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One More Episode? An Analysis of Overconfidence Behavior in Video Streaming Consumers

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An abstract of
a thesis submitted to the Faculty of Emory College of Arts and Sciences
of Emory University in partial fulfillment
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Abstract

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Binge-watching, and inability to switch from the activity of watching television has always been a staple complaint of students and adult members of the society alike. This issue is especially pronounced following the rise in popularity for subscription based video streaming services like Netflix and Hulu. Streamers find themselves under-projecting their viewing hours and unable to change their behaviors despite the direct costs to productivity and time. Heuristically, these are signs of overconfidence. The purpose of this study is to bring the phenomenon of overconfidence from the realm of anecdotal accounts to the spotlight of experimental studies regarding overconfident consumer behavior in this rising, scarcely explored industry by experimentally garnering support for the existence of overconfidence in streamers and relating it to consumer irrationalities like addiction and emotional investment. The study deployed surveys to the undergraduate population at Emory University, collecting data regarding its subscription profile-duration of ownership, frequency of usage, regularly watched content, etc- and psychological connections to their subscription services. Participants were asked to log predicted and actual streaming hours over a span of a month. Evidence for both definitions of overconfidence was found. Significant differences between predicted and actual consumption, an underestimation gap of 1 hour, was found. Participants also display a tendency to increase consumption by another hour after notified of underestimation behavior, a delay in learning. While regression of the underestimation gap and delay in learning with psychological and subscription profiles was unfruitful, the existence of overconfidence is supported, setting the stage for future works in the topic.

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Finally, to my parents: Thank you. Your faith in me and your ever-growing expectations has fueled my passion for this piece during my least productive days, and reminded me of why I am doing this.

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I. <u>Introduction</u>

The advent of Netflix, Hulu, and other subscription-based video-streaming services marks a transition point in the relationship between media entertainment and its consumers. These services symbolize the flexibility of the video-streaming industry, allowing it to cater to audiences and fit their habits much more accurately. No longer do consumers rush home for their weekly programs Friday night. No longer do they dread missing an episode of their favorite show. No longer do they search across dozens of channels and frustrate over the lack of content that fits their interests. These subscription-based video streaming services allow consumers to view at anytime and anywhere. Television now fits to our needs instead of us changing our lives to fit to its rigid schedules; however, these benefits depend on a core assumption: that consumers are rational.

Theories of the rational consumer who perfectly optimizes his utility rarely apply amid the shortcomings of psychological factors. As demonstrated through behavioral economics studies since the 1960s, consumers may prefer benefits and gratification gained closer to the present moment, instead of a higher utility choice, but further in the future, a *present bias*. While rational consumers take this present bias into account when making decisions, irrational consumers are unaware of this phenomenon and behave without considering the bias's effects. This may cause *Intertemporal inconsistency*- consumers value consumption bundles at different rates throughout time, causing the "perfect" choice made in the present to be suboptimal in the future. This causes complications for consumers when there is a time gap between the payment for the goods and the consumption of said goods. Subscription-based services like gym memberships, telephone plans, and video-streaming subscriptions are known for their monthly payments and access, exhibiting the aforementioned time gap. This implies that the perceived utility maximizing choice for the consumer varies overtime. *Present bias* and *intertemporal inconsistency* are certainly distortions to the consumer preference theory. One's inability to recognize these flaws are attributed as *overconfidence*.

The combination of the above factors underlies behavioral anomalies while streaming online television, in particular, *binge-watching*. It is not an unfamiliar anecdote where one would plan to take a break from mundane tasks by relaxing with an episode of his favorite show; however, instead of stopping after one episode like he intended, he chooses to spend unanticipated time watching TV. Such behavior can be categorized as *overconfidence*, with consumers underestimating their viewing due to their unawareness of their *intertemporal inconsistency*. By extension, this leads to problems in self-control. One's inability to accurately predict the utility gains from streaming at a certain point in the future will cause him to become overconfident about his ability to stop streaming (i.e. lacking the self-control needed to adhere to the original plan).[1]

This inherent *overconfidence* may cause consumers to misallocate their resources. While the costs of this bias could be as simple as losing productivity to procrastination, there exists explicit costs as consumers are forced to commit to the subscription service they purchased. Oftentimes, subscriptions are charged monthly, and once the costs of the current month are incurred, consumers will not be able to freely cancel until the next billing cycle, at least without obtaining a refund. Consumers are forced to endure the costs of a suboptimal choice made due to their skewed perception of their preferences. The freedom granted by video-streaming services will thus prove to be counterproductive in maximizing consumer utility.

This explanation's undoing is that it exists without experimental evidence. Such is the aim of this study: demonstrate the existence of *overconfidence* within the typical consumer for video-streaming services, and investigate potential causes, and quantify psychological factors that contribute to overconfident behavior. Understanding such behavior is useful for informing policy and practice for the protection of consumer welfare, as the combination of the theoretically beneficial flexibility to subscription options and irrational consumer behavior will likely impede the attainment of maximized utility.

Building upon the existing knowledge, the present study aims to demonstrate that underestimation of consumption and delay in learning exist in the rising video-subscription industry. By first demonstrating that such irrationalities exist within the consumers of this rising industry, I shall spark motivation for further research and studies. Ultimately, the study aims to bring awareness of *overconfidence*, and possibly incentivize policymakers and producers alike to implement changes to contracts and contents of their service to better benefit consumers. Section II is the literature review. Section III will develop a theoretical model presenting conjectures to

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[1] Given their interconnectivity, overconfidence in accuracy of future preferences and the affiliated overconfidence in self-control are used interchangeably in the remainder of the study.

overconfident consumer behavior. Section IV presents an experiment that investigates the validity of these conjectures. Section V and VI presents the results and discusses nuances and interpretations. Section VII concludes my findings.

II. Literature Review

Existing studies have identified indicators of overconfidence in consumers that can find their analogs in the video-streaming industry: **underestimation of consumption**, and **delay in learning effect.** Consumers will under-project the hours they will spend watching television when choosing the subscription plans. Consumers will also experience a lag between realizing and modifying their overconfident behavior once made aware of it. The study will define *overconfidence* as such and explore its indicators.

There are theoretical works modelling consumer intertemporal choices and preferences originating from the 1990s (Calliard & Jullien, 1999 and Roelofsma, 1996). The authors model discounting utility functions, with discounting terms representing the temporal inconsistency. Loewenstein et al (2000), and Phelps (1980) model intertemporal choices with quasi-hyperbolic discount functions. Their models place both a short-term and a long-term discount factor on the consumer utility, causing a large gap to form between perception and actual consumption, as the perception of future preferences includes a long run discount term, while the actual future preferences do not. Loewenstein and Phelps' models closely capture the present bias of consumers, as well as their tendencies to treat two future points in time as increasingly similar the further from the present period they get. The theoretical works generalize the phenomena of overconfidence as the difference between perceived enjoyment as a function of time. The works quantified the effect of time with a discount on utility.

Benesch (2007) provides empirical support for the theoretical models by experimentally showing that viewers tend to watch television more than they previously allocated time for when given a chance. Arguably, this phenomenon could be exacerbated by the higher freedom granted by the flexible video-streaming services. Yet, since the video-streaming industry garnered popularity only recently, there exists limited literature pertaining to overconfidence in the scope of streaming services. Nevertheless, ample studies have been conducted on industries from which I can draw parallels to fit into my scope.

