When Streams Come True:

Estimating the Impact of Free Streaming Availability on EST Sales

Completed Research Paper

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Abstract

The rise of online digital platforms has caused a massive increase in the number of viewers who consume entertainment via online streaming. To cater to this audience, television networks have started making their content instantly available on both paid and free online streaming platforms after broadcast. However, this raises questions as to what impact these free streaming channels have on consumption in paid channels, such as digital Electronic Sell Through (EST). In this paper, we empirically analyze whether free streaming on a major television network's online platform cannibalizes the sales on paid channels. To do this, we use a unique dataset provided by a leading television network in the United States. We exploit the natural variation in the online streaming schedules of a prominent television show in our identification strategy. Using a difference in difference approach we find that free streaming availability cannibalizes EST sales by about 8.4%.

Keywords: Digital entertainment, Distribution channels, Online streaming, EST sales, Free Streaming

Introduction

Technology has changed the way entertainment industries produce and distribute content to consumers. One notable change has been the ability of broadcasters to use Internet-based streaming channels to distribute their content alongside their existing over-the-air and cable broadcast channels. Two recent surveys reflect the increasing popularity of the streaming channel. A survey by Deloitte found that online streaming has overtaken live TV in terms of popularity, with 56% of those surveyed preferring to stream movies and 53% to stream TV shows versus viewing in traditional channels (Deloitte 2015). A similar survey by Forrester shows that this trend is particularly apparent among Millennials (those age 18-34), 40% of whom stream their content from free or paid online platforms (Forrester Research 2014).

Of course, the rising popularity of online streaming channels creates both opportunities and challenges for established broadcasters. Notable among the challenges is understanding whether and how these new streaming channels impact sales and viewership in established channels and how broadcasters can deal with the phenomenon of "cord-cutting" - increasing number of users who unsubscribe from cable subscriptions. Answering this question is complicated by the dual facts that it is difficult to run randomized experiments to analyze this question and that it is difficult to use observational data to analyze this question because of the natural endogeneity between sales in the various channels. Answering this question is also complicated by the fact that, when it comes to EST sales, free online streaming could have a negative effect (consumers watch free streaming instead of buying EST content), a positive effect (free streaming increases word-of-mouth promotion and allows consumers to discover new content), or no effect at all (these channels appeal to different customer groups).

Our goal in this paper is to analyze how free streaming availability impacts sales in a major digital download channel. We do this by taking advantage of a natural experiment that occurred for Downton Abbey (DTA), a popular show for the Public Broadcasting Service (PBS) in the United States. The streaming schedule for Downton Abbey is useful for this purpose because of the unique schedule employed for free streaming on PBS.org's site. Specifically, each episode of Downton Abbey is made available for free streaming window on PBS.org the day after the episode is broadcast on television, which is the same date the episode is first made available on digital download channels for electronic sell-through (EST). However, although the episodes enter the free streaming window at different times, all of the episodes are removed from the free streaming window on the same date (but remain available through EST).

This creates a setting where, for episodes at the same point in their lifecycle since broadcast, some are available on *both* EST and free streaming, while others are available *only* on EST. In the absence of a field study, this setting helps us to simulate a randomized experiment with our data and compare the difference in sales between those episodes that were available in the free streaming window and those that were accessible only via paid channels at the same stages in their life cycle. Our analysis shows that when episodes are available in both free streaming and paid download channels they sell 8.4% less than they do when they are only available in paid download format. The causal interpretation of this result is validated through several placebo tests, and the size of the effect is consistent with the results obtained using an alternate identification strategy.

Of course, in spite of the cannibalization, there are a variety of reasons broadcasters may want to make their content available simultaneously in free streaming and paid download channels. For example, free streaming may generate traffic to PBS' site and potential interest in other shows, allows PBS to better customize their assortment of content to specific user interests, and generates advertising revenue through on-site advertising.

Thus, our paper helps to answer an important managerial question regarding how media firms should manage their content across different channels and reduce the risk of cannibalization while still preserving consumer's interest on their platform. With this knowledge, firms can design policies that optimize the free streaming window by adopting strategies to potentially defray the revenue lost in the presence of cannibalization.

Literature Review

Our study contributes to two broad streams of research. The first research stream studies the degree to which new channels cannibalize product sales in existing channels. Channel cannibalization has been studied extensively in literature. Moorthy and Png (1992) analyze cannibalization in the context of products of differing quality from the same firm. Page and Rosenbaum (1987) create modeling approaches to estimate cannibalization by calculating the market share of products with different attributes and Mason and Milne (1994) study cannibalization of established cigarette brands by entrants. Early work in the entertainment literature (Williams Jr and Shapiro 1985) analyzes how in-home entertainment decrease theatrical attendance.

However, these studies have gained importance in recent years with the rise of digital distribution channels. A majority of the studies in this body of research have looked at the impact of online performance of movies in the offline channels. For example, Dellarocas et al. (2010) study the impact of digital WOM promotion on offline performance of movies while Hashim and Tang (2010) analyze the substitution that occurs between digital rentals and offline DVD purchases. Other work in this area includes Kumar et al. (2014) and Smith and Telang (2009) who study the impact of television broadcasts on DVD sales.

