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Substitution or Promotion? The Impact of Price Discounts on Cross-Channel Sales of Digital Movies

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Abstract

Technology is transforming the marketing function in many ways, and this transformation is particularly apparent for information goods such as movies where digital technologies provide marketers with new distribution channels, which in turn create new opportunities for cross-channel effects. However, these digital channels also provide researchers with new opportunities to measure micro-level customer behavior to understand the impact of cross-channel effects in real-world settings.

In this paper, we study cross-channel effects between movies sold in digital purchase (commonly known as Electronic Sell Through or EST) and digital rental (commonly known as Video-On-Demand or VOD) markets. We do this using a unique sales dataset from a major digital movie retailer provided by a major movie studio. Our analysis takes advantage of a 14-week field experiment that allows us to measure the impact of price discounts on own- and cross-channel sales. We use this experiment to estimate own and cross price elasticities, whether price discounts cannibalize future sales, and most importantly whether price discounts in one channel affect sales for the same product in a presumably competing channel.

Our analysis indicates that digital movie consumers are highly sensitive to price promotions. However, we also find that, contrary to expectations, price promotions in a digital sales channel for a movie do not seem to cannibalize digital rentals. Indeed, our results suggest that, if anything, price promotions for digital movie sales can increase digital rentals. We explore a variety of explanations for this counterintuitive result, including the possibility that the ease of information transmission online through third-party websites, blogs, and online discussion areas may create information spillovers such that price discounts in one channel may increase product awareness in other competing sales channels. From a managerial perspective, our results suggest that cross-channel cannibalization can be reduced or even reversed in the presence of information spillovers, and that there are many new opportunities for marketers to directly measure these cross-channel effects using experimental data from online platforms.

Keywords: Digital channel; Movie; Price; Digital products; Cross-channel sales

Introduction

Technological advances are transforming the marketing of movies in several ways. First, new distribution channels allow studios to deliver movies with better access, a wider selection, and more frequent updates of new content than was previously possible. Second, online platforms provide studios with new promotional methods, including promotional placement, free trailers, and promotional posts on social media sites. Third, digital channels frequently enable studios to directly set retail prices on their products. Finally, advances in digital rights management technologies enable firms to offer rental versions of digital content.

With the rapid adoption of Internet-enabled devices, digital channels have become increasingly popular among consumers. According to the Digital Entertainment Group (2014), U.S. home entertainment spending in digital channels increased from an estimated $5.2 billion in 2012 to $6.5 billion in 2013, accounting for 35.5% of U.S. home entertainment consumer spending.

One key challenge of managing many distribution channels is that there is an implicit belief that they cannibalize one another. In turn, these beliefs frequently lead to tension among downstream suppliers who want to protect its profits and, wherever possible, to ensure exclusivity. For example, HBO believes that digital sales channels such as iTunes and Amazon Instant Video are substitutes for its service, and uses exclusivity clauses in licensing contracts to force studios to remove their content

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from digital sales channels during the HBO broadcast window (Kumar, Smith, and Telang 2014). Likewise, managers at the studio we worked with expressed concern that price promotion in one digital sales channel could cannibalize sales in the digital rental channel on the same retailer, limiting any value they could obtain from digital price promotions.

In spite of these beliefs in the industry, there is relatively little empirical analysis of cannibalization effects across digital channels. Our goal in this paper is to analyze the degree to which price promotions in a digital sales channel cannibalize sales in a presumably competing digital rental channel.

However, estimating channel interactions comes with significant empirical challenges. Most of the channel choices and pricing strategies across channels are endogenous, making unbiased identification difficult. In this paper, we address this empirical challenge by using a unique quasi-random experiment to estimate own price elasticities for movie purchases and cross price elasticities between purchases and rentals.

Specifically, our study focuses on cross-channel effects between the digital purchase (commonly known as Electronic Sell Through or EST) and digital rental (commonly known as Video-On-Demand or VOD) markets. EST and VOD channels for a movie are essentially two differentiated products under the same umbrella brand, and since most consumers only purchase once for the same title, one would expect that the EST and VOD channels are substitutes at a movie level. Therefore, if the EST price of a movie drops, EST may become more attractive than VOD, causing the movie's VOD sales to decrease.

However, there may be other confounding effects that could reduce, or even reverse, the substitution effects across these two channels. For example, in digital markets there also may be information spillover effects between EST promotion and VOD sales for the same movie title. In online markets, the availability of various searching and browsing tools and deal-collection websites makes it easy for consumers to find discount information, and some of these visits may convert to purchases (Li and Kannan 2014). This sort of information spillover, triggered by price discounts but not directly initiated by studios or retailers, may increase the overall awareness of the discounted movies, leading to increased sales in other channels. For example, suppose a consumer browsing a deal website finds that an EST version of the 1939 movie *Gone with the Wind* is on sale from \$9.99 to \$4.99 on iTunes. She may become interested in the movie, go to iTunes, and find that the VOD price (\$1.99) is still cheaper than the discounted EST price, and she may ultimately decide to consume the VOD version of *Gone with the Wind*, even though VOD was not part of the original price promotion. Therefore, a price discount in one channel can inform consumers of the umbrella brand – the promoted movie – and this information spillover effect may increase the sales of both EST and VOD channels. As a result, the net cross-channel effect between EST and VOD is not clear.

To examine cross-channel effects between movie purchases and rentals, we use a unique dataset provided by a major movie studio documenting their sales and rental data through a major digital movie retailer. In our analysis, we take advantage of a 14-week field experiment conducted between November 14, 2011 and February 19, 2012 to explore several important managerial and academic questions. In particular, we use this data to estimate own and cross price elasticities for digital movie sales on this platform, whether (and how much) price discounts cannibalize future sales, and notably whether a price discount in one channel affects sales in other channels.

Our analysis indicates that consumers in EST channels are highly sensitive to price changes. However, we also find that, contrary to expectations, a price decrease in the EST channel does not necessarily reduce sales in the presumably competing VOD channel. In fact, if anything, we observe a potential information spillover between the two channels such that a reduction in EST prices in our sample may increase VOD sales for the same movie. We observe this in spite of the fact that there were no other studio-initiated promotional campaigns for these movies during our time period. We argue that one potential explanation for this counterintuitive finding is that in digital markets, price discounts of one type can create information spillovers (possibly through third party websites, blogs, or online discussions) that may increase the overall awareness of promoted products, leading to increased overall sales across channels (Li and Kannan 2014).

Our research makes several contributions to the literature. First, prior research has found spillover effects of a movie's television broadcast on DVD sales (e.g., Kumar, Smith, and Telang 2014; Smith and Telang 2009), of marketing-mix within umbrella brands (e.g., Erdem and Sun 2002), of patient feedback among competing drug brands (Janakiraman, Sismeiro, and Dutta 2009), and of advertising among competing retailing brands (Anderson and Simester 2013). Our study adds to these results by examining the potential for positive spillovers of price promotions on sales in presumably competing channels.

Further, while previous research has studied cross-channel relationships between online and offline channels (e.g., Brynjolfsson, Hu, and Smith 2003; Zentner, Smith, and Kaya 2013), cross-channel relationships between digital and physical products (e.g., Danaher et al. 2010; Deleersnyder, Inge, and Katrijn 2002; Hu and Smith 2013; Kannan, Pope, and Jain 2009), and the impact of multichannel marketing campaigns on within- and cross-channel sales (e.g., Dinner, Van Heerde, and Neslin 2014; Montaguti, Neslin, and Valentini 2014), little is know about the potential effects among different digital channels. Our study extends this stream of research by studying the impact of price discounts for a movie on sales in other digital channels, potentially closer substitutes than the settings studied previously given the co-location of purchase (EST) and rental (VOD) channels in a single online retailer. Our empirical findings also offer new insights for studios and online platforms to better understand cross-channel effects between purchase and rental markets, and to optimize pricing strategies across channels for higher overall profits.