Dellavigna and Malmendier (2002) examines the health club industry (gym memberships) and the overconfidence in consumers about their discipline and their future attendance, despite the existence of the commitment device (membership contract). The authors categorize the consumers into *Sophisticated* agents, and *Naïve* agents. Both types of consumers have the intertemporal inconsistency; however, the latter is not aware of it. The authors proposed "Stylized Facts" to represent the behavior of *Naïve* consumers, and predict patterns in average attendance cost, average attendance, and survivability within their data to test against the null hypothesis that the gym subscribers are *Sophisticated* agents. The authors find that not only are agents' overconfidence of their self-control obvious (from the extended periods of their choosing higher cost contracts, when a difference, lower cost contract would better match their activities) they are also reluctant to "learn" and change their contract choices, due to the automatic renewal mechanism in the monthly contract. This begs the question: when explicitly notified of their losses, will the learning effects improve? Acland and Levy (2015) addresses this question by further exploring *overconfidence* as the delay in the learning effect in the health club industry, and showing that without proper incentives (most directly, monetary), subjects will display lower learning tendencies than those with incentives.

In a sense, the video-streaming industry demonstrates characteristics examined by previous works. Dellavigna and Malmendier view the gym membership as an investment good- one where the costs are incurred in the present (effort and self-discipline), while benefits (health improvement) are gained in the future. The video-streaming services is the opposite- an experience good, where benefits are gained in the present (enjoyment of shows), and costs are in the future (loss of time) (Calliard and Jullien, 1999). Whereas a gym member can over-project his willpower to exercise, a video-streamer can under-project his desire of viewing, as well as overestimate his self-control.

The key difference between the gym and streaming service is the matter of the effort required to engage in the service. Unlike exercising, watching a streamed program is more flexible and can be started and stopped anytime, instead of requiring a mandatory warmup, and rigid schedule that must be followed every session. More importantly, it can be argued that statically, viewing television is less stressful and generally less intensive than actively working out. It can be said that rather than a cost incurred now with benefits in the future, video streamers face the reverse: gaining benefits from watching now at the cost of lost time.

Lunn (2012) focuses on the telecommunications industry. Compared to DellaVigna and Malmendier's works, Lunn's ties closer to the video-streaming industry. Lunn proposes that the telemarketing industry is unique in its simultaneous display of 4 key characteristics: **1) Consumers face complex, multidimensional judge of value, 2) Valuation depends on factors unrelated to the product, 3) The industry is subjected to constant updates in technology, and 4) Consumers make multiple decisions at different frequencies, valuing present and future cost/benefits**.

Lunn's (2012) 4 traits of the telecommunications industry can also be demonstrated in the streaming industry. 1) There are multiple criteria used to judge the quality of a subscription service, for example: the video quality, the viewing capacity, and the advertisements. 2) There are factors that are unrelated to the services themselves, but dependent on the consumers, for example, the preferences of the viewers' families, the viewers' financial freedom, etc. 3) The services not necessarily improve their technology, but constantly update their library by adding new content. 4) At any point in time, subscribers are faced with the choice of whether to unsubscribe and switch streaming companies, stay with the current subscription, or subscribe to more without terminating the current plan.

Calliard and Jullien (1999) discusses a factor in the deterrence of the learning effect- addiction. The authors present a hypothetical addictive good and outline the addicted consumers' cost and benefits of maintaining consumption, or stopping with the probability of relapsing. In a sense, the streaming behavior is addictive, with the consumers' attachment towards the content provided. While a consumer may choose to stay with the current plan, there is the possibility that another service's contents are more suitable to his preferences. The consumer is free to unsubscribe; however, there is exclusive content accessible only with the current service provider, which may trump multiple benefits of the alternative subscription. There also exists the possibility of future exclusive content from both services, which will likely deter the learning effect.

III. Theoretical Model

In each of finitely many periods t= 0,1,2,…,n, an individual must choose whether to continue streaming his video service or to switch to working on a productive task, which I henceforth refer to as doing his homework. In this case, *Period n* represents when the task is due. Suppose the individual switches from streaming to doing his homework at *Period k*. Once the individual switches to the task, he will spend the remaining periods completing the task. The individual has a present bias represented by a discount factor β that is applied to all future utility outcomes, where 0< β <1. Additionally, future utility outcomes are discounted by a factor δ in each period, where 0< δ<1, representing that the present value of future utility declines based on how far in the future it is realized. Letting u_t denote the utility value of streaming in any *Period t* and u_p denote the utility value of the streaming in the present (*Period p*), the perceived present value of the consumed content through *Period k* as of *Period p* is:

$$U_p = u_p + \beta \sum_{t=p+1}^{k} \delta^t u_t \qquad (1)$$

Equation (1) presents the individual's utility as a stream of utility starting from *t=p*, the present, to *t=k,* the decision point. While denoting the present period with p allows a more general form of the equation, for simplicity, p may be replaced with 0, as the present period is conventionally denoted *Period 0*. There are two discount terms to the utility: β and δ, representing the short term and long term discount, respectively. The β term acts as the present bias, only included once in the period immediately after the present (*t= p+1*), and stays constant as the individual moves further into the future (*t= p+1,…,k*). This phenomenon has been shown in multiple past works[2], and will be reasonably included in my model.

On the other hand, the utility from working on homework, *V*, has two components- the benefits and costs of working on the task. The benefits, whether it's the improvement in test scores, or

[2] Laibson (1997) and Phelps (1968) examined the decline in US national savings rates under the situation where commitment devices are absent, examined under the scope of quasi-hyperbolic discounting models that suggest a present bias, showing that having high liquidity and mobile assets may decrease the marginal propensity to save. Moreover, when provided with the idea of possible future earnings from owning assets, data suggests that consumers spend more than their income, suggesting a higher valuation of present enjoyment, over the potential losses of the scenario where investment fails.

return of homework grades, is denoted by $v(t)$, an increasing function of time; however, $v(t)$ increases at a diminishing rate. At low levels of t, increases in time spent working has large marginal increases to $v(t)$, for more essential components are completed. As t increases, the marginal benefits will decrease, for the individual will move on to more trivial details of the assignment. Similar to utility gains from streaming, $v(t)$ is discounted by β and δ until a fixed future *Period* z, *when* $v(t)$ is realized, which is beyond the due date at n. The cost of doing homework- energy, time, attention, etc.- is given with the exogenous constant c. Thus, the total benefits from doing homework, valued at the present period is:

$$V_p(t) = \beta\delta^{z-p}v(t) - c \tag{2}$$

The individual follows the simple principle: *if utility from streaming is greater than that from doing homework, then the student will continue streaming. The individual will stop and finish their homework if not.*

Given this rule, he anticipates that he will stop watching after period k if:

$$U_p + V_p(n-k) > U_p + \beta\delta^{k+1}u_{t+1} + V_p(n-k-1) \tag{3}$$

Inequality (3) is the condition for the individual to stop after period *k*- the utility stream from doing homework in period *k+1* is larger than the alternate option of watching for another period. The left side of the inequality shows his utility after streaming for *k* periods, and the final term showing the utility gains from doing homework, expending the remaining time until the due date, *Period n*, having spent the first *k* periods streaming. The right side shows the alternative, where the individual decides to indulge in another episode, represented with the second term. Here, the individual chooses to delay work for another period, leaving one less period for completing his homework. Inequality (3) reduces to:

Condition 1: $$\delta^{z-p}[v(n-k) - v(n-k-1)] > \delta^{k+1}u_{t+1} \tag{4}$$

The comparison of the utility offered by the two choices in Inequality (3) becomes the weighing of the cost of lost time for homework, against the benefits from streaming one more period. The left side of Inequality (3) will become larger as *k* increases towards the due date *n*, for the time loss for an extra episode watched will begin to sacrifice the time intended for more essential parts of the homework. The left side can effectively be interpreted as the cost of procrastinating an extra period. Inequality (3) thus becomes *Condition 1*.

