in reducing self-control problems. This policy works by shortening the duration of temptation—when users anticipate having to watch ads before continuing the drama, they become less tempted to keep watching future episodes. Quantitatively, I find imposing a two-minute ad break increases average user surplus from $0.33 to $0.44, reducing surplus loss from temptation by $0.11 (from $0.45 to $0.34), representing a 25.2% efficiency gain. A 10-minute break further reduces the average surplus loss to $0.20, yielding a 56.5% improvement.

Finally, I extend my structural analysis to a broader context of short video platforms, such as TikTok, by reverting to the stylized model without payment or habit formation. When each video lasts one minute, the average user derives an hourly surplus of $0.28, whereas increasing video length to the average YouTube video length (12 minutes) raises hourly surplus to $1.70. Short formats more than triple the efficiency loss, as hourly surplus loss due to temptation rises from $0.59 to $2.01. Implementing a 10-minute break for every 15 minutes of usage further increases hourly surplus to $1.72, reducing surplus loss from temptation by 71.4%. A back-of-the-envelope calculation estimates TikTok's monthly user surplus at $1.4 billion, whereas self-control problems result in a $10.2 billion monthly welfare loss. The mandatory-break policy could recover $7.3 billion of this lost welfare. This extension underscores the large-scale welfare implications of my findings, highlighting their policy relevance beyond the specific short drama series analyzed.

This project makes several contributions. First, I introduce a new perspective on self-control problems, emphasizing the *duration* of present bias, and apply this framework to explain why short-form content is particularly addictive for users who lack sophistication. Additionally, my quantitative results offer novel insights into the distribution of this duration. Second, I provide the first structural evaluation of social media addiction using field data, enabling the monetization of welfare assessments. Relatedly, I develop an approach to separately identify self-control problems and rational addiction, demonstrating both mechanisms significantly influence users' decision-making processes. Third, this paper quantifies the substantial welfare loss caused by short formats and amplified self-control problems, highlighting the potential for large policy gains when interventions are properly designed.

Related literature. Building on the behavioral framework of present bias and self-control problems (Laibson, 1997; O'Donoghue and Rabin, 1999; Gul and Pesendorfer, 2001; DellaVigna and Malmendier, 2004), my model extends the application of these theories to explain addictive behaviors on short-form contents (e.g., Gruber and Köszegi, 2001; Gul and Pesendorfer, 2007). Theoretically, this paper contributes by examining how content length interacts with self-control problems, providing new insights into the role of short format design in exacerbating impulsive consumption.[11] Additionally, my work provides further evidence of self-control problems on short-form video platforms, which have been documented in other contexts, such as health club memberships (e.g., DellaVigna and Malmendier, 2006), retirement savings decisions (e.g., Laibson, Chanwook Lee, Maxted, Repetto, and Tobacman, 2024), and digital book (Zhang, Chan, Luo, and Wang, 2022).[12]

My work also complements the discussion on digital addiction. It builds on the work of Allcott, Gentzkow, and Song (2022), who use a field experiment to estimate a model incorporating habit formation, self-control problems, and naïveté. Other studies on digital addiction primarily focus on its consequences (e.g., Vanman, Baker, and Tobin, 2018; Allcott, Braghieri, Eichmeyer, and Gentzkow, 2020; Mosquera, Odunowo, McNamara, Guo, and Petrie, 2020; Braghieri, Levy, and Makarin, 2022; Collis and Eggers, 2022) and the adoption of self-control tools (Hoong, 2021). This paper contributes to the literature by offering the first revealed-preference evaluation of digital addiction using field data, which addresses sample-selection issues, abstracts from strategic behaviors by experiment subjects, captures users' willingness to pay for different channels of addiction based on real monetary choices, and enables evaluation of counterfactual policies.

More broadly, the paper contributes to the literature on addiction across various contexts. By distinguishing between habit formation and self-control problems, I contribute to the debate on whether addiction is rational (e.g., Spinnewyn, 1981; Becker and Murphy, 1988; Orphanides and Zervos, 1995) or irrational (e.g., Gruber and Köszegi, 2001). This paper also complements studies of addiction in other markets, such as cigarettes (Chaloupka, 1991; Becker, Grossman, and Murphy, 1994; Giné, Karlan, and Zinman, 2010), alcohol (Cook and Moore, 2002; Baltagi and Geishecker, 2006), drugs (Gul and Pesendorfer, 2007; Maclean, Mallatt, Ruhm, and Simon, 2020), and sugar-sweetened beverages (Zhen, Wohlgenant, Karns, and Kaufman, 2011).

Finally, the context of short videos relates to studies on other types of entertainment goods, such as movies (Michalopoulos and Rauh, 2024), cable TV (Crawford and Yurukoglu, 2012; Craw-

[11] This insight connects to the concept of "skewness preference in the small," as proposed by Ebert and Strack (2015) in the context of prospect theory and naïveté.

[12] The existence of money makes the identification of the time-inconsistent preference possible in my setting. See Strack and Taubinsky (2021) for a complete discussion.

ford, Lee, Whinston, and Yurukoglu, 2018), sports (Buraimo, Forrest, McHale, and Tena, 2020), and video games (Lee, 2012; Gandhi, Giuliano, Guan, Keefer, McDonald, Pagel, and Tasoff, 2024). Additionally, my work contributes to the literature on social media and digital platforms (e.g., Allcott, Braghieri, Eichmeyer, and Gentzkow, 2020; Liu, Sockin, and Xiong, 2020; Beknazar-Yuzbashev, Jiménez-Durán, and Stalinski, 2024).[13]

The remainder of the paper is organized as follows. Section 2 presents the stylized model to illustrate the economic point of how short-form contents amplify addiction. In section 3, I provide background on the short drama industry, describe my data, and document evidence of self-control problems. Section 4 introduces the structural demand model of short drama series. I estimate the demand model in section 5 and discuss the main results in section 6. Section 7 extends my structural analysis of short dramas into a general short video platform like TikTok. Finally, section 8 concludes.

2 A Stylized Model of Temptation

I present a stylized model of temptation to demonstrate how short-form contents amplify present bias and the resulting self-control problem. I later extend this model into an empirically relevant framework for short drama series in section 4.

2.1 Setup

Consider a platform offering a large set of videos $\{1, \ldots, T\}$, each lasting one minute. Users make decisions at the video level, watching sequentially and deriving a constant intrinsic utility $x \in \mathbb{R}$ from each. The outside option is normalized to 0. Additionally, users experience a *temptation* to watch such videos, valued at $\kappa > 0$ per minute for a duration of $\chi \in \mathbb{N}$ minutes. Let the superscript t be the current video when the user is making a decision, and let subscript $\tau \geq t$ be the perceived video. The perceived utility from video τ at current time t is thus:

$$\widetilde{u}^t_\tau(x, \chi) = \underbrace{x}_{\text{intrinsic utility}} + \underbrace{\mathbb{1}\{\tau < t + \chi\}\,\kappa}_{\text{temptation } \kappa \text{ with duration } \chi} . \tag{1}$$

For example, starting at current video t, a user with $\chi = 0$ perceives true utility x from each subsequent videos. With $\chi = 2$, however, the user perceives biased value $x + \kappa$ from videos t and $t + 1$, and true x from the rest of videos. I am interested in users with $x \in (-\kappa, 0)$, who inherently dislike the short videos relative to outside options but may still choose to watch them due to temptation.

The temptation in preference (1) can be represented as a present bias towards immediate entertainment from viewing short videos, making users more inclined to watch than they would

[13] For an overview of related literature on social media, see Aridor, Jiménez-Durán, Levy, and Song (2024).

rationally prefer.[14] Depending on the temporal perspective t, users may perceive the same video τ differently, often overvaluing those in the near future (i.e., when $\tau < t + \chi$). For instance, Table 1a illustrates the preferences of users with $\chi = 2$. Before watching the first video ($t = 1$), they perceive the true utility $\widetilde{u}_3^1 = x$ for the third one ($\tau = 3$), because it lies outside their temptation horizon. However, at $t = 2$, the temptation effect emerges, biasing their perception to $\widetilde{u}_3^2 = x + \kappa$.

My theoretical innovation explicitly examines the duration of temptation, denoted as χ, which captures the length of the "present" from the perspective of a present-biased agent. A larger χ implies the agent disproportionately weights a longer future. Studying this duration is crucial for my analysis, because the platform can exploit it by shortening video length, thereby intensifying present bias, as I demonstrate later in this section. In my structural analysis, I estimate the distribution of temptation durations using variation induced by a non-linear pricing scheme, providing novel empirical insights into the literature on present bias.[15]

Finally, my analysis focuses on naïve users who are unaware of the time-inconsistency in their preferences. At any given current video t, they mistakenly believe their future preferences will mirror their current ones, failing to recognize their tastes will shift as they continue watching. In section 3.4, I show empirical evidence on self-control problems, which aligns well with the model prediction based on this naïveté assumption. I further discuss this assumption in section 4.3 and provide the solution for sophisticated users in Appendix A.2.

2.2 Self-control problems

The stylized model generates self-control problems that are summarized in Proposition 1. At current time t, users with $x \in (-\kappa, 0)$ think they will only watch the next χ videos ($\widetilde{u}_\tau^t = x + \kappa > 0$) and then stop ($\widetilde{u}_\tau^t = x < 0$). However, when they reach video $t + \chi$, they are once again tempted to continue watching for another χ videos, revealing a self-control problem: although they intend to stop ex ante, they fail to follow through ex post. Table 1a illustrates an example where a user always plans to watch two videos ($\chi = 2$) at each point in time, but ultimately ends up consuming all the videos provided.

Proposition 1 (Self-Control problems) *Users with intrinsic value $x \in (-\kappa, 0)$ and temptation duration $\chi \geq 1$ watch more videos than they initially prefer.*

This self-control problem induces surplus loss on the user side. In the benchmark case without temptation ($\kappa = 0$), users watch the videos if and only if they derive positive intrinsic utility $x \geq 0$. Let (x, χ) represent a user, and let $S \subset \mathbb{R} \times \mathbb{N}$ be the set of users who have self-control problems.

[14] This framework mirrors key features of the classic quasi-hyperbolic discounting model and fits naturally within the context of short-video consumption, where the additive nature of temptation aids in tractable identification (see Banerjee and Mullainathan, 2010; Allcott, Gentzkow, and Song, 2022). In Appendix A.1, I show how to represent the preference (1) from the quasi-hyperbolic discounting model, which micro founds this irrational temptation.

[15] See section 5.1 of DellaVigna (2018) for a detailed discussion regarding the duration of present bias.

Table 1: Example: Self-control problems with $\chi = 2$ and $x \in (-\kappa, -\kappa/2)$

(a) Baseline

		Current video t			
		1	2	3	4
Perceived video τ	1	$\boxed{x+\kappa}$			
	2	$\boxed{x+\kappa}$	$\boxed{x+\kappa}$		
	3	x	$\boxed{x+\kappa}$	$\boxed{x+\kappa}$	
	4	x	x	$\boxed{x+\kappa}$	$\boxed{x+\kappa}$
	5	x	x	x	$\boxed{x+\kappa}$
	6	x	x	x	x

(b) Comparative static: Video length $n = 4$

		Current video t			
		1	2	3	4
Perceived video τ	1	$4x+2\kappa$			
	2	$4x$	$4x+2\kappa$		
	3	$4x$	$4x$	$4x+2\kappa$	
	4	$4x$	$4x$	$4x$	$4x+2\kappa$
	5	$4x$	$4x$	$4x$	$4x$
	6	$4x$	$4x$	$4x$	$4x$

Notes: The tables provide examples of a naïve user with intrinsic value $x \in (-\kappa, -\kappa/2)$ and temptation duration $\chi = 2$. The perceived utility $\tilde{u}^t_\tau$ from watching video τ at perspective t is displayed in the table, with each column representing a current video and each row a perceived video. Positive utilities are marked with a box, and the highlighted box indicates the videos the user actually watches. Panel (a) illustrates the baseline scenario where the user, facing self-control problems, plans to watch two videos at every decision point but ends up watching all videos. Panel (b) depicts the case with four-minute videos, where the user perceives a flow utility of $4x + 2\kappa < 0$ for each video and thus chooses not to watch.

The *average surplus loss due to temptation* from a video can be defined as

$$\Delta(S) = -\sum_{\chi \in \mathbb{N}} \left[\int_{\{x:(x,\chi) \in S\}} x f_{x|\chi}(x)\, \mathrm{d}x \right] P(\chi), \tag{2}$$

where $P(\chi)$ is the probability mass of χ and $f_{x|\chi}(x)$ is the conditional probability density of x. Proposition 1 yields $S^* = (-\kappa, 0) \times \mathbb{N}_+$ for this baseline case, resulting in a positive user surplus loss $\Delta(S^*) > 0$.

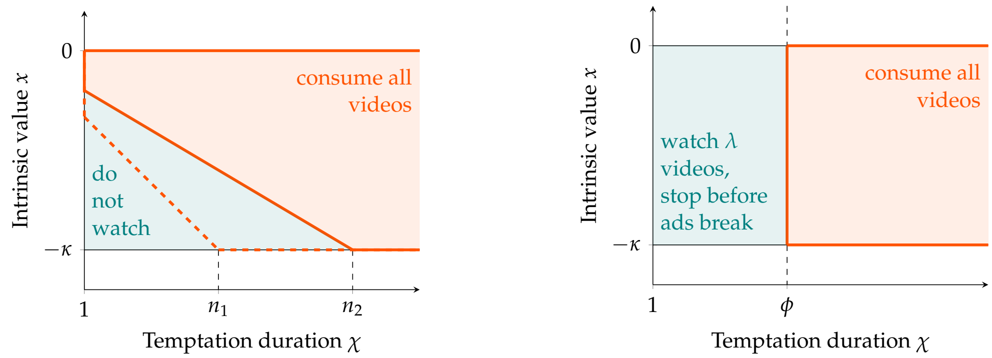
2.3 Short length exacerbates self-control problems

To understand how short video length exacerbates self-control problems, I consider a hypothetical scenario where the platform extends each video to n minutes.[16] Assume users still make decisions at the video level. The perceived flow utility is now defined as:

$$\tilde{u}^t_t(x, \chi; n) = nx + \min\{n, \chi\}\kappa, \tag{3}$$

where intrinsic value scales with video length n, and temptation is adjusted by the lesser of video length n or temptation duration χ. If the video length is shorter than the temptation duration ($n \leq \chi$), the perceived utility increases proportionally. However, when the video length exceeds the temptation duration ($n > \chi$), users anticipate losing interest before the video ends, which effectively dampens the influence of temptation.

[16]This exercise analyzes the impact of video length on self-control problems by merging n one-minute clips into a single, longer video. An analogous policy in reality is the U.S. law on "loosies," which prohibits the sale of individual cigarettes and mandates a minimum pack size of 20.



(a) Longer video length n

(b) Mandate ϕ ads after every λ videos

Figure 1: Illustration: User behavior under counterfactual scenarios

Notes: This figure illustrates user behavior under various counterfactual scenarios, where users are characterized by intrinsic value (x) and temptation duration (χ). Panel (a) presents the comparative static for video length (n) adjustments. Users with self-control problems, depicted in the orange region, watch all videos despite having a negative intrinsic value, whereas users in the teal triangular area choose not to watch any videos. Panel (b) shows user activity under a mandatory ϕ-minute ad break after every λ videos. The orange region represents users who continue watching all videos, whereas the teal area highlights users who gain their self-control and stop watching before the ad break.

Given length n, users will watch the videos iff they perceive a positive flow utility, that is, $\tilde{u}_t^t(x, \kappa, \chi; n) \geq 0$. Self-control problems can thus be characterized by the following condition:

$$\max\left\{-\kappa, -\frac{\chi\kappa}{n}\right\} < x < 0. \tag{4}$$

The self-control problem affects all users with $x \in (-\kappa, 0)$ when the video length n is shorter than the temptation duration χ. However, when $n > \chi$, users with low valuations for the videos ($x < -\chi\kappa/n$) will avoid watching. As n increases, the cutoff $-\chi\kappa/n$ approaches zero, indicating the self-control problem gradually diminishes with video length. Table 1b provides an example with $\chi = 2$ and $n = 4$, where users with $x < -\kappa/2$ escape from the self-control problem.

As a result, increasing video length mitigates welfare loss due to temptation. Let S_n^N be the set of users with self-control problems for a given length n, which is characterized by condition (4) and graphically represented by the orange area of Figure 1a. For any n_1 and n_2 such that $1 \leq n_1 \leq n_2$, we have:

$$S^* = S_1^N \subset S_{n_1}^N \subset S_{n_2}^N \quad \Rightarrow \quad \Delta(S^*) \geq \Delta(S_{n_1}^N) \geq \Delta(S_{n_2}^N).$$

When n increases, more users are exempt from the self-control problem, reducing the surplus loss due to temptation defined in equation (2). Proposition 2 summarizes this comparative static.