While more tentative because of differences in estimation techniques, we believe our second contribution is in a finding that consumers in our digital channel are extremely price sensitive relative to measured price sensitivity in traditional markets (see Bijmolt, van Heerde, and Pieters 2005 and Tellis 1988 for surveys of studies of price sensitivity in traditional industry) or online markets selling physical goods (e.g., see Brynjolfsson, Hu, and Smith 2003 and Chevalier and Goolsbee 2003 for studies in online print book markets). This may be explained by the lower search cost in digital channels, the availability of cheaper or free alternatives such as digital piracy (Smith, Bailey, and Brynjolfsson 1999), or changes in consumer price sensitivity over the past decades (Bijmolt, van Heerde, and Pieters 2005).

Our paper also advances the literature by (1) being one of a relatively small number of papers in the literature to analyze promotional impacts at digital sales channels, (2) using actual sales data as opposed to the more typical approach of using sales rank (e.g., Brynjolfsson, Hu, and Smith 2003; Chevalier and Goolsbee 2003; Hashim and Tang 2010; Smith and Telang 2009) or number of online reviews (e.g., Dellarocas, Gao, and Narayan 2010) as a proxy for missing sales data, and (3) reporting results from a field experiment executed by a major motion picture studio in a major online digital sales channel.

Literature Review

This study is related to several streams of research from different fields including Marketing, Information Systems, and Economics. The first stream of literature pertains to research on the motion picture industry. There has been a growing interest in the entertainment industry and movie market specifically within the academic literature. Eliashberg, Elberse, and Leender (2006) provide an overview of academic research on the motion picture industry and discuss important research issues including issues surrounding the theatrical movie value chain. Wierenga (2006) discusses research issues surrounding consumer behavior, marketing channels and the importance of intuition in decision making in the motion picture industry.

Despite the prevalence of research into the motion picture industry, there are relatively few studies of movie sales in digital channels. Notable exceptions include, Dellarocas, Gao, and Narayan (2010) who study how consumers' willingness to contribute online reviews affects the online and offline popularity of the movies, Hashim and Tang (2010) who study how Amazon's digital products affect DVD sales using sales rank data from Amazon, and Danaher et al. (2010) who analyze the impact of the iTunes sales channel on DVD sales and digital piracy.

The second related stream of the literature pertains to econometric models of price elasticity. Tellis (1988) conducts a survey of econometric studies until 1986 that estimated the price elasticity from about 220 brands/markets. He finds that, from the 367 elasticity estimates, the mean own price elasticity is 1.76 and the mode is 1.5 (in absolute value). A more recent meta-analysis by Bijmolt, van Heerde, and Pieters (2005) finds an average price elasticity of 2.62 (standard deviation = 2.21) among the 1,851 price elasticities reported in studies published from 1961 to 2004.

In addition to these studies of price elasticity of physical goods sold in physical markets, Chevalier and Goolsbee (2003) estimate the own-price elasticity of print books sold by Internet retailers. They use sales rank as proxy for sales on two major online book retailers and find that own-price elasticity is around 4 on Barnes and Noble, and only 0.6 on Amazon. However, we are aware of no studies of the price elasticity of digital goods sold in digital markets, and there may be systematic differences between measured elasticities of physical and digital goods given that digital goods may have lower search costs or increased availability of cheap/free alternatives than physical goods do (Smith, Bailey, and Brynjolfsson 1999).

Our research also relates to research on multichannel marketing. Technology has enabled firms to utilize multiple channels to engage customers, and it is important for firms to optimize investments across channels (Abhishek, Fader, and Hosanagar 2012; Kushwaha and Shankar, 2013; Li and Kannan 2014), and design multichannel marketing campaigns to drive sales both within- and cross-channels (Dinner, Van Heerde, and Neslin 2014; Montaguti, Neslin, and Valentini 2014). Many previous studies have documented cross-channel relationships in online versus offline channels (e.g., Brynjolfsson, Hu, and Smith 2003; Zentner, Smith, and Kaya 2013) and between digital and physical products (e.g., Danaher et al. 2010; Deleersnyder, Inge, and Katrijn 2002; Hu and Smith 2013; Kannan, Pope, and Jain 2009). While physical and digital products are usually viewed as substitutes, little is know about the potential effects among different digital channels.

Prior studies of the motion picture industry have focused on the interaction between television broadcasts and DVD sales (Kumar, Smith, and Telang 2014 and Smith and Telang 2009), between digital and DVD sales channels (Danaher et al. 2010) and between DVD purchases and DVD rentals (Knox and Eliashberg 2009). Knox and Eliashberg (2009) use a dataset from a retailer that rents and sells VHS/DVD titles to empirically model consumers' decisions to rent or buy movie titles. However, the key assumption in their analysis is that people already know which movie they are interested in purchasing when walking into the store, and the focal decision is whether to rent or to buy that particular movie. This premise would lead directly to a substitution effect between renting and buying. However, as rental and purchase are differentiated products under the same umbrella title, altering the marketing-mix may increase the awareness of the umbrella title and increase sales of both products. Therefore, the net effect of a price discount in one channel on purchases in the other channel need not be negative (see Mukherjee and Kadiyali 2011 for example in the context of DVD sales and rentals). In this context, the availability of both EST and VOD sales data along with experimental variation in prices allows us to examine cross-channel effects of a price promotion in the context of digital sales and rentals.

Lastly, our study relates to research on spillover effects among products. Table 1 summarizes related studies on spillover effects of various marketing-mix variables and among products in various relationships. Erdem and Sun (2002) show that spillover effects exist in packaged product categories where the marketing-mix seems to reduce uncertainty in other product categories, Janakiraman, Sismeiro, and Dutta (2009) find a spillover of perceptions across competing but similar drug brands, and Anderson and Simester (2013) find that competitors' advertisements have positive spillover effects on sales of an clothing retailer.

Table 1
Contribution of current research to research on spillover effects across products.

Article	Marketing-mix examined	Product relationship	Potential mechanism
Walters (1991)	Advertising	Complements	Not discussed
Erdem and Sun (2002)	Price, advertising, and others	Umbrella brands/complements (cross-category)	(1) Increase quality Perception (2) Reduce uncertainty
Balachander and Ghose (2003)	Advertising	Umbrella brands (within-category)	Increase quality Perception
Janakiraman, Sismeiro, and Dutta (2009)	Patient feedback	Competing brands	Increase quality Perception
Smith and Telang (2009)	Movie broadcast	Competing channels	Increase awareness
Anderson and Simester (2013)	Advertising	Competing brands	Increase awareness
Kumar, Smith, and Telang (2014)	Movie broadcast	Competing channels	Increase awareness
The current study	Price	Competing channels	Increase awareness

A few studies also show positive spillovers across distribution channels. For example, Smith and Telang (2009) and Kumar, Smith, and Telang (2014) show that movie broadcasts increase sales for the corresponding DVD by increasing consumer awareness. However, little is known about the effects of price promotions on nonpromoted channels. We extend this stream of research by looking at spillover effects of price discounts across purchase and rentals channels in digital movie markets.

Data and Setting

Research Context

Our data are provided by a major motion picture studio (hereafter Studio X). Studio X offers a wide selection of catalog movies[1] on a major online movie store (hereafter Store Y). Store Y offers both EST and VOD channels with a uniform pricing policy. For catalog movies, the regular EST price is $9.99,[2] and the regular VOD price is $2.99 for standard definition (SD) versions, and $3.99 for high definition (HD) versions.

Between November 14, 2011 and February 19, 2012, Studio X conducted a 14-week temporary price experiment on Store Y. Before the promotional period, Studio X proposed a master list of their catalog movies to Store Y, and assigned all movies into one of four tiers (hereafter A, B, C, and D), where the assignment to a tier was based on the previous sales performance of the movie.[3] Store Y then chose a subset of 454 movies for promotion, with minor changes in tier assignment. Each title was randomly assigned to be promoted in one of the seven 2-week periods for no more than 2 weeks. In each 2-week period, four or five titles in tier A, 20 titles in tier B, 20 titles in tier C and, and 20 titles in tier D were promoted by Store Y. While a movie was on promotion, the EST price was reduced from $9.99 to $7.99 for a tier B movie, $5.99 for a tier C movie, and $4.99 for a tier D movie. Movies in tier A were promoted with only promotional placements and no price change. Since the focus of this paper is the impact of price promotion, we remove tier A movies from the main analysis and analyze them separately. We summarize the promotional plan in Table 2.

