Fee or Free: When Should Firms Charge for Online Content?*

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Abstract

Many online content providers aim to compensate for a loss in advertising revenues by charging consumers for access to content. However, such a choice is not straightforward because subscription fees typically deter customers and a resulting decline in viewership further reduces advertising revenues. This research examines whether firms that offer both free and paid content can benefit from adjusting the amount of content offered for free. We find that firms should offer more free - and not paid - content in periods of high demand. We motivate theoretically that this policy which we term 'counter-cyclical offering' may be optimal for firms when consumers are heterogeneous in their valuation of online content, this heterogeneity varies over time, and more so for low consumer types than for high types. Using unique data from an online content provider, we then provide empirical evidence that firms indeed engage in counter-cyclical offering and increase the share of free content in periods of high demand.

Keywords: Pricing, Online Media, Counter-Cyclical, Internet, Electronic Commerce, Paid Content, Paywall

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1 Introduction

Over the last decade, a decline in print advertising and a slow uptake of online advertising revenues have put many news media into a perilous state. The Newspaper Association of America suggests more than a 50% decline in total newspaper advertising revenue from 2007 to 2012. [1] In December 2008, The Tribune, owner of the Chicago Tribune and LA Times, filed for bankruptcy protection. In 2009, the New York Times credit crisis prompted a piece questioning its continued existence (Hirschorn, 2009). Many regional newspapers, such as the Miami Herald and the San Francisco Chronicle face similar financial trouble.[2] Then, in August 2013, The Washington Post was sold, because "for much of the past decade, The Post has been unable to escape the financial turmoil that has engulfed newspapers" (Farhi, 2013).

The prevalent view has long been that on the Internet "information wants to be free" and that consumers are unwilling to pay for content online (Edgecliffe-Johnson, 2009), but the future of the news industry is now widely believed to depend on the ability of companies to monetize content online. Yet, charging for online content is difficult: Paywalls decrease viewership and as a result further depress advertising revenues (Chiou and Tucker, 2013). This trade-off between subscription and advertising revenues means that charging for all content rarely benefits firms and has lead many to try and combine both revenue streams. The New York Times, for example, offers 10 free articles per month and the Washington Post in 2013 introduced a limit of 20 free articles per month. Such policies allow to price discriminate between consumers who have heterogeneous valuations. High demand consumers will subscribe and so generate advertising and subscription revenues. Low demand consumers will not subscribe but still view free articles and generate advertising revenues.[3] This pricing policy works if consumer valuations stay constant over time or the ratio of valuations of low and high demand consumers remains similar, even as their absolute levels change.

Yet, there is evidence that demand for news varies substantially. Panel A in Figure 1 displays the normalized number of searches in the US for 'Politics', 'Earnings', 'Sports', 'Temperature', 'Movies' and 'MLB', as reported by Google Trends. It documents that the demand for news is

[1] `http://www.stateofthemedia.org/2013/newspapers-stabilizing-but-still-threatened/1-print-advertising-fall-online-grows-copy-5/`; accessed April 29, 2015.

[2] `http://www.realclearpolitics.com/lists/top_10_newspapers_in_trouble/newspapers_in_trouble.html`; accessed April 29, 2015.

[3] "Leaky paywalls' that are aimed at allowing low value consumers access to articles through search engines or social networking services serve a similar purpose.

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highly cyclical. In business the cycles are quarterly related to earnings reports, while in politics the main cycles are four-yearly, coinciding with the US Presidential elections, with additional, less pronounced intermediate cycles. For sports, there appears to be an annual cyclical pattern that becomes pronounced when focusing on any specific sport, here Major League Baseball (MLB). Demand for sport news appears to be higher at times when a sport is 'in season' and games are played. To show that this is indeed the case, we plot the number of unique daily visitors to the MLB webpage of four leading sports websites in Panel B of Figure 1 (data described in detail in Section 3). We find that consistent with the data collected via Google Trends, unique visitors to any of the websites more than double when the sport is 'in season'.

[Figure 1 about here.]

How firms can best respond to such variation in demand is not obvious. Increasing prices during periods of high demand, as classic economic theory suggests, is challenging since consumers typically sign up for long-term (mostly yearly) contracts. It is also not obvious whether demand shocks indeed affect valuations of high type consumers in the same way that they affect valuations of low type consumers. Take as an example a baseball buff who is eager on baseball news at any time and the occasional fan who only gets excited as the sport is in season. It would not surprise that the demand by the occasional fan shifts more strongly as a season starts than that of the baseball buff. Similarly, a member of a political party may read up on politics every day while the average citizen strongly increases their valuation for news on politics on election day. And indeed, in the rare occasion when online content providers respond to changes in demand they appear to offer more - not less - free content during periods of high demand. For example, the New York Times and the Wall Street Journal both lifted their paywalls during the 2012 election. Yet, apart from these few examples we know very little about how online content providers should adjust the provision of free versus paid content over time and whether increasing (decreasing) the supply of free - and not paid - content during periods of high (low) demand is indeed a viable strategy.

In this paper, we provide a theoretical motivation for an online content provider's choice of revenue model, accounting for both advertising revenues and subscription revenues from yearly contracts. We show that it can be optimal for a firm to charge for content during periods of low demand but offer content free of charge during periods of high demand, a strategy that we term

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'counter-cyclical offering'. The key characteristics of demand are that consumers have heterogeneous valuations, where valuations vary across time and across consumers. Our result is driven by the assumption that valuations of low type consumers increase more strongly in periods of high demand than valuations of high types consumers. We then turn to data to provide empirical evidence that firms use counter-cyclical offering. We use unique data from the online sports website ESPN that offers the majority of content for free but charges a fee for access to a subset of articles. Importantly, the number of free and paid articles varies by day and sport. Over a 13-month period, we collect data on the number of free and paid articles per day and sport. We complement these data with data on unique visitors and page views (the number of instances a user viewed the firm's web pages) for each article type per day and sport. We demonstrate that the firm indeed counter-cyclically adjusts its offering, and relate our results back to the theoretical motivation.

Our results add to three streams of academic research. First, we add to research that models analytically when firms benefit from charging for online content. Shapiro and Varian (1998) and Bhargava and Choudhary (2001) show that offering a paid and a free component can allow firms to implement quality differentiation, versioning, or second-degree price discrimination. But since paid content reduces the number of page impressions and thus advertising revenues, it can lead to a disadvantage in advertising markets if advertisers pay a premium to firms with a high expected share of loyal consumers (Athey et al., 2013). The level of competition (Godes et al., 2009) and consumer heterogeneity further affects the trade-off between free and paid content. With heterogeneous consumers, firms should combine pay-per-view and advertising revenues but offer options to consumers (Prasad et al., 2003). Additionally, Halbheer et al. (2014) show that advertising effectiveness determines whether a firm should offer both paid and free content and find that under intermediate levels of advertising effectiveness firms should offer both. While these studies provide insights into when charging for online content may be beneficial, they do not account for variation in valuations over time and do not cover how online content providers should respond to such variation.

A second stream of research looks empirically at an online content provider's choice of revenue model. For an online content provider targeted toward marketing professionals, Pauwels and Weiss (2008) find that moving from 'free' to 'fee' can be profitable. But Chiou and Tucker (2013) show that visits to online news sites fell by as much as 73% following the introduction of a paywall, suggesting that it is challenging to charge for news content online. Other research underlines that

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consumers respond negatively to even small fees (Shampanier et al., 2007; Ascarza et al., 2012). And while recent research has documented the conditions under which online advertising can be effective (Goldfarb and Tucker, 2011a,b; Lambrecht and Tucker, 2013; Lewis and Reiley, 2014; Goldfarb and Tucker, 2015), many news sites are unable to rely on this revenue stream alone. More broadly, our research relates to work on complementarity and substitution of online and offline content (Seamans and Zhu, 2013) and a literature that explores how providers of digital content can monetize their offering, including how a firm that offers a print and a pdf version should set prices (Kannan et al., 2009; Koukova et al., 2012), the firm's trade-off between selling or renting content (Rao, 2015), and the profit- and welfare-maximizing price format (Shiller and Waldfogel, 2011). To our knowledge, no papers have addressed the question of how firms can set prices and the trade-off between advertising and subscription revenues when consumers' valuations vary over time.

Third, we add to the literature on counter-cyclical pricing that has emerged in the area of consumer goods and builds on prior research on why firms sell products below cost (Lal and Matutes, 1994). Rotemberg and Saloner (1986) suggest that an oligopolist may benefit from decreasing prices from an optimal collusive outcome when demand is high. MacDonald (2000) shows that seasonal price declines in periods of high demand are closely linked to market concentration. Warner and Barsky (1995) and Chevalier et al. (2003) point out that for a large number of consumer packaged goods, prices decrease during periods of high demand. Chevalier et al. (2003) demonstrate that consumers are not more price sensitive during these periods but instead retailers use products as loss leaders that are seasonally in high demand. Nevo and Hatzitaskos (2006) propose that the substitution to less expensive brands explains a decline in the average prices paid during periods of high demand. As an alternative explanation, Haviv (2015) relates firms' counter-cyclical pricing to consumers searching more in periods of high demand. Most closely related to our work is the explanation by Guler et al. (2014) that counter-cyclical pricing is profitable if consumers are heterogeneous in their valuations and demand shocks affect low consumer types more strongly than high types. Along similar lines, Bayot and Caminade (2014) document the entrance of a price-sensitive segment during periods of high demand. We add to this literature by demonstrating how firms that offer contracts, and so cannot readily adjust prices, can yet respond to changes in demand by counter-cyclically adjusting the amount of content they offer.