Proposition 2 (Shorter videos exacerbate self-control problems) *Longer videos engage more users in the self-control problem, leading to greater surplus loss due to temptation. Formally, for any two video lengths n_1, n_2 such that $1 \leq n_1 \leq n_2$, it holds that $S_{n_1}^N \subset S_{n_2}^N$ and $\Delta(S_{n_1}^N) \geq \Delta(S_{n_2}^N)$.*

Table 2: Policy example: Two ads ($\phi = 2$) after every two videos ($\lambda = 2$)

(a) User with $x \in (-\kappa, 0)$ and $\chi = 2$

Perceived video τ	Current video t: 1	2	Ad1	Ad2	3
1	$\boxed{x+\kappa}$				
2	$\boxed{x+\kappa}$	$\boxed{x+\kappa}$			
Ad1	$-\varepsilon$	$-\varepsilon$	$-\varepsilon$		
Ad2	$-\varepsilon$	$-\varepsilon$	$-\varepsilon$	$-\varepsilon$	
3	x	x	x	$\boxed{x+\kappa}$	$\boxed{x+\kappa}$
4	x	x	x	x	$\boxed{x+\kappa}$

(b) User with $x \in (-\kappa, 0)$ and $\chi = 3$

Perceived video τ	Current video t: 1	2	Ad1	Ad2	3
1	$\boxed{x+\kappa}$				
2	$\boxed{x+\kappa}$	$\boxed{x+\kappa}$			
Ad1	$-\varepsilon$	$-\varepsilon$	$-\varepsilon$		
Ad2	$-\varepsilon$	$-\varepsilon$	$-\varepsilon$	$-\varepsilon$	
3	x	x	$\boxed{x+\kappa}$	$\boxed{x+\kappa}$	$\boxed{x+\kappa}$
4	x	x	x	$\boxed{x+\kappa}$	$\boxed{x+\kappa}$

Notes: The tables illustrate examples of user behavior under a policy that introduces two one-minute ads (Ad1, Ad2) after every two short videos. The perceived utility $\widetilde{u}_{\tau}^{t}$ from watching future videos or ads τ at each time t is displayed, where each column (row) represents a perspective (perceived) video. Positive utilities are marked with boxes, and the highlighted boxes indicate the videos actually watched. Panel (a) shows the behavior of a user with a two-minute temptation duration, who stops watching at the ads break. Panel (b) depicts a user with a three-minute temptation duration, who chooses to watch the ads and continues consuming videos after the break.

2.4 Counterfactual policy: Mandatory ad break

Understanding the inefficiency due to temptation, I consider a counterfactual policy that mandates a ϕ-minute ad break for users after viewing λ-minutes of videos. Such policy is realistic because online video platforms have already implemented similar practices.[17] I assume watching one minute of ads yields the outside value (0) minus an infinitesimal cost ε, which prevents the policy from having mechanical welfare effects.[18] Users do not experience temptation toward ads, which effectively shortens the duration of temptation each user faces.

For example, mandating two one-minute ads ($\phi = 2$) after every two videos ($\lambda = 2$) can change user behavior. In Table 2a, I illustrate a user with a two-minute temptation duration ($\chi = 2$). At videos 1 and 2, the user perceives positive utility from current videos and decides to watch. However, upon encountering the two ads, they incur a small cost to continue but no longer anticipate positive utility from future videos. As a result, they do not watch ads and thus avoid further self-control problems. Conversely, in Table 2b, I show the policy is ineffective for users with a longer temptation duration (e.g., $\chi = 3$). These users still perceive positive utility from the next available video after the ads ($\widetilde{u}_3^{Ad1} > 0$), making them willing to endure the small cost ε and continue watching.

In general, users with temptation durations $1 \leq \chi \leq \phi$ resist temptation when faced with the ϕ-minute break, limiting their viewing to only the first λ videos. By contrast, users with longer temptation durations watch the ads and proceed to view additional videos. These behavioral

[17] For example, YouTube embeds ads directly into videos to bypass ad blockers, making the policy of ad breaks feasible. Similarly, TikTok has the screen time control tool which reminds teenagers of their screen time after a certain period of usage.

[18] The negative infinitesimal utility helps resolve ties in users' decisions. In practice, while users may engage in other activities during ads, they still endure the effort of skipping them and tolerating the noise, leading to this minor utility loss. This assumption is conservative; the policy gain would be even larger if users faced greater utility losses.

patterns are summarized in Figure 1b. The policy gain thus arises from the decreased platform usage among users who used to have self-control problems but now engage with the platform less intensively (the teal area). Proposition 3 summarizes these insights.

Proposition 3 (Mandatory ad break reduces self-control problems) *For users with self-control problems defined in Proposition 1, mandating a ϕ-minute ad break after every λ minutes of video viewing reduces the video consumption for those with $1 \leq \chi \leq \phi$ to λ minutes.*

3 Data and Institutional Background

I take the short-drama-series industry as the empirical context for studying the self-control problem and its interaction with content length. I introduce the short drama industry in section 3.1 and provide details about the platform of my study in section 3.2. The individual-level data for my analysis are described in section 3.3, which I use to establish empirical evidence on self-control problems in section 3.4.

3.1 Short drama series

Short drama series are a mixture of drama series and short-form videos. They typically have scripts adapted from web novels and are optimized for vertical viewing on smart phones.[19] The most prominent feature of those mini-dramas is their *shortness*, with each episode of a 40- to 100-episode series lasting about one minute. With a genre similar to soap operas, these short dramas, described as "high on drama, low on glam, and full of plot twists," are designed to get viewers hooked fast, which makes this industry an ideal context for studying temptation and the resulting self-control problem.

The demand for short drama series is high and growing rapidly. In China, the country from which this industry originated in early 2022, the short drama business commanded an estimated market value of $69 billion in the year 2023, and this trend is rapidly gaining global traction. For example, global short drama platforms such as DramaBox, ReelShort, and ShortMax respectively ranked 6th, 18th, and 33rd in the U.S. Apple App Store Entertainment Top Charts for free apps on April 26, 2024.[20] Users are also willing to pay for these dramas. For instance, the superstar drama series on the platform I study reached $3.5 million revenue in one month after its first release.

Yet, the production of these short dramas is generally low in quality. The scripts are usually bought and adapted from popular web novels, which typically emphasize immediate engagement over depth and complexity. The plots often rely on sensational or emotionally charged themes such as romance, conflict, or dramatic twists to maintain viewer interest. Character development and nuanced storytelling are minimal, because the focus is on creating visually appealing and

[19] Because of its vertical display mode, this type of series is sometimes also called "vertical drama."

[20] For comparison, the Apple App Store Entertainment Top Charts on the same day had other related apps such as TikTok (2nd), Netflix (5th), YouTube TV (16th), and AMC Theatres (46th).

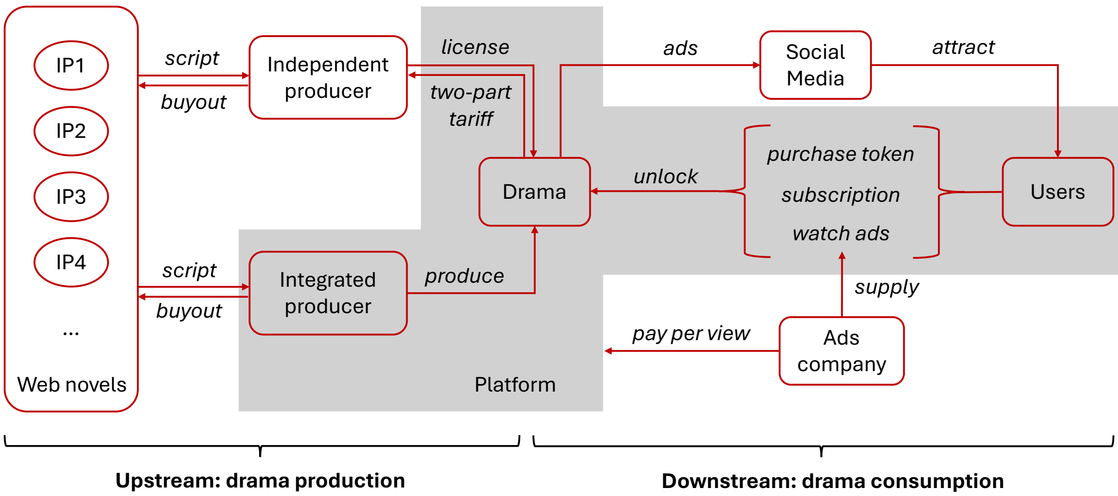


Figure 2: Institutional background of the platform

attention-grabbing content that can be easily consumed on mobile devices. Short dramas feature relatively unknown actors, avoiding A-list or B-list celebrities, and are directed and edited by mid-level or inexperienced professionals. As a result, production costs are low, mostly below $80,000 per drama, with the entire production cycle completed in seven to 10 days.

The short-drama-series industry thus shares key characteristics with platforms such as TikTok and other short video formats, where low-cost content is designed to be rapidly consumed and highly engaging, often at the expense of quality or depth. This industry offers a unique opportunity to study consumer behavior in the context of short-form video consumption.

3.2 The platform

The data for my study are provided by one of the leading short drama platforms in the industry. I outline the basic structure of this platform in Figure 2, where activities occurring on the platform are highlighted in the shaded area. Dramas are the platform's primary assets. On the supply side, scripts are purchased and adapted from web novels and then produced into short dramas. The platform can acquire existing dramas from external producers through a negotiated two-part tariff or act as an integrated producer to create dramas itself. To attract users, the platform constantly advertises its dramas on major social media platforms such as TikTok. Users need to unlock each drama episode by purchasing tokens, subscribing, or watching external ads, which form the platform's three main revenue streams. Below, I provide more details on the components relevant to my study. A more comprehensive description of the platform is available in Appendix B.

User demographics. This platform operates in global markets. The daily active users (DAU) exceeded 100,000 by May 2024, with the US contributing 23% of users and 63% of revenue. I therefore focus on the US market. Additionally, 86% of the user base is female, and the majority are from younger generations: 36% of users are under 30, 63% are under 40, and 85% are under 50.[21] User overlap with Facebook and TikTok, the two primary social media platforms on which this platform advertises, is substantial, suggesting this sample is representative of a wider audience susceptible to social media addiction.

The (superstar) drama. By March 2024, the platform offered over 400 dramas in all major languages. Adapted from web novels, these short dramas feature dramatic genres, with the most popular being "love after marriage" and "toxic love."[22] On average, 1.7 million episodes are consumed daily, with a high level of concentration where a single "superstar" drama accounts for 58.8% of viewership. Spillover across dramas is minimal, with only 3.6% (or 1.5%) of users who have unlocked the superstar drama also unlocking (or topping up for) another drama. Therefore, my main analysis focuses on user behavior related to this superstar drama, which was introduced in mid-January 2024. Consisting of 80 episodes, each lasting one minute, the first nine episodes are free to watch, whereas each subsequent episode costs 65 platform tokens. Produced in-house by the platform, this drama generated $3.5 million in revenue within a month, despite having a production cost of just $70,000. Its success can also be attributed to significant advertising efforts, with the platform investing over $20,000 daily in promotions.

Drama demand. The payoff-relevant user activity for the platform is unlocking episodes, which can be done in three ways, as summarized in Figure 2: paying tokens, subscribing, or watching ads. My analysis focuses on tokens, the primary revenue source, generating $31,028 in daily income and accounting for 78.0% of total revenue between May 2023 and May 2024.[23] Users must unlock each episode sequentially by spending a specified amount of platform tokens, providing ideal variation to identify willingness to pay on an episode-by-episode basis.

Additionally, users must purchase top-up packages with real money when they run out of tokens.[24] The platform offers four packages: $4.99 for tokens equivalent to 7.50 episodes, $9.99 for 16.62 episodes, $19.99 for 36.74 episodes, and $29.99 for 81.49 episodes. Random promotions introduce some variation in the number of tokens for each package across users and over time. As shown in Table 4, the platform employs a non-linear pricing structure, where the average price per episode decreases with larger package sizes. This structure creates a trade-off between lower

[21]The platform calculated the age for the period between March 1, 2024, and May 14, 2024. The app is labeled "18+," so only users aged over 18 are included. The age distribution may skew even younger because teenagers may access the platform using their parents' phones.

[22]The "love after marriage" genre explores romantic relationships that develop and evolve post-marriage. "Toxic love" refers to a dysfunctional relationship characterized by unhealthy behaviors, such as manipulation, control, emotional abuse, and dependency.

[23]The second-largest revenue source is subscriptions, a model commonly used by drama platforms such as HBO. The platform offers three subscription options varying by duration: a week ($29.99), a month ($59.99), and a year ($199.99), contributing an average daily income of $6,631 and 16.7% of total revenue. The final revenue stream comes from ads, where users watch 30-second ads to unlock episodes, earning the platform $4,329 in daily income and 5.4% of total revenue. The time series of these income sources is reported in Appendix B.

[24]As part of the platform's advertising strategy, users can also earn a small amount of gift tokens through daily log-ins, sharing content on social media, and following the platform's TikTok account, but these amounts are negligible compared with top-up packages.

costs and greater commitment, providing a source of identification for users' ex-ante preferences. The top-up page appears whenever users deplete tokens, and payment can be made seamlessly through the App Store or Google Play within seconds, making the process nearly frictionless.

User behavior. After unlocking an episode, users may rewatch it an unlimited number of times. However, I focus on the initial viewing of each episode and do not account for repeated viewing behavior. Users in the sample are required to unlock episodes sequentially, and they typically watch each episode in its entirety at least once before unlocking the next. This observation supports the assumption that users make viewership decisions at the video level.

3.3 Data and summary statistics

For a randomly selected 10% sample of global users, I have access to individual-level log data that encompass users' full activities, including top-ups, unlocking, subscriptions, and viewership, from November 1, 2023, to March 31, 2024.[25] I focus on two key dimensions: top-up package purchase and unlocking. Each time users purchase platform tokens, I observe the transaction time, the price paid, and the number of tokens acquired. Additionally, I record the time, method, and number of tokens spent to unlock each drama episode.[26] This information fully characterizes users' drama-watching activities via platform tokens.

Based on the institutional details, I focus on package purchasing and unlocking activities related to the superstar drama by users from the US. I exclude users who have unlocked another drama before or during their engagement with the superstar drama, those who unlocked episodes via subscription or watching ads, and those with an initial token stock exceeding five episodes. To ensure users in my sample have sufficient time to complete the drama, I select those who began watching it between January 19, 2024 and January 31, 2024. For this sample, I construct a measure of a "round," defined as the period during which any two consecutive episodes are unlocked within two hours, which will be interpreted as the window for short-term habit formation.[27] I further refine the sample by truncating users in the top percentile of this round distribution and normalize the token amount by the cost of each episode.

This data-cleaning process results in a sample of 219,064 unlocking events and 5,360 top-up activities by 11,512 users. Summary statistics for these users are presented in Table 3. On average, a user unlocks 19.03 episodes and spends \$5.80 on this drama. Considerable heterogeneity exists, with over three-quarters of users not spending anything and only unlocking free episodes. The average round measure is 1.37, with most users consuming the videos in a single round. The average amount of gift tokens and initial endowment per user equates to the value of 0.29 and

[25] Each user is randomly assigned a unique user ID upon first opening the platform app. Users in my sample are those whose user ID ends with the number "8," effectively creating a 10% random sample of all users.

[26] For free episodes, I consider the first-time viewership as the equivalent unlocking activity.

[27] I define a round in my data based on a two-hour window, within which habit formation can develop. The goal is to capture the transient nature of digital addiction. This modeling choice is not critical to my main focus of the self-control problem. All quantitative results remain robust if rounds are instead defined using a 12-hour gap.

Table 3: Summary statistics on the user level

Variable	mean	std	min	p25	p50	p75	p90	p95	p99	max	count
Episode	19.03	23.79	1	9	9	12	80	80	80	80	11,512
Top-up ($)	5.80	13.35	0	0	0	0	29.99	39.98	49.97	69.96	11,512
Round	1.37	0.73	1	1	1	2	2	3	4	5	11,512
Gift	0.29	0.96	0	0	0	0	1	2	5	12	11,512
Endowment	0.43	0.91	0	0	0	0	2	3	4	4	11,512

Table 4: Top-up packages: Tokens and market share

Price ($)	tokens	[p5,p95]	price/episode	market share
4.99	7.50	[7,9]	0.67	0.34
9.99	16.62	[16,20]	0.60	0.36
19.99	36.74	[36,46]	0.54	0.20
29.99	81.49	[62,92]	0.37	0.11

0.43 episodes, respectively, both small relative to the top-up tokens. For simplicity, I model these gifts as extra tokens included with all the top-up packages in my quantitative analysis.

