Free vs. For a Fee: The Impact of Information Pricing Strategy on the Pattern and Effectiveness of Word-of-Mouth via Social Media

Completed Research Paper

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Abstract

With the new realities of the digital age, print newspapers are experimenting with different pricing models for their online content. Using NYT's paywall rollout as a natural experiment, our study finds that a firm's information pricing policy influences the pattern and effectiveness of online word of mouth (WOM) in social media. Using difference-in-difference-indifferences analysis, we find that implementing a paywall (i.e., charging for the content which was earlier available for free) has a disproportionate impact on WOM for popular and niche articles, creating a longer tail in the content sharing distribution. Further, we find that the impact of WOM on NYT's website traffic weakens significantly after the introduction of NYT's paywall. These results show that information pricing strategy has implications for product and promotion strategies. The study offers novel and important implications for the theory and practice of strategic use of social media and information pricing strategy.

Keywords: Digital goods, social media, word of mouth

Introduction

Digital technologies and the Internet have significantly upended the business model of the newspaper publishing industry. Declining circulation of print newspapers (Vanacore 2010) and an increasing trend toward digital news consumption by consumers has driven traditional print newspapers to adopt the Internet as the medium to offer digital content. However, given the intense competition in the online news market and almost zero marginal cost for providing news online, newspapers find it difficult to charge a fee for accessing their online content. Therefore, most online newspapers have been providing content free of charge while making money from online advertising. However, as more consumers switch from print to online news consumption, the online advertising revenue (which is significantly lower than print ad revenue) does not counterbalance the loss of revenue from print newspaper subscribers (Peters 2011).

Given these realities, it is not surprising that print news publishers have been debating the tradeoff of charging a fee versus providing the content for free. Charging a fee can increase the total revenue that a publisher receives from online consumers. However, it is likely to significantly decrease online readership (Chyi 2005), which in turn, will lower the total revenue that comes from online advertisements (Dewan et al. 2002). The New York Times (NYT) is one of such newspapers that are experimenting with different pricing models for their online content. Learning from their prior failed experiment in 2005, NYT rolled out a new paywall strategy in March 2011. Since both the subscription and ad revenue are a function of the newspaper's readership, it is important for NYT to ensure that the traffic to its website does not drop significantly. Recognizing the importance of retaining the current NYT website visitors with possibly low willingness to pay (WTP), NYT has implemented a generous access policy allowing non-subscribers to read 20 articles for free (Peters 2011). However, merely retaining current customers is not enough, and like other business, a newspaper publisher need to rely on advertising and word-of-mouth (WOM) to increase awareness and to acquire new customers (subscribers as well as non-subscribers). Recognizing the importance of social media such as Twitter and Facebook in creating WOM about online content and a resulting increase in awareness and traffic[1], the NYT chose a social media policy for visitors from social media. Thus, it allows visitors to bypass the paywall when they access from links shared in social media.

Intuition would suggest that this introduction of the subscription fee model would lower the NYT's website traffic. However, it is not clear how this new pricing strategy will impact the WOM dynamics of the NYT's content in online social media. Given the importance of online social media for the sustainability and growth of the content providers such as NYT, our study examines the impact of a firm's information pricing strategy on the pattern of content sharing and effectiveness of such WOM in social media. Using the New York Times' recent adoption of a digital subscription model as a natural experiment, we first examine how a paywall influences the extent and patterns of content sharing on Twitter[2]. We further analyze how a paywall affects the effectiveness of WOM (i.e., the virality of tweets). Specifically, we examine the relationship between the volume of online content sharing on Twitter and website traffic and how this dynamic changes after a paywall implementation.

The results show that a firm's information pricing strategy not only decreases the extent of content sharing, but it also has a disproportionate impact on content sharing pattern. Specifically, the results

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[1] According to Alexa (as of March 31, 2011), Twitter and Facebook take up 2.43% and 8.63% of upstream and downstream NYT website traffic, respectively. Like other mainstream media, NYT takes advantage of the social media features by embedding a functionality to help readers transmit their news articles on online social media, including Twitter, Facebook and Google+, and facilitate WOM about their online content. Given that Twitter accounts for a significant portion of NYT's website traffic (please refer to the Alexa's statistics in footnote 1), we chose Twitter as our empirical context. However, we do believe that our theory would hold for other social media such as Facebook and LinkedIn.

[2] Online WOM in the context of this paper does not refer to a user's opinion about NYT and its product/service. Instead it refers to the diffusion of the product (i.e., the news article) itself through link sharing in online social media. A recent study measuring information sharing on Twitter shows that 18 percent of the message shared (i.e., 1.8 million messages/tweets) in July 2009 had links (i.e., URLs) to websites (Singh 2009), demonstrating the role of social media in spreading WOM about online content.

suggest that the diffusion of popular content decreases more significantly, resulting in less concentration of popular content in content sharing distribution. Our theory-driven explanation of the long tail[3] demonstrates that light users who consume popular articles have a tendency to consume popular articles. Because of this user heterogeneity, after a paywall introduction light users have higher attrition likelihoods due to low willingness to pay for paid content, thus reshaping the content sharing distribution. Combining NYT's site traffic data with its social media buzz on Twitter, we first identify a positive impact of the volume of content sharing on website traffic. Our results suggest that the contribution of social media on website traffic creation weakens after the paywall introduction. The findings imply that a decline of popular content on Twitter is associated with a decrease of virality of online content to be consumed and retransmitted.

This study makes three substantial contributions to the literature. First, it is among the first study to integrate a firm's information pricing strategy with its impact on content sharing pattern and its subsequent impacts on the effectiveness of such WOM. Our unique natural experiment created by NYT's paywall rollout helps us isolating other confounding factors. Second, our study provides empirical evidence of our theoretical explanation of the long-tail consumption pattern. The impact of a paywall on the relationship between content demand and product assortment can be generalizable in other digital goods contexts. Finally, our study establishes a theoretical link between the impact of a paywall on content sharing pattern and the impact of WOM effectiveness. Our estimates of time series models suggest that social media have a positive impact on site traffic generation, but this impact goes down after a paywall because of a decrease in popular content. This finding provides significant implications to firms considering information goods pricing, such as newspaper companies.