Our results have implications for online content providers that as of yet largely offer a fixed

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number of articles per month as free. While such policies might have other advantages (e.g. predictability for a consumer), the inflexibility to respond to demand shocks can be a drawback. Our research suggests that for online content providers it may, counter-intuitively, be optimal to increase the share of paid content during periods of low demand but offer more free content when demand increases. While many demand shocks are predictable, it is important to note that for counter-cyclical offering to work, the firm does not need to be able to predict demand in the long run. Digital technology means that online content providers can flexibly assign any new piece of content to be free or paid as they observe changes in demand.

2 Motivation for empirical analysis

We provide a theory-based motivation to show that counter-cyclical pricing can be optimal in an online news market. The setup differs from the set up for studying counter-cyclical pricing in a retail context as prices are in the form of *yearly fees*, unlike in a retail context where firms can change prices over time. Additionally, the firm trades off subscription and advertising revenues. In our model the firm decides whether to make articles free or paid in any season and the price of annual contracts. Given the content offering of the firm, consumers decide whether or not to purchase yearly contracts and whether or not to visit the website in any season.

We assume that in any season the firm offers either all articles for free or against a fee. Our objective is to demonstrate that for some parameter values, the firm will charge for content only at times of low demand. Following, we borrow the terminology of sports and refer to times of low demand as 'off season' and times of high demand as 'in season'.

2.1 Consumer decisions

We first define the consumer valuations. Assume there are two types of consumers, high types (H) and low types (L). Let s_L represent the share of consumers of type L. Assume there are two pre-determined seasons which affect consumer demand, off season (O) and in season (I), each of equal length N. The valuations $v_{i,j}$ for consumer type i and season j are shown in Panel A of Figure 2. Here $\alpha, \alpha_H, \alpha_L \in [0, 1]$. α represents the ratio of the in-season valuation for low type consumers relative to high type consumers. α_H (α_L) represents the ratio of off-season to in-season valuations

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for high (low) type consumers. We assume that the change in valuations across seasons is greater for low types than for high types and so $\alpha_H > \alpha_L$. Define $r \equiv \frac{\alpha_H}{\alpha_L}$ and by assumption we have $r > 1$.

[Figure 2 about here.]

Each consumer makes two decisions. First, they decide whether to subscribe to the paid service. We assume that low consumer types will never purchase the service. This assumption is consistent with low types having a reservation value of $R_L \geq \alpha(1+\alpha_L)$ for paying for the service.[4] We assume that high type consumers will purchase the service if $W(v_{I,H}Paid_I + v_{O,H}Paid_O) \geq p_c$ where $Paid_j$ is an indicator for the firm offering a paid (and not free) service in season j and p_c is the price of paid content. The firm offers only annual subscriptions. W is a constant that scales willingness to pay.

Second, conditional on having access to the website, each consumer decides how often to visit the website. Note that if the website is free, then all consumers have access to content. If the website is paid then only consumers who have paid for the service will have access. We assume that based on their valuations consumers determine how often to visit the website. The total number of visits by consumer i in season j is $Nv_{i,j}$. For each visit to the website the firm receives advertising revenue. We define p_A as the price for all page views a consumer makes during a visit. We assume that the advertising price per page view is fixed and does not vary across seasons. We later verify this assumption in our empirical setting.

2.2 Firm decisions

In our structure, the firm makes three decisions: First, the firm decides whether to provide free content or paid content when a sport is off season. Second, it decides whether to provide free content or paid content during a sport's season. Third, it decides on the price for an annual subscription to paid content. To define the firm's optimal strategy, we consider all four combinatorial options for charging for online content across seasons: The firm can always offer free content (*Free*), always offer paid content (*Paid All*), offer paid content only off season (*Paid Off*) or offer paid content only during the season (*Paid In*). In each season, we consider the profit maximizing subscription

[4]Note that this assumption is not necessary for our model, but simplifies our calculations.

price, that is the price p_c that will extract maximum value from the high consumer type. For each of these scenarios the high type consumers will always visit the website and generate an advertising revenue of $p_A N(1+\alpha_H)(1-s_L)$. The four scenarios differ in the subscription revenue that the firm obtains from high type consumers and the advertising revenue from the low types. Panel B of Figure 2 summarizes revenue from these two sources across the four scenarios.

Given the scenarios we state our main result and, in Proposition 1, show the existence of a set of model parameters for which counter-cyclically adjusting the content offering can be optimal.

Proposition 1. *Charging only when a sport is off season (Paid Off) yields the highest profit, or $\pi_{Paid\ Off} > max(\pi_{Free}, \pi_{Paid\ All}, \pi_{Paid\ In})$, if the following equation holds:*

$$\frac{1}{1+\frac{p_A N}{W}\alpha} < s_L < \frac{r}{r+\frac{p_A N}{W}\alpha}$$

Proof in Appendix Section A.

Panel C of Figure 2 graphically displays the intuition of this result. If the share of low type consumers (s_L) is sufficiently low, the optimal firm policy is to charge for all content as the benefit from subscription is greater than the benefit from advertising. But if the share of low type consumers (s_L) is sufficiently high, the optimal firm policy is to make all content free as the benefit from advertising is greater than the benefit from subscription. The key insight is that for intermediate values of the share of low type consumers (s_L) the firm should charge for content only when a sport is off season. This setting balances the revenue from subscription and advertising by gaining subscription revenue from attracting high value consumers off season while not alienating low type consumers during the season. It relies on the fact that in season there is a large share of low type consumers willing to visit - and thus the ability to generate advertising revenue at this time - but still unwilling to pay for access to content. We term this policy 'counter-cyclical offering'. Note that the key demand conditions for this policy to hold is that consumers are heterogeneous in their valuations, that valuations vary across time and that valuations of low type consumers vary to a greater extent than valuations of high types.

Competition: Proposition 1 focuses on a monopolist but many online news markets are competitive. We next consider a duopoly with two symmetric firms (F_1 and F_2). We assume there are two segments of consumers (of equal size) with a preference for either F_1 or F_2, and a lower

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valuation for the competing firm. In Appendix Section B we show formally that our main result holds for a duopoly. Moreover we show that even in the case of ex-ante symmetric firms, there exists an equilibrium where one firm adjusts its offering counter-cyclically (WLOG say F_1) and the other firm provides all content for free (WLOG say F_2). We discuss here the intuition of this result by describing each firms best response.

First, consider the best response for firm F_1. Since the competitor F_2 always provides content for free, F_1 can never attract consumers with a preference for F_2. Similar to Proposition 1, we find that for some intermediate values of s_L[5] it is optimal for F_1 to provide a counter-cyclical offering. Second, consider the best response for F_2. F_1 charges for content when a sport is off season, now F_2 can attract low type consumers with a preference for F_1 by offering free content. This implies that off season F_2 can earn additional advertising revenue from these consumers. We find that this additional advertising revenue lowers the threshold of the share of low type consumers (s_L) at which it is optimal for F_2 to always provide content for free. Comparing the thresholds from the first step and the second step, we find that for intermediate values of s_L, F_1 providing content counter-cyclically and F_2 providing free content is an equilibrium.

3 Empirical application and data description

3.1 Empirical setting

Empirically, our research is situated in the context of the sports website ESPN.com (henceforth ESPN). ESPN provides a wide range of coverage on sports. ESPN has a main homepage plus homepages for each sport that display article title and links but no abstracts or full articles.

Two characteristics make this an ideal setting for analyzing counter-cyclical offering of online content. First, ESPN offers two types of articles: regular articles, available free of charge to all consumers (hereafter free articles), and insider articles (hereafter paid articles), available only to subscribers. On each sport's homepage, paid articles are easily recognizable through a small orange 'in'-icon. The number of paid articles varies across days and sports. Second, consumer demand for sport news varies over time, for example based on whether a sport is off season or in season, or

[5] Exactly as in Proposition 1, we find that s_L needs to be in an intermediate range, that is low enough that the firm does not always provide content for free and high enough that the firm does not always charge for content.

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whether on a day a game is played.

We collect data on six different sports that offer both paid and free articles: college basketball (CBA), college football (CFB), professional baseball (MLB), professional basketball (NBA), professional football (NFL), and professional hockey (NHL). We do not use data from sports for which ESPN did not offer paid articles during our observation period (e.g., NASCAR, or tennis).

3.2 Website content and user activity

A typical challenge in analyzing the pricing of online content is the difficulty in obtaining data that disclose detailed usage information alongside information on content offering and pricing strategies as well as information on industry-wide demand. We circumvent this challenge by combining multiple data sets. Our data capture, over 13 months, per day and sport the number of free and paid articles featured on the firm's sport-specific homepage, the number of unique visitors to the paid and free sections on the firm's website, and page views in both sections. They also include, on a day and sport level, unique visitors and page views to the main competitor. Our data is thus disaggregated on the day and sport level. We next lay out our data in detail.