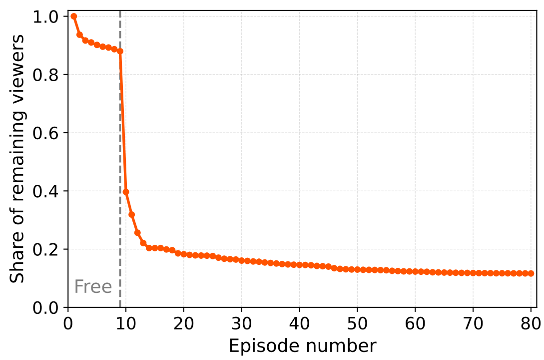
Table 4 presents summary statistics related to top-up choices. The platform employs non-linear pricing, where the average price per episode decreases with higher-price packages. This structure highlights the trade-off between a lower average cost and a larger ex-ante commitment in the top-up decision. All four packages have a positive market share, allowing for the identification of users' ex-ante preferences based on observed top-up choices through the revealed-preference argument. Additionally, I observe some variation in the number of tokens within each top-up package, resulting from promotion offers that are randomly presented to users when they access the top-up page.

Figure 3a presents the share of unlocking activity across episodes. By construction, all 11,512 users in my sample watch the first episode. After each episode, some users discontinue watching, and the share of unlocks per episode stabilizes relatively quickly. The most significant drop in viewership occurs at the 10th episode, coinciding with the end of the nine-episode free trial, when users must purchase tokens to continue.[28] Three-quarters of users exit the series without purchasing any tokens. Ultimately, 1,340 users (11.64%) complete the entire drama. Notably, apart from the sharp decline triggered by the price shock, the conditional probability of continuing remains high beyond the third episode. This pattern suggests viewers quickly assess the drama's quality, implying learning is not a key determinant of drama-watching behaviors.[29]

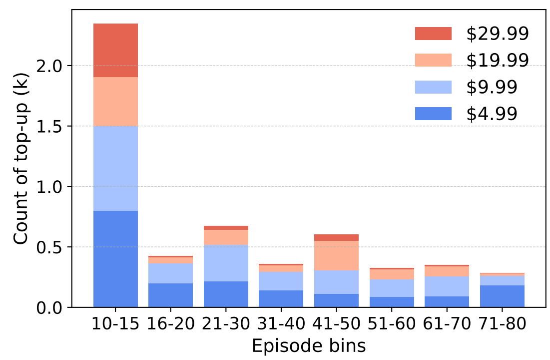
Figure 3b illustrates the dynamic pattern of top-up package choices, grouped in bins of five or 10 episodes. The largest package, priced at $29.99, is predominantly purchased between the 10th

[28] The probability of discontinuing peaks at the 10th episode but remains elevated in subsequent episodes, as some users possess a small token endowment (sufficient for one to four episodes) and delay their top-up decision until exhausting their token stock.

[29] A detailed discussion of the learning mechanism is provided in Appendix C.3.



(a) Share of remaining viewers by episode



(b) Package purchases by episode bins

Figure 3: The dynamic patterns in unlocking and top-up package purchasing decisions

Notes: Panel (a) reports the share of users who remain viewing each episode, which is monotonically decreasing because users have to unlock sequentially. The total number of users is 11,512. The first nine episodes are free to watch, accounting for the sharp drop at the 10th episode. Panel (b) summarizes the dynamic pattern in top-up package sales by bins of five or 10 episodes.

and 15th episodes by highly engaged users who are willing to commit to watching many episodes. The other three packages exhibit positive sales across all episode bins. The persistent market share of lower-priced packages across episodes suggests a self-control problem: users initially plan to watch only a few episodes ex ante but fail to stop ex post. I further investigate this pattern in section 3.4.

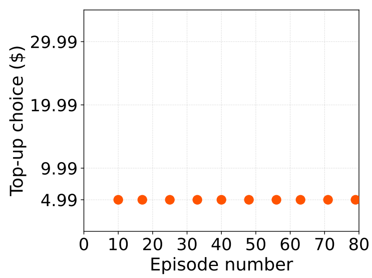
3.4 Evidence of self-control problems

In this session, I examine key patterns in user behavior related to self-control problems, which provide essential variation for identifying the structural model with temptation in section 4. As shown in Appendix C.3, these patterns remain robust even when conditioning on users who have watched many episodes.

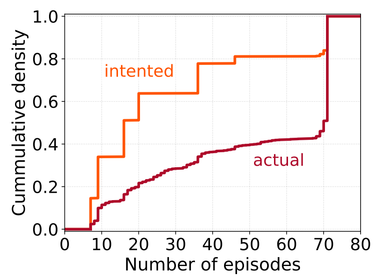
The identification of self-control problems arises from the non-linear pricing scheme in top-up package purchases. Figure 4a illustrates this idea with an actual user who repeatedly purchases the smallest top-up package and completes the entire drama in a single night.[30] The choice of the $4.99 package suggests the user initially intended to watch only the next seven episodes at each purchase; otherwise, opting for a larger package with a lower per-episode cost would have been more rational. However, their ex-post behavior—continuing to the end—reveals an inability to commit to stopping, indicating a severe self-control problem.[31] This pattern is widespread in my

[30]The fact that this user finishes the series in one night rules out alternative explanations, such as "budgeting," which might apply if they had spaced out their viewing over several weeks.

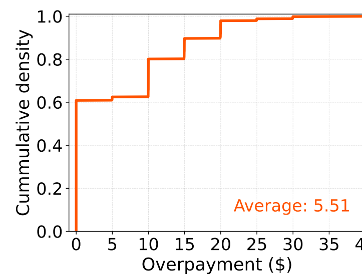
[31]An alternative explanation is that users anticipate a higher likelihood of stopping as they progress further into the series, making them more cautious in token purchases. For example, if a user is waiting for a call, the longer they wait, the more likely they are to receive it in the next few minutes. However, the aggregate viewing pattern does not support this explanation. As shown in Figure 3a and Figure C.3 in Appendix C.3, the probability of continuing to the next episode increases quickly and then remains consistently high throughout the rest of the series.



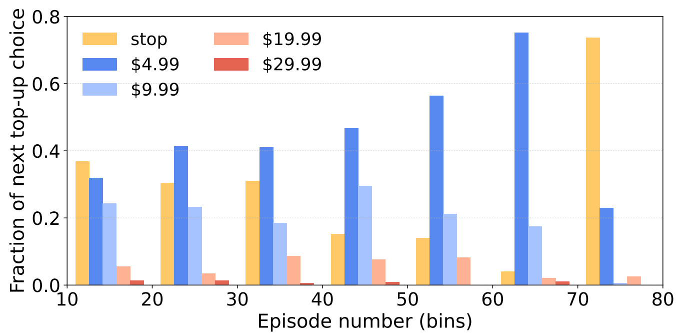
(a) Self-control problem example



(b) Intended vs. actual usage



(c) Distribution of overpayment



(d) Next top-up package choice following $4.99 purchase

Figure 4: Evidence of self-control problems

Notes: Panel (a) illustrates an example of self-control problems, where the user repeatedly purchases the smallest top-up package. The y-axis lists the available top-up options, and the x-axis indicates the episode before which each top-up occurs. Panel (b) compares the cumulative distribution of intended vs. actual number of episodes watched among users who have purchased token packages. Intended consumption is inferred from the first package they purchase. Panel (c) presents the cumulative distribution of overpayment among users who made at least one package purchase. Overpayment is measured relative to the optimal spending, which is imputed using the average token quantity in each package from Table 4. The natural lower bound for overpayment is $0. Panel (d) reports the distribution of users' next top-up decisions, conditional on having previously purchased the $4.99 package, across episode groups. A time-consistent user would choose to stop. The sharp increase in stopping behavior between episodes 70 and 80 is mechanically driven, because users must stop after completing the series.

sample, as reflected in the persistently high market share of small top-up packages throughout the drama, as shown in Figure 3b.

To further illustrate time inconsistency, in Figure 4b I compare the distribution of intended versus actual number of episodes watched for users who have purchased tokens. Intended consumption, represented by the orange cumulative density curve, is inferred from users' first token package choice. On average, users initially intend to watch 28.0 episodes when making their first top-up decision. By contrast, the actual number of episodes watched, shown by the red curve, exhibits first-order stochastic dominance over the intended distribution. The average number of episodes actually viewed is 51.0, which is 82.1% higher than users' initial intention. This significant discrepancy—where actual consumption far exceeds intended consumption—provides strong evidence of self-control problems.

Moreover, due to the platform's non-linear pricing scheme, the fact that the example user in

Figure 4a could have spent less motivates the use of *overpayment* as an indicator of self-control problems. Figure 4c presents the distribution of overpayment, measured relative to optimal spending, among users who made at least one package purchase.[32] The results indicate 39.1% of these users spend more than the rational benchmark to unlock episodes, suggesting self-control problems are prevalent in my sample. Specifically, 17.6% overpay by approximately \$10, 9.5% by \$15, and 8.2% by \$20. On average, these users overpay by \$5.51, which is 22.7% of the optimal benchmark, underscoring the substantial impact of self-control problems in this setting.

Figure 4d provides additional evidence of self-control problems through conditional choice probabilities. After purchasing the \$4.99 package, a time-consistent user would stop watching when faced with the next top-up decision. However, as shown in Figure 4d, most users deviate from their ex-ante preferences and continue topping up. Among those who purchased the \$4.99 package between episodes 10 and 70, only 30.7% manage to stop thereafter.[33] The majority instead purchase another \$4.99 or \$9.99 package, aligning with my stylized model's prediction that self-control problems arise from short-term temptation. Moreover, time inconsistency becomes more pronounced as the series progresses, with the conditional probability of stopping (the yellow bar) declining, suggesting users do not become more sophisticated in managing their self-control within this context.[34]

4 Structural model

I adopt a structural approach to systematically examine self-control problems in the short-drama-series industry. Building on the stylized model from section 2, I develop a single-agent dynamic discrete-choice model for this setting in section 4.1. The model solution is characterized in section 4.2, followed by a discussion of key modeling assumptions in section 4.3.

4.1 Setup

The superstar drama consists of T episodes indexed by t, with each one-minute episode naturally defining a time period in which the user must decide whether to purchase a top-up package and unlock the next episode. The drama-watching activity can thus be framed as a finite-horizon dynamic discrete-choice problem. The platform sets token price as $c_t = \mathbb{1}\{t > 9\}$, meaning users begin paying a normalized amount of tokens after the ninth episode.

[32] Optimal spending is imputed using the average token quantity in each package from Table 4.

[33] The spike in stopping behavior between episodes 70 and 80 is mechanically high, because users must stop after completing the series.

[34] The drama lasts only 80 minutes in total, limiting users' ability to recognize and adjust for their self-control problems over time.

Perceived flow utility. Following the stylized model in section 2, I define the perceived flow utility from episode t as:

$$u_t(h_t, \delta, \psi_t, \chi, \epsilon_t) := \underbrace{\overbrace{\delta}^{\text{drama}} - \overbrace{\psi_t}^{\text{outside}}}_{\text{intrinsic utility}} + \underbrace{\mathbb{1}\{\chi \geq 1\}\kappa}_{\text{temptation}} + \underbrace{\alpha(h_t)}_{\text{habit formation}} + \underbrace{\epsilon_t}_{\text{taste shifter}}, \tag{5}$$

which comprises intrinsic utility, temptation, habit formation, and a random taste shifter. The intrinsic utility reflects the drama's value relative to the user's outside option. The drama value δ is constant over episodes but varies across users.[35] Given the rapid convergence in viewership (Figure 3a) and consistent top-up behaviors across episodes (Figure 4d), I abstract from learning by assuming users have perfect information on δ.[36] The outside value ψ_t is time-varying to capture potential auto-correlation in the user's decision-making process from external factors. As defined in the stylized model, the per-minute temptation κ exists when its duration χ exceeds one-minute episode length.[37] The taste shifters ϵ_t captures random shocks on users' perceived utility from each episode.

Rational addiction is modeled as habit formation, which is relevant in my empirical setting of drama series (Becker and Murphy, 1988).[38] Encountering each episode t, the user has habit stock h_t, defined as the number of previous episodes watched within the current round r_t. This habit stock contributes to utility through $\alpha(h_t) = \alpha_1 h_t(h_t - \alpha_2)$. Each round evolves exogenously, with a probability ρ that, after watching an episode, the user must start a new round ($r_{t+1} = r_t + 1$).[39] By design, habit formation is temporary, building up within each round and capturing the transient nature of digital addiction. Aligning with the rationality, I assume users have rational expectations regarding habit formation and round dynamics, meaning they fully internalize these dynamics when making their drama-watching decisions.

In practice, I assume the outside value ψ_t is round-specific, depending on the time of day when the user begins watching. I normalize $\psi_t = 0$ for rounds that start during the day (11am-12am) and parametrize the outside value for nighttime (1am-10am) as $\overline{\psi}$.[40] The probability that a new

[35] For simplicity, I omit the user subscript i throughout this section because this is a single-agent problem.

[36] I could incorporate learning into the framework by modeling Bayesian users who gradually infer their value of δ from episodes they watch. Estimating this extended model reveals that the learning effect is minimal, because users can reasonably infer δ after one or two episodes. For simplicity, I exclude this mechanism in my baseline analysis. See section 4.3 and Appendix C.3 for more detailed discussions for this learning mechanism.

[37] For simplicity, I assume temptation remains constant every minute within its duration, though a more flexible model could allow it to decay over time. Although I cannot estimate the rate at which temptation decays, incorporating this feature would only strengthen the present bias, further amplifying the self-control problem and making the short video length an even greater factor in driving addiction.

[38] In drama series, episodes are linked by a continuous storyline, which helps keep users engaged and make habit formation relevant. Appendix C.1 provides evidence on habit formation by examining the relationship among habit stock, the probability of continuing watching, and the probability of purchasing higher-priced packages.

[39] The assumption of exogenous round dynamics is crucial for identifying habit formation. It is reasonable because if users stop watching because they dislike the series, they should not resume in the next round after losing all accumulated habit stock. Thus, any observed temporary disruptions must stem from exogenous factors—for example, a user might receive an unexpected email about a paper decision, interrupting their drama-watching session.

[40] This choice of time is motivated by viewing patterns in the data, which show below-average viewership between 1am and 10am. A detailed description can be found in Appendix C.2.

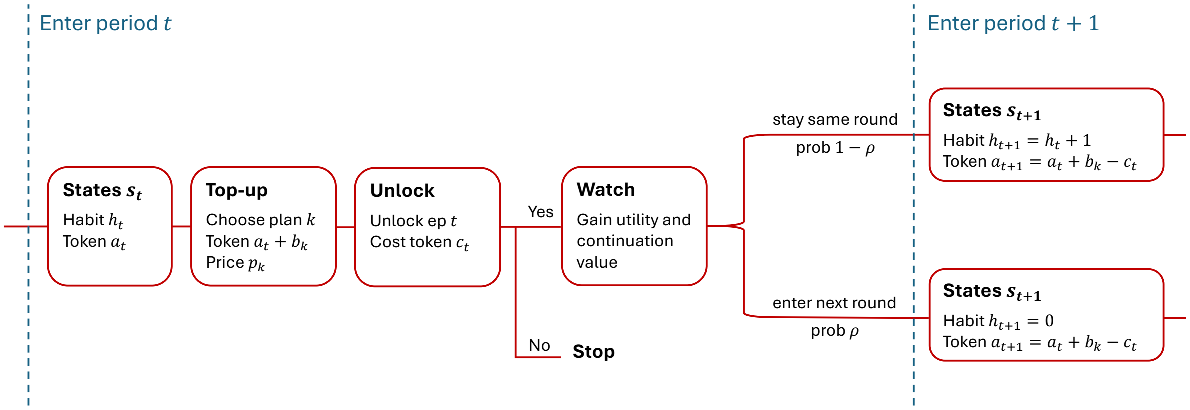


Figure 5: Timing: Decisions on top-up and unlocking within a time period

round begins at night ($\varphi = 0.27$) is directly calibrated from the data. I also assume the random taste shifter ϵ_t follows a Gumbel distribution, $Gumbel(-\beta_\epsilon \gamma, \beta_\epsilon)$.[41]

Dynamics. I formalize the dynamic components of my model. To align with the data, I assume all users choose to watch the first episode. Additionally, I assume each user experiences a temptation period lasting $\chi \in \{0, 1, ..., 30\}$ minutes and holds a naïve perception of temptation beyond this period.[42] The 30-minute limit captures the short-term nature of temptation and makes the solution algorithm more tractable.[43] At the start of each episode $t \geq 2$, the user has unlocked and watched the previous $t-1$ episodes, with a state $\boldsymbol{s}_t$ that includes their habit stock h_t and token stock a_t. The decision-making process is summarized in Figure 5, where two key decisions are made within each period: top-up package purchasing and unlocking.