Literature Review

Information (or Digital) Goods Pricing

Information goods (i.e., products that can be digitized) raise interesting pricing opportunities and challenges due to their unusual cost structure with high fixed costs, but almost zero variable cost of production and distribution (Varian 1999). Researchers have primarily employed analytical modeling approaches to analyze optimal pricing strategies for information goods under different contexts (Khouja and Park 2007; Chellappa and Shivendu 2005; Sundararajan 2004) and to study the interaction between information goods pricing strategy and a firm's product strategies such as bundling (Wu et al. 2008; Bakos and Brynjolfsson 1999), versioning (Chen and Seshadri 2007), and differentiation (Choudhary 2010). Recently, given the intense competition in the information goods markets such as online news and the low marginal cost for distribution information content online, the freemium pricing strategy is gaining popularity. A firm employing the freemium strategy offers free content (i.e., product) supported by online advertising revenue and offers premium content to paying subscribers (Anderson 2009; Oestreicher-Singer and Zalmanson 2011). However, moving from free ad-supported content to the freemium model is challenging. Researchers argue that there is a tradeoff between advertising and content subscription revenues (Prasad et al. 2003; Dewan et al. 2002) such that increasing advertising lowers the attractiveness of the content to paying subscribers, leading to lower subscription revenues. Chyi (2005), for instance, suggests that online users have lower WTP for online news access because free alternatives exist online and offline. Given the low WTP for online news, one can expect that the readership of NYT may decline after the introduction of a paywall. However, it is not evident that the transition from free to for-a-fee would impact the diffusion dynamics of the firm's news content. To the best of our knowledge, the extant literature has not examined the interaction between a firm's information goods pricing strategy and its promotion (i.e., product awareness and diffusion) strategies. Therefore, our study draws upon insights from the existing literature to investigate the impact of charging for news content on users' content consumption and sharing behavior.

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[3] The long tail, coined by Anderson (2006), describes a shift of demand distribution as niche products grow to become a larger share of total sales. For example, prior work on long tail literature examines changes of sales concentration from offline to online channels (Brynjolffson et al. 2003; Brynjolffson et al., 2011, Zentner et al. 2012).

Online WOM

Word-of-mouth (WOM) is defined as an interpersonal communication, independent of the organization's marketing activities, about an organization or its products (Bone, 1995). Online WOM is a type of WOM where the communication is mediated by Internet technologies. Further, WOM in social media about information goods (such as newspaper articles) is a special case of online WOM. Unlike traditional WOM through which users share their opinions and recommendations about a product/service, social media WOM refers to the diffusion of the product (i.e., the news article) itself through link sharing in online social media. In a social media WOM process, individuals transmit articles that they evaluate to be worth sharing. A user's sharing of a tweet[4] containing the link to a newspaper article can be considered as implicit WOM (e.g., article recommendation). Such WOM not only acts as a signal about the importance or relevance of the article content (in the view of the sender) but it also allows dissemination of the content itself within the social network. Thus, WOM about newspaper articles also affords an opportunity to the receivers to consume the content. A recent study measuring information sharing on Twitter shows that 18 percent of the message shared (i.e., 1.8 million messages/tweets) in July 2009 had links (i.e., URLs) to websites (Singh 2009), demonstrating the role of social media in spreading WOM about online content. A significant body of WOM research has emerged which had examined a wide variety of issues related to WOM. Of particular interest is the research on effectiveness of WOM and patterns of WOM.

Effectiveness of WOM: Research suggests that online WOM impacts various performance measures such as product adoption and sales (Godes and Maylin, 2004; Chevalier and Mayzlin, 2006; Liu 2006). It has been argued that awareness and persuasion are significant underlying cognitive processes of WOM that impact consumer behavior and consequent outcomes (Liu 2006; Duan et al. 2008). Volume and valence are among the most important WOM attributes that have been examined to understand such effectives (e.g., Liu 2006). Volume measure the total amount of WOM interactions, while valence captures the nature of WOM messages (i.e., positive or negative). Research suggests that both volume and valence of WOM has a significant impact of product sales (Chevalier and Mayzlin 2006) while some prior empirical studies indicate that the volume of WOM is more effective than the valence through the awareness effect (Liu 2006). Diffusion models often used to examine the outcomes of WOM focus on the social influence to explain the effects of awareness or persuasion (e.g., Sinal and Walker 2012; Susarla et al. 2012). For example, a recent study examines the relationship between a firm's design of WOM features and social contagion in consumer's product adoption in social media (Aral and Walker 2011).

While most prior studies have examined online WOM for physical product-related communication, with the emergence of social media such as YouTube, Twitter and Facebook, emerging literature has begun to examine WOM for of information (content) over online social networks. A key difference between the online WOM of physical products and the online WOM of digitized information over online social networks is that digital products are often consumed through consumer's action (i.e., social transmission) rather than merely evaluating and sharing opinions (e.g., online product reviews). For example, Berger and Milkman (2012) examine how certain content characteristics (i.e., emotion-related content valence, as well as practical utility and interestingness) drive greater diffusion outcomes of online content using the "most emailed" New York Times articles. Our study extends this emerging literature on the effectiveness of implicit WOM of digital goods.

Patterns of WOM: To understand the patterns of WOM, research has examined distributions of online WOM, such as distribution of positive and negative review ratings (Hu, Bose, Koh, and Liu, 2012, Hu, Pavlou, Zhang, 2007), propensity to review in terms of product popularity (Dellarocas, Gao, and Narayan, 2010), and the influence of online reviews across product popularity (Zhu and Zhang, 2010). Recent literature examines the long tail effect on the consumption of information goods (Dewan and Ramaprasad 2012). Our study examines the distribution of WOM for hit/niche content after a pricing policy changes.

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[4] Tweet is a short message sent by a sender to its recipients on Twitter platform.

Hypotheses Development

In this section we develop our hypotheses, based on the research framework shown in Figure 1. As shown in the figure, our primary interest is on the impact of a paywall on content sharing pattern and on WOM effectiveness.