[Figure 3 about here.]

ESPN website content: We collect on a daily basis the number of free and paid articles on each of the six sports home pages at ESPN from December 2010 to December 2011. For free articles, we collect the links with the url-format espn.go.com/sportname. For paid articles, we collect the links with the url-format insider.espn.go.com/sportname.[6] On average a sport's home page displays 34 articles per day, of which 30% are in the paid section (Figure 3, Panel A; Appendix B compares free and paid articles in more detail.)

ESPN user activity: For the same time period, we obtain daily data from Comscore on consumer activity by sport. These data include the number of unique visitors, the number of pages viewed, and the total time spent for both free and paid articles. We do not have access to

[6]We then identify links that remain on a sports homepage for a long time period (more than 100 days). These links typically do not represent content-based news articles but provide general information that often does not change over time (e.g., links to pages on the NBA draft for previous years, or games timetables). We count as articles all links that appear on the sports home page for less than 100 days. We note that we collect data on the number of links and not the content within each link.

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consumer-level data. Consistent with our definition of free and paid articles, we use the url-formats espn.go.com/sportname and insider.espn.go.com/sportname to identify website activities.

Comscore collects its data from a panel of consumers whose web activities they follow and weighs the individual-level observations to obtain a data set that is representative of the US population.[7] This approach means our data sometimes artificially record zero visitors (mostly to the paid section) even though the true number for the US population is nonzero. We exclude these 218 out of 2,250 day-sport observations but in unreported robustness checks find that all our results are robust to including these observations. On average, we observe about 650,000 unique visitors to a sport's website on a day (Figure 3, Panel A). Anyone visiting a web page with the url-format espn.go.com/sportname (insider.espn.go.com/sportname) on a day is counted as a visitor to the free (paid) section for that sport on that day. This includes the sport's homepage but excludes ESPNs main homepage. Each visitor reads on average 5.2 articles for about a minute per article. The paid section of each sport's website attracts about 28,000 unique visitors per day. This represents 4% of all visitors.

Competitor user activity: To control on a day and sport level for demand for sport news, we obtain Comscore data on the number of unique visitors, page views, and time spent per day and sport at the main competitor sports.yahoo.com that offers free content only. Page views and time spent per visitor at Yahoo is comparable to those for free ESPN articles. We collect similar data for the sports' websites of two other competitors that also offer free content, Sports Illustrated (CNNSI.com in 2011) and CBS Sports (cbssports.com).

Demand shifters: We identify factors that may shift consumer valuations over time. First, for each sport, we identify the start and end of each season. In the off-season, no regular games are scheduled though sports news are still available, such as about free-agency signing, drafts, and scores for pre-season games, results of which are not considered in the teams final performance. During the season, scheduled games and a sport's final games (playoff in MLB, NBA, NFL, NHL; the bowl season for college football and March madness in college basketball) are played.

Second, we collect data on sport events that may shift consumer valuation of sport news. This includes whether or not a game was played in a sport on a day, the date of the final game within each sport, for professional sports the dates of the draft, and for college sports college-signing day

[7] Our data is an extract from a larger proprietary database held by Comscore.

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and the dates of the NBA lockout in the 2011 season. We also record days of the week.

Third, as a measure of demand shocks in a particular sport specific to ESPN, we collect data from Google Trends on the number of searches for ESPN + sport for every day in our data. We scale the data to numbers between 0 and 10.

3.3 Subscription and advertising revenues

Customers can sign up for one of three membership plans to access paid articles. A two-year membership costs \$2.50 per month, a yearly membership plan \$3.33 per month, and a monthly membership \$6.95 per month. We obtain data from Comscore on the number of customers that sign up for each of the plans for December 2010 to December 2011. They suggest that 82% of customers choose a yearly or a two-year plan (47% of customers choose the yearly plan, 35% choose the two-year plan) and 13% choose the monthly plan, giving us an average subscription price of \$40.44 per year, or \$3.37 per month.

ESPN features advertising on all webpages, including the home pages for each sport and the page for each article. Each page typically displays one ad, independently of whether an article is free or paid. From Comscore, we obtain additional data on monthly page views and advertising revenues at ESPN during our observation period that allow us to compute the average advertising revenue per page view. We find that, on average, ESPN earns \$9.11 per 1000 page views. We obtained informal confirmation from ESPN that this value broadly reflects their advertising prices. To understand the variation of the advertising price across advertisers and time, we collected two pieces of information: the average monthly advertising price per 1000 page views from December 2010 to December 2011 and the average advertising price per 1000 page views paid by each of 612 advertiser for the month of June 2011[8]. We find the coefficient of variation across months is 0.06 and the coefficient of variation across 612 advertisers is 0.08. This suggests that consistent with our theoretical motivation, advertising prices vary little. Further, we examined the advertising prices ESPN communicates to advertisers on their website. We find that ad prices vary by sport but do not vary by season or by whether an ad appears in the free or paid section (see Appendix Section D for more details).

[8]We chose June as some sports are in season and some off season: MLB is in season for the full month; NBA and NHL are in season until June 12 and June 15 respectively; the remaining three sports are off season. We plot the distribution of the average advertising price per page views in Appendix Section D

4 Empirical evidence for counter-cyclical offering

4.1 Sports' seasons as demand shifters

To understand whether the firm is in a position that it can counter-cyclically adjust its content offering, we explore the key shifters of demand for sport news at ESPN. The left column of Panel B, Figure 3 illustrates that sports fixed effects explain about 40% of the variation in unique visitors and page views per visitor to the free section and most of the variation in the time visitors spend per page, suggesting that consumption of sport news is driven by the type of sports. Importantly, a sport's season - and so a variable that changes over time - likewise explains 42% of variation in unique visitors and 32% of variation in page views per visitor, suggesting that season is a key driver of demand. Other indicators of demand, including demand at the corresponding sports' websites of Yahoo, CNNSI and CBS, explain additional variation in user activity. The right column of Panel B, Figure 3 explores demand for the paid section of ESPN. It demonstrates that sports fixed effects explain almost all variation in unique visitors, page views per visitor, and time spent per page in the paid section while season explains relatively little variation in any of these variables.

The last bar on both sides displays the variation in articles available on ESPN. It illustrates that the total number of articles available (left column) and the share of paid articles (right column) vary with sport and season, suggesting that a sport's season is important in the supply of articles.

We further explore the role of sports' seasons in the demand for and supply of paid content. Panel A, Figure 4 provides descriptive statistics by season. Demand, as measured by unique visitors to the free section of ESPN, any of the other sport website (Yahoo, CNNSI, CBS) or Google searches, is unequivocally higher when the sport is in season. Interestingly, when the sport is not in season the number of unique visitors drops by more than 500,000 (about 50%) and visitors to the site view on average two pages less. Panel B, Figure 4 graphically illustrates the great drop in demand for sport news when a sport is off season. The results are consistent with the fact that there is less news to report in the off-season when no games are played and further confirm that sports' seasons strongly impact demand

Together, these data point to season as an important shifter of demand and further are consistent with the assumptions taken in Section 2. First, consumer valuations are heterogeneous as evidenced by the fact that some consumers subscribe to the paid section while others do not. Consumers who

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visit only the free section are likely low type consumers whereas subscribers to the paid section are high types. Second, valuations of low type consumers, i.e. those that visit only the free section, vary over time and are particularly low when a sport is off season – unique visitors, page views per visitor and time spent per page view increase significantly when a sport is in season. Third, the fact that for the paid section unique visitors, page views per visitor and time spent per page view exhibit significantly less variation suggests that valuations of high type consumers vary far less.

[Figure 4 about here.]

4.2 Evidence for counter-cyclical offering

We next examine the firm's policy in offering paid content. Panel A, Figure 4 shows that the share of paid articles follows the opposite trend than the demand for sport news. It increases from 25% when the sport is in season to 35% off season. Panel B, Figure 4 again graphically illustrates that when a sport is off season, i.e. when demand drops by more than 50%, the firm increases the share of paid articles by 40%. Yet, the total number of visitors to the paid section does not change depending on a sport's season (statistically insignificant at a 95% confidence level). These results suggests that indeed the firm may be engaging in counter-cyclical offering.

To provide non-parametric evidence for counter-cyclical offering, we plot in Figure 5 the distribution of visitors to ESPN (left column) and the share of paid articles (right column) separately for each of the six sports in our data. The black solid line represents days when the sport is in season and the dashed gray line represents days when the sport is off season. We see that for all sports the distribution of daily visitors is shifted to the right when the sport is in season and the mean of unique daily visitors during a sport's season is significantly higher than when a sport is off season. We find the opposite when we consider the share of paid articles. Here, the mean of the percentage of paid articles is lower during a sport's season for any of the sports and the empirical distribution of the percent of paid articles when the sport is in season is stochastically dominated by the distribution when the sport is off season. This result further supports that the firm increases the share of paid content at times of lower demand and so engages in counter-cyclical offering.