First, users decide whether to top up when their current token stock a_t is lower than the cost of unlocking the next episode, c_t.[44] I assume this top-up process is frictionless, because users can complete purchases within seconds.[45] They choose from a menu of $K = 4$ packages, indexed by $k \in \{1, ..., K\}$, with price p_k and token quantity b_{kt}, along with an outside option denoted as $p_0 = b_0 = 0$. The packages are ordered such that price p_k increases with k. The token amounts are randomly drawn for each user-period pair from a distribution $F_{\boldsymbol{b}}(\cdot)$ set by the platform, reflecting random promotions. In practice, the platform employs a non-linear pricing strategy, where the

[41] The parameter β_ϵ is the scale parameter that controls the dispersion of a Gumbel distribution. The location parameter is set to $-\beta_\epsilon \gamma$, where γ is the Euler constant, such that the expectation of ϵ_t is 0 (e.g., Rust, 1987).

[42] As shown in Appendix A.2, sophisticated users who dislike the videos would never engage with the platform. Therefore, I assume all users in my sample are naïve. In Section 4.3, I discuss potential bias from this assumption and conclude that including sophisticated users would further strengthen the case for self-control problems.

[43] This 30-minute upper bound of temptation duration is verifiable using the estimated distribution for χ. See Section 5.2 for more details.

[44] In practice, the top-up page only appears when users have insufficient token balance. Users could, in principle, stop watching, return to the main page, and manually access the top-up page at any time, but fewer than 1% of users choose to do so when they have sufficient tokens.

[45] This assumption is quantitatively conservative because introducing friction would reduce users' willingness to top up, implying that the structural model would estimate an even stronger present bias to account for the time-inconsistent behaviors observed in the data.

average price per token, $\mathbb{E}[p_k/b_{kt}]$, decreases as the package price increases, highlighting a trade-off between lower token prices and greater ex-ante commitment to watching more episodes. Thus, top-up choices reveal users' ex-ante preferences for how many episodes they intend to watch. Additionally, I assume an idiosyncratic taste shifter ν_{kt} follows a standard Gumbel distribution for each top-up package. I use $V_t(h, a; \delta, \psi, \chi, \boldsymbol{b}, \boldsymbol{\nu})$ and $EV_t(h, a; \delta, \psi, \chi)$ to denote the value and expected value functions associated with the top-up decision, which I formulate in more detail in section 4.2.

Second, users decide whether to unlock episode t, given their habit stock h_t and token stock $a_t + b_{k^*t}$. By unlocking, users expect to receive their perceived flow utility u_t as defined in equation (5), along with a perceived continuation value, $\mathcal{C}_t\,(h, a; \delta, \psi, \chi)$. This continuation value stems from the ability to unlock the next episode, $t+1$, where users perceive themselves to be one minute less tempted under the naïveté assumption. Notation-wise, I use $W_t\,(h, a; \delta, \psi, \chi, \boldsymbol{\epsilon})$ and $EW_t\,(h, a; \delta, \psi, \chi)$ to represent the value and expected value functions associated with the unlocking decision.

Finally, I assume no continuation value exists for habits and tokens outside of this superstar drama, which yields the terminal condition:

$$EV_{T+1}(\cdot) \equiv EW_{T+1}(\cdot) \equiv 0. \tag{6}$$

This assumption is based on the empirical observation that spillover across dramas is minimal, and most users do not watch anything else after completing this one.[46] Thus, condition (6) converts the user's dynamic problem into a finite-horizon framework.

4.2 Solution

In this section, I define the recursive solution to this single-agent dynamic problem and characterize the conditions under which each top-up and unlocking option is selected. This analysis provides the foundation for identification in the empirical analysis.

Recursive definition of value functions. Following O'Donoghue and Rabin (1999), I use the concept of *perception-perfect equilibrium strategies* to account for the behavioral forces in my model. Under this framework, users maximize their *perceived* utility, which can lead to irrational self-control problems. I define the value functions iteratively by using backward induction, which, combined with the terminal condition (6), fully characterizes the solution.

For any episode $t \leq T$, the perceived value function associated with the top-up decision for a user with habit stock h, token stock a, drama value δ, outside value ψ, token amounts b_k, perceived

[46] See more details in Appendix C.4.

temptation duration χ, and taste shifter ν_k is given by:

$$\begin{aligned} V_t(h, a; \delta, \psi, \chi, \boldsymbol{b}, \boldsymbol{\nu}) = \quad & \mathbb{1}\{a < c_t\} \max_{k \in \{0,1,\ldots,K\}} \{EW_t(h, a + b_k; \delta, \psi, \chi) - \omega p_k + \nu_k\} \\ & + \mathbb{1}\{a \geq c_t\} EW_t(h, a; \delta, \psi, \chi), \end{aligned} \tag{7}$$

where $EW_t(\cdot)$ is the perceived value from unlocking and ω represents price sensitivity. If the token balance is insufficient ($a < c_t$), the user must choose one of the top-up options k; otherwise, they skip topping up and proceed to the unlocking stage. Because the taste shifter ν_{kt} follows a standard Gumbell distribution, the expected value can be written as:

$$\begin{aligned} EV_t(h, a; \delta, \psi, \chi) = \quad & \mathbb{1}\{a < c_t\} \mathbb{E}_{\boldsymbol{b}} \left[\log \left(\sum_{k=0}^{K} \exp \left[EW_t(h, a + b_k; \delta, \psi, \chi) - \omega p_k \right] \right) \right] \\ & + \mathbb{1}\{a \geq c_t\} EW_t(h, a; \delta, \psi, \chi), \end{aligned} \tag{8}$$

where the expectation $\mathbb{E}_{\boldsymbol{b}}(\cdot)$ is taken over the token amount $\boldsymbol{b}$.

In the unlocking stage, the user decides whether to unlock episode t. By unlocking, they derive the flow utility $\widetilde{u}_t(h, \delta, \psi, \chi, \epsilon)$ and gain the perceived continuation value defined as:

$$\begin{aligned} \mathcal{C}_t\left(h, a; \delta, \psi, \chi\right) = \quad & (1 - \rho)\, EV_{t+1}\left(h + 1, a - c_t; \delta, \psi, \max\{\chi - 1, 0\}\right) \\ & + \rho \mathbb{E}_{\psi'} \left[EV_{t+1}\left(0, a - c_t; \delta, \psi', \max\{\chi - 1, 0\}\right) \right], \end{aligned} \tag{9}$$

where the user forms rational expectation over the future habit stock and outside value according to the round dynamics. Because users are naïve regarding temptation, they perceive themselves as being one minute less tempted when approaching the next episode $t + 1$, until the temptation diminishes. The value function associated with this unlocking stage is therefore:

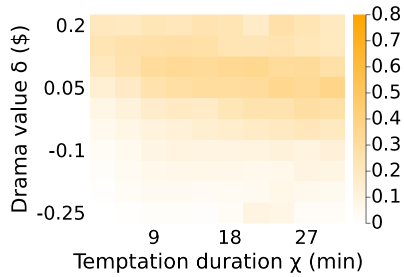
$$W_t\left(h, a; \delta, \psi, \chi, \boldsymbol{\epsilon}\right) = \mathbb{1}\{a \geq c_t\} \max \Big\{ \underbrace{u_t(h, \delta, \psi, \chi, \epsilon)}_{\text{flow}} + \underbrace{\mathcal{C}_t(h, a; \delta, \psi, \chi)}_{\text{continuation}}, \epsilon_0 \Big\} + \mathbb{1}\{a < c_t\}\epsilon_0, \tag{10}$$

which, with $\epsilon \sim Gumbel(-\beta_\epsilon \gamma, \beta_\epsilon)$, yields the expected value function:

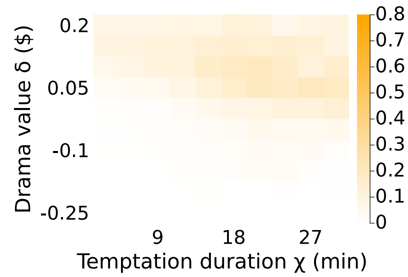
$$EW_t\left(h, a; \delta, \psi, \chi\right) = \mathbb{1}\left\{a \geq c_t\right\} \beta_\epsilon \log\left(1 + \exp\left(\frac{u_t(h, \delta, \psi, \chi, \epsilon) + \mathcal{C}_t\left(h, a; \delta, \psi, \chi\right)}{\beta_\epsilon}\right)\right). \tag{11}$$

The solution of this single-agent dynamic model is fully characterized by the recursive system of equations (7)–(11) and the terminal condition (6). Numerically, one can solve these value functions and the corresponding policy rules by iterating over perceived temptation duration χ and episode t.

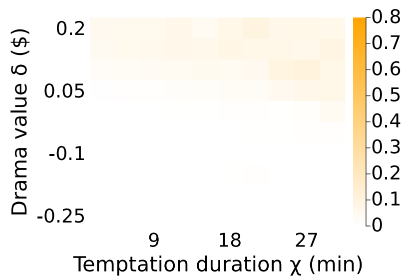
Top-up package choices. With the full solution in hand, I can characterize the conditions under which users purchase each top-up package. For better intuition, consider the case without taste shifters ($\nu_k \equiv 0$). When $t > 9$ and the token balance is $a_t = 0 < c_t$, the perceived value of top-up



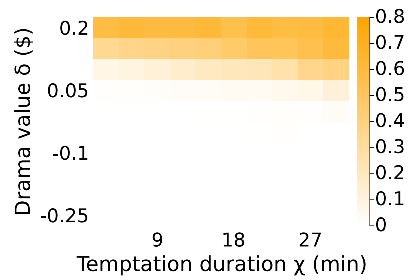
(a) Choice probability of $4.99



(b) Choice probability of $9.99



(c) Choice probability of $19.99



(d) Choice probability of $29.99

Figure 6: Choice probability of each top-up package between episodes 10 and 15

Notes: The four heat maps report the estimated choice probability of each top-up package between episode 10 and 15 conditional on value δ and temptation duration χ. The warmer the color, the larger the choice probability. The probabilities from the four figures do not sum to 1, with the gap being the share that choose the outside option ($k = 0$).

package k is given by:

$$\pi_{kt}(h; \delta, \psi, \chi) = EW_t(h, b_k; \delta, \psi, \chi) - \omega p_k. \tag{12}$$

The top-up choice, therefore, depends on the shape of the value function $EW_t(h, b_k; \delta, \psi, \chi)$, which is monotonically increasing in all its arguments. For illustration, I plot the estimated choice probability for each package, conditional on user type, in Figure 6.

The outside option ($k = 0$) yields a value of zero and will be selected if $\pi_k(h; \delta, \psi, \chi) < 0$ for all $k \in \{1, ..., K\}$, which typically occurs when users dislike the drama (low δ). When the intrinsic value δ is low enough, users will be unwilling to unlock the episode, regardless of their token stock, habit stock, or temptation duration. In this extreme scenario, $\lim_{\delta \to 0} \pi_{kt}(h; \delta, \psi, \chi) = -\omega p_k < 0$. Given the monotonicity and continuity, a cutoff value $\underline{\delta}(h, \psi, \chi)$ exists below which users will choose not to top up. As Figure 6 shows, users with lower δ are more likely to select the outside option, as indicated by the lower choice probability for all packages.

At the other extreme, the largest package becomes most desirable when users plan to watch many episodes, which occurs when they derive high intrinsic value δ. When δ is sufficiently large, users believe ex ante they will finish the entire series, turning the problem into cost minimization. The highest-priced package, which offers the lowest price per token, is thus chosen early on, for example, around period $t = 10$. By monotonicity and continuity, a cutoff value $\overline{\delta}(h, \psi, \chi)$ must exist above which users opt for the largest package K. This intuition is supported by Figure 6d, where most high-value users purchase the \$29.99 package between episode 10 and 15.

The medium-priced packages ($k \in \{1, \ldots, K-1\}$) are mostly purchased by users with medium intrinsic values, driven by varying durations of temptation. All else being equal, the longer this perceived temptation lasts, the more episodes the user anticipates watching. Mathematically, the value function $EW_t(h, a; \delta, \psi, \chi)$ increases more rapidly in a when $a \leq \chi$, and then slows down afterward. As a result, users with longer temptation durations are more likely to purchase higher-priced packages with more tokens. However, these users often continue topping up when running out of tokens again and ultimately finish the entire series, highlighting the self-control problem. This prediction is confirmed by the first three panels in Figure 6, where the average temptation duration increases with the price of the top-up packages purchased by users. The choice probability of these medium-priced packages therefore informs the distribution of temptation duration.

Unlocking choices. With sufficient tokens, the user will unlock an episode if and only if their perceived value exceeds the outside option, namely, $u_t(h, \delta, \psi, \chi, \epsilon) + \mathcal{C}_t(h, a; \delta, \psi, \chi) > 0$. Because both the flow utility and continuation value are monotonically increasing in drama value δ, habit stock h, and temptation duration χ, the unlocking decision follows a threshold rule: users will continue unlocking if and only if the combination of intrinsic value, habit stock, and temptation is sufficiently high. For identification, the unlocking decision thus provides information on the relative magnitudes of habit formation, temptation, and the drama's intrinsic value.

4.3 Discussion

I discuss my model assumptions in this section, with the goals of being transparent in my modeling choices, reasonings, and potential biases.

Sophistication. In my structural model, I assume users are naïve about their temptation beyond its duration, because the data lacks sufficient variation to identify their level of sophistication. This assumption aligns with most findings in the behavioral literature (DellaVigna, 2018; Augenblick and Rabin, 2019) and is commonly imposed in the structural analysis (DellaVigna, Lindner, Reizer, and Schmieder, 2017; Laibson, Chanwook Lee, Maxted, Repetto, and Tobacman, 2024). Moreover, I argue the estimated temptation would be even higher if the analysis included sophisticated users. As shown in Appendix A.2, sophisticated users avoid the self-control problem by anticipating it and choosing not to watch the drama. In their presence, the naïve users would need to exhibit even stronger addiction to account for the same level of the self-control problem given in the data. Thus, incorporating this sophistication would only strengthen my quantitative results.

Naïveté about habit formation. I model irrationality in my framework through temptation and the associated naïveté. As summarized in Allcott, Gentzkow, and Song (2022), irrational digital addiction can also stem from naïveté about habit formation. Although this type of irrationality could also lead to repeated top-up purchases, we would expect users to gradually shift to higher-priced top-up plans as their habit stock grows over time. However, this pattern is inconsistent with what is shown in Figure 4d, where users frequently purchase another $4.99 package, regardless of how many episodes they have watched. Thus, I conclude naïve temptation is the more relevant story in the context of this short drama.

Learning. For simplicity and tractability, I abstract from the model of learning, where Bayesian users infer the unknown drama quality δ based on the utility from previously watched episodes, and instead assume that users learn δ immediately after watching the first episode. Estimating an earlier version of this extended model reveals the learning effect is minimal, because users can reasonably infer δ after one or two episodes. Indeed, the empirical evidence suggests this learning process is not a primary driver of demand in the short drama industry.

First, Figure 3a shows viewership stabilizes quickly after the first two episodes, suggesting users efficiently assess the drama's quality early on. Similarly, in Figure C.3 of Appendix C.3, I demonstrate the conditional probability of continuing to the next 10 or one episodes increases significantly only during the first two episodes, after which it stabilizes. Moreover, the effect of learning on this conditional probability is negligible compared with the strong price effects observed around the 10th episode, providing further evidence that learning plays a minimal role in shaping users' drama-watching behavior.

Second, I show the user behavior persists even after they have watched many episodes. If learning played a central role, these users should have gained substantial information from their viewing history and, consequently, made more rational package-purchasing decisions. However, Figure 4d shows the time-inconsistent pattern prevails regardless of how many episodes users have watched. Furthermore, in Figure C.4 of Appendix C.3, I report the distribution of overpayment after the 40th episode, which aligns with the unconditional distribution shown in Figure 4c. These findings indicate learning cannot explain the observed irrational spending behavior.

Constant episode value. Instead of allowing the drama value to vary by episode, I assume users have a constant value δ to all episodes. This simplification is supported by the empirical observation that viewership evolves smoothly across episodes, as shown in Figure 3a. If episode values differed systematically, we would expect greater volatility in viewership patterns. Additionally, the random taste shifter ϵ_t captures idiosyncratic shocks for each episode, and its estimated magnitude (in section 5.2) is quite small, suggesting episode-specific value is not a key factor in explaining user behavior.

Network externality. Social media platforms often benefit from network externalities, which can contribute to user addiction (Barwick, Chen, Fu, and Li, 2024) or heighten the fear of "missing out" (Bursztyn, Handel, Jimenez, and Roth, 2023). I exclude this mechanism from my structural model for two main reasons. First, the platform analyzed here is small relative to mainstream social media, limiting potential network effects. Second, user utility on this platform is primarily driven by content–the short dramas–rather than social interaction, because users cannot message each other or leave comments on episodes.

Disutility from monetary payments. The behavioral literature emphasizes that when modeling present bias, the timing of payoffs should be linked to consumption rather than money receipt (DellaVigna, 2018). In my model, the price-sensitivity parameter, ω, can be interpreted as the discounted present value of spending each dollar as perceived by the user. Because present bias arises from the immediate entertainment of video consumption rather than the timing of monetary payments, this assumption is not critical for my analysis. Accounting for delayed consumption yields qualitatively similar results, reinforcing the robustness of my findings. DellaVigna and Malmendier (2006) present a similar argument.