Assume here that *Condition 1* is satisfied, and the individual made plans to stop streaming at *Period k*. The individual re-evaluates his choice at every period and deems that *period k* is the instant when utility from doing homework outweighs the utility from continuing to stream. Before entering *Period k+1*, again, the streamer is faced with the comparison of utility between doing homework or watching television in *Period k+1*. In this instant, *Period k+1* is the equivalent of *Period p*, for what used to be the future, is now the present. Now, the streamer will stop streaming if:

$$V_{k+1}(n-k) > u_{t+1} + V_{k+1}(n-k-1) \quad (5)$$

Like the decision process in Inequality (3), the streamer will make the similar valuation in Inequality (5): stop streaming and work if the left side of the inequality is larger than the right. Simplifying the inequality, I arrive at Inequality (6) below, creating *Condition 2*:

Condition 2: $$\beta\delta^{z}[v(n-k) - v(n-k-1)] > \delta^{k+1}u_{t+1} \quad (6)$$

The distinction between *Conditions 1* and *2* is that *Condition 1* is derived from the anticipated decision in *Period k*, which includes the hyperbolic discounting term β as *Period k* is in the future, while *Condition 2* is derived from the actual utility as of *Period k*, which is thus not subject to the hyperbolic discount factor. As a result, *Condition 1*'s anticipated valuation of doing homework at *Period k* will always be higher than *Condition 2*'s actual valuation. This shows that just because *Condition 1* holds true, does not guarantee that *Condition 2* will as well. In the case that *Condition 1* holds true, but *Condition 2* does not, the streamer would have originally planned to stream until *Period k*, and start working on homework, given that he anticipates that at *Period k*, his future-self will value utility gains from homework higher than from an extra episode; however, at *period k*, the extra β term appears with *Period k* as the present, for *k+1* is the first period that the individual either switches task or continues watching, and the present bias phenomenon appears once more. As a result, at *P*eriod *k,* the streamer will choose to stream instead of adhering to the plan made at *Period 0*.

Condition 2 => Condition 1

Two inferences can be drawn from this statement. First, if an individual decides to switch to the task in *Period k*, then in any earlier period, the individual would have anticipated switching to the task in *Period k* if he had not done so already. Second, if an individual anticipates streaming through any future period k, then he will continue streaming through at least period k.

$\neg$ *Condition 1 =>* $\neg$ *Condition 2*

This shows that the streamer anticipates that he will continue streaming at *period k*, for the utility from streaming is higher than doing homework. If that is the case, the streamer will most definitely continue streaming at *period k*. Yet, if the streamer predicts that he will do homework at *period k*, it will not necessarily hold true when *period k* comes.

With this model, I show that subscribers suffer from the inconsistent preferences through time, which causes them to deviate from their previously made consumption plan. This summarizes to two key conjectures to be demonstrated experimentally in the remainder of this paper:

Conjecture 1: Individuals will stream no less than anticipated. While individuals predict a given number of hours they will stream, they will not stop like planned.

Conjecture 2: Any underestimation of streaming hours is due to the hyperbolic discounting factor, caused by addiction and emotional investment to the act of streaming, which I will explain later in Section V.

IV. Methodology

The aim of this study is to provide evidence for *overconfidence* in online-streaming subscribers and investigate the possible causes of this *overconfidence*. As mentioned in the previous section, I define *overconfidence* as the **underestimation of consumption**, and **delay in learning effect**. To this effect, I conducted an experiment in which I collected survey data that can observe indicators of this overconfidence.

The participants are given a survey at the end of every week for a month requesting information about their anticipated and actual consumption of streaming services (Appendix B). Participants may submit their responses at any location, eliminating the “monitoring” and time constraints to the data collection process. This process addresses concerns with the Hawthorne Effect, the behavioral skew in participants in the presence of researchers. By adopting this “hands off” approach, I can avoid the risk of participants’ feeling the need to exhibit any trends or meet any expectations, eliminating potential skew in data due to the interaction with researchers. Participants may also submit their responses at any time throughout the week, before the next survey is sent out. I recognize that subjects have different schedules and time commitments, so this flexible and autonomous process makes their responses the most authentic.

Though there are not many criteria for eligibility, the participants must have existing subscriptions to at least one video-streaming service, as they are integral to the topic of the study. I recruited 99 Emory University students from one of its on-campus residential housing units, social media, as well as from the experimental and behavioral economics classes. Participation was incentivized by extra credit offered by the instructors of these courses in exchange for full participation in my trial. All participants signed a waiver of consent to bear any associated risks (none anticipated) and agree to disclosure of their video-streaming habits (Appendix C).

The surveys were split into 2 Phases:

Phase 1 (weeks 1 and 2) aims to investigate underestimation of hours spent streaming videos, as an indicator of overconfidence. In Phase 1, participants are recruited in the first week, and I collected general information regarding the participants’ streaming subscriptions (See Appendix B for survey). My questions for week 1 represent the costs that factors into the utility function in the consumer choice model I presented in the theoretical section. Participants also answer a series of questions that measure how quickly they adapt to changes, how objectively they make decisions while facing uncertainty, etc. These questions compile a “bias index”, that rates participants’ susceptibility to biases and the extent to which their behavior is impacted by psychological factors. Mainly, I propose 2 broad categories of psychological factors: Addiction, and Emotional Investment. More on rationale behind the addiction and investment in the later subsection. The bias index is created to account for psychological factors that do not fit into these 2 categories. To a certain extent, by quantifying the participants’ likelihood of responding to spontaneous and fickle urges, I generalize these unknown factors’ effects.

In week 2, participants report their weekly consumption. Those who show statistically significant underestimation were notified of their behavior before moving into Phase 2.

Phase 2 (weeks 3 and 4) measures the delay in learning effect. At the end of week 2, before week 3, I notify participants who underestimated in their prediction and prompt them to re-estimate their consumption for the upcoming week. Likewise, I also notify participants who overestimated their viewing hours. Those whose predictions are accurate are not notified of their behavior. In week 4, participants report their actual hours watched during the week.

Phase 2 serves another function- to alleviate the skew in data from deviations to regular schedules. Though the methodology grants autonomy to every participant by minimizing restraints and allowing freedom for the participants to watch TV on their own time, in their most comfortable environment, there exist exogenous shocks to the participants' time and ability to watch according to their desires; the biggest of which are mid-term exams and course work. Since these shocks are uncontrollable, yet participants' viewing behavior can change significantly during exam periods, these events can be effectively seen as outliers. Thus, repeating the prediction and reporting process in **Phase 2** can reduce the effects of the "outliers".

From the data collected in **Phase 1**, I find the participants' expected and actual viewing hours. I will use a t-test of differences to test the difference between the expected and actual hours to be zero, against the null hypothesis that they are not. I hypothesize that I'll find a significant difference, an "estimation gap" between the perceived viewing and actual viewing hours. *This essentially demonstrates that consumers underestimate/ overestimate their consumption.*

I will compare the perception gap from **Phase 2** with that of **Phase 1** with a t-test of differences. I hypothesize that I'll find an insignificant difference between the two, meaning *they are reluctant to change their behavior- a delay in their learning effect.*

Furthermore, I shall regress both the underestimation and delay effect on explanatory variables collected regarding their profile as TV viewers. I will conduct both the F-test on my regression models, as well as t-test to test the statistical significance of the relationship between *overconfidence* and my individual variables.