In our sample, we also remove Christmas themed titles as they tend to have different sales patterns during Christmas period, and we exclude titles that have been temporarily removed from the store during the observational period[4] and titles with other promotional activities not in our promotional plan. We are left with a sample of 372 catalog movies, among which 272 titles have VOD content available in both SD format and HD format. During the experimental period, 73 titles assigned to be promoted in Period 4 were canceled for promotional reasons unrelated to the titles themselves. We summarize the number of movies canceled by tier and period assignment in Appendix I. Studio X confirmed that the reason of cancelation is unrelated to this experiment, and the cancelation is not based on any movie characteristics. We keep these titles in the main analysis to serve as additional control group and we run robustness checks in Appendix VI to test whether these titles have significantly different behavior from the promoted titles.

Data Description

Our data include sales information over a 17-week period from November 14, 2011 to March 11, 2012. We use the first 14 weeks as the experiment period and the last 3 weeks as the control period. In the dataset, we observe weekly prices[5] and unit sales of each product type (*EST SD*, *VOD SD*, and *VOD HD*) of each title. The *VOD HD* and *VOD SD* prices were unchanged and uniform across titles. Promotional placement is recorded as dummy variables: *one_click* and *two_click*.[6] The dummy variable *one_click* indicates a title that is shown on the front page of

[1] We define catalog movies as any movie that has been available in the digital channel for more than six months. Although catalog movies are older movies sold at lower prices, the total number of catalog movies is large. Therefore, the total revenue generated from catalog movies is substantial. For example, for Studio X, catalog movies account for more than 50% of the total EST revenues sold in Store Y in both 2010 and 2011.

[2] The movies in our sample have only standard definition versions available for EST.

[3] Tier A movies are highest in prior sales performance, while tier D movies are lowest in prior sales performance.

[4] Which typically occurs due to contractual blackout restrictions from other distribution channels (typically pay cable channels such as HBO).

[5] In our sample, the starting time of price changes vary across titles in each period. Therefore, we use an average weekly price weighted by sales quantity for each title per week in our analysis.

[6] Promotional placements feature movie titles instead of specific versions, similar to major online channels such as iTunes movie store and Amazon Prime Instant Video. In the focal store, movies are featured by including only the title

Table 2
Promotion summary.

Tier	Original EST price	Promotional EST price	# Titles in the data	# Titles with price promotion	# Titles with *VOD SD* and HD versions
B	$9.99	$7.99	115	114	100
C	$9.99	$5.99	134	98	101
D	$9.99	$4.99	123	87	71
Total			372	299	272

Table 3
Summary statistics.

	Obs.	Mean	Std. Dev.	Min	Max
Weekly unit sales					
EST SD	6,324	22.42	45.42	0	976
VOD SD	4,624	27.53	46.20	0	881
VOD HD	4,624	20.22	45.44	0	1,217
Total number of *one_click* per title	372	0.42	0.99	0	6
Total number of *two_click* per title	372	1.72	2.71	0	17

Store Y, and the dummy variable *two_click* indicates a title that is shown on a page that is directly hyperlinked from Store Y's front page. Table 3 shows summary statistics for our dataset. The average movie in our sample receives 22.42 sales per week in *EST SD*, 27.53 in *VOD SD*, and 20.22 in *VOD HD*. A movie is displayed on Store Y's front page on average for 0.42 weeks, and is displayed on a page linked to the front page for 1.72 weeks on average.

Table 4 summarizes the average weekly *EST SD* sales for each tier in both the price promoted and non-promoted weeks across all 372 titles in our sample. We define price promoted weeks for a given title as the weeks when the title's price is discounted in our experiment. The differences in the mean sales levels are substantial among the three tiers: comparing average sales in the promoted period (Table 4, Column 3) versus the non-promoted period (Column 4), we see that sales increase by 217% (55.58 during the promoted period versus 17.56 during the non-promoted period) across all titles, and increase by 95%, 395%, and 998% across tier B, C, and D titles respectively.

Table 5 summarizes the average weekly sales quantity across the three product types by focusing on the 272 movie titles that have both EST and VOD versions available in Store Y. The average weekly sales for *EST SD* are similar to those in Table 4 for the whole sample of movies. The average weekly sales of *EST SD* in non-promotional periods are higher than *VOD HD* sales, but lower than *VOD SD* sales. Comparing sales during promotional weeks (Column 2) and non-promotional weeks (Column 3), we see that the average sales for all product types are higher when the *EST SD* prices are on promotion, which provides some initial data evidence that a reduction in EST purchase price may have a potential positive spillover effect on VOD sales.

Table 6 summarizes the frequency of promotional placements (i.e., *one_click* and *two_click*), and how these variables differ across price promoted and non-price promoted weeks. In our sample, movies with price discounts are more likely to be placed on Store Y's promotional pages. Note that *one_click* is a rare event in our sample, especially for tier C and D movies and especially during non-price promoted weeks. Due to insufficient observations with *one_click* equal to 1 during non-promoted weeks, in the remainder of our main analysis we drop *one_click* from the main analysis and focus on titles with *one_click* equal to zero.

In addition to the data described above, we also collected movie characteristics including the IMDb rating and release year from different sources (e.g., Store Y, IMDb.com and RottenTomatoes.com).

Econometric Model

For our analysis, we are interested in changes to unit movie sales across the EST (SD) and VOD (SD and HD) channels. Our goal therefore is to model the sales response of these product types to *EST SD* price changes, promotional placements, and other time-varying covariates.

Weekly unit sales in our sample are highly skewed. Figs. 1–3 present the sales distributions of movie titles across channels. As can be seen from the figures, weekly unit sales range from 0 to more than 1,000, with standard deviations twice as large as the sample means (Table 3) for each tier. In addition to skewness, around 10% of the observations in our data have zero unit sales. To account for the skewness of sales distribution, one commonly used approach is to using the logarithm of unit sales as the dependent variable (e.g., Elberse 2010; Hendricks and Sorensen 2009). To treat zero sales, one way is to drop observations with zero values. However, in our setting this is undesirable given the large number of zeros and the potential selection bias that could result. Another way to handle zero sales is to add a small number (say 1) to sales before transformation. However, a limitation of this latter approach is that the estimates are sensitive to the choice of number that is added.

name and a related picture. Other product specific information (such as version and price) is not displayed on promotional pages.

Table 4
Average weekly *EST SD* unit sales – all 372 titles.

Tier	Overall average sales	Price promoted weeks: average sales[a]	Non-promoted weeks: average sales
B	57.46	96.18	49.31
C	10.47	36.00	7.27
D	2.68	14.50	1.32
Overall	22.42	55.58	17.56

Note: We computed the average unit sales based on all 372 movie titles in our sample.
[a] Price promoted weeks for a given title are defined as the weeks when the title is price discounted.

Table 5
Average weekly unit sales by product type – 272 titles.

Type	Tier	Overall average sales	Price promoted weeks: average sales[a]	Non-promoted weeks: average sales
EST SD	B	58.12	98.74	49.56
	C	10.59	37.15	7.25
	D	3.00	15.88	1.37
	Overall	26.08	61.73	20.52
VOD SD	B	61.21	71.22	59.10
	C	11.60	15.28	11.14
	D	2.78	3.76	2.65
	Overall	27.53	39.30	25.70
VOD HD	B	46.05	51.72	44.85
	C	7.65	11.49	7.17
	D	1.71	3.06	1.54
	Overall	20.22	28.73	18.89

Note: We computed the average unit sales based on 272 movie titles in our sample that have both EST and VOD versions available.
[a] Price Promoted weeks for a given title are defined as the weeks when the title is price discounted.

Table 6
Percentage of weeks with promotional placements – all 372 titles.