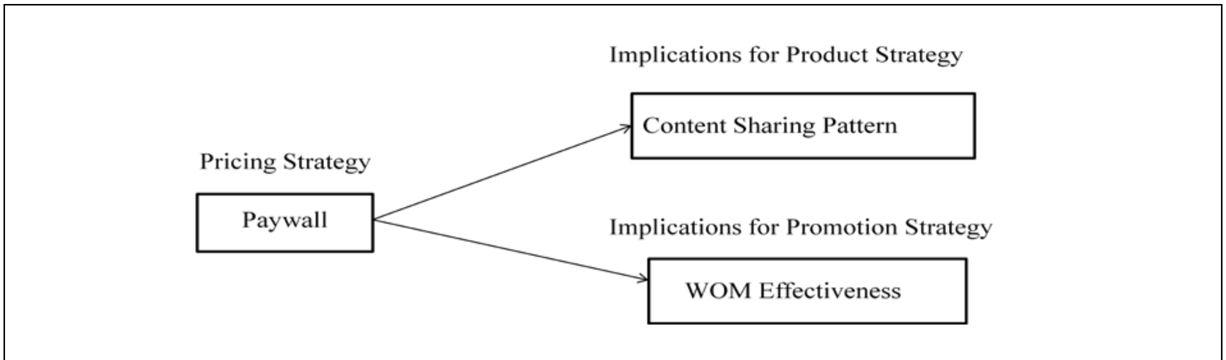

Figure 1. Research Overview

The Impact of Paywall on Content Sharing Pattern

Extent of Content Sharing (H1). Research has suggested the difficulty of charging a fee for content because of consumers' low WTP (Picard 2000; Chyi 2005). Given that in social media information spreads through relationships among members of the social network, news content becomes popular within the social media only if there are people to link to them. Therefore, fewer users on Twitter who have access to NYT content would mean a lower number of seeds for its NYT content. The loss of visitors to NYT's website will also affect the retransmission of seeds, which facilitates diffusion outcomes of information. Thus, we hypothesize the following:

H1a: The introduction of a paywall will decrease the diffusion of NYT content over social media.

Pattern of Content Sharing (H2). H1a predicts a reduction of the diffusion extent because a significant proportion of users who have low WTP for paid content (Chyi 2005) will not be likely to adopt the subscription model, and will thus discontinue or reduce their consumption of NYT content. Next, we develop predictions about shifts in the concentration patterns of the articles consumed and shared by consumers after the implementation of a paywall. Though the heterogeneity among subscribers in terms of the WTP for accessing an online newspaper site may depend on a variety of factors (Chyi 2005), we focus on the usage intensity (i.e., the number of articles read and/or shared).

In the context of subscription for accessing content, usage intensity is one of the important factors that will influence how valuable the product/service is, and consequently whether a consumer will subscribe for the content at a given price or not (Danaher 2002). Given that the NYT paywall pricing strategy essentially creates two versions of the product – a "*free version*" that allows access to fewer than 20 articles and the "*subscription version*" that allows unlimited access to NYT. The consumers who are "light users (i.e., read/share few articles) are very sensitive to price (Danaher 2002) and therefore are more likely to select the free version or switch to alternative news sources if they get annoyed by the paywall restriction. On the other hand, those consumers who are "heavy users" (i.e., read/share more articles) will be more willing to subscribe and select the paid version of the content because of their high willingness to pay. As a result, after the paywall implementation, the distribution of users in terms of their usage will shift toward heavy users as the paywall will disproportionately affect light users who will have a higher attrition rate due to the paywall restriction.

We argue that this shift in the distribution of consumers after the paywall will affect the distribution of the NYT articles read and shared. Prior research suggests that the frequency of usage is associated with consumption patterns in terms of content popularity. According to the theory of exposure (McPhee 1963), popular products monopolize the consumption of light consumers, whereas heavy consumers choose a mix of hit and niche products. The theory suggests that consumers who choose niche products tend to be familiar with many alternatives while those who know of few alternatives tend to stick with popular products. Likewise, the variety-seeking literature suggests that users' preference of niche products is positively associated with their quantity of consumption. Simonson (1990), for instance, finds that those customers who buy larger quantities per purchase tend to select a greater variety of items. Employing the long-tail theory, Elberse (2008) finds evidence that customers with a higher frequency of usage have a tendency to consume niche products in the tail of the sales concentration distribution within the online DVD-rental service context.

To summarize, as illustrated in Figure 2, we expect that the light user segment is more likely to consume popular articles (i.e., articles which appear in the head of the content popularity distribution) whereas the heavy user segment is more likely to consume niche articles (i.e., articles which appear in the tail of the content popularity distribution). Juxtaposing this statement with the earlier argument that light user segments are more likely to discontinue or reduce their contribution to the NYT's content diffusion after the paywall implementation, we expect that light users who read more popular articles will exhibit stronger attrition vis-à-vis heavy users who read a mix of niche and popular articles.

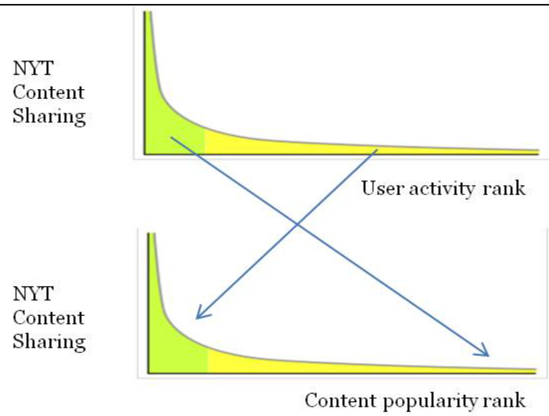

Figure 2. The Inverse Relationship between Content Popularity and Consumer Usage

As a consequence of the attrition of light users who are expected to disproportionately consume more popular articles, there would also be a change in the distribution of the NYT content shared in social media after a paywall implementation. Specifically, as the number of consumers sharing popular content will decrease, the distribution of content in terms of popularity will shift towards the tail (i.e., a decrease in the frequency of content sharing at "heads" of the content popularity distribution will be stronger vis-à-vis decrease in the frequency of content sharing at the "tail" of the content popularity distribution. Therefore, we expect a longer tail (less concentrated) in the content distribution pattern. Formally, we posit that:

H1b: The introduction of a paywall will lead to a longer tail of content diffusoin (i.e., the quantity of popular content sharing diffusion will decrease more than the quantity of niche content diffusion).

The Impact of Paywall on WOM Effectiveness

Next we focus on WOM effectiveness. In our context, WOM effectiveness refers to the ability of the WOM to increase the number of individuals who consume the information good. Given that the consumption of newspaper articles occurs at the newspaper's website, increase in consumption is synonymous with the increase in website traffic. Therefore, we examine the association between the volume of online WOM (also referred as social media buzz) and website traffic.