V. Results

In this section, I will introduce the data set generated from the survey responses, and conduct data inference and hypothesis tests using it as sample population. Additional figures and tables available in Appendix A.

i. Data Set and Summary Statistics[3]

The data set consists of 99 observations (responses). Among the participants, 56.57% are male and 43.43% female. Participants were asked to identify their primary service- the platform they most frequently use. 67.7% identified Netflix, 17.2% Hulu, 9.10% Amazon Prime, 5.05% others, and 1.01% xfinity.

The range of most free numerical answers are quite large. The minimum number of months a participant has subscribed to their primary service is 2, while the maximum is 168, which is more than 10 years. The median is around 36 months, or 3 years. The minimum number of services subscribed is 1, while the maximum is 7. Both the mean and median number of services subscribed is 3.

On average, respondents regularly watch episodes from 2 series, but some may watch up to 15 series, and others have no regularly viewed series. On the other hand, 79.8% of the participants watch primarily TV shows, while 19.2% watch either movies, documentaries, or others.

The bias index, constructed from a series of questions that ask participants to rate on a scale of 1-10 their ability to adapt to changes, make decisions, accept new experiences, etc. shows the median and mean score of 16, and maximum at 28, and minimum, 7.

On average, in Phase 1 participants watch 1.028 hours more than they anticipated and rated their enjoyment of the time spent viewing 7.48 on a scale of 1-10. In Phase 2, participants watch an average of 2.38 hours more than they anticipated and rated the enjoyment at an average of 7.74. This indicates that consumers have a generally consistent satisfaction in their TV viewing decisions. The minuscule changes in

[3] For specific figures and tables, refer to Appendix A

enjoyment rating suggests that the changes in underestimation hours aren't coupled with an increase in enjoyment, ruling out the possibility that participants fortuitously found contents that immensely sparked their interest, and caused them to binge-watch.

All the numerical variables collected resemble a normal distribution. (Appendix A.3) This satisfies the normal distribution assumption for multiple regression that I will conduct in the next subsection.

ii. Regression Models

In investigating possible causes of *overconfidence*, I propose they are factors associated with **addiction** and **investment**. These hackneyed terms are to be defined explicitly to serve as foundations of my regression models.

ii.i Addiction

As explored by Calliard and Jullien (1999), Addiction demonstrates its influence over an individual's behavior through a dependence and necessity to consume a product regularly, even when consumption of the product has significant costs that might outweigh the tangible benefits. One may choose to consume the good or service due to their subjective valuation of the benefits being higher than the cost. Under this description, to categorize one's need for the act of streaming as a means to unwind, to distract, or gain utility, is not farfetched. As can be seen in the survey data, the average participant finds himself scrolling through the library, without a specific program in mind, only fueling the desire to stream. The time spent seeking programs instead of targeting specific shows indicates a sense of dependence with the act of streaming.

Thus, I reason that continuing streaming more than previously planned and foregoing the time allotted for work may be motivated by "addiction". Theoretically, if "addicted", the consumer exhibits behavior that ignores potential costs, or foregoes benefits that come with stopping streaming like predicted.

The data exhibit a positive correlation between underestimation of hours watched and my addiction variables (Appendix A.4). Though the correlation between the underestimation gap and the addiction variables are all weak, they follow the logic proposed in my rationale. The number of days participants can refrain from viewing directly suggests a level of dependence and susceptibility to following participants' desires of streaming instead of completing other tasks. The number of times viewed per week is explained with a similar argument. The action of idly browsing is a proxy variable used to indicate the dependence on the act of streaming itself. The streamer does not have specific content in mind, but instead seeks out content to fill his desire to stream, suggesting addiction; this may explain the underestimation gap, for the more "addicted" a participant is, the more likely he will put off the task to continue streaming.

ii.ii Investment

Another reason for the short run discounting term, or abstractly, the desire for the one to stream more than originally intended is the emotional attachment he has towards the current subscription, due to the happiness brought by the shows he has already watched, which may manifest in the form of re-watching content.[4] For content not yet viewed, investment to the plot, to the characters, to the content offered accessible simply by clicking "next episode", may cause streamers to view more than expected. By association, oftentimes due to emotional investment of the content, viewers will watch more than planned, and as a result, under-projecting their actual streaming hours.

The state of emotional attachment towards the content may exacerbate the underestimation, for users experience the fear of missing out when they stop streaming. Driven by the need for closure of a cliffhanger, the excitement of unseen content or perhaps the nostalgia from previously viewed content, emotionally invested streamers may discount future utility at a higher rate than others who are less invested, thus increasing the underestimation gap.

[4] The difference between investment and addiction is that investment is geared towards switching primary services, and the reluctance to forego the current content the streamer is watching, while addiction is focused on the act of streaming itself, regardless of content. Thus, addiction is the investment towards streaming, and the reluctance to switch tasks.

The data exhibit a positive correlation between underestimation of hours watched and my investment variables (Appendix A.4). The duration that the respondent has had his subscription is positively correlated with the underestimation, as the longer the respondent has had the service, the more invested he is to the content. A similar argument can be made for the number of shows the respondent is watching, and the number of extra content offered on another service platform required for the respondent to switch his primary service.

<u>iii. Models</u>

Using multiple regression, I will investigate "addiction" and "investment" as causes of the overconfidence- the size of the underestimation gap, and the learning delay. The definitions and explanations of each variable can be found in Appendix A.6. My regression models are created with three lines of reasoning.

Model 1: $diffhours = \beta_0 + \beta_1 serviceprice + \beta_2 nservices + \beta_3 gender$

Model 2: $\text{percchange} = \beta_0 + \beta_1 serviceprice + \beta_3 gender$

The first is the "basic" model, with regressors being objective measures of a consumer's subscriber "profile": the price of their subscription and the number of services they are subscribed to. Models 1 and 2 estimate the size of the underestimation gap and the learning delay under this scope. These serve as a baseline frame of reference for Models 3 and 4 which estimate the impact of psychological factors associated with addiction and investment. The other two types of models correspond to variables that quantifies "addiction" and "investment".

Model 3: $diffhours = \beta_0 + \beta_1 serviceprice + \beta_2 nservices + \beta_3 gender + \beta_4 duration + \beta_5 currentshows + \beta_6 extrashowsforswitch + \beta_7 bias + \beta_8 enjoyment$

Model 4: $percchange = \beta_0 + \beta_1 serviceprice + \beta_2 nservices + \beta_3 gender + \beta_4 duration + \beta_5 currentshows + \beta_6 extrashowsforswitch + \beta_7 bias + \beta_8 percenjoy$

Models 3 and 4 examine emotional investment to the content provided by the viewers' primary services- consecutive months of their subscription, number of shows they are currently following, number of movies or documentaries they frequently view, number of extra content required for them to switch primary services, etc.

Model 5: $diffhours = \beta_0 + \beta_1 serviceprice + \beta_2 nservices + \beta_3 gender + \beta_4 bias + \beta_5 notvdays + \beta_6 browse + \beta_7 useperweek$

Model 6: $percchange = \beta_0 + \beta_1 serviceprice + \beta_2 nservices + \beta_3 gender + \beta_4 bias + \beta_5 notvdays + \beta_6 browse + \beta_7 useperweek$

Finally, Models 5 and 6 examine the effect of addiction to streaming behavior. This ties in the number of days participants can refrain from streaming, likelihood of browsing instead of watching, and number of uses per week.

iv. Hypothesis Tests and Inference[5]

To begin, I conducted a T test of differences in means to determine the statistical significance of the underestimation gap for Phase 1. I previously found that the mean is at 1.028 hours more than anticipated. From the T test, I tested the hypothesis that the mean is not equal to 0 against the null hypothesis that the mean is equal to 0. The results allow me to reject the null hypothesis at the 5% significance level, thereby allowing me to conclude that there is a statistically significant underestimation for the average participant.