One notable stream of the literature analyzes whether digital piracy has a causal impact on paid sales in legal channels, with the vast majority of studies finding significant cannibalization of legal sales (see reviews by Oberholzer-Gee and Strumpf (2009), Danaher et al. (2013) and Liebowitz (2013)).

Other studies have analyzed the degree to which availability in legal digital channels impacts the demand for piracy, and demand through physical channels. For example, Danaher et al. (2010) show that removing NBC content from iTunes caused an 11.2% increase in piracy for NBC's content relative to ABC, CBS and FOX content, and no change in the demand for sales of this content on DVD. Similarly, Danaher et al. (2015) find that ABC's decision to add its content to the Hulu platform caused a decrease in the demand for piracy on the added content and no change in demand through DVD channels.

Although substitution between channels of different formats has been well studied, the interplay between channels of the same format has not garnered much attention with the exception of Knox and Eliashberg (2009), who study the impact of DVD rentals on DVD sales and Gong et al. (2015) who leverage a field experiment to show how promotions in digital purchase channels change sales in digital rental channels. Our paper extends this literature by analyzing the impact of digital streaming on digital sales channels.

With an increasing number of consumers accessing content through digital streaming format, content producers are racing to provide high-quality content to consumers instantly after the release of content on TV broadcasts or on theatre, in an attempt to compete with piracy. Thus, the question of optimal time to release content on subsequent channels, especially for content broadcast on television networks, seems to have been resolved by managers in media firms. However, the spillover effects between channels of similar format and whether release in a free channel cannibalizes the sales on a paid channel is still unclear and merits attention.

Data

We obtained our data by partnering with Public Broadcasting Service (PBS), one of the largest and the oldest television content provider in the United States. PBS is watched by 82% of American households and approximately 198 Million viewers, making it one of the largest distributors of television content in the United States.

Our data comprise sales of different shows on a major digital sales platform and streaming activity of different shows available on PBS.org. In this dataset, we observe the date each show was broadcast on TV, and the date is was made available both on free and on iTunes. In our analysis, we focus on one show in particular: Downton Abbey. Downton Abbey is useful for analysis because of the way the show is licensed.

Specifically, the license requires that PBS remove all episodes of the content from their free streaming channel on the same date, whereas all episodes are originally broadcast on different weeks (and then made available one day later on free streaming and EST download channels). As figures 1 and 2 demonstrate, this means that episode 1 is in the free streaming window for nine weeks, episode 2 is in the free streaming window for eight weeks and so on.

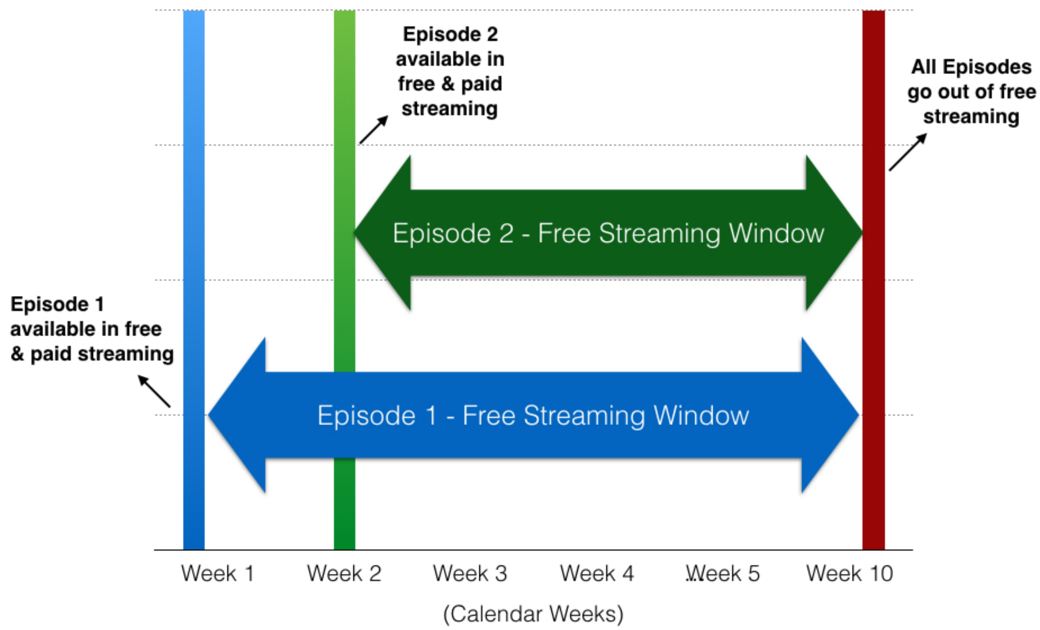

Figure 1: Streaming schedule of a show in the variable window category

Figure 2 provides an additional way to observe the impact of this licensing strategy, using Season 4 of Downton Abbey as an example. As this figure shows, each episode is broadcast in a different consecutive week starting in the first week of January. All episodes are available for free streaming on PBS.org and for purchase on other channels the day after broadcast. In Figure 2, rows represent episodes of Season 4 and columns indicate if a particular episode was available for free streaming at a certain week after broadcast. The availability of a show in the free window at a particular week is denoted by a check mark. For example, episode 1 is available for free streaming for nine weeks and episode 8 is available for free streaming for only two weeks after broadcast. All the episodes of Season 4 go out of free streaming on March 9, 2014.