[Figure 5 about here.]

We next show that these results hold when controlling for parameters other than a sport's season that might possibly shift demand and supply of paid content. In Column (1) in Panel A, Figure 6 the dependent variable is the log of unique visitors to ESPN. Again, demand increases during a sport's season relative to when a sport is off season, on average by 36%. [9] Column (2) illustrates that this pattern is not unique to ESPN but holds when the dependent variable is the log of unique visitors to Yahoo's sports websites where demand increases by on average 39%. Column (3) shows that this effect does not exist when the dependent variable is the log of unique visitors to ESPN. Contrast the results in Columns (1) and (2) with the results in Column (4) where the logit transformation of percent of paid articles ($log(\frac{\text{percent of paid articles}}{1-\text{percent of paid articles}})$) is the dependent variable. Here, the percentage of paid articles is significantly lower when a sport is in season.

Panel A, Figure 6 yields further insights with respect to the firm's policy on counter-cyclical offering: It illustrates that demand for news at ESPN is significantly higher on game days and at times when demand at the respective sport's website on Yahoo is high, a variable that we take as indicator for other unobserved demand shocks. At both times, ESPN reduces the share of paid content which suggest that the firm engages in counter-cyclical offering along a variety of demand shifters. Together, these results provide strong evidence that the firm counter-cyclically adjusts the share of paid content it offers.

[Figure 6 about here.]

4.3 Linking the empirical analysis with the theory

We link our empirical results to the assumptions and predictions of the simple model presented in Section 2. Section 4.1 demonstrated that consumer valuations are heterogeneous and that valuations vary over time and across consumer types. To further support the assumption that valuations of high type consumers vary less than of low types, we examine in Column (1) of Panel B, Figure 6 the share of unique visitors that visit the paid section of ESPN. This serves as an empirical proxy for the share of high type consumers. Consistent with the model assumption, we find that the share of high type consumers is significantly lower when sports are in season.

[9] Note the interpretation of the regression coefficient as a percentage change assumes that the error term does vary across seasons, formally we assume $E(e^{\epsilon}|\text{Off season}) = E(e^{\epsilon}|\text{In Season})$. We maintain this assumption throughout this section.

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The simple model also assumed that conditional on visiting, the number of articles a unique visitor reads does not vary by season. Column (2) takes as dependent variable the number of page views per visitor. In line with the assumption, we find no evidence for a change in the number of pages viewed across seasons. We note that page views significantly increase on game days, which is not surprising as consumers can log on to check scores.

We turn to the implicit assumption of our model that if the firm counter-cyclically adjusts its offering, we should observe less low type consumers visiting the website on days when the firm provides paid content. Column (3) shows that even after controlling for season the the number of unique visitors to ESPN is negatively correlated with the percent of paid content. We note that this coefficient should be interpreted as a correlation and not as a causal link. Instead, consistent with our theoretical motivation, our interpretation is that it can be optimal for ESPN to increase paid content on days with a lower number of visitors to the site. Our model further suggests that the change in the amount of paid content offered is driven by low type consumers visiting the website. We test if the correlation is more pronounced during sports' seasons when more low type consumers are likely to visit. Column (4) interacts the percent of paid articles with season and indeed shows a stronger relationship between total visitors and paid articles only when the sport is in season (we note that the estimate is statistically significant at the 90% level).

In Appendix Section E, we calibrate our analytical model with the empirical means from the data. We find that the calibrated model does suggest that counter-cyclical offering is optimal for ESPN.

5 Conclusion

Pricing access to online content is a key challenge for news media, especially as advertising revenues have dramatically declined in the recent past. The first difficulty is that many consumers are not willing to pay for online content and so firms need to trade off advertising and subscription revenues. Second, demand for online content varies greatly over time and across customers, making it difficult to determine the profit-maximizing price. Third, online content providers sign long-term contracts with consumers, preventing them from flexibly adjusting prices in response to changes in demand.

We propose that online content providers can respond to this challenge by counter-cyclically

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adjusting their offering of paid content. While there has been anecdotal evidence for this idea, we provide a theoretical motivation and empirical support that firms indeed engage in counter-cyclical offering and show that such a policy can be profit-maximizing. We first show in a simple model that it can be optimal to offer paid content during periods of low demand and free content during periods of high demand. We then use data from ESPN, an online sports' website, to demonstrate that firms indeed implement such counter-cyclical offering. We show that consumers are heterogeneous in their valuations, that valuations vary over time, and that low consumer types are more sensitive to demand shocks than high types - the three conditions required for making counter-cyclical offering an attractive strategy. We then provide evidence that the firm counter-cyclically adjusts its share of paid content. That is, in periods of high demand ESPN offers a lower share of paid content than in periods of low demand. We conclude that counter-cyclical offering allows online content providers that sign long-term contracts with their customers to flexibly respond to changes in demand.

Our results contribute to marketing research by showing how firms that offer contracts can apply a policy broadly related to counter-cyclical pricing to respond to changes in demand without actually varying prices. It also has important implications for the management of online content providers. Our findings suggest that online content providers may be better off by flexibly adjusting how much content they offer for free instead of setting a static paywall, as often is managerial practice. While it appears that in exceptional instances firms have experimented with such an approach, we argue that this may be optimal more broadly. We suggest that managers should more broadly identify demand shocks and respond to an increase in demand by offering more free, relative to paid, content. While we demonstrate our empirical results in the market for sport news, we believe that our results have implications for many other types of news content and hold whenever there is demand heterogeneity coupled with strong seasonality in demand. As we discussed in the introduction to this research, anecdotal evidence suggests that both conditions hold in many types of news markets.

Of course, our work has limitations. Most importantly, we focus on one dimension along which firms can optimize their revenue model, a dynamic versus a static policy. There are many other important questions that we leave to future research to explore such as whether content providers should bundle their online and offline offering, what optimal price to set, and whether such prices should vary with article type or quality. We also do not study the actual news content provided. Additionally, while our empirical setting demonstrates that firms can indeed benefit from counter-

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cyclically adjusting the amount of free content, we cannot rule out that there may be instances when consumers respond negatively to firms adjusting the provision of free content over time (e.g. backlash by non-subscribers who can access little or no content during off season). Our analytical model does not capture such a response. Lastly, our empirical study is set in an industry in which many firms (still) offer all content for free. If all or most competitors charge for access to content, a different kind of subscription model may be optimal. We leave such questions for future research.

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Appendix

A Proof of Proposition 1

Proof. We prove this proposition in the following steps:

Step 1: Consider $\pi_{\text{Paid Off}}$ versus $\pi_{\text{Paid In}}$

$$\begin{aligned}\pi_{\text{Paid Off}} > \pi_{\text{Paid In}} \quad &\iff \quad p_A N s_L \alpha(1-\alpha_L) > W(1-\alpha_H)(1-s_L) \\ &\iff \quad \frac{s_L}{1-s_L} > \frac{W(1-\alpha_H)}{p_A N\alpha(1-\alpha_L)}\end{aligned}$$

Step 2: Consider $\pi_{\text{Paid Off}}$ versus $\pi_{\text{Paid All}}$

$$\begin{aligned}\pi_{\text{Paid Off}} > \pi_{\text{Paid All}} \quad &\iff \quad p_A N s_L \alpha > W(1-s_L) \\ &\iff \quad \frac{s_L}{1-s_L} > \frac{W}{p_A N\alpha}\end{aligned}$$

Step 3: Consider the two equations from Step 1 and Step 2

$$\alpha_L < \alpha_H \Rightarrow \frac{1-\alpha_H}{1-\alpha_L} < 1 \Rightarrow \frac{W(1-\alpha_H)}{p_A N\alpha(1-\alpha_L)} < \frac{W}{p_A N\alpha}$$

Therefore if $\pi_{\text{Paid Off}} > \pi_{\text{Paid All}}$, we must have $\pi_{\text{Paid Off}} > \pi_{\text{Paid In}}$. Overall steps 1 to 3 give us a lower bound for s_L that is $\frac{s_L}{1-s_L} > \frac{W}{p_A N\alpha}$.

Step 4: Consider $\pi_{\text{Paid Off}}$ versus π_{Free}

$$\begin{aligned}\pi_{\text{Paid Off}} > \pi_{\text{Free}} \quad &\iff \quad W(\alpha_H)(1-s_L) > p_A N\alpha\alpha_L s_L) \\ &\iff \quad \frac{s_L}{1-s_L} < \frac{W\alpha_H}{p_A N\alpha\alpha_L} = \frac{Wr}{p_A N\alpha}\end{aligned}$$

This gives us an upper bound for s_L that is $\frac{s_L}{1-s_L} < \frac{Wr}{p_A N\alpha}$.