Similarly, for Phase 2, I conducted the same T test, for the hypothesis that the underestimation gap, in terms of hours viewed is more than 0, against the null hypothesis that it is. The results show that there's a statistically significant mean of 2.2 hours in underestimation gap.

These two initial tests provide evidence of overconfidence in the form of underestimation in the participants, providing support for the theoretical model proposed in Section III. On the other hand, what was unexpected was the fact that there is a statistically significant difference between underestimation in Phase 1 and 2. Conducting a Paired T Test of difference in means, I find that on average, a participant's underestimation increases by 1.04 hours as he enters Phase 2. This indicates that not only is there evidence of a delay in learning effect, but also an exacerbation in the underestimation, suggesting that participants become more overconfident despite being

[5] All tests in this section are conducted at a 5% significance level

notified of their inaccurate prediction in Phase 1. The investigation continues with my regression models. Specific results can be found in Appendix A.5.[6]

iv.i “Basic” Models

The basic models suggest that the underestimation gap, but also the learning effect decrease as the price of the service decreases. Underestimation increases as the number of subscriptions to other services increases, but the learning effect decreases. Despite the lack of statistical significance, the coefficients for each variable indicate effects worth noting. We see that as subscriptions get more costly, consumers have more accurate predictions of their viewing appetite. Yet, as the number of services increases, consumers find themselves increasing their underestimation, which makes sense, as consumers who have more services have a larger appetite for streaming. Streamers also have access to a larger selection of shows to watch, which increases the threshold for the satiation point. The coefficient for gender of the respondent suggests that male participants tend to have a lower underestimation gap.

Similar arguments can be made for the delay learning effect. Having more services reduces the incentive to change viewing behavior as there are more shows and more content to view and more alternatives to consume from other services, which overall, decreases the desire to reduce watching hours. Unlike in the underestimation gap, male participants have a larger underestimation effect.

iv.ii “Investment” Models

The “Investment” models also face the same issue of having no significant regressors. The directions of the regressors are still worthy of mentioning. In Model 3, The duration the consumer has had the service, the minimum extra content offered on other services to prompt a cancellation of the current service, and the enjoyment of the content all positively influence the size of the underestimation gap, as those variables indicate a growing level of emotional investment in the content provided. Yet the negative coefficients of number of regularly viewed content and the bias index are unexpected. Logically, I would argue that these variables have positive coefficients given

[6] Since results are practically and statistically insignificant, specific numbers are not cited, but instead included in Appendix A.5. The logical coherence in directions of the coefficients are noteworthy.

that one would expect a viewer to be more invested in services when he has more regularly viewed content, and same goes for the bias index, as consumers with higher scores are more affected by their emotions and biases. Unlike in the basic models, when emotional investment is considered, male participants tend to underestimate their consumption more.

Similarly, in Model 4, for the learning effect, we see a positive relationship from only the change in enjoyment. As the viewers enjoy the content more, they are more reluctant to change their behavior, as they derive increased emotional investment in their streaming behavior. What is unforeseen is all the other variables. Their increase in values all indicate a rising investment in streaming; however, the regression results suggest the opposite. Like in the basic models, male participants have a larger learning delay effect.

iv.iii "Addiction" Models

Once again, the "Addiction" Models are also insignificant. The directions of the coefficients are still pertinent to interpretation. Model 5 presents positive coefficients for number of days the viewer can go without streaming, the number of uses per week, and the time spent idly browsing. This shows that the higher the level of addiction, the more a consumer will underestimate their consumption. Surprisingly, the bias index has a negative coefficient. Similarly, considering "addiction" variables, male participants have a negative coefficient, demonstrating a lower underestimation effect.

In Model 6, the coefficients are not as homogenous. We see positive coefficients from the days viewers can refrain from streaming, and bias index, again supporting the idea that addiction causes the lack of learning effect; however, counterintuitively, the coefficients of number of uses per week and time spent browsing- variables I predict to have positive coefficients- are negative. Like in the basic models, male participants have a larger learning delay effect.

Gender's effects on overconfidence are inconclusive. While its coefficients on the learning delay for all models are homogenously positive, the gender variable seems to have differing effects on the underestimation gap. I cannot draw a definitive conclusion on gender's association with overconfidence. Regardless of the directions, the gender variable's effects are small, which suggests that the two genders are influenced by overconfidence in a similar manner.

Notwithstanding the fact that all models have insignificant explanatory variables, the directions of the variables' effects mostly align with my conjecture that "addiction" and "investment" are prominent psychological factors that causes overconfidence in viewers. The ubiquitous statistical insignificance amongst all variables will be discussed in the next section.

VI. Discussion

The results have shown that there is a statistically significant underestimation effect across my sample population of around 1 hour for Phase 1, and 2 hours for Phase 2. What was unforeseen was that participants on average increased their consumption after being notified of their underestimation- an average of 1.36 hours. This suggests that not only is there a delay in learning, there is also a significant increase in viewing hours before and after the intervention. Yet, Phase 1's mean predicted hours is 6.2 hours, while in Phase 2, it is 4.9 hours. The participants predicted less hours of viewing for Phase 2, which could contribute to the larger underestimation gap in Phase 2.

Regardless, this paper found evidence suggesting overconfidence behavior, in the form of underestimation, and delay in learning, supporting *Conjecture 1*; however, experimental data fails to support *Conjecture 2:* psychological factors related to "addiction" and "investment" can explain the source of the overconfidence.

Heuristically, works regarding overconfidence have attributed mistakes in choosing commitment devices for a service consumed in the future to intertemporal inconsistency; however, alternative explanations are available, of which, flat rate bias is prominent.

This alternative explanation seems plausible, as the nature of a TV streaming service is similar to the buffet style scenario explored in Just and Wasink's paper (2011). At the beginning of the month, subscribers pay a flat fee that grants them unlimited access to the content, much like how diners pay the flat fee for the all-you-can-eat deal.

The subscribers' underestimation effect when predicting their viewing, and the subsequent overconsumption of their subscription can be attributed to their sense of "getting their money's worth". The TV subscribers' "satiation point" will thus be contingent on their own appetite for TV, and the sense of "getting their money's worth". At our switching period *k*, it can be interpreted that the unforeseen effect of the latter will cause consumers to continue streaming their services, instead of stopping like originally planned.

Yet, this interpretation may fail to account for the fact that the consumers show statistically significant satisfaction with their unforeseen consumption. From the previously investigated the correlation between the extra viewing hours and the overall subsequent utility gained from the total TV viewed for the week, value of 0.0239 suggests that there is a weak, but positive relationship: the more extra hours viewed, the more the consumer enjoyed the content. This phenomenon suggests that the extra hours viewed are motivated by the consumers' enjoyment of the current content, and the desire to continue the momentum of positive utility. Whereas theoretically, in the case of flat rate bias, one would reasonably infer that the correlation between the extra hours and utility gained would be negative, as that one more episode is caused by the pressure to reach a benchmark that justifies paying for the subscription.

Furthermore, the fact that flat rate bias is at play implies that the higher the price of the subscription, the larger underestimation effect, as the pressure for "getting one's money's worth" is larger. Yet, the correlation between price of service and extra hours watched is not positive like suggested, but instead negative, at -0.0649. As can be seen, the two predictions made for behaviors aligning with the flat rate bias are not present in my data; however, there is not enough statistical significance to support the correlation between of price and extra hours, and extra hours and enjoyment. While the correlations are not in the direction that the flat rate bias explanation suggests, there is not enough evidence pushing towards the theoretical model presented in Section III.