5 Estimation

I estimate my demand model using individual-level data from the short drama platform. The estimation approach is detailed in section 5.1, and the results are reported in section 5.2.

5.1 Estimation approach

To map my model to the data, I assume users, indexed by i, differ in their values δ_i, temptation durations χ_i, and initial endowments a_{i1}. For each individual, the data includes observations on their unlocking history $\boldsymbol{d}_i$, round $\boldsymbol{r}_i$, habit stock $\boldsymbol{h}_i$, token stock $\boldsymbol{a}_i$, and selected top-up packages $\boldsymbol{k}_i^*$ and token amounts $\boldsymbol{b}_{ik^*}$ for every episode t they have watched. I define my estimator and then discuss the identification strategy.

Estimator. The parameters to be estimated are:

$$\boldsymbol{\theta} := \{ \underbrace{\mu_\delta, \sigma_\delta, \overline{\psi}, \beta_\epsilon}_{\text{intrinsic value}}, \underbrace{\kappa, \mu_\chi, \sigma_\chi}_{\text{temptation}}, \underbrace{\alpha_1, \alpha_2, \rho}_{\text{habit}}, \underbrace{\omega}_{\text{price sensitivity}} \}.$$

For intrinsic value, the parameters μ_δ and σ_δ represent the mean and standard deviation of the drama value δ, which follows a Gaussian distribution $\mathcal{N}(\mu_\delta, \sigma_\delta^2)$. The outside value during nighttime is captured by $\overline{\psi}$, and the dispersion of the unlocking taste shifter ϵ_t is captured by β_ϵ. Regarding temptation, κ represents its per-minute magnitude, whereas its duration χ follows a log-normal distribution $\log \chi \sim \mathcal{N}(\mu_\chi, \sigma_\chi^2)$. The habit-formation utility is modeled with a quadratic function parameterized by (α_1, α_2), and ρ controls for the likelihood that a round will end after watching an episode. Finally, ω represents price sensitivity.

Because the user value δ_i is unobserved, the standard Maximum Likelihood Estimator does not apply in this case. Therefore, I estimate my dynamic demand model using the Simulated Method of Moments (SMM) by minimizing a simulated criterion function:

$$\widehat{\boldsymbol{\theta}}_{SMM} = \arg\min_{\boldsymbol{\theta}} \left(\widehat{\boldsymbol{m}} - \widehat{\boldsymbol{m}}^S(\boldsymbol{\theta})\right)' \boldsymbol{W} \left(\widehat{\boldsymbol{m}} - \widehat{\boldsymbol{m}}^S(\boldsymbol{\theta})\right), \tag{13}$$

where $\widehat{\boldsymbol{m}}$ is a set of moments constructed from the observed data, and $\widehat{\boldsymbol{m}}^S(\boldsymbol{\theta})$ represents the average moments from S simulations of user behavior in the model (McFadden, 1989; Pakes and Pollard, 1989). The weighting matrix $\boldsymbol{W}$ is constructed via bootstrap, following Agarwal (2015). In each simulation, I simulate the sequence of top-up and unlocking decisions made by each user i, taking their initial endowment a_{i1} and the observed part of round sequence from the data. To ensure my estimator reaches a global solution to problem (13), I first conduct a series of grid searches to find an initial value close to the global optimizer, and then apply a local gradient-free Nelder-Mead algorithm to refine the optimization. Detailed estimation routines and intermediate results are documented in Appendix D.1.

I construct three categories of moments for estimation: habit stock, top-up package purchase, and unlocking. For habit stock, I target the probability of stopping after episode 9 among users with zero initial endowment, conditional on the user's last habit stock being $h_9 \leq 4$ or $h_9 \geq 5$. In addition, I include the average habit stock conditional on purchasing each top-up package. Second, for top-ups, I target the sales of each top-up package across different episode bins (10–20, 21–40, 41–60, and 61–80), which reveal the level and evolution of top-up choices. Regarding unlocking, I track the share of users unlocking the second and third episodes, as well as episodes 4–9, 10–14, and 15–80. These episode ranges are intended to capture the most informative changes in unlocking behavior, as shown in Figure 3a. I also target the fraction of viewership that occurs during nighttime. A complete list of moments is provided in Appendix D.1. All parameters are jointly identified from the selected moments, though certain moments provide more information for specific parameters, for which I discuss the intuition below.

Intuition for identification. I first discuss the identification of temptation, which is the only source of irrationality in the model that generates self-control problems. Therefore, the positive market share of medium-sized top-up packages (\$4.99, \$9.99, \$19.99) across all episodes, which reflect time inconsistency, provides insights into the magnitude of per-minute temptation κ. Furthermore, as discussed in section 4.2, users with longer-lasting temptation are more likely to choose higher-priced package, making the shares of different packages informative about the distribution of temptation duration (μ_χ, σ_χ).

Habit formation (α_1, α_2), representing the channel of rational addiction, is identified through variation in habit stock. Empirical evidence suggests users with higher habit stock are more likely to continue watching, which makes the conditional probability of stopping for users at different habit stock levels informative.[47] Moreover, habit formation influences both the flow and continuation value, affecting users' top-up package purchasing decisions. As a result, the habit stock conditional on top-up choices provides information about (α_1, α_2) and the perceived probability

[47] See Appendix C.1 for a complete discussion of related empirical patterns.

of losing habit stock in the next period, ρ.

The intrinsic value is identified from the "residual" variation in unlocking and top-up choices after accounting for the temptation and habit formation. As discussed in section 4.2, users with higher δ are more likely to purchase the $29.99 top-up package and unlock the entire series, whereas those with lower δ are more inclined to stop watching. Thus, the top-up shares of the $29.99 package, the outside option, and the fraction of users who complete the series provide variation to identify this distribution $(\mu_\delta, \sigma_\delta)$. The nighttime outside value $\overline{\psi}$ is informed by the fraction of users unlocking episodes during this period. Lastly, β_ϵ captures the impact of the unlocking taste shifter on each episode, with more negative shocks increasing the likelihood that users will stop watching. As a result, the overall viewership dynamics offer information on the magnitude of this static utility shock.

Finally, the price sensitivity, ω, is reflected in users' top-up choices when they pay with real money, making the market shares of top-up plans at different prices informative. Because these packages are virtual products with no distinguishing characteristics beyond their observed prices and token amounts, the identification of ω is free from the usual concerns about endogeneity.

5.2 Results

I report the estimation results for $\widehat{\boldsymbol{\theta}}_{SMM}$ in Table 5 and graphically in Figure 7. The targeted moments are displayed in Appendix D.2. The estimated price sensitivity is $\omega = 0.80$, which serves to normalize the magnitude of other components using real money (USD) as the numeraire. Accordingly, I use this numeraire in reporting all quantitative results.

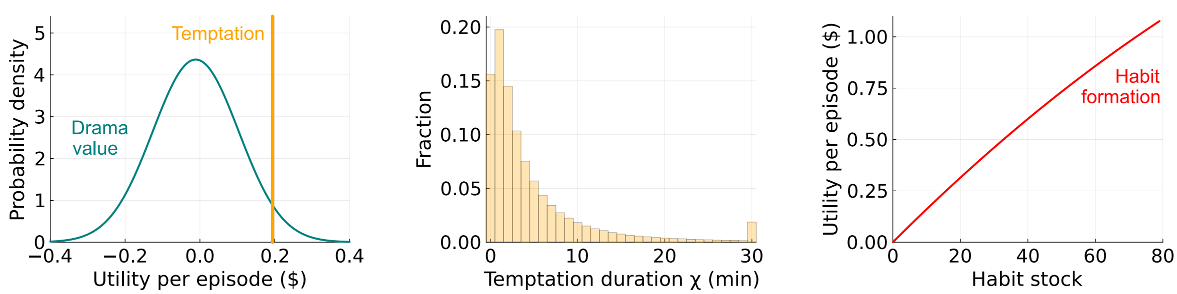
The first set of parameters describes the distribution of intrinsic value, which is also represented in Figure 7a. The estimated per-episode drama value δ has a mean of -0.0089 (-1.1¢) and a standard deviation of 0.091 (11¢). The outside value during nighttime is 0.015 (1.9¢) per minute, whereas the daytime outside value is normalized to 0. The idiosyncratic taste shifter ϵ has a scale parameter of 0.055, resulting in a standard deviation of 0.071 (8.8¢). These results indicate that, on average, users experience a net loss of 1.6¢ per one-minute episode compared with their outside options, highlighting the potential loss in user surplus.

Temptation is estimated at 0.15 (19¢) per minute, placing it at the 96th percentile of the drama value distribution. As shown in Figure 7b, temptation lasts an average of 4.7 minutes, with a standard deviation of 6.1 minutes and a long right tail from the log-normal distribution. Approximately 19% of users experience temptation lasting beyond 8 minutes (the duration covered by a $4.99 top-up package), whereas 5.8% have temptation exceeding 17 minutes (covered by the $9.99 package). Only 1.9% of users exhibit temptation durations over 30 minutes, for whom I set $\chi = 30$, which thereby supports my parametric assumption that temptation lasts less than 30 minutes. The large magnitude and short duration of temptation make self-control problems an important factor in drama-watching behaviors.

I identify a substantial degree of habit formation, as shown in Figure 7c. The estimated habit-

Table 5: Estimation: SMM estimators and standard error

Parameter	Estimator	Std	Meaning
1. Intrinsic value			
μ_δ	-0.0089	0.015	Mean of drama value distribution
σ_δ	0.091	0.025	Standard deviation of drama value distribution
β_ϵ	0.055	0.064	Magnitude of unlocking taste shifter
$\overline{\psi}$	0.015	0.014	Outside value during nighttime
2. Temptation			
κ	0.15	0.060	Magnitude of naive temptation
μ_χ	1.11	0.30	Mean of temptation duration (log)
σ_χ	1.10	0.49	Standard deviation of temptation duration (log)
3. Habit formation			
α_1	-2.8e-5	1.5e-6	Habit formation utility $\alpha(h) = \alpha_1 h (h - \alpha_2)$
α_2	464.78	5.9e-4	Habit formation utility $\alpha(h) = \alpha_1 h (h - \alpha_2)$
ρ	0.039	0.0075	Probability of entering next round after watching
4. Price sensitivity			
ω	0.80	0.041	Price sensitivity



(a) Relative magnitude (b) Temptation duration (c) Habit formation

Figure 7: Estimation: Intrinsic value, temptation, and habit formation

Notes: Panel (a) shows the estimated distribution of drama value δ (teal curve) alongside the temptation level (orange bar), all normalized in dollars using the estimated price sensitivity. Panel (b) displays the estimated distribution of temptation duration χ, which follows a lognormal distribution with an average of 4.7 minutes. For tractability, I cap χ at 30 for all values exceeding this threshold, affecting 1.9% of users. Panel (c) illustrates the estimated function for habit formation $\alpha(h)$, which is nearly linear with respect to users' habit stock.

formation function (depicted by the red curve) is convex and nearly linear in relation to habit stock, ranging from 0 to 0.86 ($1.1) per episode. Watching an additional episode in the round contributes, on average, 1.4¢ in per-episode utility via habit formation. This strong level of habit formation aligns with the high willingness to pay observed among users in the data. The estimated probability of a round change, ρ, is 3.9%, influencing users' decisions through their expectations of future habit formation.

Estimation results reveal that both temptation and habit formation are significant in this short-drama-series industry. The structural model leads to further decomposition of the perceived flow utility and comparison between the relative magnitudes of these two components, which I report in Appendix D.3.

6 Main results

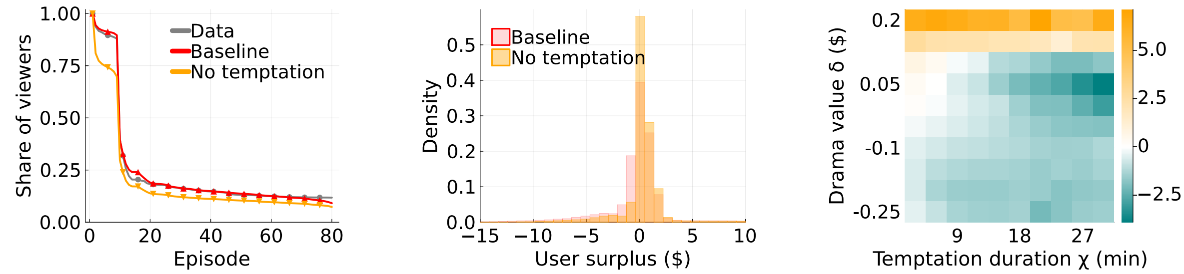
In this section, I present my quantitative findings on how short video length intensifies self-control problems. I begin by defining in section 6.1 the user surplus loss due to temptation. In section 6.2, I assess the comparative static over video length, demonstrating the magnitude of surplus loss due to the short form. Finally, in section 6.3, I examine a counterfactual policy that mandates a break before making top-up decisions.

6.1 Surplus loss due to temptation

To evaluate welfare implications and efficiency loss due to temptation, I define user surplus as the utility from both intrinsic value and habit formation. This metric represents the surplus that a rational user would seek to maximize, treating temptation as an irrational component. My analysis is qualitatively robust with other measures of welfare, such as the pure surplus using only the intrinsic value.

With temptation, even users who dislike the drama may continue watching multiple episodes, leading to potential surplus loss. Figure 8a illustrates the share of remaining viewers per episode. The baseline model prediction (red line) closely replicates the observed data pattern (gray line), validating the effectiveness of my structural estimation. Removing temptation by setting $\kappa = 0$ results in a substantial decline in viewer retention across episodes. For instance, without temptation, 19.1% of users stop watching after the first episode, versus just 5.6% in the baseline. By the final episode, only 7.3% of users complete the series, which is a 19.8% reduction from the baseline completion rate of 9.1%. This gap represents users who succumb to temptation and continue watching despite wishing they had stopped, indicating a significant surplus loss attributable to self-control problems.

I compute user surplus and report its distribution in the histogram of Figure 8b. In the baseline scenario (red bars), the average user derives a surplus of $0.33 from the drama series. However, 48.3% of users experience a negative surplus, with the most extreme one losing $32.8. Removing



(a) Share of viewers by episode (b) Surplus distribution (c) Surplus by user type

Figure 8: User surplus and the loss due to temptation

Notes: I present the model outcomes with and without temptation. The counterfactual scenario without temptation is obtained by setting $\kappa = 0$. Panel (a) displays the predicted share of remaining viewers per episode with temptation (red line) and without temptation (orange line), alongside the observed data (gray line). Panel (b) shows the histogram of user surplus under both conditions, with red bars representing the baseline model and orange bars depicting the no-temptation scenario. Panel (c) shows the baseline distribution of surplus for users with different temptation duration χ and drama value δ. The surplus is more negative when the color is colder, and more positive when warmer.

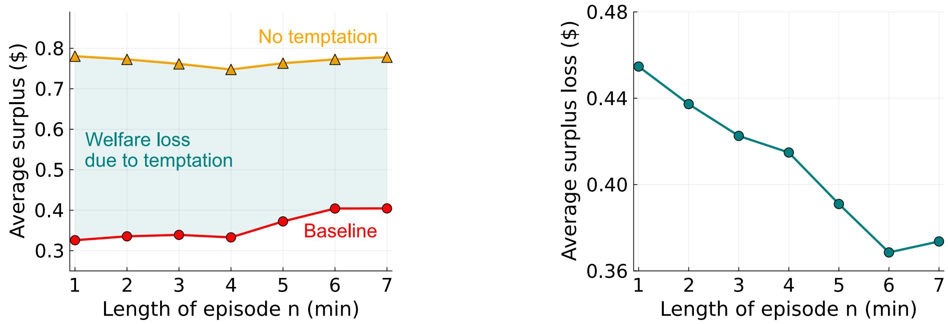
temptation (orange bars) significantly reduces the share of negative-surplus users, while those with positive surplus remain unaffected, indicating temptation primarily impacts users who dislike the drama. Without temptation, the average surplus rises to \$0.78. The resulting surplus gap of \$0.45 per user quantifies the *average surplus loss due to temptation*, serving as a key welfare metric for evaluating its broader implications.

Figure 8c further reports the baseline user surplus using a heat map, which follows a U-shaped relationship with respect to drama value δ. Intuitively, users with the highest drama values δ achieve the greatest rational surplus regardless of temptation duration, whereas those with the lowest δ stop after only a few episodes and incur a small negative surplus. Users with mid-range δ, however, suffer the most from self-control problems, leading to the largest surplus losses. Additionally, user surplus generally declines with longer temptation duration χ. Users with very short temptation durations (represented near the y-axis) experience mostly positive surplus, suggesting near-rational behavior, whereas those with longer χ and low δ mostly experience surplus losses. This result aligns with the stylized model that users who are more deeply tempted are more likely to remain locked into content they dislike.