Step 5: Rearrange to get main result. From steps 3 and 4 we have

$$\frac{Wr}{p_A N\alpha} > \frac{s_L}{1-s_L} > \frac{W}{p_A N\alpha} \iff \frac{r}{r+\frac{p_A N}{W}\alpha} > s_L > \frac{1}{1+\frac{p_A N}{W}\alpha}$$

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By assumption we have $r > 1$ therefore the lower bound ($\frac{W}{p_A N \alpha}$) must be less than the upper bound ($\frac{Wr}{p_A N \alpha}$). We can rearrange the terms in the equation and get

$$\frac{r}{r + \frac{p_A N}{W}\alpha} > s_L > \frac{1}{1 + \frac{p_A N}{W}\alpha}$$

□

B Extension to Competitive Markets

In this subsection we consider a competitive market with two symmetric firms (F_1 and F_2). We assume that there are two segments of consumers (of equal size) one with a preference for F_1 and one with a preference for F_2. Consumers discount their valuation for the other firm by $\gamma < 1$. Formally, valuations across segments, types and seasons are given in the table below. Here the first value in parenthesis represents the value for F_1 and the second value in parenthesis represents the value for F_2.

	Prefer F_1 Consumer Type		Prefer F_2 Consumer Type	
Season	H	L	H	L
N	$(1, \gamma)$	$(\alpha, \gamma\alpha)$	$(\gamma, 1)$	$(\gamma\alpha, \alpha)$
O	$(\alpha_H, \gamma\alpha_H)$	$(\alpha\alpha_L, \gamma\alpha\alpha_L)$	$(\gamma\alpha_H, \alpha_H)$	$(\gamma\alpha\alpha_L, \alpha\alpha_L)$

For simplicity of notation in this section define $\Delta = \frac{W(1-\gamma)}{p_A N \alpha}$.

Proposition 2. *When both firms are symmetric, there exists an equilibrium where one firm will charge for content when a sport is off season (Paid Off) and the other firm will always provide content for free, when the following conditions hold*

$$\begin{aligned} \Delta(r) > \quad \frac{s_L}{1-s_L} &> \Delta\left(\frac{r}{1+\gamma}\right) \\ r &> 1+\gamma \end{aligned}$$

Proof. We will prove this result in the following steps. In step 1, we will show that if F_k ($k \in \{1, 2\}$) decides to always provide content for free then F_l's ($l \neq k$) best response will be to charge for

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content off season (counter-cyclical offering) if $r\Delta > \frac{s_L}{1-s_L} > \Delta$. In step 2 we will show that if F_l decides to charge for content off season (counter-cyclical offering) then F_k's best response is to provide content for free if $\frac{s_L}{1-s_L} > \Delta\left(\frac{r}{1+\gamma}\right)$. By the condition $r > 1+\gamma$, step 2 defines the lower bound for s_L.

Step 1: F_l's best response if F_k provides content for free

If F_k always provides content for free, F_l can never attract any consumers with a preference for F_k. However if F_l charges for content then it can lose consumers to F_k. In particular, for high type consumers who prefer F_l, the willingness to pay for F_l changes to: $(1-\gamma)(1Paid_I + \alpha^H Paid_O) \geq \frac{p_c}{W}$. To see this, suppose that F_l charges for content when a sport is off season ($Paid_O = 1$) and not when a sport is in season ($Paid_I = 0$). Consider the subscription decision for F_l by high types with a preference for F_l. If a consumer subscribes they get a utility of $\alpha_H - \frac{p_c}{W}$ and if they do not subscribe they get a utility of $\gamma\alpha^H$ from visiting F_k off season. Therefore the consumer will subscribe if $\alpha^H(1-\gamma) \geq \frac{p_c}{W}$.

Therefore this case mirrors the monopoly case with the parameter of willingness to pay transformed to $W(1-\gamma)$ and from Proposition 1 we get that the optimal response for F_l is to charge for content when a sport is off season if

$$r\Delta > \frac{s_L}{1-s_L} > \Delta$$

Step 2: F_k's best response if F_l charges for content off season and provides content for free during the season (counter-cyclical offering)

In this case, low type consumers with a preference for F_l will visit F_l only during the season. These consumers may visit F_k during off season if F_k provides content for free. Therefore if F_k provides content for free during off season it will get an additional advertising revenue of $p_A N\alpha\alpha_L\gamma s_L$ from low type consumers with a preference for F_l.

Now we can consider conditions under which 'Always Free' is the best option for F_k

Step 2i: Consider π_{Free} versus $\pi_{\text{Paid Off}}$

$$\begin{aligned}\pi_{\text{Free}} > \pi_{\text{Paid Off}} \quad &\iff \quad p_A N\alpha\alpha_L(1+\gamma)s_L > W(1-\gamma)(\alpha_H)(1-s_L)\\ &\iff \quad \frac{s_L}{1-s_L} > \frac{W(1-\gamma)}{p_A N\alpha}\left(\frac{r}{1+\gamma}\right) = \Delta\left(\frac{r}{1+\gamma}\right)\end{aligned}$$

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Step 2ii: Consider π_{Free} versus $\pi_{\text{Paid All}}$

$$\begin{aligned}
\pi_{\text{Free}} > \pi_{\text{Paid All}} &\iff p_A N s_L \alpha(1+\alpha_L(1+\gamma)) > W(1-\gamma)(1+\alpha_H)(1-s_L) \\
&\iff \frac{s_L}{1-s_L} > \frac{W(1-\gamma)}{p_A N\alpha}\left(\frac{1+\alpha_H}{1+\alpha_L(1+\gamma)}\right) = \Delta\left(\frac{1+\alpha_H}{1+\alpha_L(1+\gamma)}\right)
\end{aligned}$$

Now

$$\begin{aligned}
r > 1+\gamma &\Rightarrow \frac{r}{(1+\gamma)} = \frac{\alpha_H}{\alpha_L(1+\gamma)} > 1 \\
&\Rightarrow \frac{\alpha_H}{\alpha_L(1+\gamma)} > \frac{1+\alpha_H}{1+\alpha_L(1+\gamma)} \\
&\Rightarrow \Delta\left(\frac{r}{1+\gamma}\right) > \Delta\left(\frac{1+\alpha_H}{1+\alpha_L(1+\gamma)}\right)
\end{aligned}$$

When $r > 1+\gamma$, if $\frac{s_L}{1-s_L} > \Delta\left(\frac{r}{1+\gamma}\right)$ (as in 2i) then we must have $\frac{s_L}{1-s_L} > \Delta\left(\frac{1+\alpha_H}{1+\alpha_L(1+\gamma)}\right)$ (as in 2ii).

Step 2iii: Consider π_{Free} versus $\pi_{\text{Paid In}}$

$$\begin{aligned}
\pi_{\text{Free}} > \pi_{\text{Paid In}} &\iff p_A N s_L \alpha > W(1-\gamma)1(1-s_L) \\
&\iff \frac{s_L}{1-s_L} > \frac{W(1-\gamma)}{p_A N\alpha} = \Delta
\end{aligned}$$

When $r > 1+\gamma$, if $\frac{s_L}{1-s_L} > \Delta\left(\frac{r}{1+\gamma}\right)$ (as in 2i) then we must have $\frac{s_L}{1-s_L} > \Delta$ (as in 2iii).

From 2i, 2ii and 2iii we esablish that when $r > 1+\gamma$ and $\frac{s_L}{1-s_L} > \Delta\left(\frac{r}{1+\gamma}\right)$, F_k's best response is to always provide content for free.

From step 1 and step 2 we prove that if (i) $r > 1+\gamma$, (ii) $\frac{s_L}{1-s_L} > \Delta\left(\frac{r}{1+\gamma}\right)$ and (iii) $\frac{s_L}{1-s_L} < r\Delta$ we have an equilibrium where one firm will provide content for free and the other firm will counter-cyclically adjust its offering. □

C Article length

We compare free and paid articles in more detail. For a sample period of seven days (November 9 - 15, 2011), we collect data on the length (measured as the word count) of all free and paid articles featured in the two most prominent sections of the sports homepages (sections Headlines and Top

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Stories) as well as in the Insider section that lists paid articles. Paid articles are on average longer but the standard deviation in article length is high, particularly among free articles (word count free articles: mean=968, SD=965, N=824; word count paid articles: mean=1332, SD=654, N=274) because of a high number of very short free articles: 10% of free articles have less than 200 words. We compare all 274 paid articles with the top 274 free articles by word count and find that in this subset, free articles are on average longer (word count: mean=1832, SD=921, N=274). This finding suggests that both the paid and the free sections feature many detailed articles. Lastly, we broadly examine the type of articles in both sections. While the free section includes both news and editorial content (e.g., comments on a teams performance) the paid section focuses on editorial content and in-depth reports (e.g., interview with a coach). This finding makes sense because readers could substitute news articles with content from a competing site, whereas such substitution is more difficult for editorial content or in-depth reporting.

D ESPN advertising data

We obtain data for all 612 firms that advertised on ESPN.com in June 2011. We chose June as some sports are in season and some off season: MLB is in season for the full month; NBA and NHL are in season until June 12 and June 15 respectively; the remaining three sports are off season. For each advertiser, the data include the total number of impression and the total adverting spend in US dollars. We find that on average each advertiser has about 2.5 million impressions and spends about \$24,000. However there is strong heterogeneity across advertisers: the standard deviation of impressions by advertiser is 10.4 million (coefficient of variation of 4.2) and the standard deviation in spending is about \$101,000 (coefficient of variation of 4.3). We obtain an average price per 1000 impressions of \$9.25 with a standard deviation of \$0.77 (coefficient of variation of 0.08). This suggests that despite the heterogeneity in impressions and spend across advertisers, the price per impression is fairly homogeneous. We plot the distribution of price per 1000 impressions across all 612 advertisers in the chart below.