Weeks since broadcast (age)	1	2	3	4	5	6	7	8	9	10
Episode 1	✓	✓	✓	✓	✓	✓	✓	✓	✓	×
Episode 2	✓	✓	✓	✓	✓	✓	✓	✓	×	×
Episode 3	✓	✓	✓	✓	✓	✓	✓	×	×	×
Episode 4	✓	✓	✓	✓	✓	✓	×	×	×	×
Episode 5	✓	✓	✓	✓	✓	×	×	×	×	×
Episode 6	✓	✓	✓	✓	×	×	×	×	×	×
Episode 7	✓	✓	✓	×	×	×	×	×	×	×
Episode 8	✓	✓	×	×	×	×	×	×	×	×

Figure 2: Streaming schedule for Season 4

In the absence of a randomized field trial, such a design of the free streaming window provides us with a natural experiment to compare episodes of the same show when they are of the same age in their lifecycle and where some are available in both free and EST channels and others are only available in the EST channels. For example, in Figure 2, we can compare sales of episode 1 in its ninth week after broadcast (when it was available on both free and EST channels) with the sales of episode 2 in its ninth week after broadcast (when it was only available on the EST channel) after controlling for other observable characteristics. This forms the basis of our identification strategy.

We make use of Seasons 3, 4, and 5 of Downton Abbey, which were broadcast in 2013, 2014, and 2015. Downton Abbey accounts for about 60% of sales on PBS and has the highest viewership of any PBS show. Each season is broadcast in January and February and consists of 8 episodes. Therefore, we use the sales for a total of 24 episodes in our analysis. We track the sales of each of the episodes for 13 weeks from the week an episode is broadcast and, available on paid streaming until the week after all the episodes go out of free streaming.

We provide summary statistics for our data in Table 1. Across seasons, the average number of units sold in the free streaming window is 11,308. Note that 46.8% of the sales occur in the first two weeks followed by a gradual decline in sales. This pattern is quite similar to the number of streaming views on PBS.com. Most of the streaming occurs in the first two weeks after broadcast after which the streaming activity gradually declines. Also note, that consistent with the licensing restrictions outlined above, time in the free streaming window changes both within and across the seasons. For example, episode 1 of Season 1 is in the free streaming window for 55 days. However, episode 2 of Season 1 is the free streaming window for 48 days while episode 1 of Season 2 is in the free streaming window for 62 days. We make use of both types of variation in our analysis.

One may be concerned that the design of the free streaming windows is determined based on the performance of the shows and hence might be endogenous. However, the representatives from PBS informed us that these time windows are negotiated with the producers of the content, *before* the series is aired for the first time, and before anyone knows the potential reception from the audience. The managers strive to provide free access on PBS.org as long as possible unless the streaming window is explicitly negotiated on the agreement with the producers. With DTA, the rule was to make sure that the last episode had at least one week within the free streaming window before all the episodes of a season went out of free streaming on the same day.

Variable	N	Mean	SD	Total	Min	Max
Length of free streaming window in Weeks	24	5.5	2.48	NA	1	10
Number of units sold on iTunes in the first thirteen weeks after broadcast for each episode	304	11,308	18,885	3,437,782	1,638	145,160
Number of units sold in the first two weeks after entering in the free streaming window	46	34,950	40,034	1,607,721	7,192	145,160
Number of streaming views on PBS.com	230	139,546.84	263,704.58	32,095,775	0	1,179,702
Number of streaming views on PBS.com in the first two weeks after entering in the free streaming window	46	560,298.41	344,585.03	25,773,727	0	1,179,702

Table 1: Summary Statistics

Empirical Model and Results

In this section, we address our main question: Does free streaming substitute for or compliment EST sales? The primary challenge in answering this question is to isolate the effect of removing content from free streaming from the natural changes in sales that occur in the lifecycle of the content. We do this by comparing the difference in mean sales of all episodes that were available in free streaming (control group), with the mean sales of all the episodes in paid streaming (treated group) given a particular week since broadcast. However, this identification relies on the assumption that episode 1 is comparable to episode 8 or, said another way, that we can control for the differences between these two episodes based on observable factors. It is possible that the first episode of the season is more popular than the later episodes and that users' interest might wane after the first episode. Therefore, this model needs to be extended to account for the potential unobservable differences between the episodes within a season. We can deal with the episode level unobservable effect by adding an episode level fixed-effect υ_i to the model as follows:

$$\log(Sales_{it}) = \beta_0 + \beta_{stream} \times FS_{it} + \delta_{age} \times WSB_{it} + \delta_{year} \times Month_{it} \times Year_{it} + \upsilon_i + \varepsilon_{it} \quad (1)$$

Since we have three seasons and since each episode has 8 episodes, $i \in \{1,2,3...24\}$ where 24 is the total number of episodes in this show. Here $Sales_{it}$ refers to the EST sales of an episode in week t, where $t \in \{2,3,4...10\}$, refers to the sales of the episode since broadcast. FS_{it} is an indicator variable that is equal to one when the episode is in the free streaming window and is equal to zero when the episode goes out of the free streaming window. WSB_{it} it is the age of the episode in weeks since broadcast. $Year_{it}$ is a dummy variable that can take values 2013, 2014 or 2015 depending on the broadcast of the season the episode is a part of. $Month_{it}$ refers to the month in which the sales occur. We interact $Year_{it}$ and $Month_{it}$ variables to capture the decay in sales of each episode every year.