6.2 Short length amplifies self-control problems

Using a comparative static exercise that changes the episode length, I now investigate into the mechanism of short length amplifying self-control problems. Specifically, I evaluate the effects of counterfactual policy that sets a minimum episode length. Other industries have implemented a similar approach, such as with US laws on "loosie," which require cigarettes to be sold in packs of at least 20.

In this exercise, I keep the length of the first nine free episodes unchanged to avoid interaction



(a) Average user surplus

(b) Surplus loss due to temptation

Figure 9: Comparative static: Episode length and user surplus

Notes: These figures illustrate the counterfactual effects of setting a minimum episode length on user surplus. Panel (a) shows the average user surplus with temptation (red line) and without temptation (orange line). The gap in between (teal area) represents the surplus loss due to temptation. Panel (b) plots the evolution of this surplus loss with regard to the episode length n.

with the dynamic pricing rule. For subsequent episodes, let $n \in \mathbb{N}$ represent the counterfactual episode length, effectively merging n consecutive original one-minute episodes into a single and longer episode.[48] Let τ denote the index for these counterfactual episodes, with each τ containing a set of original episodes, $Q_\tau \subset \{1, ..., T\}$. As in the stylized model in section 2, I assume users must watch the entire episode once it is unlocked. The perceived flow utility thus becomes:

$$\tilde{u}_\tau(h, \delta, \psi, \chi, \epsilon; n) = \mathbb{E}_\tau \left[n\delta - \sum_{t \in Q_\tau} \psi_t + \sum_{t \in Q_\tau} \alpha(h_t) + \max\{\chi, n\}\kappa + \sum_{t \in Q_\tau} \epsilon_t \right], \tag{14}$$

where the expectation is conditional on information from the first original episode in set Q_τ.[49] As in the stylized model, the addiction-reduction effect of this policy arises from the dampening of temptation, represented by the $\max\{\chi, n\}$. Using the same top-up framework, this counterfactual model can be solved similarly to the baseline.

Figure 9 presents the welfare outcomes of this comparative static exercise as episode length (n) increases from one to seven minutes.[50] As n increases, baseline user surplus gradually rises from \$0.33 to \$0.40, reflecting a 24.3% increase. By contrast, the no-temptation surplus remains stable at approximately \$0.77, as episode length only affects outcomes through its interaction with temp-

[48] I use one minute as the unit of time and examine the effects of a policy that restricts episode length to n minutes. The reason for not using a smaller time unit is that the platform faces inherent constraints in minimizing episode length; the drama format requires a certain amount of time to convey a coherent narrative arc and engage viewers emotionally. Extremely short episodes would disrupt the storytelling flow, weakening dramatic buildup and reducing viewer attachment to characters and plot. I therefore assume one minute–the current episode length–is the minimum feasible length, reflecting the platform's optimized balance between narrative depth and user engagement.

[49] I assume users observe the information for the first original episode in Q_τ, including habit stock, outside value, and taste shifter, and form beliefs about subsequent episodes. This assumption ensures users have the same amount of information when making decisions compared with the baseline.

[50] We exclude cases where $n > 8$ to avoid interactions with the top-up package menu, because the \$4.99 package covers an average of seven episodes.

tation. Consequently, the average surplus loss due to temptation (teal line) declines from \$0.45 to \$0.37, representing an efficiency gain of 17.8% by increasing the length to seven minutes. This result quantitatively confirms the mechanism proposed in Proposition 2, demonstrating shorter episode lengths exacerbate self-control problems.

6.3 Counterfactual policy: Mandatory break during top-up

I now turn to policy interventions designed to mitigate the effects of self-control problems. Building on the concept of ad breaks discussed in section 2.4, I consider a counterfactual policy that mandates a break when users face a top-up decision, by introducing a required ad of ϕ minutes. During this time, users experience their outside value but derive no intrinsic utility from the ad itself, nor do they feel tempted to continue watching it.[51] Thus, mandatory ads serve as a mechanism to shorten the duration of temptation at the moment of the top-up decision.

To incorporate such a feature in my model, I adjust the (expected) value function of top-up equations (7) and (8) with a mandatory break accordingly:

$$\begin{aligned} V_t^B(h, a; \delta, \psi, \chi, \boldsymbol{b}, \boldsymbol{\nu}) = \quad & \mathbb{1}\{a < c_t\} \max_k \left\{ EW_t(h, a + b_k; \delta, \psi, \max\{\chi - \phi, 0\}) - \omega p_k + \nu_k \right\} \\ & + \mathbb{1}\{a \geq c_t\} EW_t(h, a; \delta, \psi, \chi), \end{aligned} \tag{15}$$

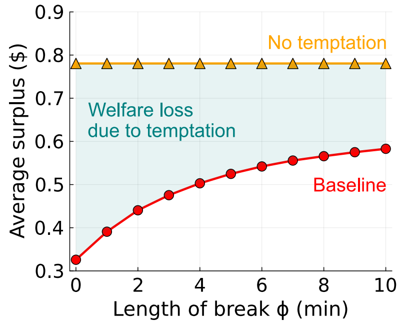
$$\begin{aligned} EV_t^B(h, a; \delta, \psi, \chi) = \quad & \mathbb{1}\{a < c_t\} \mathbb{E}_{\boldsymbol{b}} \left[\log \left(\sum_{k=0}^{K} e^{EW_t(h, a+b_k; \delta, \psi, \max\{\chi - \phi, 0\}) - \omega p_k} \right) \right] \\ & + \mathbb{1}\{a \geq c_t\} EW_t(h, a; \delta, \psi, \chi), \end{aligned} \tag{16}$$

which, combined with the unlocking (expected) value functions (10) and (11) and terminal condition (6), define the new system of value functions. This mandatory break effectively reduces the user's perceived temptation duration into $\max\{\chi - \phi, 0\}$ when making top-up decisions. The solutions to this system yields the decision rules for each individual user under this counterfactual policy.

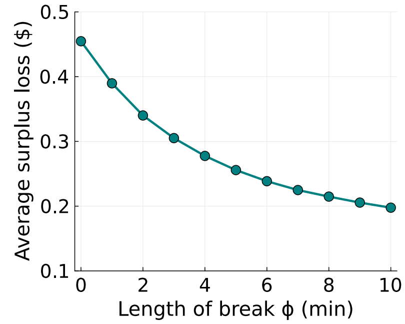
I report the counterfactual user surplus in Figure 10. Panel 10a shows average user surplus increases rapidly with the length of the ad break (ϕ). Compared with the no-break benchmark ($\phi = 0$), a two-minute ad break raises user surplus from \$0.33 to \$0.44, a 35.2% increase. The policy has no effect in the absence of temptation, resulting in a constant no-temptation surplus of \$0.78. Consequently, the surplus loss due to temptation—measured by the gap between baseline and no-temptation surplus—declines sharply as ϕ increases.

Panel 10b shows a two-minute break reduces surplus loss from \$0.45 to \$0.34, representing a 25.2% efficiency gain. A 10-minute break further reduces average surplus loss to \$0.20, yielding a 56.5% improvement. This exercise confirms the prediction in Proposition 3 and demonstrates

[51] The assumption that users derive outside value during ads reflects the reality that they often engage in other activities while ads play, ensuring the policy does not mechanically alter welfare. This assumption likely underestimates the policy's effectiveness—if users actively dislike ads and experience negative utility, the policy's impact on reducing addiction would be even greater.



(a) Average user surplus



(b) Surplus loss due to temptation

Figure 10: Counterfactual policy: Mandatory ad break with length ϕ

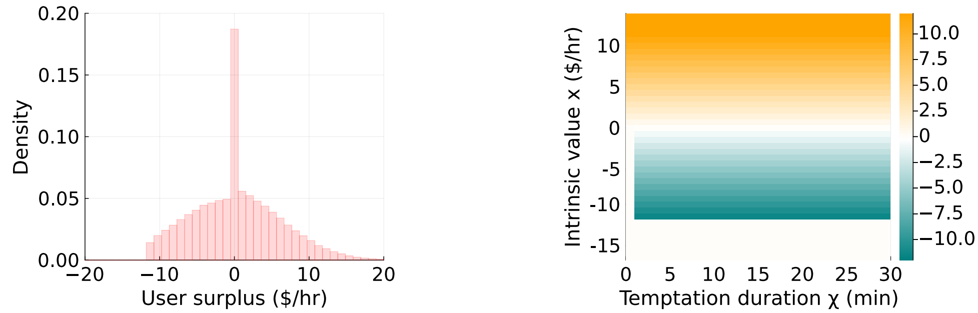
Notes: These figures illustrate the counterfactual effects of an ad break of length ϕ at the top-up decision. Panel (a) shows the average user surplus with temptation (red line) and without temptation (orange line). The gap in between (teal area) represents the surplus loss due to temptation. Panel (b) plots the evolution of this surplus loss with regard to the break length ϕ.

such a policy could generate substantial welfare benefits for users.

7 Extension: From short dramas to short videos

I extend my structural analysis on the short drama platform to a broader short video platform such as TikTok. The key distinction is that TikTok does not charge users, and TikTok videos are not interconnected like episodes in a drama series. Thus, I revert to the stylized model in section 2, omitting both payment and habit formation. For the quantitative analysis, I use the estimated temptation parameter, κ, along with the distributions for intrinsic value ($x := \delta - \psi$) and temptation duration (χ) from my structural estimation reported in Table 5 and Figure 7. Because the stylized model does not predict stopping behavior, I focus on hourly outcomes when users are given an hour of short videos.

User surplus. When given an hour of short videos, the average sample user derives a surplus of \$0.28. Approximately 13.8% of users choose not to watch any videos. However, as shown in Figure 11a, 41.9% of users experience welfare losses due to the platform, with an average loss of \$4.80 and the most affected losing up to \$11.6 in surplus per hour. These losses contribute to an overall average hourly surplus reduction of \$2.01 due to temptation. Figure 11b further breaks down user surplus by type, characterized by temptation duration χ and intrinsic value x. Non-tempted users ($\chi = 0$) behave rationally, watching only when their intrinsic value is positive. By contrast, tempted users ($\chi > 0$) with negative valuations ($-\kappa \leq x < 0$) continue watching due to self-control problems, leading to the surplus losses represented by the blue area. The significant welfare loss highlights opportunities for policy intervention.



(a) Distribution of user surplus

(b) User surplus by type

Figure 11: Extension: Users' hourly surplus on short video platforms

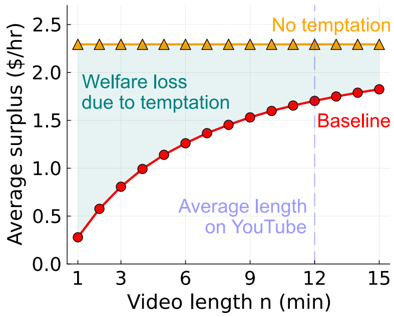
Notes: Panel (a) is the histogram of users' hourly surplus under the context of short videos. Panel (b) reports the user surplus conditional on user type (χ, x).

Short length amplifies self-control problem. I begin by quantifying the effects of increasing video length, as outlined in Proposition 2. Figure 12a presents the average hourly surplus for different video lengths (n). The baseline hourly surplus (red line) rises significantly with n, increasing from \$0.28 at $n = 1$ to \$1.70 at $n = 12$, the average length of YouTube videos.[52] In the efficient benchmark without temptation (orange line), the average user surplus is \$2.29 per hour for all n. Consequently, the hourly surplus loss due to temptation declines from \$2.01 to \$0.59, representing a 70.6% efficiency gain when extending video length to the average YouTube length. Figure 12b further illustrates the distribution of these surplus gains as video length increases from $n = 1$ to $n = 12$. Users with short-duration temptation and low intrinsic valuations benefit the most, because longer videos help mitigate self-control problems. These findings align with the theoretical predictions in Proposition 2 and Figure 1a.

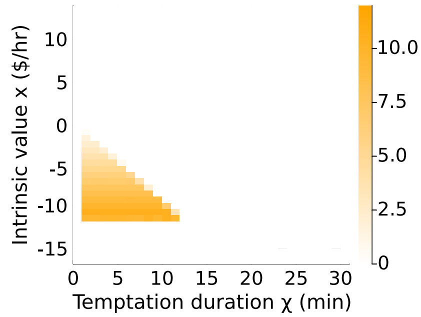
Counterfactual policy: Mandatory ad break. I now consider a more practical policy, mandating an ad break for every $\lambda = 15$ minutes of usage, on the short video platform. As described in section 2, I model the mandatory ϕ-minute break as a period of ads during which users experience a negative infinitesimal utility and face no temptation. Proposition 3 suggests users with $x \in (-\kappa, 0)$ would watch the first few videos because the temptation outweighs their disutility. However, when faced with the ad break, users whose temptation duration is shorter than the break ($\chi \leq \phi$) will calm down and stop watching. Meanwhile, users with longer temptation duration will sit through the break and resume watching. As in the short drama case (section 6.3), the mandatory break works by effectively shortening users' temptation duration, thereby reducing the self-control problem and enabling them to more easily stop watching addictive content.

Quantitatively, Figure 12c illustrates the welfare effects of this policy. Compared with the no-break benchmark ($\phi = 0$), mandating an ad break significantly increases average user surplus (red

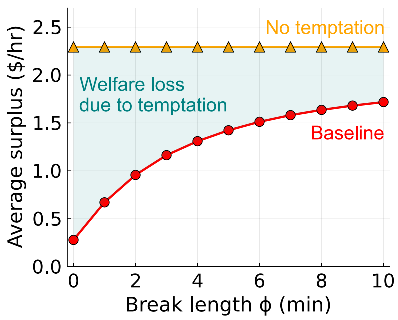
[52] As of December 2018, the average video length on YouTube was 11.7 minutes (Source: Statista).



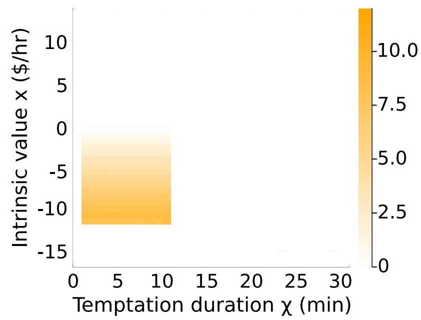
(a) Surplus with varying length n



(b) Distribution of surplus gain ($n = 12$)



(c) Surplus with varying break length ϕ



(d) Distribution of surplus gain ($\phi = 10$)

Figure 12: Extension: Welfare implication on short video platforms

Notes: These figures report the counterfactual effects of increasing video length n and introducing ad break of length ϕ in the short-video-platform setup. Panels (a) and (c) show the average user surplus with temptation (red line) and without temptation (orange line). The gap in between (teal area) represents the surplus loss due to temptation. Panels (b) and (d) plot the distribution of surplus change from the baseline ($n = 1, \phi = 0$) to the counterfactual cases with $n = 12$ and $\phi = 10$, respectively.

line). For instance, a 10-minute break raises hourly surplus from \$0.28 to \$1.72, reducing surplus loss due to temptation by \$1.44 (a 71.4% improvement). In terms of distributional effects, Figure 12d shows the efficiency gains primarily benefit users with short-duration temptation, reinforcing the insights from Proposition 3. Users with lower intrinsic valuations experience the greatest benefits, because the policy helps them avoid self-control traps.

Aggregate welfare implication. Finally, I examine the welfare implications for TikTok through a back-of-the-envelope calculation. According to a 2024 eMarketer survey, the average U.S. TikTok user spends 58.4 minutes per day, or 29.2 hours per month, on the platform.[53] This usage translates to an average monthly surplus of \$9.3 per active user relative to their outside options. However, self-control problems lead to a substantial reduction in surplus, with an average monthly loss of \$68.3 due to temptation. Comparative static analysis suggests short video length is a key driver

[53]Source: https://www.emarketer.com/content/5-charts-on-video-marketing-momentum

of this efficiency loss. Extending video length to the average YouTube length (12 minutes) could increase the average monthly surplus to \$57.7, recovering \$48.3 (70.7%) of the surplus lost due to temptation. Similarly, implementing a 10-minute break after every 15 minutes of usage could raise the average monthly surplus to \$58.2, recovering \$48.8 (71.4%) of the loss.

Given TikTok's large user base and the addictive nature of short videos, the aggregate welfare effects are substantial. With 150 million monthly active US users reported in March 2023, TikTok's total monthly consumer surplus is estimated at \$1.4 billion. However, 72.9 million of these users (48.6%) suffer from self-control problems, contributing to an estimated monthly welfare loss of \$10.2 billion. Imposing a 10-minute break after every 15 minutes of usage could recover \$7.3 billion per month, demonstrating significant potential to enhance user welfare.