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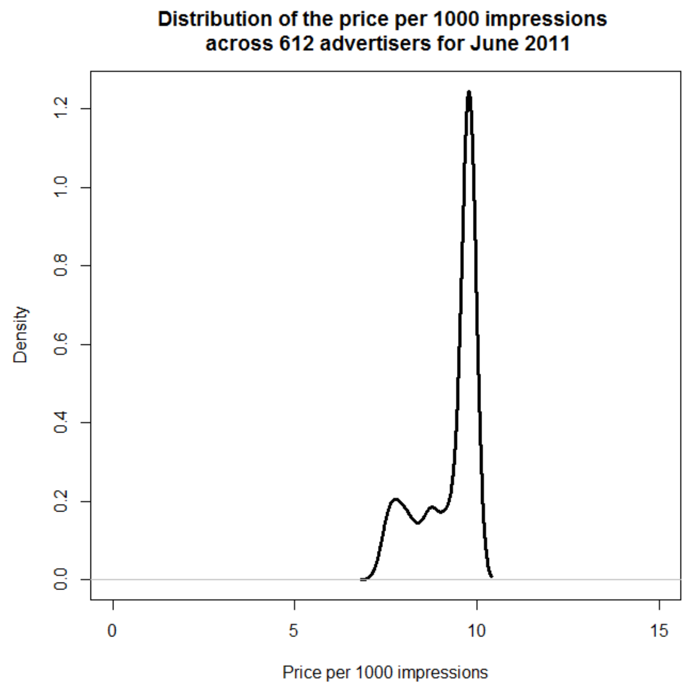

To further test the variation in advertising rates across season, we created an advertiser account on ESPN.com (on the web `http://espn.adready.com/ads/public`). Here an advertiser selects the timing, channel and targeting of their campaign. Consistent with our model ESPN allows advertisers to select as 'channel' the different sports.[10] The targeting of advertisements is based on geography (for the US an advertiser can select the entire country, a state or a city). Importantly, consistent with our model assumptions, the advertiser cannot select advertising only on paid versus free pages within a sport. To understand pricing the table below displays the quoted CPM for advertising in the United States. We picked two dates to test: August 14th 2015 when all sports except MLB are off season and December 3rd 2015 when all sports except MLB are in season. Importantly we find that though the quoted CPMs from ESPN vary by sport they do not vary across season.

[10]The options for channels are: Run of Site, Boxing, College Basketball, College Football, Fantasy Games, MLB, MMA, NASCAR, NBA, NFL, NHL, Racing, Cricinfo, Deportes Los Angles, Deportes Mobile ROS, Deportes ROS, FC, Footytips, Jayski ROS

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Quoted CPMs from ESPN.com

	In Seaon		Off Season		Difference in CPM
Sport	Date	Quoted CPM	Date	Quoted CPM	across season
College Basketball	4-Dec-15	$6.00	14-Aug-15	$6.00	$0.00
College Football	4-Dec-15	$9.00	14-Aug-15	$9.00	$0.00
MLB	14-Aug-15	$6.00	4-Dec-15	$6.00	$0.00
NBA	4-Dec-15	$6.00	14-Aug-15	$6.00	$0.00
NFL	4-Dec-15	$9.00	14-Aug-15	$9.00	$0.00
NHL	4-Dec-15	$5.00	14-Aug-15	$5.00	$0.00

Based on searches on http://espn.adready.com/ads/public (last accessed 13th August 2015)

E Analytical model with empirical means

We use estimates from our data to show that for ESPN the conditions laid out in Proposition 1 in Section 2.2 hold. Our approach is to show for which range of parameter values counter-cyclical pricing would be optimal and then demonstrate that the setting we study falls within this parameter range. We estimate the ratio of off-season to in-season valuations for high type consumers, α_O^H, as the ratio of visitors to the paid section during off season relative to when a sport is in season ($\alpha_O^H \equiv \frac{\text{Paid Visitors}_{\text{Off Season}}}{\text{Paid Visitors}_{\text{In Season}}} = 0.98$). We estimate the corresponding ratio for low type consumers, α_O^L, as the scaled number of Google searches for 'sport + ESPN' during that sport's off season relative to the scaled number of Google searches for 'sport + ESPN' when the sport is in season ($\alpha_O^L \equiv \frac{\text{Google}_{\text{Off Season}}}{\text{Google}_{\text{In Season}}} = 0.25$). Therefore, $r \equiv \frac{\alpha_O^H}{\alpha_O^L} = 3.99$. We estimate the share of low type consumers, s_L, as the share of unique visitors during off season that do not visit the paid section, $s_L = 0.98$.

Using these estimates, we rewrite Proposition 1 as $0.08 > \frac{p_A \alpha N}{W}\alpha > 0.02$. We estimate $\frac{p_A}{W} = \frac{1.14}{1000}$[11] and αN represent the number of visits of low type consumers during a sport's season that is over six months. As we do not observe the average number of monthly visits per consumer in the free section, we use the data to compute upper and lower bounds for the number of monthly visits of low type consumers during a sport's season and find these to be 11.69, respectively 2.92

[11] Based on Figure 2, Panels A and B, W is the average subscription price of $41.26 from Section 3.3 divided by α_O^H which has a value of 0.98. The total advertising revenue per visit, $\$p_A$, is defined as (page views per visit) x (advertising revenue per page view). The average number of page views per visit in the free section is 5.15 (see Panel A, Figure 3). The average advertising revenue per 1000 page views is $9.11 (see Section 3.3).

visits. From Comscore we obtain additional data that documents that on average paid subscribers (i.e. high type consumers) make 7.22 daily unique visits in a month so it seems plausible that the visit frequency of low type consumers falls indeed within these bounds.

In sum, the analysis supports that the conditions that our simple model predicts must hold for counter-cyclical offering to be optimal, indeed hold for the specific empirical setting of a firm that counter-cyclically adjusts content.

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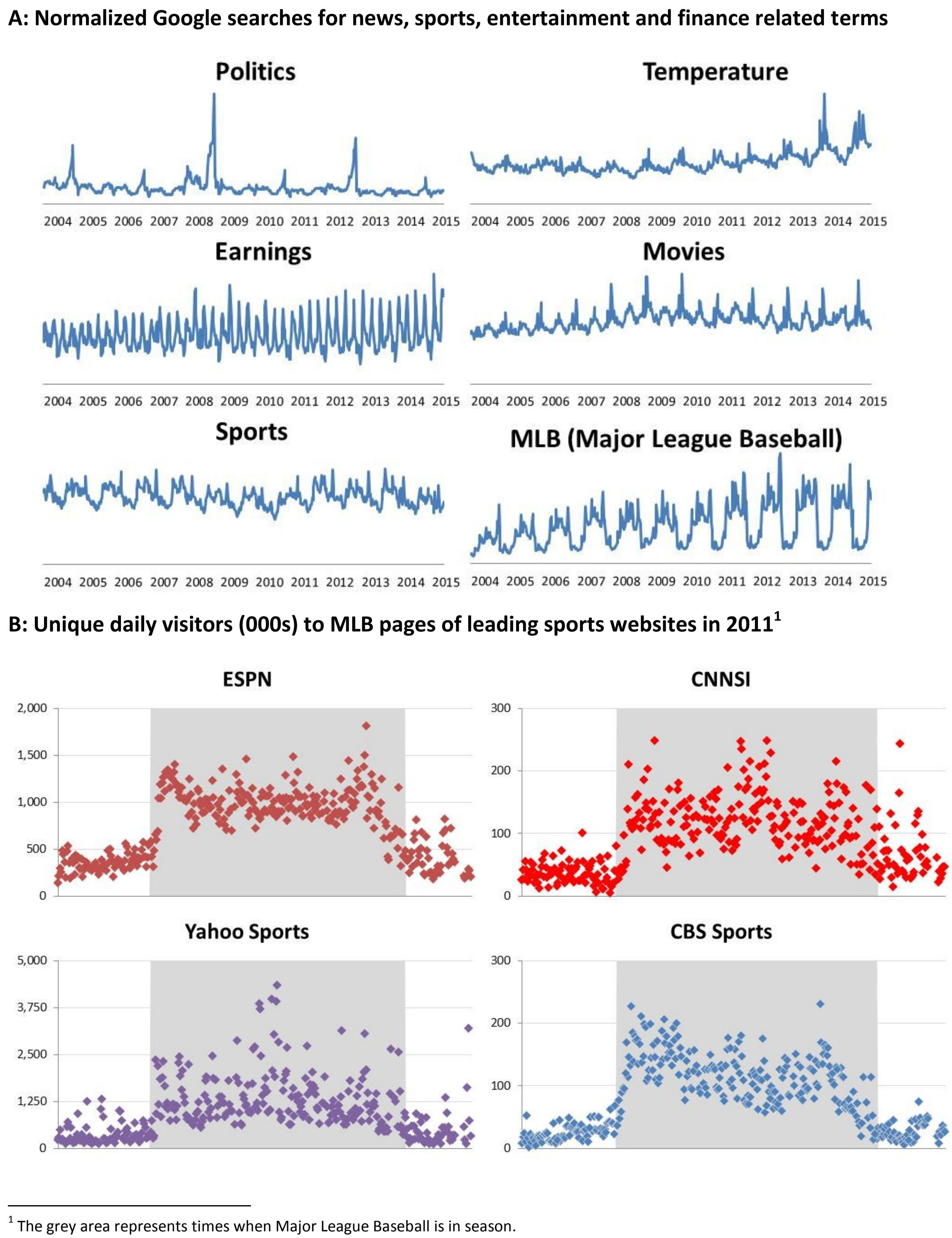