The diffusion of information as a result of content spreading over an online social network through transmission, consumption and retransmission of information (Stephen et al. 2010; Berger and Iyengar 2012) creates awareness about the content and increases the set of potential users who can consume the content. The initial group of users who post a message containing a link to an article, also referred as seeders, broadcasted their opinion about the importance or relevance of an article to their followers. The WOM literature suggests that the behavior of these followers in the network and the resulting dynamics are driven by two cognitive processes, that is, awareness and persuasion (Liu 2006).

First, a follower's exposure to the content shared by the seeder creates awareness effect. The follower, then, goes through a decision making process to determine whether to read the linked article and to further transmit it to their followers. Given that followers have social ties with the sender of the content, they are likely to infer that the content is worthwhile to visit. In the presence of uncertainty about content quality, persuasion effect occurs through ties in the social network which establish the credibility of source (i.e., seeder characteristics). It is important to note that the persuasion effect in traditional WOM context is primarily a result of the valence of the WOM. However, in our context, WOM is generated for those articles that are judged to be above a minimal threshold in terms of importance/relevance and the valence in primarily positive. Once a recipient visits the link, a subsequent decision-making would be whether to retransmit to his/her own network audience.

We can assume the seeders to be regular visitors to NYT's website. To the extent the WOM by these initial seeders reaches those network members (either to their direct followers and/or other network members who are exposed to the WOM spread through retransmission decisions by follower) who are not frequent visitors to NYT website and a significant proportion of them decide to visit the newspaper's website, the increase in WOM would lead to higher website traffic. To summarize, in aggregate, the diffusion of a firm's content in online social networks is likely to bring new readers who follow the seed reader. Therefore, we expect that WOM in social media influences news consumption (i.e., site traffic) and posit that:

H2a: The volume of online WOM (i.e., social media buzz) will have a positive relationship with website traffic.

After establishing the relationship between WOM and website traffic, we examine how this association differs before and after a paywall implementation. In this highly connected digital age, firms are aware of the value of social media and actively engage them in their business strategy. For example, NYT allows visitors to come from links on social media to bypass its paywall. If this bypass effect is dominant in website traffic generation, the relative strength of the relationship between social media buzz and site traffic should increase after a paywall implementation.

On the other hand, research suggests that content characteristics are related to the virality of online content, which can drive social transmission (Berger and Milkman 2012). In our context, it is reasonable to assume that the quality and usefulness of information are consistent before and after a firm's paywall introduction. Given this assumption, we expect that other changes of certain characteristics can affect the degree of virality after paywall implementation. As discussed above, our previous hypothesis (H1b) predicts that the social transmission of popular articles will decrease more significantly after a paywall because light users are more likely to discontinue content sharing. By definition, popular articles are the content that is appreciated more by a larger audience (Zentner et al. 2012). Accordingly, we should expect that a decrease in the proportion of popular content will in turn impact the virality (both site traffic generation of the shared content and retransmission of the content) of this online content. This effect works in the opposite direction to the bypass argument that a firm's active social media strategy can mitigate the decrease of its site traffic after a paywall. Hence, it is an empirical question as to which effect is dominant, leading to the following hypothesis.

H2b: The association of the volume of online WOM (i.e., social media buzz) with website traffic will be weakened after a paywall introduction.

Data

Our goal in the natural experimental setting is to analyze whether content sharing pattern on Twitter and WOM dynamics related to site traffic significantly differ before and after NYT's paywall rollout on March 28, 2011. To test our hypotheses, we combine data from two sources: NYT link sharing on Twitter and website traffic. One potential concern here is whether the treatment effect of a paywall might be biased because of a greater proportion of interesting news events in the pre-paywall period, or vice-versa. In order to isolate this time trend effect and the influence of other extraneous factors, we employ a difference-in-difference approach (Chevalier and Mayzlin 2006) and chose the LA Times (LAT) as a control group. LAT is a major national newspaper in a different geographic region. We collected tweets that contain newspaper link sharing for both NYT and LAT for 21 days before and after NYT's paywall rollout (between February 26, 2011 and March 18, 2011, and between April 4, 2011 and April 24, 2011, respectively). In the time periods, we collected the exhaustive sets of NYT and LAT link sharing. Our final data sets contain 1,287,570 tweets embedding NYT links and 226,911 tweets containing LAT links. We were also able to obtain daily website traffic data of the two newspapers for the same time period from HitWise.

Measures for News Link Sharing on Twitter

The population-size of the data allows us to create and analyze the long tail distributions of content sharing. To test the impact of the paywall on diffusion extent, we compute the counts of NYT Content Sharing and LAT Content Sharing at the content-level as the dependent variables. To examine the diffusion pattern, we computed *Content Popularity Rank*[5] from both the NYT and LAT datasets. Our measure of content popularity is guided by the notion that a news article is inherently an experience good, in that its properties cannot be determined by evaluation prior to consumption, as opposed to search goods, where this assessment can be done at pre-consumption stage (Nelson 1970). In line with long tail studies (Brynjolffson et al. 2003; 2011; Zentner et al. 2012), popularity of content is measured in a relative sense. Finally, a significant proportion of tweets in our sample contained NYT and LAT links to past articles, which may create positive information of the paywall effect because the articles in the pre-paywall block simply had a longer duration in our sample. To prevent this bias, we use a 1-day diffusion horizon in measuring the dependent variables. Table 1 presents the summary statistics of our data sets.

Table 1. Summary Statistics: Content-level Data

	Before Paywall Roll-out				After Paywall Roll-out			
	Mean	SD	Min	Max	Mean	SD	Min	Max
NYT Content sharing	55.20	265.87	1	8563	47.41	140.66	1	4517
	N = 10604				N = 10578			
LAT Content Sharing	10.84	33.66	1	1563	11.00	23.57	1	586
	N = 4618				N = 4512			

Measures for WOM Effectiveness

For site-level analysis, we created the measures of WOM volume and website traffic. Among multiple website traffic measures that show similar trends (total visits, total page views, and page views per visit), we chose total page views as our measure of website traffic as this metric is widely used in online advertising to determine where and how to advertise. $PageViews_t$ is counted when a webpage is accessed by a visitor. In addition, we counted the total volumes of daily NYT and LAT link sharing. Table 2 presents the summary statistics of our site-level data sets. As our data shows that news link sharing has a significant variation depending on the week-days, we create two weekend dummy variables. Table 3 provides the description of the key variables used in the empirical analysis.