8 Conclusion

This paper explores how small quantities amplify addiction, applying a theoretical framework to the short video industry. I find social media platforms offering short-form videos exploit users' self-control problems, leading to substantial losses in consumer surplus. Comparative statics reveal that shorter video lengths intensify user addiction, whereas policies mandating breaks can effectively reduce these self-control problems and alleviate the economic impact of social media addiction. My quantitative works provide an evaluation of potential policies in reducing self-control problems. A follow-up field experiment is desirable to verify the economic mechanisms and the magnitude of policy gain.

The implications of this study extend beyond social media. Evidence shows consumers frequently purchase small packages of goods (e.g., beer) at a premium, even when buying larger quantities would save money—a behavior likely driven by self-control problems similar to those observed in short video consumption. Additionally, regulatory policies, such as laws mandating cigarettes be sold in packs of at least 20, reflect an understanding of how quantity restrictions can reduce irrational addiction. By connecting these diverse contexts, this paper highlights a broader economic principle: restrictions on quantity or access may serve as effective tools in curbing addictive behaviors across various industries.

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Appendix

Appendix A Model

Appendix A.1 Represent temptation with present-biased preferences

In this section, I demonstrate my model of temptation can be micro-founded within a class of standard quasi-hyperbolic discounting models. This formulation shows that the economic insights derived from my baseline model can be generalized within the classic present-biased preference framework.

Consider a large set of one-minute videos $\{1, ..., T\}$, where each minute represents a unit of time. At any given moment, the agent chooses between watching videos and working (the outside option). Working provides future utility u_0 per minute, whereas watching a video yields immediate utility $u_0 + x$. Consistent with the baseline model, x captures the intrinsic utility of watching a video relative to the agent's outside option.

Regarding time preferences, I assume the agent is present-biased, with the present defined as a window of χ minutes. Let δ denote the standard per-minute discount factor. Following the quasi-hyperbolic discounting framework, the agent over-discounts future utility beyond χ minutes by a factor of $\beta < 1$. The discounted perceived utility at time 0 is therefore:

$$\widetilde{U}^0 = \sum_{\tau=1}^{\chi} \left[\delta^\tau \max\left\{u_0 + x, \beta u_0\right\}\right] + \sum_{\tau=\chi+1}^{+\infty} \left[\delta^\tau \max\left\{\beta(u_0 + x), \beta u_0\right\}\right], \tag{A.1}$$

where the immediate utility from watching videos $u_0 + \kappa$ is not discounted by β within the next χ minutes of perception.

Given the preference structure in (A.1), the set of users experiencing self-control problems can be characterized as:

$$-(1-\beta)u_0 \leq x \leq 0. \tag{A.2}$$

Agents with $x \leq 0$ should not watch any videos. However, due to present bias, those with $x \geq -(1-\beta)u_0$ find video-watching more appealing because $u_0 + x \geq \beta u_0$, making them willing to watch videos for the next χ minutes. These users fall into a self-control trap, as their bias continually shifts toward the next set of future videos, leading them to consume more than they initially intended.

This quasi-hyperbolic discounting specification serves as the micro foundation for my baseline model of temptation. The temptation duration χ can be equivalently interpreted as the span of present bias, whereas the magnitude of temptation κ is micro-founded in present bias, taking the value $(1-\beta)u_0$. This equivalence demonstrates that the economic insights derived from my baseline model are directly applicable to the standard present-biased preference framework.

Appendix A.2 Solution for sophisticated users

Sophisticated users recognize their preferences will shift as they continue watching videos. Those with $x \in (-\kappa, 0)$ can anticipate self-control problems, meaning they understand that once they start watching, they will be unable to stop. Their perceived value of watching the first video is given by:

$$\widetilde{U}^1_{sophisticated} = \underbrace{\chi(x+\kappa)}_{\text{videos within temptation duration}} + \underbrace{(T-\chi)x}_{\text{videos beyond temptation duration}}, \tag{A.3}$$

where the first term captures the positive perceived utility from videos consumed within the temptation duration, whereas the second term reflects the negative intrinsic utility associated with videos watched beyond that period.

Thus, sophisticated users will choose not to watch at all if:

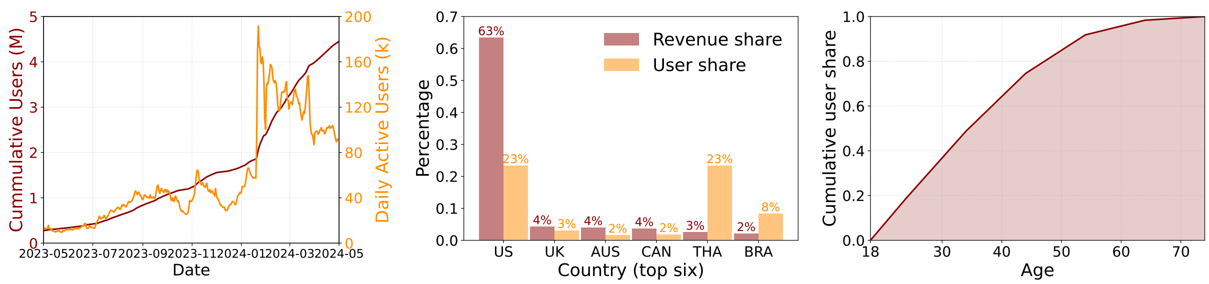
$$\widetilde{U}^1_{sophisticated} < 0 \quad \Leftrightarrow \quad x < -\frac{\chi}{T}\kappa. \tag{A.4}$$

For sufficiently large T, this condition converges to $x < 0$, implying only users with positive intrinsic value will choose to watch videos. As a result, self-control problems diminish among sophisticated users.

Appendix B Background

I provide further details on the platform in this section, including the descriptive facts on users, dramas, revenue, pricing, and the supply-side details.

Users. The platform size and user characteristics are summarized in Figure B.1. According to panel (a), the total number of users has reached 4 million worldwide and the Daily Active Users (DAU) remains around 100,000 by the May of 2024. Figure B.1b shows a large fraction of users are from US (23%), Thailand (23%), and Brazil (8%), whereas most of the platform revenue is contributed by US users (63%). Country boundaries create a natural form of market segmentation, and I therefore focus on the biggest market, the US market, in our main analysis. Panel B.1c indicates users of this platform are mainly young people, with 36% aged below 30, 63% below 40, and 85% below 50.

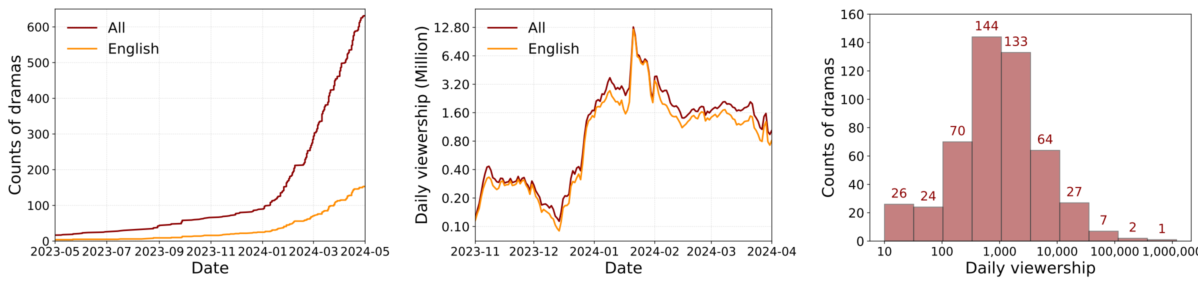


(a) Number of users (b) Geographical distribution (c) Cumulative distribution of age

Figure B.1: Users on the platform

Notes: Panel (a) shows the evolution of the accumulative number of users (left, red) and the daily active users (right, orange) between May 2023 and May 2024. My sample period is highlighted by shaded areas. Panel (b) reports the six countries with the highest revenues and most users up to May 8, 2024. Panel (c) displays the cumulative distribution function of age for new users who entered between March 1, 2024, and May 14, 2024. These aggregate data are directly provided by the platform.

Drama. I report the number and viewership of dramas in Figure B.2. Figure B.2a shows the evolution of the number of drama-language pairs over time. Over my sample period, the total number of drama-episode pairs increased from 67 in November 1, 2023, to 461 in March 31, 2024, where the number of English dramas increased enormously from 16 to 114. The corresponding viewership trends are displayed in Figure B.2b. Consistent with the geographical distribution in Figure B.1b, 83% of viewership during my sample period is in English. The daily viewership is 1.7 million episodes on average, which increased drastically in January 2024 due to the introduction of one "superstar" drama. I further report the distribution of daily viewership in Figure B.2c, which showcases a remarkable heterogeneity between dramas. The superstar drama, which was introduced on January 19, 2024, has about 1 million daily viewership, whereas most dramas have viewerships below 10,000 per day.



(a) Number of dramas (b) Aggregate viewership (c) Viewership distribution

Figure B.2: Drama entry and viewership

Notes: Panel (a) shows the evolution of the number of drama-language pairs on this platform over time. The shaded area indicates for the sample period for my study. Panel (b) reports the aggregate viewership of dramas over my sample period for all dramas and English dramas. Panel (c) plots the distribution of viewership on drama-language level. Note that viewership is displayed in log scale in both the y-axis of panel (b) and x-axis of panel (c).

Revenue. I present the time-series sequence of the three revenue sources in Figure B.3. The main source of all time is the token income, whereas the revenue from subscription has been increasing quickly since February 2024. The ad revenue remains at a relatively low level for the whole sample period.

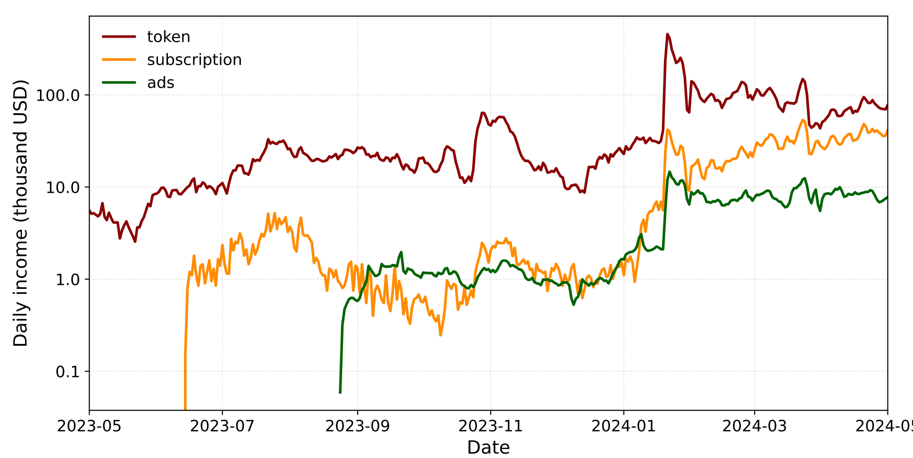
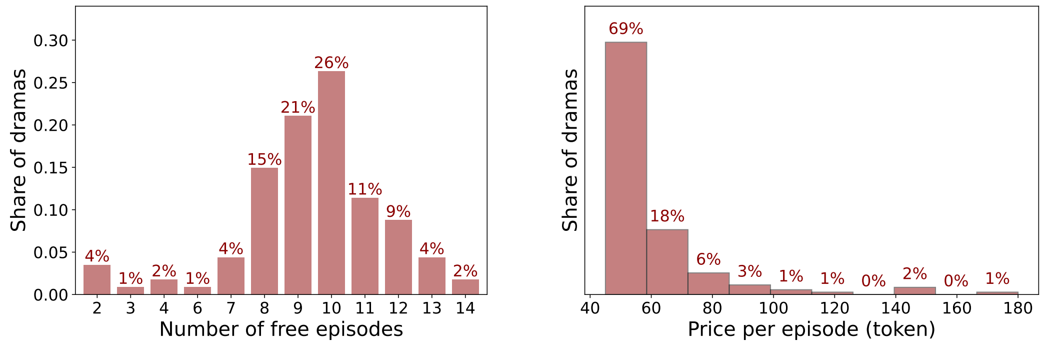


Figure B.3: Three sources of revenue: Token, subscription, and ads

Notes: This figure shows the evolution of different daily revenue sources. My data for subscription and ads started in June 2023 and August 2023, respectively. The level of revenue is displayed in log scale on the y-axis.

Drama pricing. In Figure B.4a, I report the length distribution of free episodes for each drama. Most dramas have eight to 10 free episodes to attract users, whereas the minimum and maximum numbers are two and 14. Figure B.4b displays the price distribution of episodes by dramas in terms of platform tokens. Within a drama, each episode costs the same amount of tokens to unlock, whereas price varies substantially across dramas. Most drama episodes are priced between 45 and 80 tokens.



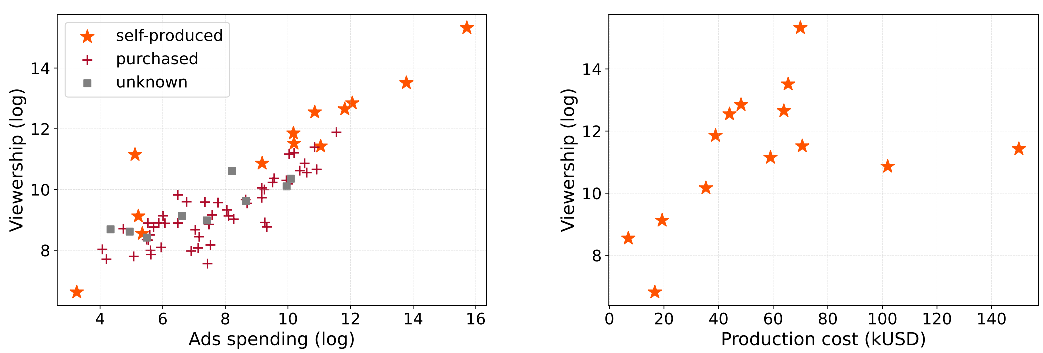
(a) Length of free episodes

(b) Price per episode

Figure B.4: Drama prices and token purchase

Notes: Panel (a) shows the distribution of the number of free episodes by dramas for all English dramas in my sample. Panel (b) plots the distribution of price per episode for those dramas.

Drama supply. In Figure B.5a, I show a positive relationship between ads spending and total viewership on drama level. Consistent with the aggregate description, self-produced dramas in general have higher ads spending and viewership. Conditional on ads spending, self-produced dramas also have higher viewerships than purchased ones, which indicates for some unobserved quality differences. I also observe the total production costs for platform-owned dramas, which are plotted in Figure B.5b against their total viewership. The production costs for dramas are fairly low, because most dramas are produced with costs below \$80,000. In general, dramas that cost more are more popular among users, highlighting the need to consider heterogenous quality among different dramas.



(a) Ads spending

(b) Production cost

Figure B.5: Drama ownership, ads spending, and production cost

Notes: Panel (a) plots the total viewership and total ads spending between November 1, 2023, and March 31, 2024, for each drama. The plot distinguishes three types of ownership: self-produced (orange, star), purchased from independent producers (red, square), and dramas whose ownership is unknown to me (grey, circle). In panel (b), I plot the production costs for self-produced dramas against their total viewership.

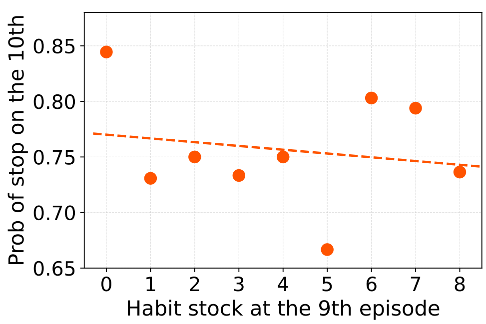
Appendix C Empirical Evidence

I present more empirical evidence from the platform to complements my main analysis.

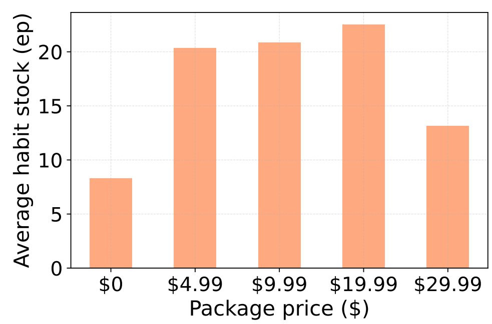
Appendix C.1 Rational addiction

In Figure C.1, I provide suggestive evidence of habit formation in users' drama-watching behaviors, which is commonly interpretted as rational addiction (Becker and Murphy, 1988). Panel C.1a shows the fits of regression described in section 3.4. Among users who have to top up before unlocking the 10^{th} episode of the superstar drama, a negative relationship exists between the likelihood of stopping and the corresponding habit stock. Those with one additional unit of habit stock are, on average, 0.3% more likely to continue watching.

Panel C.1b shows the average habit stock conditional on selecting each top-up package. A higher-priced package is in general selected by users with higher habit stock, supporting the habit-formation effect. The drop for the \$29.99 package is mechanical, because users no longer need the largest package when they have already watched most episodes, and few remain to unlock.