Figure 1: Demand for news

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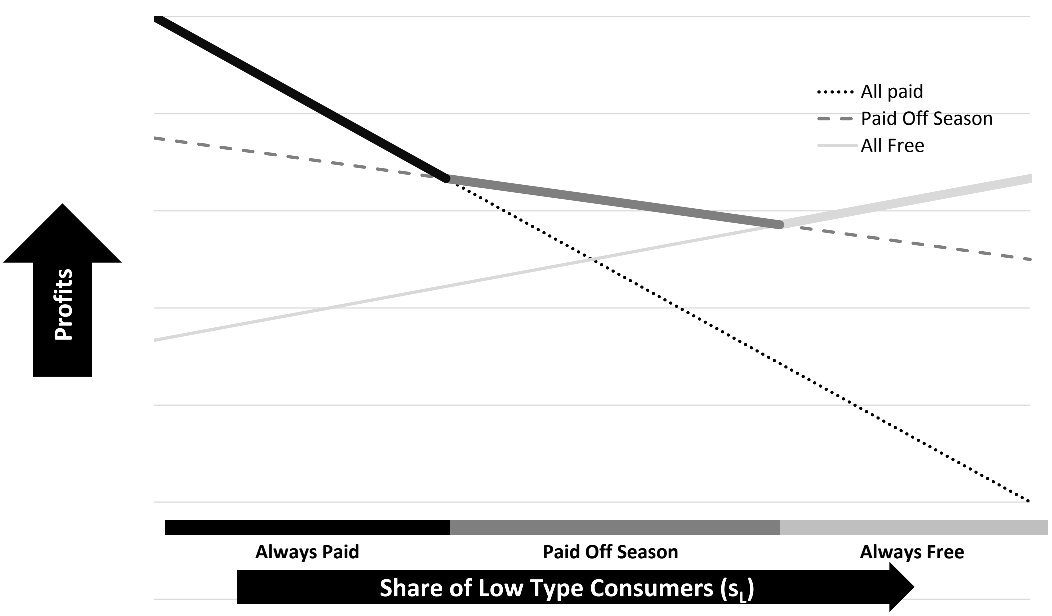
A: Model setup: Heterogeneity in valuations across types and seasons

	Consumer Type	
Season	H	L
I	$v_{I,H} \equiv 1$	$v_{I,L} \equiv \alpha$
O	$v_{O,L} \equiv \alpha_H$	$v_{O,L} \equiv \alpha\alpha_L$

B: Firm options: Implication of firm policy on profit

		High Type	Low Type		
		Subscription	Visit		Advertising
Firm Option	Price (p_c)	Revenue	Off	In	Revenue
Always Free		0	✓	✓	$p_A N\alpha(1+\alpha_L)s_L$
Always Paid	$W(1+\alpha_H)$	$p_c(1-s_L)$			0
Paid Off Season	$W\alpha_H$	$p_c(1-s_L)$		✓	$p_A N\alpha s_L$
Paid In Season	W	$p_c(1-s_L)$	✓		$p_A N\alpha\alpha_L s_L$

C: Illustration of main result (Proposition 1): Shows how firm profits by pricing policies vary with the share of low type consumers[1].



[1] The profit from the policy "Paid In Season" is always less than from the policy "Always Paid" (see proof of Proposition 1, step 3 in the Appendix)

Figure 2: Analytical model setup and results

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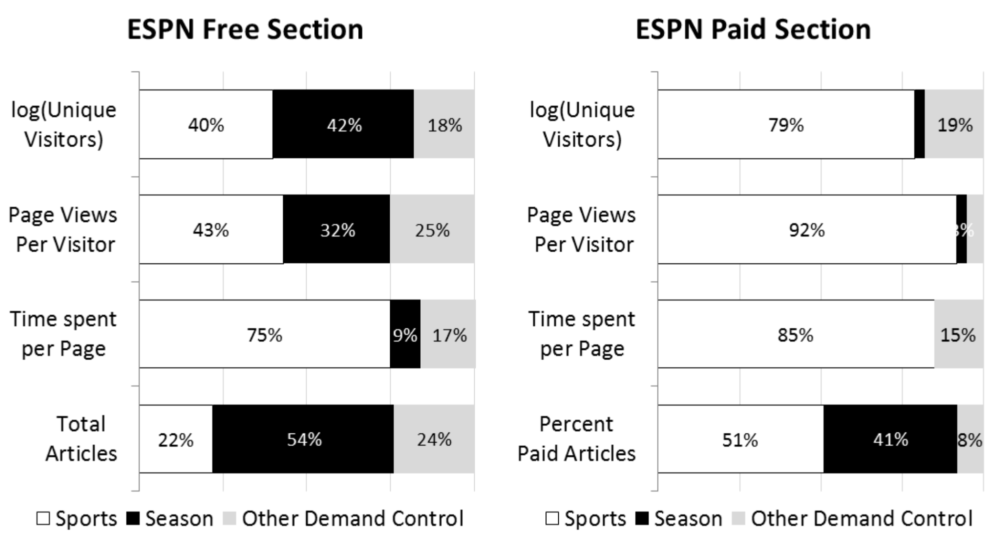
A: Descriptive statistics

Metric		Mean	Std. Dev.	Median
ESPN articles	Number of articles	33.78	17.82	30.00
	Share of paid articles	30%	12%	30%
ESPN free section	Unique visitors (000s)	648.71	504.73	490.50
	Page views per visitor	5.15	2.38	4.54
	Time spent per pageview	0.94	0.27	0.91
ESPN paid section	Unique paid visitor (000s)	28.31	42.82	19.27
	Paid page views per paid visitor	2.06	1.71	1.62
	Time spent per paid pageview	0.84	0.51	0.77
Yahoo	Unique visitors (000s)	879.75	989.63	562.75
	Page views per visitor	5.54	3.27	4.59
	Time spent per pageview	1.11	0.40	1.07
CNNSI	Unique visitors (000s)	78.26	70.42	58.57
	Page views per visitor	3.52	5.56	2.83
	Time spent per pageview	0.88	0.36	0.84
CBS	Unique visitors (000s)	81.77	104.23	52.11
	Page views per visitor	4.39	3.75	3.38
	Time spent per pageview	0.96	0.43	0.92
Google Scaled (10s)		1.29	1.25	0.77

B: Percentage of explained variance by demand shifters[1]



[1] Sports refers to sports fixed effects. Season is an indicator for a sport being in season. Other Demand Controls include indicator variables for Gameday, Draft, Strike, Final Game, Weekend, and corresponding variables for Yahoo, CNNSI, CBS and Google Scaled. Percentage explained variance based on a R^2 from a linear regression.

Figure 3: Descriptive statistics

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A: Summary statistics across seasons

	Metric	In Season (n = 1,100) Mean	In Season (n = 1,100) Std. Dev.	Off Season (n = 932) Mean	Off Season (n = 932) Std. Dev.	Difference in Means Mean	Difference in Means p-value
ESPN articles	Number of articles	40.74	20.12	25.57	9.50	-15.18	0.00*
	Share of paid articles	25%	11%	35%	11%	10%	0.00*
ESPN free section	Unique visitors (000s)	891.18	524.09	362.54	282.98	-528.64	0.00*
	Page views per visitor	6.08	2.52	4.07	1.63	-2.01	0.00*
	Time spent per pageview	0.99	0.28	0.89	0.25	-0.10	0.00*
ESPN paid section	Unique paid visitor (000s)	26.83	26.60	30.06	56.20	3.24	0.11
	Paid page views per paid visitor	1.86	1.18	2.31	2.15	0.45	0.00*
	Time spent per paid pageview	0.85	0.55	0.83	0.45	-0.02	0.35
Yahoo	Unique visitors (000s)	1172.31	1069.03	534.45	752.98	-637.86	0.00*
	Page views per visitor	6.40	3.43	4.54	2.76	-1.86	0.00*
	Time spent per pageview	1.09	0.28	1.13	0.50	0.04	0.05*
CNNSI	Unique visitors (000s)	99.84	72.46	52.80	58.49	-47.04	0.00*
	Page views per visitor	4.04	7.01	2.91	2.94	-1.13	0.00*
	Time spent per pageview	0.91	0.34	0.85	0.38	-0.05	0.00*
CBS	Unique visitors (000s)	115.32	126.13	42.18	44.95	-73.14	0.00*
	Page views per visitor	5.79	4.22	2.74	2.15	-3.05	0.00*
	Time spent per pageview	1.06	0.40	0.84	0.44	-0.22	0.00*
Google Scaled (10s)		1.97	1.25	0.48	0.62	-1.49	0.00*