[5] Consistent with prior empirical studies (Brynjolfsson et al. 2003; 2011), the highest NYT Content $Sharing_i$ is assigned the lowest value for Content Popularity $Rank_i$.

Table 2. Summary Statistics: Site-level Data								
	Before Paywall Roll-out				After Paywall Roll-out			
	Mean	SD	Min	Max	Mean	SD	Min	Max
PageViews	7,233,946	624550.7	6,167,817	8,511,589	5,380,597	295,546.6	4,775,525	5,838,583
Tweets	33,772.67	9,595.23	20,260	54,100	27,540.19	5,313.42	16,934	34,513

Table 3. Variable Definitions	
Site-level Variables	
$Paywall_t$	A dummy variable indicating if day *t* is in the post-paywall period
$PageViews_t$	Total volume of daily website traffic in day *t*
$Tweets_t$	Total volume of NYT link sharing on Twitter in day *t*
$Saturday_t$	A dummy variable coded as 1 if the day is Saturday
$Sunday_t$	A dummy variable coded as 1 if the day is Sunday
Content-level Variables	
$Paywall_i$	A dummy variable coded as 0 if an observation is prior to the paywall rollout, otherwise 1
NYT_i	A dummy variable coded as 1 if an observation is a NYT link, otherwise 0
NYT Content $Sharing_i$	1-day diffusion count of NYT article link sharing on Twitter
LAT Content $Sharing_i$	1-day diffusion count of LAT article link sharing on Twitter
Content Popularity $Rank_i$	Rank of an article by sorting articles based on the content of each article shared in descending order (i.e., the highest shared articles get the lowest rank)

Econometric Models and Results

The Impact of Paywall on Content Sharing Pattern

Extent of Content Sharing: Difference-in-Differences (DID) Approach

We first compare the diffusion outcomes for 21 days before and after the paywall rollout. Because the dependent variable is the count of link sharing from either NYT or LAT on Twitter, we employ a Poisson framework. As the dependent variable is a count variable, we use Poisson regression. We specify the *difference-in-differences* model for content *i* as follows:

$$\text{Content sharing}_i \sim \text{Poisson}(\theta_i),$$

$$\ln(\theta_i) = \beta_0 + \beta_1 \text{Paywall}_i + \beta_2 \text{NYT}_i + \beta_3 \text{Paywall}_i \times \text{NYT}_i + \varepsilon_i,\ \ \varepsilon_i \sim N(0, \sigma^2), \qquad (1)$$

where $Paywall_i$ is a dummy that equals one if the time period is after the paywall rollout period. The paywall dummy captures the aggregate factors that would cause changes in the dependent variable in both the treatment and control groups. The dummy variable, NYT_i, captures the possible differences between the treatment and control groups prior to the paywall rollout. The coefficient of interest, β3, is an estimate of the interaction term, $Paywall_i \times NYT_i$, which equals one if an observation is in the treatment group in the post-paywall period.

The estimates for Equation (1) are presented in Table 3. Consistent with our prior expectation, *Paywall* is negative and significant in Model 1. The β_3 coefficient on the interaction term is negative and significant in Model 2. The interaction plot in Figure 3 indicates that after the paywall implementation, NYT content sharing decreases, whereas the change of the rivals' content sharing shows the opposite trend to the NYT treatment group. Therefore, the results support H1a.

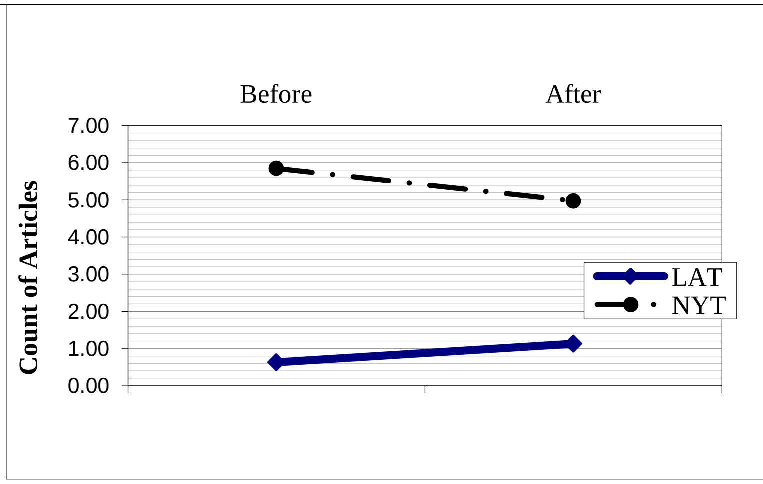

Figure 3. Interaction between NYT Paywall and NYT's vs. LAT's Content Sharing

Pattern of Content Sharing: DDD Analysis

To test examine H1B, We employ the long-tail measures[6] of the Gini coefficients and log-linear regression specification to examine how a paywall reshapes the content sharing distribution with respect to content popularity (Brynjolfsson et al. 2003; Brynsolfsson et al. 2011). More specifically, we fit Content Sharing and Content Popularity Rank to log-linear regressions that model the power-law distributions of content sharing at the content level. We create a *Paywall* dummy (defined as 0 if pre-paywall, otherwise 1) and interact it with ln(Content Popularity Rank). Finally, in line with our prior DID formulation, our model incorporates LAT as a control group. $Paywall_i \times \ln(\text{Content popularity rank}_i) \times NYT_i$ is the three way interaction between the dummies of the treatment and control groups and content popularity rank, an indicator of changes in the importance of niche content. The purpose of including the three way interaction term is to compare the long tail effect on content sharing across the treatment (NYT) and control (LAT) groups before and after paywall rollout. The *difference-in-difference-in-differences* (DDD) specification is as follows:

$$\ln(\text{Content Sharing}_i) = \beta_0 + \beta_1 \ln(\text{Content popularity rank}_i) + \beta_2\,\text{Paywall}_i + \beta_3 \text{NYT}_i + \beta_4 \text{Paywall}_i \times \ln(\text{Content popularity rank}_i) + \beta_5 \text{Paywall}_i \times \text{NYT}_i + \beta_6 \text{NYT}_i \times \ln(\text{Content popularity rank}_i) + \beta_7\,\text{Paywall}_i \times \ln(\text{Content popularity rank}_i) \times \text{NYT}_i + \varepsilon_i \quad (2)$$