Tier	Overall		Price promoted weeks[a]		Non-promoted weeks	
	one_click	*two_click*	*one_click*	*two_click*	*one_click*	*two_click*
B	5.12%	19.90%	17.35%	36.47%	2.54%	16.41%
C	1.89%	5.58%	8.66%	37.80%	1.04%	1.53%
D	0.67%	5.88%	3.26%	40.00%	0.37%	1.97%
Overall	2.48%	10.10%	10.88%	37.82%	1.25%	6.04%

Note: We computed the average unit sales based on all 372 movie titles in our sample.
[a] Promotional weeks for a given title are defined as the weeks when the title is price discounted.

A Negative Binomial model is commonly used in settings similar to ours where there is significant skewness in sales and a large number of zeros in the dependent variable (e.g., Brynjolfsson, Hu, and Rahman 2009; Elberse and Oberholzer-Gee 2008; and Manchanda, Rossi, and Chintagunta 2004; also see Cameron and Trivedi 2013 for several references to this literature). We follow this approach, and use a Fixed Effects Negative Binomial model with the following probability mass function:

$$Pr(y_{it}^j|\lambda_{it}^j,\delta_i^j)=\frac{\Gamma(\lambda_{it}^j+y_{it}^j)}{\Gamma(\lambda_{it}^j)\times\Gamma(y_{it}^j+1)}\left(\frac{1}{1+\delta_i^j}\right)^{\lambda_{it}^j}\left(\frac{\delta_i^j}{1+\delta_i^j}\right)^{\lambda_{it}^j} \tag{1}$$

where y_{it}^j is the unit sales of movie i of product type j in week t, and where $j \in \{EST\,SD, VOD\,SD, VOD\,HD\}$. Among the variables, δ_i^j is the movie-specific fixed effect (i.e., characteristics assumed to be constant over time), and λ_{it}^j depends on time-varying covariates such as price and other promotional placements. The conditional mean of y_{it}^j is $E(y_{it}^j|\delta_i^j,\lambda_{it}^j)=\delta_i^j\lambda_{it}^j$, and the variance is $\delta_i\lambda_{it}^j(1+\delta_i^j)$. Eq. (1) allows different variance/mean ratios for different movies. In addition, this specification allows δ_i^j to be correlated with covariates.

The sales of titles with different levels of performance may respond to price discounts and promotional placements differently. It is also likely that high and low performing titles may have different time trends. Therefore, we run separate regressions for each tier within our sample of movies.

Applying maximum likelihood estimation directly to the Fixed Effects Negative Binomial models will result in the incidental parameters problem when T is fixed and $n \to \infty$ (Cameron and Trivedi 2013). To avoid this problem, we follow Hausman, Hall, and Griliches (1984) and estimate the coefficients using the conditional maximum likelihood approach. For a given movie, we assume y_{it}^j is independent over time, conditional on the

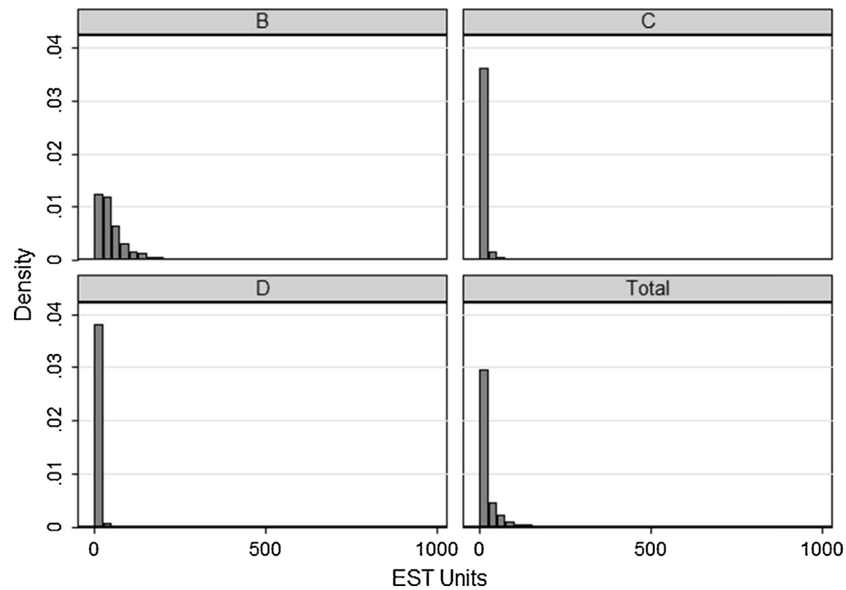

Fig. 1. Sales distribution by tier (EST).

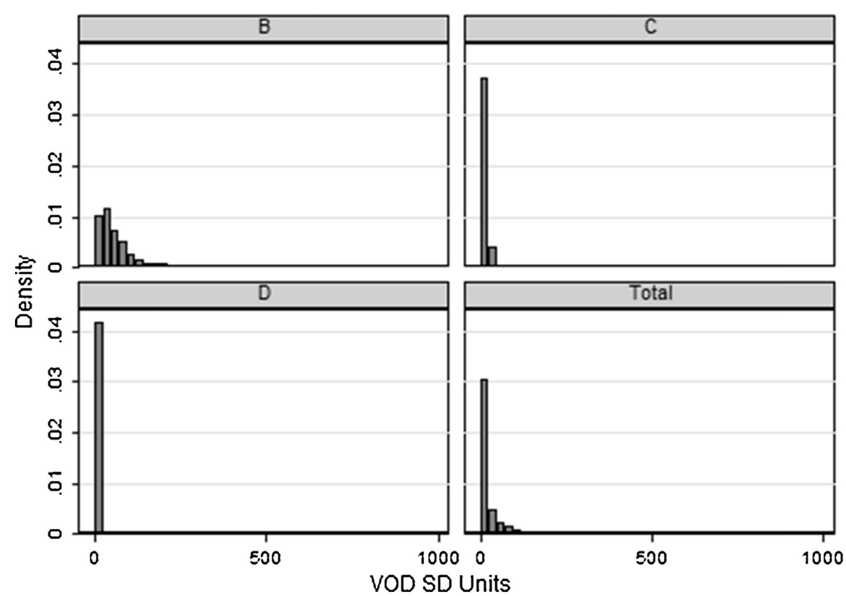

Fig. 2. Sales distribution by tier (*VOD SD*).

covariates and δ_i^j, which implies that the total sales of movie i over time $\left(\sum_{t=1}^{T} y_{it}^j\right)$ follows a negative binomial distribution with parameters δ_i^j and $\sum_{t=1}^{T} y_{it}^j$. Similar to a fixed effect logit regression, we can eliminate δ_i^j by writing the likelihood function for movie i conditioning on total sales:

$$Pr\left[y_{i1}^j, \ldots, y_{iT}^j | \sum_{t=1}^{T} y_{it}^j\right] = \frac{\Gamma\left(\sum_{t=1}^{T} \lambda_{it}^j\right) \Gamma\left(\sum_{t=1}^{T} y_{it}^j + 1\right)}{\Gamma\left(\sum_{t=1}^{T} \lambda_{it}^j + \sum_{t=1}^{T} y_{it}^j\right)} \prod_{t=1}^{T} \frac{\Gamma(\lambda_{it}^j + y_{it}^j)}{\Gamma(\lambda_{it}^j)\Gamma(y_{it}^j + 1)} \quad (2)$$

Thus, we estimate the coefficients of interest by maximizing the conditional likelihood as shown in (2) instead of estimating the full likelihood, avoiding the incidental parameters problem.