To provide more definitive evidence to support or reject my model of streamer behavior, future research must gather experimental evidence of the aforementioned second part of my theoretical model, the accurate prediction of binge-watching behavior. My experiment as it stands, only demonstrate evidence against the flat rate bias explanation, instead of provide support that the intertemporal inconsistency explanation provided by my theoretical model is the reason behind binge-watching.

Notwithstanding, I fully recognize that there more than likely exists the possibility that streamers often face an assortment of biases. It is highly unlikely that a typical consumer is influenced by simply one type of bias. In reality, perhaps both the present bias (i.e. intertemporal inconsistency), and the flat rate bias, on top of other potential biases yet to be uncovered cause the binge-watching behavior we examine in this paper.

Yet another part of my theoretical model- addiction and emotional investment as the source of the discount term- is unsupported, as demonstrated by the statistical insignificance of my explanatory variables in my regression models. Though these phenomena are significant and cannot be ignored, results suggest that “addiction” and “emotional investment” cannot be credited to them.

There are potential explanations for the lack of supporting evidence. I suspect the inconclusive data to stem from the time during which the data was collected. It is likely that midterm examinations and projects were prominent during Phase 2. Participants are students after all, and while fulfilling the course load from an institute of high academic rigor as Emory, students have coursework to be completed, which oftentimes warrants hours of work manifold beyond regular classes. This academic pressure is both anecdotally and logically expected to increase during the exam season, when assignments are generally worth more points than the typical ones are. The data collection process falls right in the middle of February, when the students’ first round of exams take place. Amid the month of stress, it is likely that students’ watching habits might be disrupted due to unfinished work or increased workload. Some may experience a significant decrease in their viewing hours due to their need to allocate more time towards their studies, while others may procrastinate. Students might also alternate between studying and procrastinating, at random, spasmodic intervals, which may affect their enjoyment of the shows, as well as whether the utility gained from streaming accurately reflects their true utility. To control for the effects of exams and assignments, I can include a “busyness” variable, which allows participants to rate how busy they are during the week; this can account for the effects of schoolwork on the underestimation effect.

Another source of inaccuracy in data comes from the fact that the data are self-reported, which poses inherent risks. By allowing participants to report their consumption behavior under an uncontrolled environment, I subject the accuracy of my data to reasonable doubt. Constructing the profile of each participant is meant to gauge how or what inherent psychological factors influence the behavior of the students; however, the human mind is shaped by countless biases unbeknownst to both researchers and participants themselves. As a result, it is extremely difficult to capture a comprehensive list of psychological factors that contribute to overconfidence. While the proxy variables I derived from the viewer profiles of each respondent provide different ways to quantify abstract concepts like “addiction” and “emotional investment”, other researchers may theorize more robust and reliable indicators. For example, I can collect their feeling of happiness and level of stress before streaming. This study already collected participants’ enjoyment after watching; however, it would be valuable to see their stress levels that prompted them to stream, which can examine their viewing behavior in conjunction to their emotions while streaming.

All these reasons are proposed under the assumption that the participants are truthful in their answers. To a typical person, and moreover students who are immersed in the highly productive and merit-based environment of academia, procrastination carries a negative connotation, as it suggests that one is lethargic, and lacks the mental endurance and fortitude to complete their coursework. There is a possibility that students deliberately reported fewer hours than their actual streaming hours, which may account for the lack of effects from each explanatory variable. The one week increments between reporting predicted and actual viewing hours in my experiment design was meant to encourage the participants to forget their prediction; however, it is entirely possible that they may remember fully what they predicted the week prior. I have identified the possibility of the hidden psychological factors’ influence affecting the data, and I have implemented mechanisms within the experimental design as an attempt to reduce their effects. I invite future researchers to tackle these issues in ways I have not devised.

Overall, I recognize that the study was conducted in a short span of time, and that one month is not enough to draw substantial conclusions for a study that tracks changes in participants’ behavior, especially one that minimizes contact between participants and the researcher. It is possible that participants display the lack of changes in their streaming behavior due to the fact that there is no impetus that incentivizes a learning behavior. It is also possible that there simply was not enough time elapsed between notifying the participants of their underestimation gap and asking them to predict their consumption again. The participants might not have had enough time to change their behavior.

Viewing the raw data, there also appears to be outliers in the responses. Some participants report suspiciously extreme responses. For example, one claimed that they would require 100 shows offered on another service to incite a switch in primary service, and another claimed that they can spend 365 days without streaming (at that point, why would they even purchase their streaming service?); however, I am reluctant to remove these potential outliers for removing data points in my analysis may jeopardize my ability to carry out the regression analysis. At the same time, having these large values also reflect the preferences of participants. The variety of subscription plans exist to provide a wider range of choices for viewers of contrasting tastes and viewing habits. Thus, by removing outliers, I might fail to capture the diversity in the population I am studying.

For future work, it will be a worthy endeavor to recruit a minimum number of participants of each streaming service, and for each type of content watched. Currently my data is heavily skewed to include around 68% Netflix viewers, while the other 32% is split between Hulu, Amazon Prime, xFinity, and others. The data is at risk for overemphasizing the consumption behavior of Netflix users, for I recognize that every service has differences in their interface, their service conditions, their features, etc. Up until 2010, Netflix awarded the "Netflix Prize" every year for winners of their open competition for machine learning algorithms designed to best predict user ratings and improve recommendation system. As a result, Netflix is adept at learning the habits and preferences of viewers and suggesting content that fit to their needs at an allegedly much higher accuracy than other services can. This may influence the streamers' choice of continuing to stream as they're constantly intrigued by the content suggested. The design of the Netflix user interface also incites further desire for streaming. The black background allows the viewers to direct their attention towards the "next episode" button, or the wide-scrolling list of suggestions Netflix offers at the end of every video. Other services, with different suggestion algorithms, and different interface design might achieve the goal of encapsulating the streamers' attention differently. It will be interesting to see the changes in the overconfidence effect for viewers of different primary services and will be support for my theory if streamers are overconfident universally throughout all services.

Similarly, my 80% of my sample population watches TV shows, while the other 20% is split between movies, documentaries, and others. The duration of each type of video varies- TV shows are generally 20 to 60 minutes, while documentaries are at least 60 minutes, movies generally are 1.5 hours to 2.5 hours. While studying the consumers' desire to continue watching, the marginal increase in time must be brought into consideration. It is arguably easier to watch another episode of a TV show when the time increase for every episode is 20 minutes, compared to movies, which increases the watching time by hours every time a consumer makes the decision. It is also more common for TV shows to end with cliffhangers that lead the consumers to continue streaming, searching for a sense of closure. Movies and other videos generally do not offer the same degree of suspension for the audience, which might deter their desire to continue streaming.

VII. Conclusion

In the end, this paper provides support for the existence of overconfidence in consumers of the growing video streaming industry, shown through the underestimation of streaming hours, and delay in learning. This paper employs a theoretical model of intertemporal inconsistent valuation of utility gained from streaming instead of working on a hypothetical task. While one may predict a stopping point in the future, when arriving at that point, he may deviate from the previously made plans due to the changes in discounting terms, specifically the return of the short run discounting term as the future becomes the present. Experimental evidence collected from college students' streaming behavior over a month brings this phenomenon from the realm of anecdotal recounts into the light of experimental significance. Data shows that on average, participants watch 1 hour more than they predicted, and instead of learning to change their behavior after being notified of their underestimation, streamers increase their consumption by another hour. The study brings attention to behavior that might be motivated by innate psychological factors but lacks evidence to identify the concrete causes. In conclusion, the study supports that the video streaming industry, like many of its predecessors in subscription based services- health club, telecom market, magazines, to name a few- have overconfident consumers, and it merits the implementation of contractual mechanisms just like that of other industries to protect the benefits to its subscribers.