The coefficient of interest is β_{stream}. This represents the difference in sales between the episodes that were in the free streaming window (control group) and the episodes that were out of the free streaming window (treatment group) .Thus this co-efficient captures the cannibalization effect. We add a WSB_{it} variable in order to make sure that we compare the sales of the episodes that are all at the same point in their lifecycle. This control variable enables us to compare the sales of all the episodes at a particular week from broadcast. By controlling for the year and the month, we make sure that this comparison is done within the seasons that each episode is a part of and that we capture the natural decline is sales as much as possible.

This model enables us to capture the unobservable sales patterns of each episode. Note that we control for episode level fixed effects and also characterize the decay in sales over specific months within each year of our time window. The coefficient of interest β_{stream} represents the Average Treatment Effect (ATE), which is the effect of being inside the free streaming window, on the treated groups at set time periods from the week of broadcast. The average treatment effect is given by $\log(Sales_{it}^{T}) - \log(Sales_{it}^{C})$.

Intuitively, this model captures the difference in weekly sales for each episode, using the average sales of an episode as a baseline. At any given point in their lifecycle, each episode can either be in the treated group or the control group. The identification lies in the argument that, all else being equal, the change in sales from the average sales of episodes in the treatment and the control group varies because only one group of episodes lie in the free streaming window while the others lie in the paid streaming window.

There are two assumptions that are essential for the identification. *First*, the free streaming windows should be exogenously determined, which means the windows should not be designed based on the performance of a TV show or the expectation of cannibalization. *Second*, there should be at least one episode in the control and at least one episode in the treated groups during the weeks of the experiment.

Weeks since broadcast (age)	1	2	3	4	5	6	7	8	9	10
Episode 1	✓	✓	✓	✓	✓	✓	✓	✓	×	×
Episode 2	✓	✓	✓	✓	✓	✓	✓	×	×	×
Episode 3	✓	✓	✓	✓	✓	✓	×	×	×	×
Episode 4	✓	✓	✓	✓	✓	×	×	×	×	×
Episode 5	✓	✓	✓	✓	×	×	×	×	×	×
Episode 6	✓	✓	✓	×	×	×	×	×	×	×
Episode 7	✓	✓	×	×	×	×	×	×	×	×
Episode 8	✓	×	×	×	×	×	×	×	×	×

Figure 3: Streaming schedule for Season 3

We addressed the first concern in the data section showing that PBS negotiated the streaming windows for the entire series before the broadcast of the first season and for the shows with a variable window, the general rule is to make sure that the last episodes are the in the free streaming window at least for two weeks before all the episodes go out of free streaming window at the same time.

We address the second concern by taking into account only those weeks where there is at least one episode in both the control and treatment groups. For example, in Figure 3 we note that all the episodes in Season 3 are in the free streaming window in the second week after they are broadcast, and all the episodes also go out of free streaming in the ninth week after broadcast. Across seasons, the first episode is in the free streaming window at most for 10 weeks, and the last episode is in the free streaming for at least one week. The basic idea is explained in Figure 3 where columns containing *only* crosses or checks represent those weeks where there is no variation and these are periods in our dataset where we cannot simulate our experiment. Therefore, we should consider only Weeks 2 to 10 since broadcast in our analysis.

Estimates for EST sales	
Dependent Variable: Log(Sales)	**Specification (1)**
Free Streaming Window dummy	-0.084*** (.016)
N	213 (24 episodes)
R sq	0.9681

Table 2: Estimates from Specification 1

*** Statistically significant at the 1% level (two-sided test), Robust standard error reported in parentheses

Another important assumption we make here is that sales decay in a similar manner across the different episodes of the same season. Though episode level fixed effects take care of innate episode level differences to a certain extent, we need to make sure that the sales of different episodes follow the same pattern of decay so that they are comparable to one another at the same stages in their life cycle. Figure 7 shows the sales of different episodes in Season 3 across different calendar weeks of 2013 (when Season 3 was broadcast). We truncate the anomalously high first week of sales to observe the sales in the other calendar weeks more clearly in the figure. It can be seen that the sales across different episodes indeed follow a similar decay pattern.

Figure 8 shows the sales of episodes from Season 3 with respect to the age since broadcast. We notice that all the episodes follow a similar pattern of sales. i.e, their rate of decay is very similar. This plot provides a better intuition of our model. For example, when each episode is five weeks old from the week of broadcast, episodes 1-4 are *inside* the free streaming window whereas episodes 5-8 are *outside* the free streaming window. One may notice that some episodes outsell other episodes in most of the weeks. However, by adding an episode-level fixed effect in our model we account for the episode invariant effects. Therefore, our *first difference* arises from the episodes being in or out of the free streaming window and the *second difference* comes from the episode level fixed effects.