Identifying Assumptions

Our empirical analysis takes advantage of a field experiment by examining the impact of price changes on own- and cross-channel sales. Our approach is similar to a difference-in-difference model by comparing the difference in sales of promoted movie titles with and without price promotion, and the difference in sales between promoted and canceled movies. We use the sales of promoted movies at discounted EST prices as the treatment group, and use two control groups: (1) the sales of promoted movies at regular EST price ($9.99), and (2) the

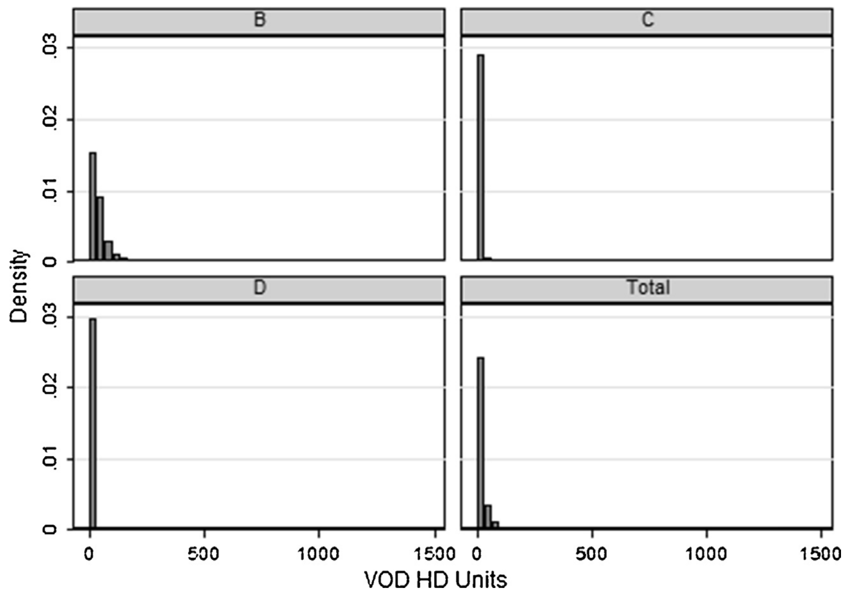

Fig. 3. Sales distribution by tier (*VOD HD*).

sales of movies which were originally scheduled for promotion but eventually were canceled for promotion as described above. With multiple groups, we use regressions with fixed effects. Comparing the sales of promoted movies over time allows us to control for movie-specific characteristics. Comparing the sales between movies discounted at different periods, and between promoted and canceled movies allows us to control for common time trends.

One underlying assumption of our approach is that the sales trend would be similar between the treatment and control groups in the absence of price promotion. We test this similarity assumption by comparing sales trend within tier. Specifically, each time we compare the sales trend of movie titles assigned to be promoted at a specific period with the sales trend of other titles at regular EST price ($9.99) within the same tier. We visualize one such comparison in Figs. 4–6, where we compare the average log sales of Tier B movie titles that are promoted during Weeks 11 and 12 (labeled as "focal group") with the average log sales of other titles that are not promoted (labeled as "control group"). From Fig. 4, we first note that a substantial jump for the *EST* sales of the focal group occurs during Week 11 and Week 12, corresponding to the EST price discount of the focal group. We also observe that the sales trends are similar between the focal group and the control group at regular EST prices. For *VOD SD* and *VOD HD* sales as presented in Figs. 5 and 6 respectively, we also observe jumps in sales for the focal group during Week 11 and Week 12, and similar trends between the focal group and the control group at regular EST prices.

Another potential concern of our identification is the endogeneity of prices: if firms set prices in anticipation of future sales changes, we would get biased price coefficients. Also note that a difference-in-difference model attributes the differences in trends between the treatment and control groups that occur at the same time as the treatment (i.e., price discount) to the treatment. Therefore, if there are other time-varying factors (i.e., omitted variables) that affect both the treatment and the difference in trends, the price coefficients estimated will be biased. However, Studio X confirmed that within each tier, movie titles are randomly assigned to be discounted at different periods. To further test this assertion, we run additional tests in Appendix VII and

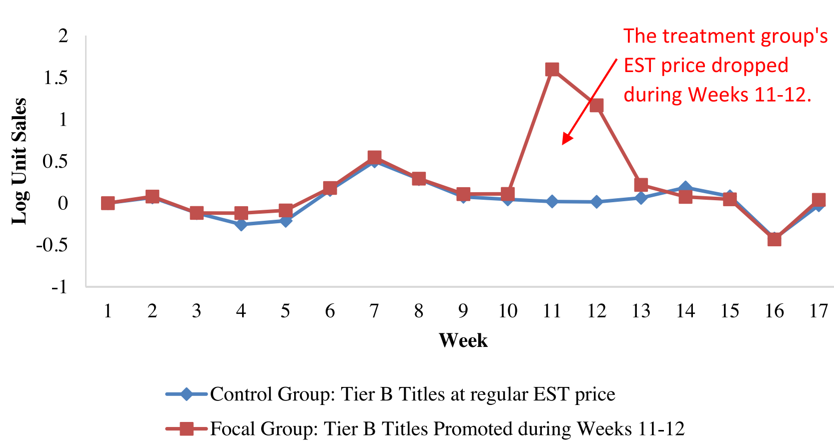

Fig. 4. EST weekly sales trend.

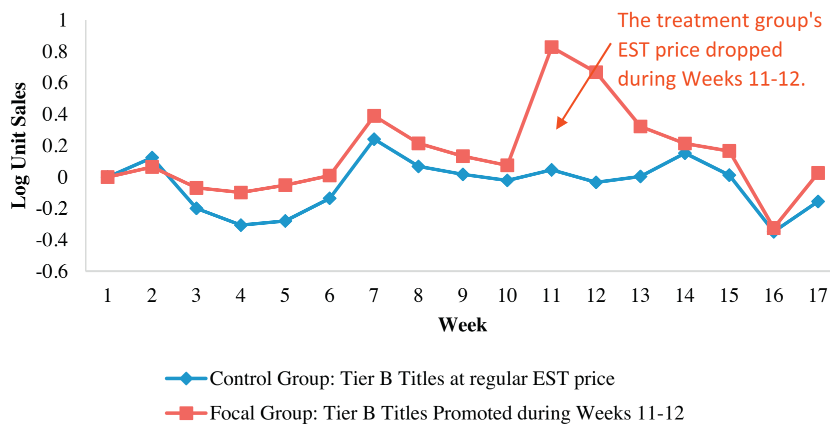

Fig. 5. *VOD SD* weekly sales trend.

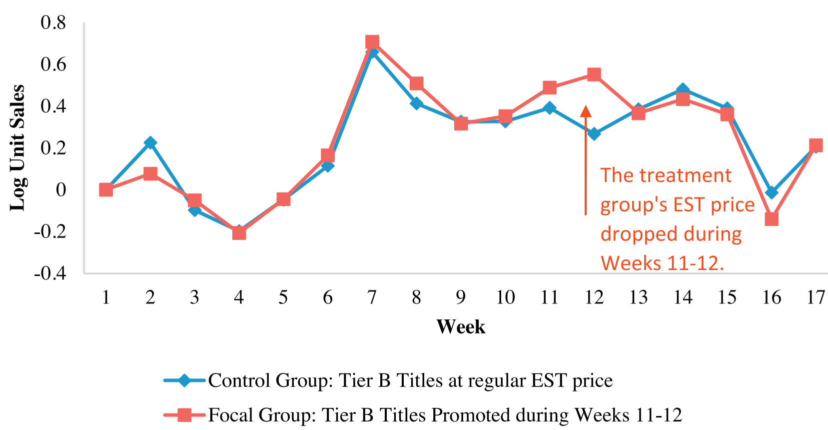

Fig. 6. *VOD HD* weekly sales trend.

find that the observable characteristics of movies (e.g., IMDb rating, release year, sales in the last 3 weeks of our sample period when products are sold at regular prices) are essentially the same for movies scheduled to be promoted at different periods.

As a further test, we run a falsification exercise by examining the impact of EST prices on sales of two weeks before. That is, we regress the weekly unit sales of movie *i* at week *t* on movie *i*'s EST price at week *t*+2 using a two-way Fixed Effects Negative Binomial model, and find no significant effects.

Empirical Results

In this section, we first focus our analysis on EST sales, and then we move to the analysis of all three product types by focusing on a subset of movie titles that have all three product types available. We then use these estimates to calculate own and cross price elasticities, and the total revenue gain from temporary EST price reduction for a representative title. In the final subsection, we examine the effects of promotional placements of Tier A movies.