(a) Conditional probability to stop



(b) Top-up package choice

Figure C.1: Suggestive evidence on rational addiction (habit formation)

Notes: Panel (a) shows that, among users who have to top up before unlocking the 10^{th} episode of the superstar drama, a negative relationship exists between the likelihood of stoping and the corresponding habit stock. Those with one additional unit of habit stock are, on average, 0.3% more likely to continue watching. Panel (b) presents the average habit stock based on the top-up package choice, where higher-priced packages are generally chosen by users with higher habit stock, indicating habit formation. The drop for the \$29.99 package is mechanical, because users no longer need the largest package when they have already watched most episodes and few remain to unlock.

Appendix C.2 Viewership conditional on time of a day

Figure C.2 reports the number of unlockings conditional on hour of a day (Eastern time). It suggests the usage between 1am and 10am is below average, depending on which I define the "night-time" outside option for my structural analysis.

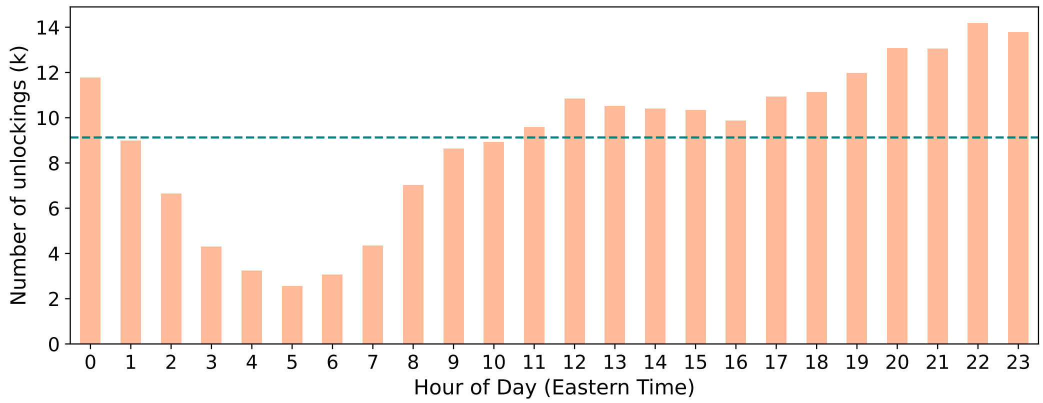


Figure C.2: Usage conditional on time of a day

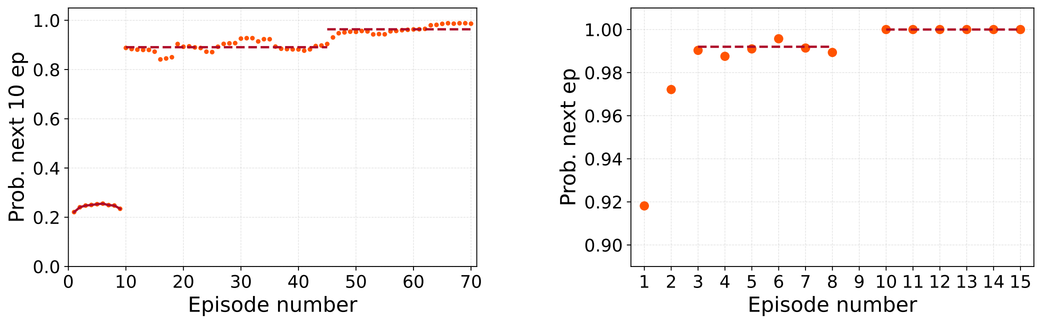
Notes: This figure represents the total number of unlocking activities that happened in each hour of a day within my sample. The hour is based on Eastern time. The teal, dashed line is the average number of unlocking per hour.

Appendix C.3 Minimal learning effect

In this section, I provide evidence that learning or information effects are not the primary drivers of users' drama-watching behavior. Two key observations support this conclusion. First, the conditional probability of continuing to watch stabilizes within one or two episodes, indicating learning happens quickly, making the assumption of perfect information reasonable. Second, drama-watching patterns remain consistent even after 40 episodes, suggesting the influence of learning is minimal.

Evidence 1: The probability of continuing watching stabilizes quickly. In Figure C.3a, I present the evolution of the probability of continuing to the next 10 episodes, conditional on each episode. This probability initially rises from 22.1% at the first episode to 24.8% by the third, and then stabilizes around 25% until the ninth episode. A sharp increase occurs at the 10th episode—when users must start paying for new episodes—pushing the probability to 89.1%, where it remains stable between episodes 10 and 45. As the show nears its conclusion (episodes 45–70), the probability of continuing rises further to 96.3%. This analysis yields two key insights. First, the conditional probability increases significantly only during the first two episodes, after which it stabilizes quickly, suggesting learning occurs rapidly. Second, the price effect at the 10th episode is substantial, causing a 64.1-percentage-point increase in the continuation probability, whereas the learning effect accounts for only a few percentage points overall. Thus, I conclude learning plays a minimal role in shaping users' drama-watching behavior.

These insights are further confirmed in Figure C.3b, which illustrates the evolution of the conditional probability of continuing to the next episode. Initially, this probability is relatively low, at 91.8% for the first episode and 97.2% for the second. From the third episode onward, it stabilizes around 99%, indicating any learning effect occurs primarily within the first two episodes.



(a) Next 10 episodes (b) Next episode

Figure C.3: Conditional probability of watching the next few episodes

Notes: This set of figures presents the probability that a user will continue watching 10 (panel (a)) or one (panel (b)) conditional on watching each episode. The orange circles are the conditional probability, whereas the red, dashed lines provide fitted values. For a clean comparison, the conditional probability is calculated among users with zero initial token endowment.

Evidence 2: Persistent overpayment even after 40 episodes. Figure C.4 provides further evidence of overpayment among users who have already watched 40 episodes. If learning played a central role, these users should have gained substantial information from their viewing history and, consequently, made more rational package purchasing decisions. However, 33.6% of users continue to overpay for tokens, with an average overpayment of $2.79 for the remaining 40 episodes. Both figures are substantial and closely align with the unconditional distribution reported in Figure 4c, where 39.1% of users overpay, with an average overpayment of $5.51 for 80 episodes. This consistency suggests that the observed irrational spending behavior cannot be attributed to learning.

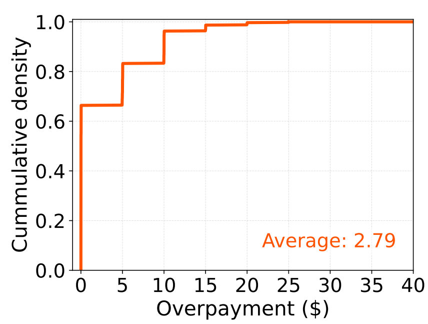
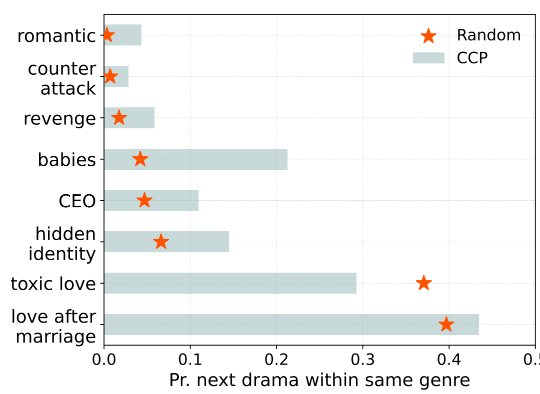


Figure C.4: Distribution of overpayment after the 40th episode

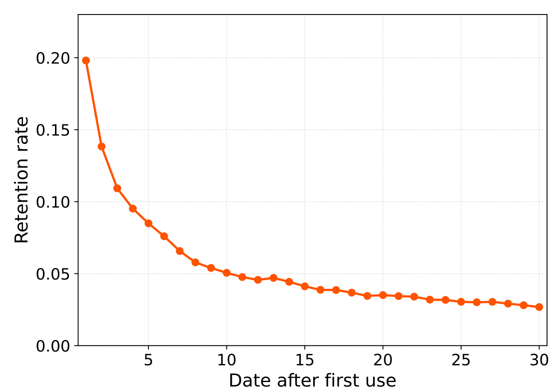
Notes: This figure presents the cumulative distribution of overpayment among users who made at least one package purchase after the 40th episode, following the same idea as the unconditional distribution in Figure 4c. Overpayment is measured relative to the optimal spending, imputed using the average token quantity in each package from Table 4. The natural lower bound for overpayment is 0.

Appendix C.4 No spillover across dramas

I do not find evidence for addiction beyond a drama, which justifies my analysis on the single, superstar drama. I check the history dependence on the level of both genre choice and platform usage. In Figure C.5a, I report the conditional choice probability (CCP) of a user who has just finished one drama to watch another drama that shares the same genre (the teal bar), along with the probability if the user just randomly selects the next drama following the empirical distribution (the orange star). The results show no sizable difference between the two, let alone the fact that user selection may mechanically make CCP greater than random probability. I therefore conclude no significant addiction occurs on the genre level. On the platform level, I plot the retention rates in Figure C.5b, which is defined as the fraction of users who are still active on the X^{th} day after their first appearance. The retention rate is fairly low relative to other digital platforms. For example, the 30-day retention rate on this platform is 2.7%, which is lower than Netflix (30.0%), Netflix (14.4%), and GoodNovel (7.5%). I therefore conclude no strong evidence exists for addiction beyond the drama level.



(a) No spillover within a genre



(b) No spillover within the platform

Figure C.5: No spillover across dramas

Notes: The teal bars in panel (a) show that, conditional on users just finishing a drama with the corresponding genre, the probability that the next drama they watch will share the same genre. The orange star indicates the probability if the users randomly select the next drama to watch based on the empirical distribution. Panel (b) plots the retention rate on the platform with varying number of days, which is the fraction of users who are still active X days after their first use. The 30-day retention rate is 2.7%, which is lower than other online platforms such as TikTok (30%), Netflix (14.4%), and GoodNovel (7.5%).

Appendix D Estimation

Appendix D.1 Estimation algorithm

For estimation, I calculate model moments associated with each set of parameter $\boldsymbol{\theta}$ by simulating the economy 20 times and taking the average. To ensure my estimation routine converges to the global solution, I apply a two-step procedure that combines a global grid search with a subsequent local solver in approaching the SMM optimization problem (13).

Global grid search. I first conduct a global search over a large grid on my parameter space. I calculate the objective function on each grid point and locate the on-grid minimizer. The outcome-minimized objective function takes a value of 2418.14 and yields the initial estimators reported in Table D.1.

Local solver: Nelder-Mead algorithm. I then refine the first-step global minimizer $\widehat{\boldsymbol{\theta}}^{(1)}_{SMM}$ with a local solver. I apply a gradient-free solver, Nelder-Mead algorithm packed in `Optim.jl`, using programming software Julia. This process yields a final estimator with an objective value 2412.00.

Table D.1: Two-stage estimation procedure

	Parameter											
	μ_δ	σ_δ	$\overline{\psi}$	β_ϵ	κ	μ_χ	σ_χ	α_1	α_2	ρ	ω	obj.
First stage	-0.0089	0.091	0.015	0.055	0.15	1.11	1.04	0.000028	465	0.039	0.80	2418.14
Second stage	-0.0089	0.091	0.015	0.055	0.15	1.11	1.10	0.000028	465	0.039	0.80	2412.00

Appendix D.2 Targeted moments

I report the targeted moments in Table D.2. I normalize the habit stock by the total number of episodes (80), top-up user share by the number of users in each episode bin, and unlocking share by the total number of users. My model predictions match reasonably well with data moments.

Appendix D.3 Decomposition of perceived utility

The estimated model suggests both rational and irrational addiction are significant in this short drama industry. I further decompose the perceived flow utility into three components: intrinsic value, temptation, and habit formation. Figure D.6 displays the average value of each component for users who have watched episode t. The teal area represents the average intrinsic value per episode, increasing from -1.1¢ for the first episode to 16¢ for the last, reflecting user selection over episodes as low-valuation users gradually stop watching. The sharp rise between episodes

Table D.2: Targeted moments

No	Moment	Note	Data	Model
1	E_ccp_j10_h_leq_4	Mean of stopping CCP for the 10th ep, conditional on last h <= 4 and no endowment	0.76	0.80
2	E_ccp_j10_h_5_8	Mean of stopping CCP for the 10th ep, conditional on 5 <= h <= 8 and no endowment	0.75	0.73
3	E_h_k_0	Mean of last habit stock when user chooses k = 0, normalized by T	0.09	0.11
4	E_h_k_1	Mean of last habit stock when user chooses k = 1	0.25	0.27
5	E_h_k_2	Mean of last habit stock when user chooses k = 2	0.27	0.29
6	E_h_k_3	Mean of last habit stock when user chooses k = 3	0.30	0.19
7	E_h_k_4	Mean of last habit stock when user chooses k = 4	0.17	0.10
8	q_k1_j_10_20	User share of package k=1 sold at $t \in [10,20]$	0.34	0.56
9	q_k1_j_21_40	User share of package k=1 sold at $t \in [21,40]$	0.18	0.33
10	q_k1_j_41_60	User share of package k=1 sold at $t \in [41,60]$	0.12	0.30
11	q_k1_j_61_80	User share of package k=1 sold at $t \in [61,80]$	0.19	0.30
12	q_k2_j_10_20	User share of package k=2 sold at $t \in [10,20]$	0.29	0.17
13	q_k2_j_21_40	User share of package k=2 sold at $t \in [21,40]$	0.23	0.16
14	q_k2_j_41_60	User share of package k=2 sold at $t \in [41,60]$	0.21	0.15
15	q_k2_j_61_80	User share of package k=2 sold at $t \in [61,80]$	0.17	0.07
16	q_k3_j_10_20	User share of package k=3 sold at $t \in [10,20]$	0.15	0.06
17	q_k3_j_21_40	User share of package k=3 sold at $t \in [21,40]$	0.09	0.04
18	q_k3_j_41_60	User share of package k=3 sold at $t \in [41,60]$	0.21	0.01
19	q_k3_j_61_80	User share of package k=3 sold at $t \in [61,80]$	0.07	0.00
20	q_k4_j_10_20	User share of package k=4 sold at $t \in [10,20]$	0.15	0.28
21	q_k4_j_21_40	User share of package k=4 sold at $t \in [21,40]$	0.02	0.00
22	q_k4_j_41_60	User share of package k=4 sold at $t \in [41,60]$	0.04	0.00
23	q_k4_j_61_80	User share of package k=4 sold at $t \in [61,80]$	0.01	0.00
24	unlock_2	Share of unlockings at ep 2	0.94	0.94
25	unlock_3	Share of unlockings at ep 3	0.92	0.93
26	unlock_4_9	Share of unlockings at ep 4-9	0.89	0.91
27	unlock_10_14	Share of unlockings at ep 10-14	0.28	0.30
28	unlock_15_80	Share of unlockings at ep 15-80	0.14	0.15
29	unlock_night	Fraction of unlockings in the night	0.26	0.27

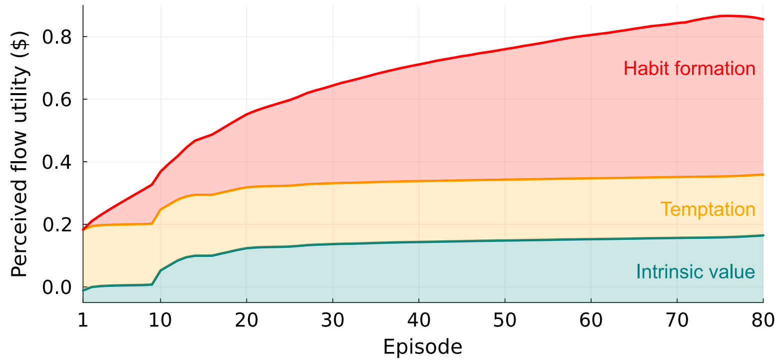


Figure D.6: Decomposition of perceived flow utility by episode

Notes: This figure decomposes the perceived flow utility into three components by episode: intrinsic value, temptation, and habit formation. For each episode, I report the average level of each utility component conditional on unlocking. All the components are normalized in dollars.

10 and 14 is due to an exogenous increase in episode prices from 0 to 1 token, leading over three-quarters of users to stop watching. On average, users derive $1.5 intrinsic utility from this drama relative to their outside options.

Addiction utility is substantial relative to intrinsic value. The orange area represents the value of temptation, valued at 19¢ per one-minute episode, providing an average perceived value of $3.8 for each user from the drama series. However, this temptation is irrationally perceived and should be excluded from the subsequent welfare analysis. The red area at the top reflects the average level of habit formation for each episode, which gradually increases as users build habit stock over episodes. For most episodes, habit formation is the primary component of utility, explaining users' high willingness to pay for this drama, conditional on paying. However, the majority of users stop watching between episodes 10 and 15, which reduces the average impact of habit formation across users. On average, users derive $4.3 from habit formation throughout the series, suggesting the realized value is similar between rational and irrational addiction.