We present the results of specification (1) in Table 2. We find that β_{stream} is negative and significant. This suggests that episodes in the free streaming window had 8.4% lower sales than comparable episodes in the paid streaming window, showing that free streaming in this case cannibalizing EST sales.

Alternate Specification

In this section we test an alternate approach to identify the effect of free streaming on paid EST sales. To do this we use the fact that each of the seasons were broadcast on the first Sunday of January every year, but because of licensing issues, each season was taken out of the streaming window one week later every year after 2013. For example, episode 1 of Season 3 was available for free streaming for 55 days, while episode 1 of Season 4 was available for 62 days and episode 1 of Season 5 was available for 69 days. We can make use of this variation to identify the impact of free streaming on paid consumption. For convenience, we will use e where $e \in \{1,2,...8\}$ to denote the ordinal value of episodes within each season.

Intuitively, in the event that free streaming cannibalizes sales in EST, episodes that spend a longer time on the free streaming window should sell fewer copies than those episodes with the same value of e

across seasons which spend less time on the free streaming windows. For this analysis we consider sales within the time period from calendar week 1 to calendar week 13. We refer to this as Total Time (see Figure 4).

The time periods of interest in this analysis are calendar weeks 10 and 11 for 2013, 2014 and 2015. During calendar week 10 of 2013, all the episodes of Season 3 go out of the free streaming window while Season 4 and Season 5 are still in the free streaming window in the calendar weeks 10 of 2014 and 2015 respectively. Similarly, because Season 4 is taken off the free streaming window one week earlier than Season 5, Season 4 is out of free streaming in the calendar week 11 of 2014 while Season 5 is still in free streaming.

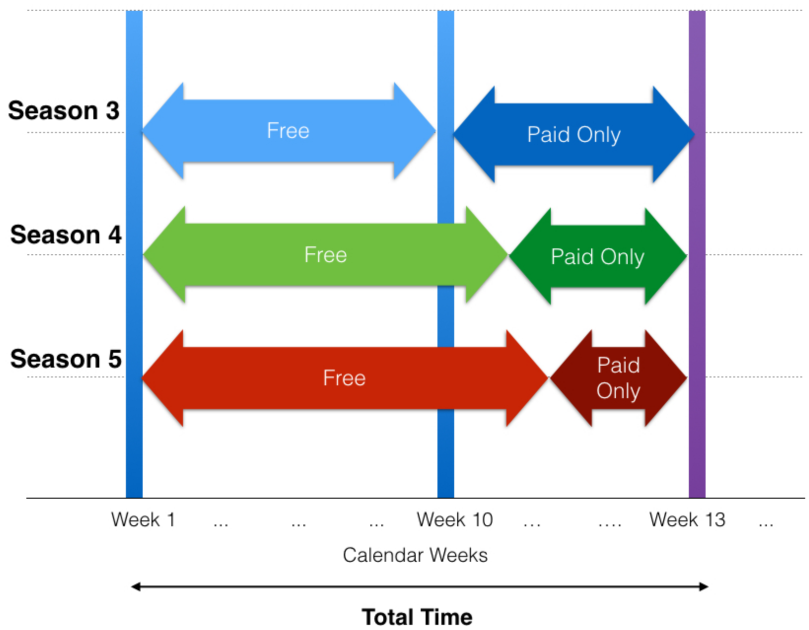

Figure 4: Experimental Setup for Specification (2)

This structure provides us with an experimental framework similar to specification 1. In this set up, we are comparing episodes with the same value of e where $e \in \{1,2,...8\}$ across different seasons, during the same calendar weeks. Note that the experimental time period was the "weeks since broadcast" or the "age of an episode" in our first specification, while we use calendar weeks as the experimental time period in this specification, as illustrated in Figure 5.

All episodes with the same value of e in Seasons 3, 4 and 5 were broadcast on the same calendar week but on different years and are in the free streaming window in calendar week 9. All episodes of Season 3 go out of the free streaming window in calendar week 10 and all episodes of Season 4 go out free streaming window in calendar week 11. Therefore, controlling for other confounding factors, we can compare the sales of episodes with the same value of e across different seasons in calendar weeks 10 and 11 such that the only difference between the episodes with the same value of e is their presence or absence in the free streaming window.

This set up is similar in spirit to the first specification where we compared the sales of different episodes *within* the same season at the same week after broadcast. In specification 1, we use the fact that all the episodes within the same season *start at different times in the free streaming window*, but end at the same time. In this alternate specification, we exploit the fact that episodes of different *season start at the same time* in the free streaming window, during specific calendar weeks of every year, *but end at different calendar weeks.*

Calendar Weeks	9	10	11	12
Season 3	✓	×	×	×
Season 4	✓	✓	×	×
Season 5	✓	✓	✓	×

Figure 5: Experimental Setup for Specification 2

More specifically, in Specification 2, we compare sales of episodes with the same value of e, *across* different seasons at specific calendar weeks at the end of their life cycle where the episodes lie in or out of the free streaming window. Figure 6 shows this set up in detail. We consider calendar weeks 10 and 11 as the experiment weeks and use the sale in these two weeks for each episode e where $e \in \{1,2,...8\}$.