Prior studies, notably Kaul and Wittink (1995) and Bijmolt, van Heerde, and Pieters (2005), have examined potential interaction effects between price and other marketing-mix variables. Following this literature, we estimate the Fixed Effects Negative Binomial model by adding interaction terms between price and placement variables.[7] Because of insufficient observations with *one_click* promotional placements during non-promotional weeks (see Table 6), we drop *one_click* from the regression, and focus on titles with *one_click* equal to 0 throughout the sample period.[8] We are left with 310 movie titles, among which 223 titles have VOD versions available.

We allow for percent changes in sales by using the log-link function, and specify that the log of λ_{it}^j is linear in the relevant parameters as follows:

$$\log(\lambda_{it}^j) = \alpha_t^j + \beta_1^j\, EST\_price_{it} + \beta_2^j\, two\_click_{it} + \beta_3^j\, EST\_price_{it} * two\_click_{it} + \sum_{p=1}^{4} \beta_4^{j,p}\, promo_{it}^{(p)}, \quad (3)$$

[7] We present results without interaction terms in Appendix III. Compared with regressions without interaction effects, regressions that include interaction effects perform better in terms of log-likelihood, AIC, and BIC measures of fit.

[8] We also run a model that includes the interaction term between *one_click* and *EST_price*. The results are summarized in Appendix IV. As shown in Appendix IV, our results are robust to including an interaction term between *one_click* and *EST_price*.

Table 7
Estimates of *EST SD* sales response (Negative Binomial, 310 titles).

	Tier B	Tier C	Tier D
Log likelihood	−7,098.35	−5,560.03	−2,976.74
AIC	14,248.71	11,172.06	6,005.49
BIC	14,393.74	11,321.07	6,152.27
Coefficients			
EST_price	−0.302***	−0.364***	−0.385***
	(0.016)	(0.011)	(0.015)
two_click	1.501***	1.269***	1.390***
	(0.232)	(0.223)	(0.234)
EST_price * *two_click*	−0.142***	−0.130***	−0.111***
	(0.025)	(0.033)	(0.034)
$promo^1$	0.019	−0.034	−0.174
	(0.040)	(0.070)	(0.128)
$promo^2$	0.054	0.013	−0.249*
	(0.038)	(0.066)	(0.136)
$promo^3$	0.078*	−0.022	−0.173
	(0.041)	(0.067)	(0.131)
$promo^4$	0.048	0.181***	−0.080
	(0.040)	(0.062)	(0.125)
# of titles	77	117	116
# of obs	1,309	1,989	1,972

Note: This table reports coefficients based on 310 movie titles in our sample that have no *one_click* promotional placements in the 17-week period.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

where EST_price_{it} is the *EST SD* price for movie i at week t. VOD prices are not included in Eq. (3) as they are constant over the period of interest and uniform across titles. two_click_{it} is equal to 1 if the title is on a web page that requires two clicks to the movie's page, α_t^j are week fixed effects, and $promo_{it}^{j,p}$ is equal to 1 if movie i is in the pth week after a price promotion. The inclusion of time fixed effects helps control for seasonality, and the inclusion of post-promotion dummy variables helps identify potential inter-temporal cannibalization.[9]

EST SD *Sales*

We report the estimated coefficients for (3) in Table 7 for *EST SD* sales by running separate regressions for each tier across the 310 titles that have no *one_click* promotional placements.[10] The standard errors are standard errors for maximum likelihood estimators obtained from observed information matrices.

The price coefficients in Table 7 range from −0.385 to −0.302 across tiers B, C, and D. Since we use the log-link function in modeling the Negative Binomial regression, the interpretation of these coefficients is that a $1 drop in *EST SD* price leads to approximately a 35% to 47%[11] increase in expected *EST SD* sales. The coefficients of *two_click* are positive and significant, indicating that promotional placements have positive effects on sales. The coefficients for the interaction terms between *EST_price* and *two_click* are negative and significant, indicating that placing a movie on promotional pages further increases the effectiveness of price promotion.

The coefficients for the post-promotion dummies are, however, notably different across tiers. For tier B titles, the coefficients are all positive, suggesting that temporary price discounts have a positive spillover effect on future sales for high performing titles. For tier C titles, $promo^{EST\,SD,4}$ is positive and significant, indicating temporary spillover effect for medium performing titles. For Tier D titles, however, the coefficients are all negative, indicating a stronger purchase acceleration effect for low performing titles.

VOD Sales

Table 8 reports coefficient estimates using the subset of 223 movie titles that have all three product types available. For *EST SD* sales, we get similar results to those in the previous subsection. Therefore, we mainly discuss the results for *VOD SD* and *VOD HD* sales in this subsection.

For regressions on *VOD SD* and *VOD HD* sales (as reported in the second and third sections of Table 8), five of the estimated coefficients of EST_price_{it} are negative, and four of them are statistically significant. The negative estimates suggest that the temporary EST price discount may have a positive informational spillover effect on VOD sales of the same movie even after controlling for the interaction between EST price and promotional placements. Thus, while one would expect the rental version to act as a substitute for the purchase version, our findings suggest that in this setting price discounts in one channel (movie purchases) can stimulate sales in another channel (movie rentals).

One possible explanation for this result could be that in this setting, price promotions in one channel result in information spillovers on the product that yield sales increases in other channels. For example, one possible source of spillovers could be the many sites online that aggregate and publicize "deals" from online retailers. We provide examples of third party websites for our product category in Appendix II.[12] It is possible that in our

[9] We tried different numbers of post-promotion variables, and found that when adding more than four post-promotional dummy variables, the effect becomes insignificant. We also infer inter-purchase time from the average units purchased per customer. Based on a report by the focal studio, the average number of unit purchased per customer is four in 2010. Therefore, the inter-purchase time of a typical customer tends to be longer than a month given that the sales distribution in our sample are right skewed. In Appendix IX, we also report the estimation results with more post-promotion variables, the main results are very similar to those in Table 8. We also note that all the post-promotion dummies are either insignificant, or significantly positive, indicating little evidence of inter-temporal substitution effect.

[10] We run a likelihood-ratio test by treating the pooled model as the restricted model, and the full model that allows for heterogeneous coefficients across tiers as the unrestricted model. The chi-squared test suggests that the full model fits the data better than the restricted model does, indicating that some of the coefficients vary across tiers.

[11] Suppose that the price coefficient is β (which is negative), then the interpretation is that a $1 drop in price leads to a $100(e^{-\beta}-1)$% increase in expected sales.

[12] There are currently many third party deal sites that list movies with price drops on major online stores. Examples include itmsmoviedeals.com for deals on iTunes, camelcamelcamel.com for deals on Amazon Instant Video, and bluray.com for deals on both iTunes and Amazon Instant Video. Most of these sites

Table 8
Estimates of sales response across product types (Negative Binomial, 223 Titles).

	Tier B	Tier C	Tier D
Panel A: EST SD			
Log likelihood	−3,948.73	−3,601.45	−1,707.55
AIC	7,945.45	7,250.90	3,463.11
BIC	8,066.00	7,378.63	3,584.38
Coefficients			
EST_price	−0.311***	−0.367***	−0.358***
	(0.017)	(0.013)	(0.020)
two_click	1.420***	1.356***	1.665***
	(0.242)	(0.256)	(0.292)
*EST_price * two_click*	−0.132***	−0.140***	−0.116***
	(0.026)	(0.037)	(0.042)
promo^1	−0.003	−0.014	−0.266*
	(0.044)	(0.080)	(0.158)
promo^2	0.029	0.014	−0.314*
	(0.041)	(0.076)	(0.167)
promo^3	0.049	−0.017	−0.149
	(0.044)	(0.076)	(0.156)
promo^4	0.030	0.188***	−0.067
	(0.043)	(0.071)	(0.151)
# of titles	66	89	68
# of obs	1,122	1,513	1,156
Panel B: VOD SD			
Log likelihood	−3,940.71	−3,621.63	−1,816.60
AIC	7,929.42	7,291.25	3,681.20
BIC	8,049.97	7,418.98	3,802.47
Coefficients			
EST_price	0.009	−0.010	−0.039*
	(0.019)	(0.017)	(0.023)
two_click	0.679**	0.297	0.927***
	(0.273)	(0.272)	(0.317)
*EST_price * two_click*	−0.065**	−0.005	−0.083**
	(0.028)	(0.034)	(0.040)
promo^1	−0.026	0.019	0.105
	(0.040)	(0.069)	(0.111)
promo^2	−0.050	−0.034	−0.033
	(0.039)	(0.067)	(0.114)
promo^3	0.020	0.070	−0.198
	(0.041)	(0.066)	(0.128)
promo^4	0.012	0.077	0.015
	(0.040)	(0.065)	(0.111)
# of titles	66	89	68
# of obs	1,122	1,513	1,156
Panel C: VOD HD			
Log likelihood	−3,617.84	−3,290.27	−1,522.48
AIC	7,283.67	6,628.54	3,092.96
BIC	7,404.22	6,756.26	3,214.22
Coefficients			
EST_price	−0.039*	−0.088***	−0.073**
	(0.020)	(0.018)	(0.029)
two_click	0.293	0.521*	1.467***
	(0.301)	(0.315)	(0.414)
*EST_price * two_click*	−0.025	−0.054	−0.129**
	(0.031)	(0.042)	(0.056)
promo^1	−0.032	0.065	−0.132
	(0.045)	(0.077)	(0.165)
promo^2	−0.063	0.041	−0.060
	(0.042)	(0.075)	(0.154)
promo^3	−0.045	0.100	−0.058
	(0.046)	(0.073)	(0.157)
promo^4	−0.024	0.044	−0.177
	(0.043)	(0.075)	(0.164)
# of titles	66	89	68
# of obs	1,122	1,513	1,156