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Appendix:

A. **Figures and Tables:**

Variable	**Levels**	Count (Percentage)
gender	M= Male F= Female	56 (56.6%) 43 (43.4%)
primary	Amazon Prime Hulu xFinity Netflix Others	9 (9.09%) 17 (17.2%) 1 (1.01%) 67 (67.7%) 5 (5.05%)
content	Documentaries Movies Others TV Shows	4 (4.04%) 13 (13.1%) 3 (3.03%) 79 (79.8%)

Figure A.1: Proportions in Categorical Variables

Variable	**Mean/Median***	**Std. Dev**	**Max**	**Min**
diffhours	1.03	4.04	13.0	-16.0
diffhours2	2.38	3.65	12.0	-6.00
percchange	1.39	4.97	19.5	9.00
nservices	3.00	1.27	7.00	1.00
currentshows	2.00	1.84	15.00	0.00
useperweek	4.00	2.14	15.00	0.00
notvdays	3.00	36.4	365	0.00
bias	16.0	4.35	28.0	7.00
extrashowsforswitch	5.00	15.1	100.	0.00
duration	36.0	30.4	168.	2.00
enjoyment	8	-	10	1
enjoyment2	8	-	10	1
percenjoy	4.00	0.59	0.060	-0.800
browse	7	-	10	1

Figure A.2: Summary Statistics

*Discrete Variables use Median, while Continuous Variables use Mean

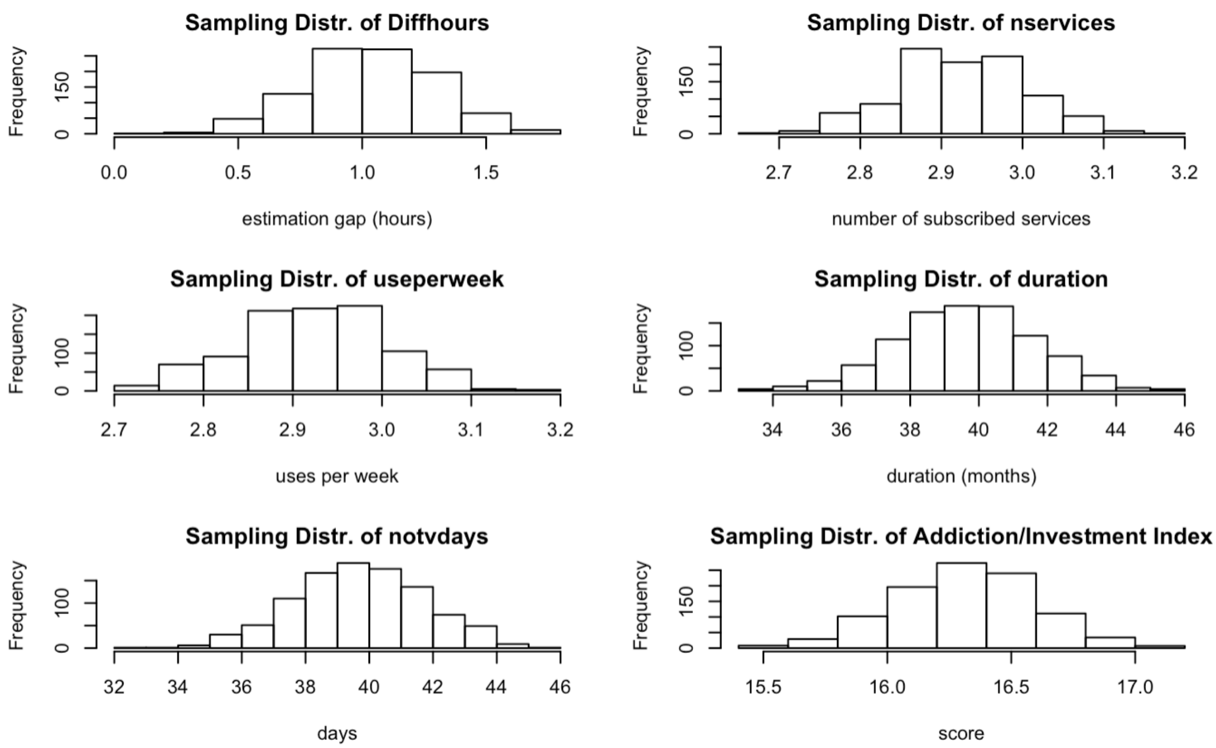

Figure A.3: Sampling Distribution of Key Variables. Resulting from sampling means of 70 observations for 1000 times.

	Phase 1	Phase 2
notvdays	0.061	0.092
usesperweek	0.087	0.043
browse	0.106	0.0935
duration	0.045	-0.0018
extrashowsforswitch	0.0498	0.0226
currentshows	-0.0446	-0.097
enjoyment	0.0239	0.0186

Figure A.4: Correlation between key variables and underestimation gap of Phase 1 and 2

Table A.5: Results from Regression

	Model					
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	1.952	1.703	2.631	0.926	0.993	1.392
	(1.805)	(2.226)	(2.441)	(2.913)	(2.758)	(3.434)
serviceprice	-0.074	-0.029	-0.068	0.016	-0.031	-0.032
	(0.114)	(0.141)	(0.200)	(0.146)	(0.122)	(0.152)
nservices	0.040	0.022	0.122	0.135	-0.065	0.065
	(0.327)	(0.404)	(0.381)	(0.462)	(0.351)	(0.437)
gender (male)	-0.156	0.145	0.046	0.153	-0.249	0.121
	(0.831)	(1.025)	(0.873)	(1.069)	(0.849)	(1.057)
duration			0.006	-0.011		
			(0.015)	(0.018)		
extrashowsforswitch			0.010	-0.152		
			(0.029)	(0.312)		
currentshows			-0.143	-0.006		
			(0.259)	(0.035)		
enjoyment			0.278			
			(0.733)			
percenjoy				1.265		
				(0.892)		
bias			-0.074	0.037	-0.056	0.053
			(0.100)	(0.123)	(0.097)	(0.121)
notvdays					0.006	0.003
					(0.012)	(0.015)
browse					0.159	-0.034
					(0.162)	(0.202)
useperweek					0.133	-0.094
					(0.172)	(0.212)
R-squared	0.004	0.0004	0.019	0.029	0.028	0.005
Adjusted R-Squared	-0.016	-0.020	-0.057	-0.059	-0.036	-0.071
Obs	99					

Variable Name	Variable Type	Explanation
diffhours	Continuous numerical, dependent	The difference between expected and actual hours viewed over the week Phase 1
diffhours2	Continuous numerical, dependent	The difference between expected and actual hours viewed over the week Phase 2
percchange	Continuous numerical, dependent	The difference of the diffhours variable between Phase 1 and Phase 2
primary	Categorical	The service the respondent uses the most often
serviceprice	Continuous numerical	The price of the primary service
nservices	Discrete numerical	The number of services the respondent is subscribed to. This presents direct alternatives to using the primary service.
currentshows	Discrete numerical	The number of shows currently following. This measures the "investment" the respondent has in the TV viewing activity.
useperweek	Discrete numerical	The number of times the respondent views TV per week.
notvdays	Discrete numerical	The number of days the respondent can spend without watching TV. This Directly measures the addiction
bias	Ordinal Categorical	Measures the influence of one's emotions and biases, as well as uncertainty over their decisions and ability to act "rationally"
extrashowsforswitch	Discrete numerical	The number of extra shows that must be offered on another service for respondent to switch primary service. Measures level of investment consumer has in the current service.
duration	Discrete numerical	Number of months the respondent has had the subscription to the primary service
enjoyment	Ordinal Categorical	The self-reported level of enjoyment streamers derive from their viewing hours Phase 1
Enjoyment2	Ordinal Categorical	The self-reported level of enjoyment streamers derive from their viewing hours Phase 2

content	Categorical	Type of content watched mainly
percenjoy	Continuous numerical	Percentage difference between enjoyment between Phase 1 and Phase 2
browse	Ordinal Categorical	Likelihood of browsing for content to watch (i.e. begin streaming without a specific content in mind)

Figure A.6: Descriptions of variables

B. Survey Questions

Signup Pre-Survey

(Consent Form)

(If Consent)

Name:

Email:

Phone Number:

(If not consent)

"Thank you, have a good day!"