B: Percentage change in key variables from a sport being in season to off season

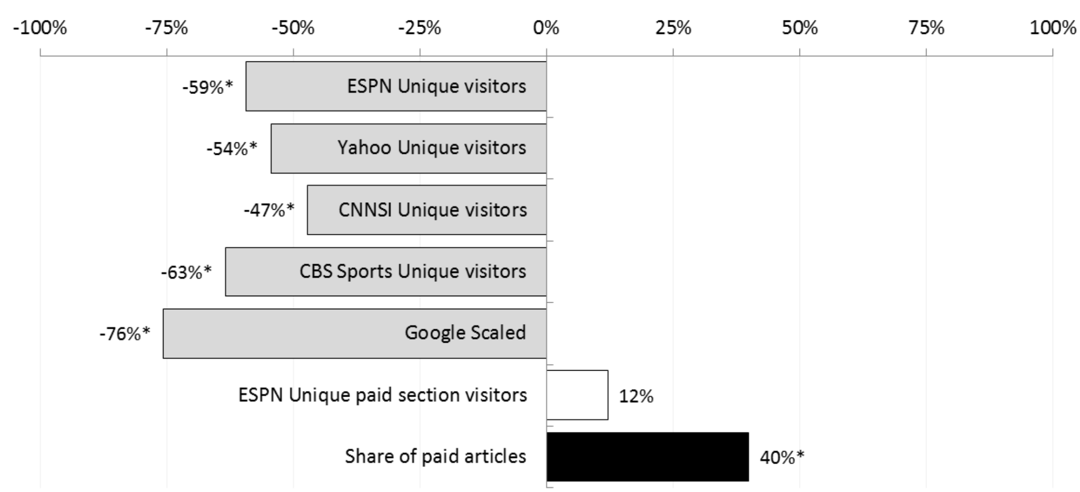

Figure 4: Descriptive statistics across seasons (* refers to significance at 95% confidence level)

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A: Density plots by sport and season: Each row represents one of our six sports. We plot the density of unique ESPN visitors (left column) and percent paid articles (right column). The black line refers to when the sport is in season and the grey dotted line refers to when a sport is off season. The difference in means is the mean(in Season) – mean(off season). * represents significant difference of means at a 95% confidence level.

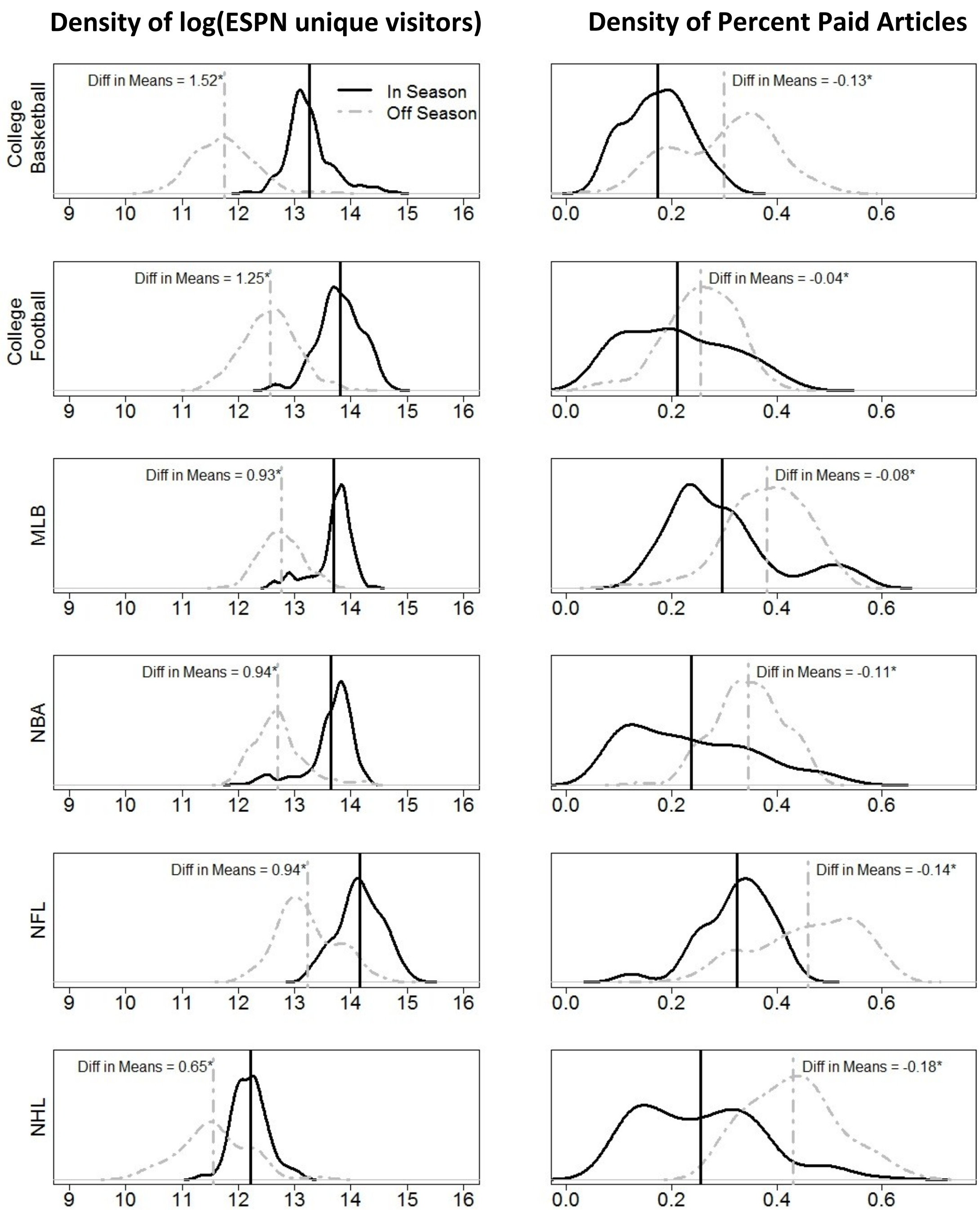

Figure 5: Evidence for counter-cyclical offering

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A: Regression results to show counter-cyclical offering

Parameters	(1) **log(Unique ESPN Visitors)**	(2) **log(Yahoo unique visitors)**	(3) **log(Unique ESPN Paid Visitors)**	(4) **Logit(Percentage of Paid Articles)**
In Season	0.36 (0.05)*	0.39 (0.10)*	-0.24 (0.13)	-0.29 (0.11)*
Game day	0.07 (0.04)	0.05 (0.07)	0.00 (0.13)	-0.20 (0.14)
log(Yahoo unique visitors)	0.14 (0.01)*		0.12 (0.04)*	-0.10 (0.02)*
log(SI unique visitors)	0.14 (0.01)*	0.22 (0.04)*	0.09 (0.04)*	0.01 (0.03)
log(CBS unique visitors)	0.12 (0.02)*	0.22 (0.04)*	0.02 (0.06)	0.03 (0.03)
Google Scaled	0.16 (0.02)*	0.02 (0.00)*	0.01 (0.00)*	-0.00 (0.00)
Draft	-0.06 (0.12)	0.02 (0.23)	1.12 (0.33)*	0.08 (0.17)
Strike	0.04 (0.06)	0.32 (0.15)*	-0.78 (0.26)*	0.22 (0.18)
Special	-0.23 (0.15)	0.16 (0.11)	0.02 (0.29)	-0.37 (0.25)
Weekend	-0.18 (0.02)*	-0.25 (0.04)*	-0.27 (0.04)*	-0.08 (0.02)*
Fixed effect	Sports			
Standard Errors	Clustered by Sports-Month			
R^2	0.88	0.67	0.40	0.43

B: Regression results to show consistency with simple model[1]

Parameters	(1) **Logit(Share of paid visitors)**	(2) **Page views per visitor**	(3) **log(Unique ESPN Visitors)**	(4) **log(Unique ESPN Visitors)**
In Season	-0.65 (0.14)*	0.08 (0.22)	0.34 (0.05)*	0.35 (0.05)*
Percent of Paid Articles			-0.40 (0.14)*	-0.15 (0.23)
xIn Season				-0.42 (0.24)
Controls	Competing Websites, Demand Controls and Sports Fixed Effects			
Standard Errors	Clustered by Sport-Month			
R^2	0.28	0.37	0.88	0.88

Numbers represent parameter estimates with standard errors in parenthesis. * represents significance at a 95% confidence level.

[1] Competing website controls for Columns (1), (3) and (4) are unique visitors to Yahoo, CNNSI, and CBS and for Column (2) page views per visitor at Yahoo, CNNSI, and CBS. Demand controls are Google Scaled, Gameday, Draft, Strike, Special and Weekend

Figure 6: Further evidence for counter-cyclical offering

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