Models 3 and 4 in Table 5 present the results of the Pareto curve estimation. We focus on the results of the DDD model. The β_7 coefficient on the three-way interaction of the paywall, NYT and content popularity rank terms is statistically significant. The interaction plots in Figure 4 plots the two-way interactions

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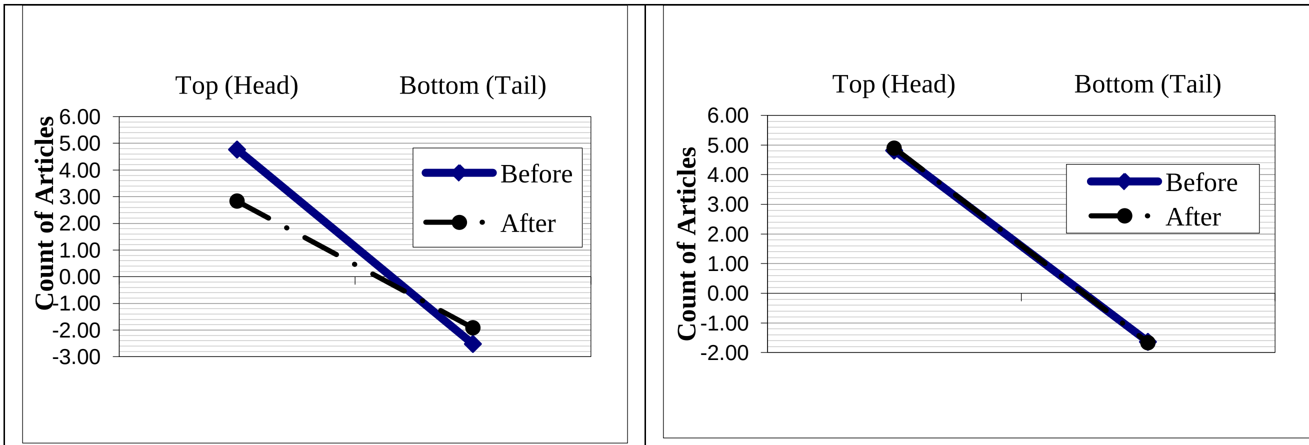
[6] Following Brynsolfsson et al. 2011, we calculated the Gini coefficients of the content sharing distribution based on the Lorenz curves. The results indicate that the Gini coefficient for NYT in the pre-paywall period (0.816) is greater than the coefficient in the post-paywall period (0.762). On the other hand, the Gini coefficients of LAT do not exhibit differences before or after NYT's paywall rollout (0.653 and 0.630, respectively).

between Paywall and Content popularity rank. As shown in Figure 4A, the absolute value of the slope coefficient for NYT decreases after the paywall implementation. The results suggest that the paywall rollout leads to a shift of NYT's content sharing distribution. More specifically, a decrease of popular content in the lower rank is more significant, thus confirming Hypothesis 1B. It is noteworthy that the slope coefficient for LAT does not exhibit any significant changes before and after NYT's paywall rollout, suggesting that the shift of NYT's content sharing distribution is not caused by extraneous factors such as time trends. Therefore, we conclude that NYT's content sharing distribution becomes less concentrated (a longer tail) after the paywall rollout than the distribution before the paywall rollout.

Table 4. Content-level Analysis

Dependent Variable	(1) NYT Content Sharing	(2) DID: Content Sharing	(3) ln(NYT Content Sharing)	(4) DDD: ln(Content Sharing)
$Paywall_i$	-0.153*** (-0.002)	0.0133** (0.00633)	0.702*** (0.0825)	-2.688*** (0.0850)
NYT_i		1.619*** (0.00466)		1.988*** (0.0115)
$Paywall_i \times NYT_i$		-0.166*** (0.00662)		4.600*** (0.0938)
ln(Content popularity $rank_i$)			-1.586*** (0.00627)	-1.451*** (0.00492)
$Paywall_i \times$ln(Content popularity $rank_i$)			-0.0707*** (0.00919)	0.334*** (0.0105)
$Paywall_i \times NYT_i \times$ ln(Content popularity $rank_i$)				-0.540*** (0.0111)
$Saturday_i$	0.128*** (0.00281)	0.109*** (0.00273)	-0.0380*** (0.0136)	-0.0242** (0.0110)
$Sunday_i$	0.167*** (0.00291)	0.152*** (0.00281)	-0.0575*** (0.0144)	-0.0483*** (0.0113)
Constant	3.974*** (0.00143)	2.359*** (0.00449)	16.50*** (0.0566)	13.30*** (0.0407)
No. of observations	21,182	30,312	21,182	30,312
R-squared	0.003	0.0861	0.855	0.858

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1



(a) New York Times

(b) LA Times

Figure 4. Interaction between NYT Paywall and Content Popularity

Long-tail Explanation

To support our long-tail explanation, we perform a direct test of the inverse relationships between user activity and content popularity. We assume that the paywall treatment effect is not caused by changes in users' inherent characteristics regarding WTP for paid content, but is rather caused by the attrition of certain user segments having low WTP. Hence, we employ a user matching sample in our analysis. Note that the observations in our sample are at the tweet message-level, and the measures are created by aggregating either at the content or user-level. We incorporate the insights from these two dimensions. Specifically, based on the *Content popularity rank* of content *i*, we create a user's *Average content popularity rank* at the user level. The metric captures a user's tendency to consume popular versus niche content. A lower mean reflects a user's preference for popular content. Then, we crate *User activity rank* for user *j* by sorting users based on the count of the total articles shared by each user in descending order (i.e., the highest sharer gets the lowest rank). Finally, we create $Attrition_j$ as a dependent variable. It is a user-level variable and is coded as 1 if a user in the pre-paywall sample is not found in the post-paywall sample.