We perform this comparison using the following specification:

$$Log(Sales_{it}) = \gamma_0 + \gamma_{stream} FS_{st} + \omega_{c.wk} \times WOS_{it} + \omega_e \times Episode_e$$
$$+\omega_{yr} \times Year_s + \omega_{sales} \times SalTWk10_i + \omega_{stream} \times StrmTWk10 + \psi_{it} \qquad (2)$$

Here $i \in \{1,2,...24\}$ for eight episodes in each of the three seasons and the ordinal value of each episode is indexed by e where $e \in \{1,2,...8\}$. The variable s refers to the seasons that each episode belongs to, $s \in \{1,2,3\}$. Note that the variation occurs at the season level, therefore episodes (indexed by i) with the same value of s have the same binary value of the free streaming indicator variable (FS_{it}). Said another way, episodes within the same season are all either in or out of the free streaming window at a given calendar week. WOS_{it} is an indicator variable for calendar weeks 10 and 11.

We control for the season and the yearly time trends using the year in which they are broadcast ($Year_s$). $SalTWk10$ controls for the sales of an episode prior to calendar week 10 and $StrmTWk10$ controls for the number of streaming views for each of the episodes. We add these controls to account for the popularity of the episodes.[1]

The variable γ_{stream} is the co-efficient of interest. This variable captures the Average Treatment Effect which is the effect of being outside the free streaming window, on the treated groups at set calendar weeks as given by $\log(Sales_{it}^{T}) - \log(Sales_{it}^{C})$. By controlling for other observable characteristics, the difference in sales should arise only from their presence or absence in the paid streaming window. We present the results of Specification (2) in Table 2. This table shows that γ_{stream} is negative and significant, which means all else equal, sales decreases by 9.9% for an episode in the free streaming window (where content is accessible on both free streaming and EST sales channels) compared to an episode that is outside the free streaming window (where content is accessible only on EST sales channels). The effect of

[1] We also control using sales and streaming in each week before the experimental weeks and this provides the same result as using the sum of sales before the experimental weeks (calendar week 10 and 11)

cannibalization estimated through this strategy is approximately same as the effect estimated by the specification in (1) both in the direction of effect and in the magnitude of the effect, which shows that our first specification is robust.

To ensure that our model specified by (1) is capturing the intended effect of cannibalization and an unrelated sales decay pattern, we conduct a series of falsification tests. Specifically, we use a set of randomly selected dates in weeks before and after the actual day the free streaming window expires. We run the same specification as in (1) but with these altered dates as opposed to the true date free streaming expires. We find that the coefficients of interest in each of this falsification models are statistically insignificant. This suggests that the coefficients from our primary model in (1) are estimating the effect of cannibalization and not any other decay in sales.

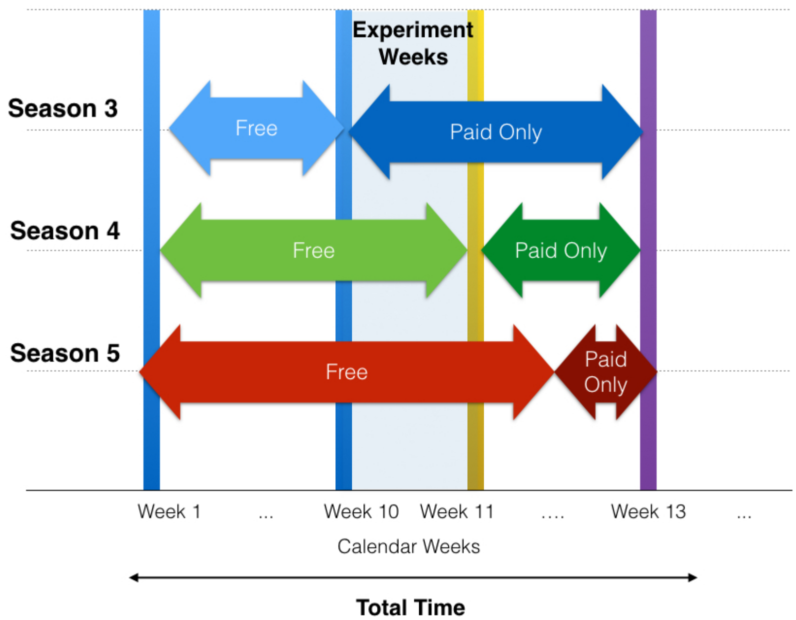

Figure 6: Experimental Weeks for Specification 2

Similarly, for the model specified by (2) we perform a falsification analysis where we use randomly chosen pairs of calendar weeks as the experimental weeks instead of calendar week 10 and 11. In this falsification test, we also find that the coefficient of interest γ_{stream} is statistically insignificant, again suggesting that the coefficient of interest robustly identifies the effect of cannibalization using the variation in free streaming window between the seasons.

Estimates for Robustness Test	
Dependent Variable: Log(Sales in Week of Experiment)	**Specification (2)**
Days in paid streaming	-0.0996*** (.0133)
N	48
R sq	0.998

Table 2: Estimates from Specification 2

In this paper, we present two specifications to understand the impact of free streaming on sales. The following paragraphs provide a summary of differences between these two specifications.