Week 1

Participant ID:

What is your primary subscription (i.e. the service you use the most often for TV)?

1. Netflix
2. Hulu
3. Amazon Prime
4. xFinity
5. Others

What content do you mainly stream?

1. TV Shows
2. Movies
3. Documentaries
4. Others

How many months have you been a subscriber to the service? (approx. months)

How many service subscriptions do you currently have? (e.g. 3)

How many shows are you regularly viewing? (e.g. 2)

How many times do you use the subscription every week? (e.g. 5)

If identical shows were offered in another service, how likely would you switch? (1-10)

How many extra shows/films/content must be offered on another service for you to decide to switch? (e.g. 5)

Hypothetically, if there's a consistent dissatisfaction of the content offered by your service, how many subscription periods will you wait before switching to another service provider? (e.g. 3 periods)

To what extent do you agree with the statement: "I make decisions easily" (1-10)

To what extent do you agree with the statement: "I adapt to changes quickly" (1-10)

How many days can you typically spend without consuming the service? (e.g. 2)

Please estimate the hours you'll be viewing using the primary service over the next week. (e.g. 5)

Please estimate the hours you'll be viewing using any other service over the next week. (e.g. 5)

Week 2

Participant ID:

Please give an estimate of the hours you've used your primary service over the past week.

Please give an estimate of the hours you've used any other services over the past week.

On a scale of 1-10, please rate your enjoyment of the time spent.

Week 3

Participant ID:

"Welcome to Phase 2 of our study.

(*if underestimate*) Data collected from the previous 2 weeks suggest that you've underestimated the number of hours viewed over the week."

On a scale of 1-10, how much do you agree with the statement: "I spend a considerable amount of time browsing for content to watch"?

Please estimate the hours you'll be viewing using the primary service over the next week.

Please estimate the hours you'll be viewing using any other service over the next week. (e.g. 5)

Week 4

Participant ID:

Please give an estimate of the hours you've used your primary service over the past week.

Please give an estimate of the hours you've used any other services over the past week.

On a scale of 1-10, please rate your enjoyment of the time spent.

C. Consent form

Study Title: An exploration of Television consumption decisions

Principal Investigator: Peter (Tun-Shuo) Lee, Emory Economics Undergraduate (class of 2021)

Introduction and Study Overview

Thank you for your interest in our study about online-television viewing decisions behaviors.

This document serves as an overview so you are fully aware of your role in the study, should you decide to take part after reading it. Please note that your decision to participate or not, is entirely to your freedom; there are no consequences to your decision. We understand that the information we're requesting from each participant may be personal, so even if you consent after reading this document, at any point should you feel uncomfortable with your participation in the study, you have the choice to withdraw, and any data we've collected from you will deleted. There's no penalty from your withdrawal at any point in this study.

1) The purpose of this study is to examine the consumers' decision for online-television viewing/streaming duration.
    a. You must have an existing subscription to at least one online streaming service (e.g. Netflix, Hulu, Amazon Prime, etc)
2) The study will span over a month, with participants filling out a survey each week.
3) Each survey will take around 5-10 minutes to complete, reaching a total of 20-40 minutes over the month of participation
4) If you join, you will be asked to fill out an initial survey, with questions about your status as a viewer: expected hours of viewing a day/week, number of family members, how many shows you regularly view, whether you have cable, how many services do you have, etc.
5) Each subsequent survey (weeks 2-4) will simply be asking for the time you spent streaming through your primary subscription.
6) The Principal Investigator will contact you with an assigned ID, which you will use whenever you fill out the surveys
    a. Your ID will be recorded along with your contact information, which will only be available to the Principal Investigator
7) There are no direct benefits to you for your participation; however, the study will assist in building our understanding of online-streaming behavior
8) Your privacy is important to us. Though your contact information is recorded, it will only be used to contact you for sending out, following up, and reminding you of each week's survey. Your identifiable information (i.e. email, phone number, name) will be accessible only to the Principal Investigator, won't be used for any other purpose, and won't be directly linked to your responses.
9) Repeated failed attempts to reach out to you would likely result in termination of your participation in the study.

10) You may revoke your authorization at any time by contacting the Principal Investigator, and your data will be erased from all records.

Potential Risks

Since the study only involves participants' responding to surveys, there's inherently minimal risks involved. Hence, procedures to lessen the probability of injuries or damages to the health and wellbeing of the participants are redundant, as there's an infinitesimal magnitude of risk, if not none. The experiment will involve participants' filling out a survey every week, on their own time, in their own homes. There's no further action necessary on participants' parts, other than recording down their TV viewing habits. Hence, risks and discomforts, as well as hazards to the participants' wellbeing is minimal.

We do acknowledge that there exists psychological stress, to varying degrees, from divulging information closely related to a private activity.

Should participants feel like the stress from participating in the study is unmanageable, they can terminate their involvement in the data collection process. To that end, any potential stress from the study that rises is beyond our control.

For participants who suffer from previously identified psychological stress and require resources for recuperation, mental health counseling, and psychological services are available locally in Atlanta. Emory undergraduates (which will make up most of the participants of the study) will have access to the free Counseling and Psychological Services (CAPS) Office for individual and group therapy appointments.

Risks of participating in the study should subside after the data collection process. In other words, there are no long-term detriments to the participants.

If events that alter your daily routine (travel, death of family members, injuries, illness, etc) arise, you can contact us to arrange for having your participation halted, and continued in a future time.

Potential risks include breach of confidentiality and potential loss of social standing. Specifically, breach of confidentiality refers to the risks of your data being obtained via theft, and loss of social standing refers to the risks of being scrutinized by the public if your information is stolen and publicized. We evaluate these risks as unlikely given the safeguards taken by the research team, and technological advancements, intended to safeguard data.

Confidentiality

We value your privacy and confidentiality. Therefore, all data we collect from you will be separated from your name and contact information. You'll be given an ID number you'll use to fill out the surveys we send you. There will be a separate spreadsheet stored in the Principal Investigator's google drive that contains your name and contacts, which will be accessible only to the Principal Investigator. Furthermore, your data from this study will not be shared with anyone outside this study, even if we take out all the information that can identify you. We will use your sample and data only for research. We will not sell them.

Contact Information

If you have any questions about the study, your part in it, your rights as a research participant, any questions/concerns/complaints about the study, you may contact the following:

Peter (Tun-Shuo) Lee , Principal Investigator Tel: 805-807-1985 Email: tleejr@emory.edu

Emory Institutional Review Board: 404-712-0720 or toll-free at 877-503-9797 or by email at irb@emory.edu

Consent

By checking the box below, you acknowledge that you're aware of a participants' role in the study, and the tasks you will complete, and the risks associated with them, should you decide to sign up. You understand that you are not obligated to participate in this study, and are able to withdraw at anytime.

(Check BOX) I have read the document in its entirety and am providing consent to participating in the study.

In place of a signature, please write your full name and the date in the space provided below.

Full Name: (Blank box)

Date: (mm/dd/yyyy)

D. Recruitment Flyer