Table 5 presents the estimation results of a standard logit regression analysis. The results indicate that User activity rank is positive and statistically significant, while Average content popularity rank has significant negative effects on user attrition. In other words, we find that users with a lower consumption level and users who have a higher tendency to share popular content are more likely to decrease or discontinue NYT content sharing after the paywall rollout. To further analyze a differential impact of a paywall with respect to user heterogeneity, we conduct a latent user segment analysis using finite mixture modeling[7].

[7] The purpose of our latent segment analysis is to identify differential impacts of paywall with respect to user heterogeneity in terms of consumption level and preference for content popularity. The latent user segment analysis results using a finite mixture model indicates that the light users who read less (more) are more likely to read popular (niche) content. Then, the user segment that reads more popular articles exhibit a greater likelihood for attrition vis-à-vis the user segment that reads less popular articles. To conserve space, we omit the estimation and post-estimation results of our finite mixture model, and the results are available upon request from the authors.

Table 5. Long-tail Explanations	
Dependent Variable	Attrition
ln(user rank$_j$)	4.356(0.0326)***
ln(content popularity rank$_j$)	-0.119(0.00383)***
Constant	-51.00(0.407)***
No. of observations	167,475
Pseudo R-squared	0.1482

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

The Impact of Paywall on WOM Effectiveness

Time-series Model of WOM and Website Traffic

In the second part of our analysis, we employ a vector autoregression model with exogenous variables (VARX) at the site-level. Because website traffic both affects the volume of WOM and is influenced by WOM, VARX is well suited to capture the dynamic interactions between WOM and site traffic and the feedback effect that affect website traffic over time (Luo et al. 2013). We find that the optimal lag length of the VARX model is 1, according to the Schwartz's Bayesian Information Criterion (SBIC) and Akaike information criterion (AIC). We estimate the following VARX model:

$$\begin{pmatrix} \ln\text{PageViews}_t \\ \ln\text{Tweets}_t \end{pmatrix} = \begin{pmatrix} \alpha_p \\ \alpha_w \end{pmatrix} + \begin{pmatrix} \varphi_{11} & \varphi_{12} \\ \varphi_{21} & \varphi_{22} \end{pmatrix} \begin{pmatrix} \ln\text{PageViews}_{t-1} \\ \ln\text{Tweets}_{t-1} \end{pmatrix} + \begin{pmatrix} \beta_p X_t \\ \beta_w X_t \end{pmatrix} + \varepsilon_t, \qquad (3)$$

where ln(PageViews$_t$) denotes the daily gross site traffic at day *t*, and its one-day lagged variable is defined as ln(PageViews$_{t-1}$). Similarly, ln(Tweets$_t$) represent the total number of tweets that contain the NYT link at day *t*. The dummy variables, Saturday$_t$ and Sunday$_t$, are included in all questions to control for variations due to different news articles on the weekends.

We first conducted the unit root tests. The Dickey-Fuller test results confirm that the variables are stationary rather than evolving in 95% confidence intervals. Table 6 presents the estimation results. We find that there is a positive and statistically significant relationship between ln(Tweets$_{t-1}$) and ln(PageViews$_t$) before NYT's paywall rollout (confirming H2a), whereas this interdependence becomes insignificant after the paywall rollout (supporting H2b). The results provide evidence that social media buzz is a significant predictor of website traffic; however, a firm's information pricing changes these dynamics.

Robustness Tests

As an alternative model specification, we conducted a three-stage least-square (3SLS) using split-samples of before and after the paywall: one equation with daily page views as the dependent variable (the site traffic equation) and one with daily tweets volume as the dependent variable (the tweet equation). Given the interdependence between WOM volume and website traffic, we include the lagged dependent variables as instruments for the endogenous relationships between the site traffic and tweet volume. As shown in Table 7, the results of 3SLS estimation are consistent with the VARX model[8].

[8] In addition to split sample analysis (i.e., comparing the coefficient of tweet volume on website traffic in the sample collected before paywall with the same coefficient in the sample collected after paywall), we tested the moderation effect by including the interaction term (i.e., paywall and tweet volume interaction) in the 3SLS model and tested it using the full sample. We find that both paywall and the interaction of paywall and WOM volume are negative and significant. The interaction plot shows that the magnitude of WOM's effect on website traffic generation decreases after NYT's paywall, confirming the moderating effect. Due to paucity of space, we do not omit the results. However, the results of both split-sample and full sample 3SLS model estimation are available upon request from the authors.

$$\ln(\mathrm{PageViews}_t) = \theta_t + \alpha_1 \ln(\mathrm{Tweets}_{t-1}) + \alpha_2 \ln(\mathrm{PageViews}_{t-1}) + \alpha_3 \mathrm{Controls}_t + u_t \quad (4)$$

$$\ln(Tweets_t) = \eta_t + \beta_1 \ln(PageViews_{t-1}) + \beta_2 (Tweets_{t-1}) + \beta_3 Controls_t + v_t \quad (5)$$

Table 6. Estimation Results from VARX Model for WOM and Website Traffic

	NYT		LAT	
	Before Paywall	After Paywall	Before Paywall	After Paywall
Dependent Variable: ln(PageViews$_t$)				
ln Tweets$_{t-1}$	.176 (.075)**	.095(.062)	.134(.131)	.229(.101)**
ln PageViews$_{t-1}$	.211(.213)	.459(.189)**	.682(.207)***	.446(.156)**
Saturday$_t$	-.019(.048)	-.052(.028)*	-108(.080)	-.069(.039)*
Sunday$_t$	.106(.049)**	.023(.032)	-.072(.081)	.054(.047)
Constant	10.601(2.959)***	7.415(2.933)**	3.308(2.219)	5.715(2.038)**
Dependent Variable: ln(Tweets$_t$)				
ln PageViews$_{t-1}$	1.046(.501)**	-.171(.324)	.665(.297)**	-.019(.275)
ln Tweets$_{t-1}$	.299(.177)**	.016(.106)	.098(.188)	.502(.179)**
Saturday	-.474(.112)***	-.310(.048)***	-.605(.114)***	-.383(.069)***
Sunday	-1.885(.116)	-.492(.055)***	-.510(.117)***	-.359(.083)***
Constant	-9.160(6.938)	12.804(5.008)**	-1.408(3.178)	4.641(3.581)

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Discussion

By using NYT's paywall rollout as a natural experiment, our study finds that a firm's information pricing policy has a disproportionate impact on content consumption pattern in social media, leading a long tail pattern of content sharing distribution. We further analyze that such a paywall effect on social transmission patterns affects the effectiveness of WOM. These findings offer novel and important implications for the theory and practice of the strategic use of social media under information pricing policy.