Note: This table reports coefficients based on 223 movie titles in our sample that have no *one_click* promotional placements in the 17-week period and have both EST and VOD versions available.
* $p<0.10$.
** $p<0.05$.
*** $p<0.01$.

setting consumers who view these "deal" sites use this information to become aware of the product itself, and then purchase the product in a different, non-price promotion, channel. What is important for our setting is that this promotion function is not something that the firm initiates directly, but is rather something that occurs organically through the online community.

In addition to this finding, we note that the interaction terms between *two_click* and *EST_price* are all negative, and three of the six coefficients are statistically significant, indicating that promotional placements may further increase the spillover effect of EST price promotion on VOD sales.

We also note that the increase in cross-channel sales from information spillovers does not seem to occur at the expense of future sales in our setting. Specifically, all the coefficients of post-promotion dummies are not statistically significant, suggesting that the observed increase in VOD sales comes primarily from purchases that would not have otherwise occurred, as opposed to inter-temporal substitution effects.

Own and Cross Price Elasticities

The estimated price coefficients from log-link functions can be calculated as price elasticities using the following formula (re-arranged based on Cameron and Trivedi 2013):

$$\frac{\partial E(y_{it}^j|\delta_i^j,\lambda_{it}^j)/E(y_{it}^j|\delta_i^j,\lambda_{it}^j)}{\partial EST\_price_{it}/EST\_price_{it}}, \tag{4}$$

where $j\in\{EST\,SD, VOD\,SD, VOD\,HD\}$. Eq. (4) can be further simplified since $E(y_{it}^j|\delta_i^j,\lambda_{it}^j)=\delta_i^j\lambda_{it}^j$, which yields

$$\frac{\partial E(y_{it}^j|\delta_i^j,\lambda_{it}^j)/E(y_{it}^j|\delta_i^j,\lambda_{it}^j)}{\partial EST\_price_{it}/EST\_price_{it}}=\frac{\partial(\delta_i^j\lambda_{it}^j)/(\delta_i^j\lambda_{it}^j)}{\partial EST\_price_{it}/EST\_price_{it}}.$$

As δ_i^j does not depend on EST_price_{it}, we have

$$\frac{\partial E(y_{it}^j|\delta_i^j,\lambda_{it}^j)/E(y_{it}^j|\delta_i^j,\lambda_{it}^j)}{\partial EST\_price_{it}/EST\_price_{it}}=\frac{\partial\lambda_{it}^j/\lambda_{it}^j}{\partial EST\_price_{it}/EST\_price_{it}}. \tag{5}$$

use APIs provided by the online stores to obtain price information on promoted products at least daily, and provide links to promoted titles on these online stores. The sites earn money through commissions on "affiliate sales" directed to the retailer through their site.

From Eq. (3), the partial effect of EST_price_{it} on λ_{it}^{j} is:

$$\frac{\partial \lambda_{it}^{j}}{\partial EST\_price_{it}} = \lambda_{it}^{j}(\beta_1^{j} + \beta_3^{j}\, two\_click_{it}), \tag{6}$$

By multiplying each side of Eq. (6) by EST_price_{it}, rearranging the equation, and combining it with Eq. (5), we get the derivative-based elasticity[13] as

$$\frac{\partial E(y_{it}^{j}|\delta_i^{j}, \lambda_{it}^{j})/E(y_{it}^{j}|\delta_i^{j}, \lambda_{it}^{j})}{\partial EST\_price_{it}/EST\_price_{it}} = (\beta_1^{j} + \beta_3^{j} two\_click_{it}) \cdot EST\_price_{it} \tag{7}$$

Therefore, the price elasticity evaluated at any EST price is the product of the estimated price coefficient (after controlling for promotional placements) and the evaluated price. This is similar to a linear regression model where the dependent variable is log-transformed.

Based on the price coefficients reported in Table 7, we calculate the own price elasticities of *EST SD* titles at both the regular price ($9.99) and the discounted prices ($7.99 for tier B movies, $5.99 for tier C movies, and $4.99 for tier D movies). The elasticity estimates are reported in Table 9. The estimated elasticities range from 1.9 to 4.6, and are larger in magnitude when $two\_click = 1$.

To consider these estimated elasticities in the context of the literature, we note that Tellis (1988) conducts a survey of own price elasticity estimates published in the literature between 1961 and 1985 from about 220 different brands/markets, and finds that the mean of the 367 elasticity estimates (in absolute values) is 1.76 and the mode is 1.5. A more recent survey by Bijmolt, van Heerde, and Pieters (2005) finds an average elasticity of 2.62 based on studies between 1961 and 2004. In the context of physical goods sold in digital markets, Chevalier and Goolsbee (2003) examine book sales on two major online retailers, and find that the price elasticity is around 4 on Barnes and Noble, and 0.6 on Amazon.

However, while there are many estimates of price elasticities of physical goods sold in both traditional and digital markets, to the best of our knowledge there are no studies of the price elasticity of digital goods. Since there are many differences between digital goods and physical goods, in that digital goods may have lower search costs or increased availability of cheap/free alternatives than physical goods do (Smith, Bailey, and Brynjolfsson 1999), it is possible that elasticities of digital goods might be higher than those of physical goods. In addition, consumer price sensitivity may have increased over time (Bijmolt, van Heerde, and Pieters 2005), resulting in higher elasticities in our study as compared with many prior studies.

We also calculate the cross price elasticities of VOD at both the regular price and the discounted prices based on Table 8. The cross elasticity estimates are reported in Table 10 for *VOD SD* and in Table 11 for *VOD HD*. Most of the cross elasticities are negative, indicating positive spillover effects between promotions in one channel and sales in the other channel. The estimated cross elasticities of *VOD SD* sales are positive only for tier B titles when $two\_click = 0$.

Revenue Analysis

Based on the coefficients reported in Table 8, we estimate the weekly gross revenue gain (weighed by average unit sales) from the temporary price discounts, taking into account both temporal and inter-temporal effects for a representative movie. We present the resulting estimates in Table 12.

In Table 12, we calculate total revenue when there is no price drop based on average weekly unit sales without a price promotion. We find that the total revenue increase across product types is 20.1% for a tier B movie, 70.1% for a tier C movie, and 85.0% for a tier D movie. As digital content has near-zero marginal costs, most of these revenue increases translate directly into profit.[14] The strong increase in overall profitability following the price promotion should offer new insights to studios and movie retailers regarding the use of price discounts online as an effective marketing strategy.