In Equation 1, we compare the demeaned sales of episodes (provided by the episode level fixed effect), within same season that are at the same stages in their life cycles. All the episodes within each season enter the free streaming window at different weeks but exit the free streaming window on the same week. This provides us with the variation that is the basis of our first identification strategy. Note that the comparisons take place at the unit of "weeks since broadcast".

In Equation 2, we compare similarly indexed or numbered episodes across three seasons. We make this comparison in calendar weeks 10 and 11 where at a season level these episodes are either in or out of free streaming. Here we make use of the fact that different seasons entered the free streaming window in the same calendar week but exited the free streaming window at different calendar weeks. Since the comparison is at a particular calendar week in each year, we can control for sales and streaming till that calendar week. Here the comparisons between the same episodes of different seasons take place at the "calendar week" level which is different from the "weeks since broadcast" level.

For example, during calendar week 4, episode 1 of Season 3 is at two weeks since broadcast, but episode 2 is at one week since broadcast. In Equation 1, we are comparing the demeaned sales of episodes 1 and 2 when they are one week old – i.e, we compare the demeaned sales in calendar week 3 for episode 1 and demeaned sales in calendar week 4 for episode 2.

In Equation 2, we compare Episode 1 of Seasons 3, 4, 5 in calendar weeks 10 & 11. These similarly indexed episodes (the index being 1 in this example) are all of the same age since they were all released on the same day in different years but go out of free streaming on different calendar weeks. Since they are of the same age, when we make the comparison, we are able to account for the sales and popularity till the week we are making the comparison in.