Theoretical Implications

This is among the first study that integrates information pricing (a firm's adoption of paid subscription model) and WOM literature. With the emergence of social media, content sharing in online social networks has become an integral part of consumers' online WOM behavior. Consequently, researchers have examined the role of WOM in content diffusion (Susarla et al. 2012) as well as its impact on various aspects of performance (Chevalier and Mayzlin, 2006). Our study contributes to the literature by examining both the pattern and effectiveness of WOM via social media. We also theorize about the impact of changes in the pattern of WOM distribution (i.e., frequency of WOM about niche versus popular content) on the effectiveness of WOM. Specifically, we argued that such pattern changes influence the virality of the WOM diffusion, which in turn affects the WOM effectiveness. We also contribute to this literature by showing that pricing strategy can act as a moderator in the relationship between WOM and firm performance. This study open promising avenues for future research which can examine different WOM patterns such as frequency of WOM originating from popular versus niche seeders as well as role of moderators other than pricing strategy.

Our study also extends the information pricing literature by proposing and empirically showing the significant interplay between a firm's pricing strategy (i.e., paywall) and its WOM pattern as well as WOM effectiveness. Prior work in the information pricing literature had primarily examined, mostly analytically, the interaction between information pricing and product strategies (Wu et al. 2008; Bakos and Brynjolfsson 1999, Chen and Seshadri 2007, Choudhary 2010). We conduct an empirical study that shows the impact of pricing strategy on WOM pattern, which can have significant implications for product assortment and bundling strategies. Since the WOM pattern is likely to affect the type of content that is shared and consumed, a change in WOM pattern may require a firm to rethink its content assortment decision (for example, firm may want to focus on creating content that generates greater WOM). Thus, the pricing strategy may have implications for product strategy.

Further, to the best of our knowledge, this is the first study that theorizes about the interaction between information pricing strategy and promotion strategy. Specifically, we argue and empirically validate that shifting from “free” to “for a fee” pricing may weaken the impact of WOM promotion strategy. An implication of these results is that researchers developing analytical models to understand alternative pricing strategies for information goods need to take into account the impact of such pricing on the online WOM which in turn determines the potential demand for content and revenue.

Finally, our study also contributes to the literature focusing on long-tail phenomenon, particularly in the online context. Theorizing about the impact of information pricing on content consumption pattern, we provide a theory-driven explanation of the long tail phenomenon. This study is in line with the recent literature on online long tail effect that examine, for instance, the impact of social media buzz on music consumption pattern (Dewan and Ramaprasad 2012) and the role of product popularity on consumer choice and sales distribution (Elberse 2008). Our work enrich this stream of research, by highlighting that a firm’s information pricing can be a demand side driver of long tail outcomes (Brynjolfsson, Hu, and Smith, 2010).

Managerial Implications

Our findings not only have the potential to enrich the stream of research on strategic use of social media, but also provide managerial implications for firms’ product and promotion strategies. This study provides several managerial implications for information goods providers in general and online newspapers publishers in particular. A content publisher that has implemented a paywall should be aware of its impact on the changes in the content sharing and content consumption distribution. To achieve this objective, the publisher may need to invest in information systems that capture, monitor, and analyse the clickstream data from their webservers as well as link sharing data from social media platforms like Twitter.

Concerning promotional strategies, an information goods provider should note the implications of our long tail results (i.e., a paywall is more likely to reduce popular content consumption) in developing its product and promotion strategies. After paywall implementation by a firm, social transmission of its content may becomes less viral, thus lowering the effectiveness of WOM in generating website traffic. This negative influence of paywall on the firm’s website traffic will in turn lower the online advertising revenue which is a function of website traffic.

Given our findings, a information goods provider’s strategy of offering popular content such as “most e-mailed articles” free may help increasing its website traffic that generates through social media, while gaining subscription revenue from loyal consumers who consume more niche content. Our suggestion would also help mitigate a concern regarding the sustainability and presence of NYT’s opinion leadership as influential mainstream journalism after the paywall implementation.

The long tail results of our study provide implications for firms’ product strategies. Our findings confirm a significant relationship between content demand and product variety. NYT might want to pay more attention to its product assortment and niche content for its loyal readers, which offering differential pricing schemes, depending on user’s consumption level. Though unbundling such as unit pricing may be impractical because of inconvenience of micro-payment in the current information technology infrastructure, innovative pricing strategies such as device-specific pricing would help viability of a firm’s adoption of information pricing strategy.

Limitations and Suggestions for Future Research

This study has some limitations that could be addressed in future research. First, NYT's paywall, used as the treatment of our natural experiment, was implemented as a single pricing strategy. As such, depending on the design of information pricing policies (e.g., NYT's single pricing strategy vs. online Wall Street Journal's content-based pricing), the magnitude of the paywall effect may vary; however, the implications of the paywall adoption on content diffusion patterns would provide insights to understand different pricing schemes of digital goods. Given that NYT and other content providers are currently introducing new pricing strategies (e.g., plans for iPhone and iPad apps), future research could provide interesting insights by comparing our results with the impact of such changes.

One caution warranted in generalizing our findings is a possible first mover effect of NYT's paywall. While our findings are limited in only a particular case of NYT's paywall, users may become used to paid subscription models over time. However, we believe that this first mover effect can only impact the magnitude of our findings. Based on our theory, if consumers become more used to pay for information goods, the proportion of heavy users will be relatively less decreased, weakening the long tail pattern of content consumption. In such case, we expect that our theoretical explanation of user preference for product variety and the resulting long tail pattern would hold. Future research on later adoption of paywall would provide more salient implications for firms considering information pricing strategy.

Conclusion

The emergence of social media and online WOM has provided the opportunities to access rich data sets to address a significant set of behaviorally and managerially relevant questions. Our study is motivated by an observation that consumers have increasingly become consumers of digital content, while the news and media industry is facing revenue issues. In this study, we integrate research on diffusion and the long tail consumption pattern to understand how a firm's adoption of information pricing affects its WOM dynamics. We hope that our work will contribute to and promote future research that enhances our understanding of consumer behavior and digital markets regarding paid content.

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