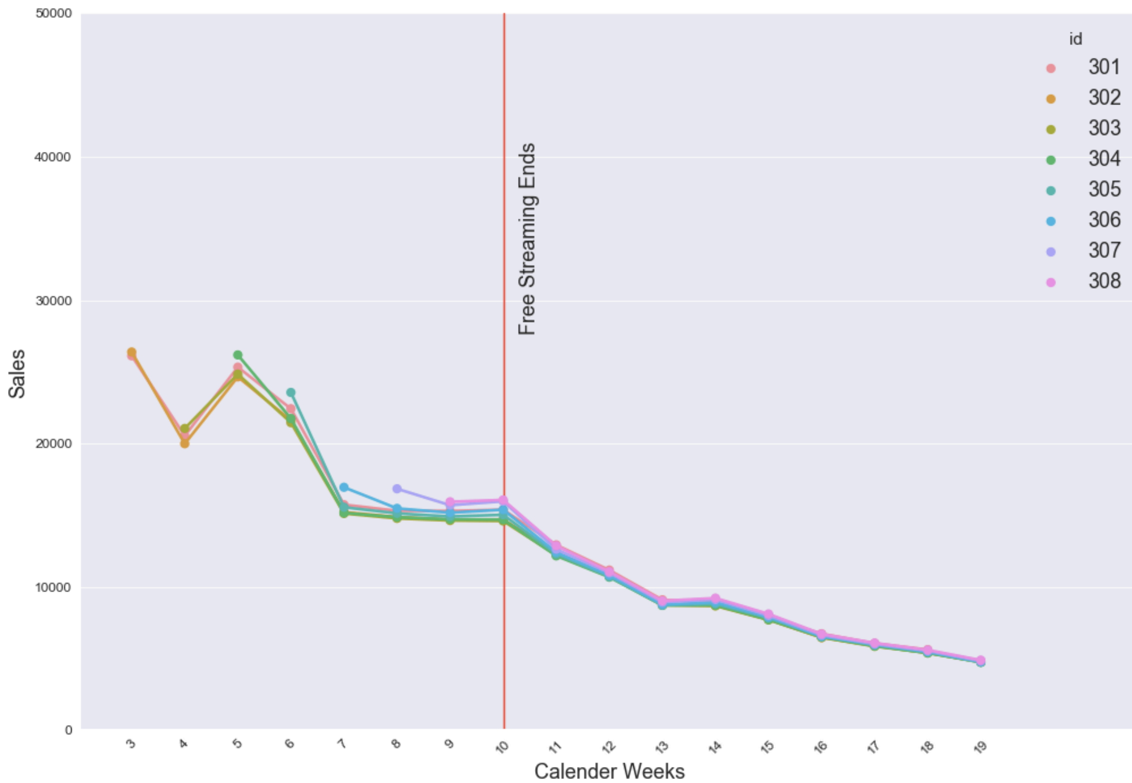

Figure 7: Sales of Episodes in Season 3 across calendar weeks in 2013

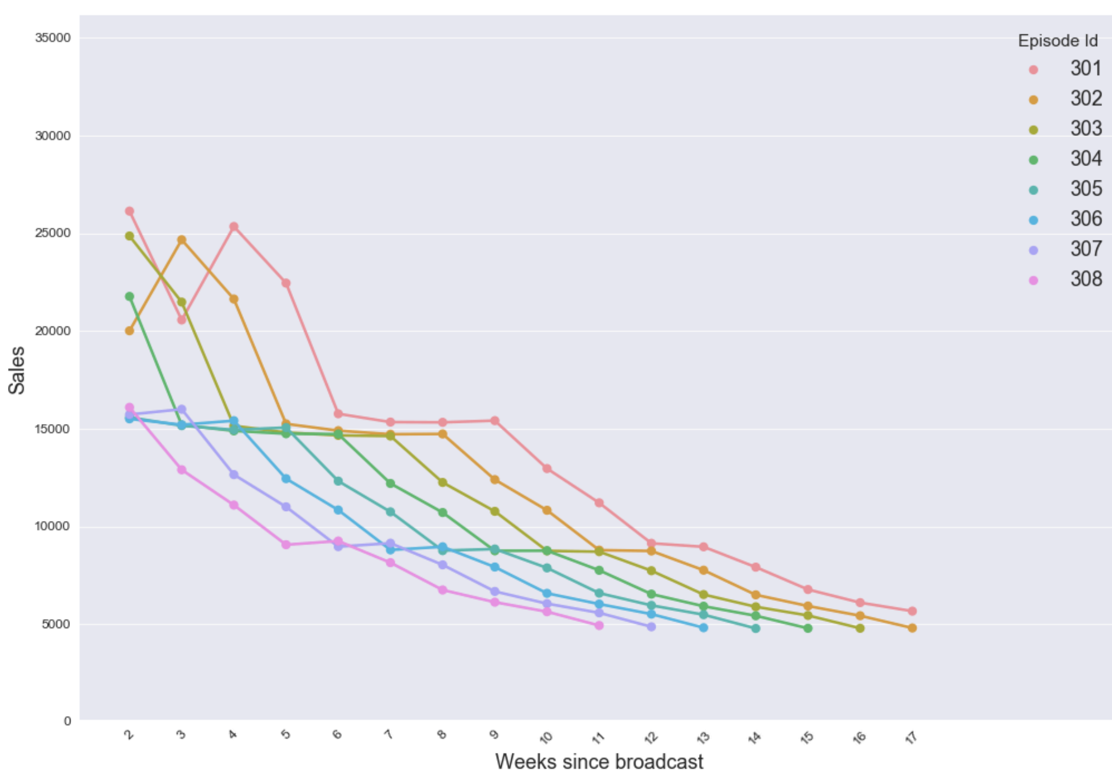

Figure 8: Sales of Episodes in Season 3 across their age (Weeks since broadcast)

Conclusion

Our paper aims to answer an important managerial and academic question: To what degree does availability of digital free streaming programming impact sales through digital download channels. We address this question by conducting an empirical analysis of a popular show on a leading television broadcast network. We do so by taking advantage of an exogenous variation in the free streaming availability of episodes on a free streaming channel. In our main specification, we compare the sales of episodes *within* a season at a given week after broadcast. We use the fact that for every season, earlier episodes stay in the free streaming window longer than later episodes, as all the episodes of a particular season go out of free streaming on the same day. The length of free streaming window is a product of licensing negotiations and therefore, is determined prior to broadcast. Therefore, each episode of the same season having a "variable" free streaming window structure are broadcast one week after another, and are either in the free streaming or the paid streaming window at a given week after broadcast. Such an experiment forms the basis of our identification.

Our analysis in our primary specification indicates that availability in the free streaming window reduces EST sales by 8.4%. Using an alternative specification we find that free availability reduces EST sales by 9.9%. In monetary terms, using the most conservative results we find that for this series, reducing the length of the free streaming window by one week increases EST revenue by 10,200 transactions, which amounts to $21,400 increase in revenue. As noted above, there several potential advantages to free streaming that may outweigh the negative impact of lost EST sales. For example, free streaming platforms owned by the broadcast network can draw new users to the platform, providing the network with valuable data about its viewers, and a stronger platform as consumers switch from consumption through broadcast television to online stream. Networks also benefit from advertising sponsorship on their streaming channels. Streaming platforms may also enable customer discovery of other shows, or increase overall consumer goodwill.

Finally, we note that our paper has several limitations. First, our analysis is done on three seasons of one series. Although this is the highest selling show on PBS and thus is a managerially important series, this show may not be representative of what would happen with other shows on this or other networks. Unfortunately, the structure of free streaming windows for other shows in our data does not provide us with a statistically valid identification strategy. Second, our analysis focuses on sales through iTunes, a popular sales platform and one used by many studies in the literature. It would be useful for future studies to analyze whether cannibalization observed on iTunes generalizes to other similar channels such as Amazon, Google Play, and Roku. Third, we are not able to measure the impact of other business considerations, such as the benefits from word-of-mouth promotional effects, which might supersede the cannibalization effect for a less popular or newly released show. Measuring these promotional effects by analyzing online reviews is a useful direction for future work. Fourth, we do not consider other user level impacts such as customer goodwill, series adoption, platform adoption and discovery of new content. Finally, we do not analyze the impact that free streaming availability has on the demand for piracy. Danaher et al (2010) study the impact of NBC removing content from iTunes and how this increased the demand for piracy for this content in illegal channels. Similarly, Danaher et al (2015) show that ABC's decision to add content to Hulu reduced piracy for this specific content. These studies look at the binary decision of adding or removing content to paid legal streaming channels. In our context, the managerial question pertains to removing content from one legal digital channel while the same content is made available in another legal digital channel.

In spite of these limitations, we believe that our work addresses an important managerial and academic question and opens up a new area of work on the impact of online streaming platforms on consumption in other channels.

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