Potential Effects on Non-Promoted Titles

From the perspective of movie studios and retailers, it is important to examine the effect of promotions on non-promoted titles, especially when movie titles are close substitutes. If price promotion has a negative effect on other titles, we would overestimate (in absolute value) the own- and cross-price elasticities. Although our empirical approach does not allow us to separately identify the effect of promotions on other titles from time trends, given the magnitude of sales increase we observe for promoted titles and the movies we examine in this study (catalog movies), it is unlikely that such cannibalization effects, if any, would mitigate the revenue gain from promoted titles. We also note that while we do not have direct evidence to test whether and how promotions affect other movie titles, we do find indirect evidence that the average units of non-promoted titles are larger in the first 14 weeks (when a subset of movies were price discounted each week) and the last 3 weeks (when no movie was price discounted). We have also run additional tests and find that, for the movies in our sample, there appears to be no significant relationship between the number of titles promoted each week and the average unit sales of non-promoted titles per week. Although it is beyond the scope of the current

[13] Another method to compute elasticity is based on the two unique price points. In our experimental design, all movies have the same regular price, and have at most one promotional price. Therefore, computing the sales at the two different price points and compare the difference may lead to a different elasticity estimate. However, during the estimation of a Fixed-Effects Negative Binomial model, the fixed effect parameter δ_i^{j} is canceled out and not estimated. Therefore, such elasticity and its standard error become difficult to solve analytically.

[14] The online movie retailer in our data shares revenue with the studio such that the revenue to the studio is directly proportional to the total revenue from the sale. In contrast, the marginal cost for each copy sold is nearly zero.

Table 9
Own price elasticities for EST sales.

	Tier B		Tier C		Tier D	
EST price evaluated	\$9.99	\$7.99	\$9.99	\$5.99	\$9.99	\$4.99
Elasticity						
two_click = 00	−3.013*** (0.164)	−2.409*** (0.131)	−3.640*** (0.114)	−2.183*** (0.068)	−3.845*** (0.152)	−1.920*** (0.076)
two_click = 1	−4.427*** (0.183)	−3.541*** (0.147)	−4.936*** (0.311)	−2.960*** (0.187)	−4.957*** (0.316)	−2.476*** (0.158)

Note: The reported own price elasticities are based on Table 7.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

Table 10
Cross price elasticities for *VOD SD* sales.

	Tier B		Tier C		Tier D	
EST price evaluated	\$9.99	\$7.99	\$9.99	\$5.99	\$9.99	\$4.99
Elasticity						
two_click = 0	0.093 (0.190)	0.074 (0.152)	−0.099 (0.173)	−0.060 (0.104)	−0.393* (0.231)	−0.196* (0.115)
two_click = 1	−0.555*** (0.209)	−0.444*** (0.167)	−0.149 (0.306)	−0.089 (0.183)	−1.219*** (0.330)	−0.609*** (0.165)

Note: The reported cross price elasticities of *VOD SD* are based on Table 8.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

Table 11
Cross price elasticities for *VOD HD* sales.

	Tier B		Tier C		Tier D	
EST price evaluated	\$9.99	\$7.99	\$9.99	\$5.99	\$9.99	\$4.99
Elasticity						
two_click = 0	−0.394* (0.204)	−0.315* (0.163)	−0.877*** (0.180)	−0.526*** (0.108)	−0.728** (0.286)	−0.364** (0.143)
two_click = 1	−0.640*** (0.237)	−0.512*** (0.189)	−1.421*** (0.387)	−0.852*** (0.232)	−2.015*** (0.494)	−1.006*** (0.247)

Note: The reported cross price elasticities of *VOD HD* are based on Table 8.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

study, the potential effect among movie titles is an interesting research topic that researchers may pursue if additional data are available.

Effects of Promotional Placements on Tier A Titles

Tier A titles were high performing titles that are promoted with promotional placements, but without price discounts. Because tier A movies have on average higher sales performance than tier B, C, and D movies do, we cannot use them as a control group in the main analysis. However, we have added additional regressions (Table 13) for just tier A movies to study the effects of promotional placements on purchase and rental sales. For tier A movies, we find that placing a movie on the front page increase sales substantially. In addition, EST sales seem to experience a higher increase from promotional placements than VOD sales do.

Robustness Checks

We have also run several robustness checks, including inclusion of interaction terms between *EST_price* and *one_click*, alternate model specifications, tests on promotion cancelation and period assignment, regressions on a subset of titles without promotional placements, and inclusion of more post-promotion dummy variables. Our results seem to be robust to these different specifications. The robustness checks are summarized in Appendixes IV–IX.

Discussion

Online markets have introduced new sales channels for media products, and increased the opportunities for media firms to directly set consumer prices. These new channels, and new

Table 12
Estimated weekly revenue by tier and product type.

	Tier B	Tier C	Tier D
EST SD			
No price drop	$495.07	$72.41	$13.64
Price drop	$665.74	$159.81	$35.98
VOD SD			
No price drop	$176.70	$33.30	$7.93
Price drop	$176.09	$34.53	$8.49
VOD HD			
No price drop	$178.95	$28.59	$6.14
Price drop	$179.71	$34.03	$6.79
Total from VOD			
No price drop	$355.65	$61.89	$14.08
Price drop	$355.80	$68.56	$15.28
Change	0.04%	10.79%	8.55%
Total			
No price drop	$850.72	$134.30	$27.71
Price drop	$1,021.53	$228.37	$51.26
Change	20.08%	70.05%	84.96%

Table 13
Sales response of tier a movies to promotional placements.

	EST SD	*VOD SD*	*VOD HD*
Log likelihood	−21,487.68	−20,115.71	−14,832.74
AIC	43,013.37	40,269.42	29,703.49
BIC	43,143.90	40,399.68	29,828.37
Coefficients			
one_click	1.068***	0.703***	0.595***
	(0.041)	(0.031)	(0.040)
two_click	0.743***	0.229***	0.238***
	(0.024)	(0.020)	(0.025)
# of titles	427	521	323

* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

price-setting opportunities have increased the importance of measuring cross-channel effects from price promotions.

Our paper reports the results of a unique pricing experiment in an online marketplace where we worked with a major motion picture studio to analyze the effectiveness of price promotions on media sales. In our experiment, the studio lowered prices for movies purchased in an Electronic Sell Through (EST) format, and wanted to calculate the profitability of these price changes taking into account both sales changes for the EST format, and sales changes for the (presumably) competing VOD format of the movie.

Our results show that the own-price elasticity for these digital movies is in line with, but generally higher than, price elasticities reported in the literature for physical products. However, we also find that the increased sales for the promoted product do not necessarily come at the expense of reduced sales in a presumably competing channel (in our case movie rentals). Instead we find that, if anything, price promotion in sales channels for digital movies can lead to increased rentals for the same movie. Our robustness checks suggest that this cross-channel spillover effect persists (1) after adding interaction terms between EST price and promotional placements, and (2) when focusing on a subset of movies that had no promotional placement throughout our time frame.

A potential explanation for this counterintuitive result is that price discounts of one type (i.e., movie purchase) create information spillovers initiated by third party websites or individual consumers for the movie, leading to increased awareness of the product and thus increased overall sales for both the purchase and rental versions of the movie. We believe this characteristic of "organic promotion" may be significantly enhanced by the characteristics of information discovery in online markets. Specifically, digital channels may make it easier for consumers to initiate secondary promotion of the product through websites, blogs, and online discussion areas, and this promotion, in turn, can have spillover effects across sales channels.

Our empirical results have several important managerial implications. First, the relatively high degree of price sensitivity in digital channels suggests that studios and other digital media companies may be able to profitably lower prices for products sold in digital markets. Moreover, our findings suggest that, contrary to expectations, the overall revenue increase from the direct effect of price promotions in one digital channel (as a result of high own-price elasticity), may not be significantly reduced from lost sales in presumably competing digital. Indeed, in our data, we seem to find a positive information spillover across channels, which create an additional source of benefit from price promotions, and to the best of our knowledge, one that is not taken into account by firms in their promotional decisions (including the firm providing the data for this study).

Our empirical results are of course not without limitations. First, we do not observe a pure experiment relative to what movies were selected by Studio X for promotion. More studies are needed to confirm the robustness of our results. Ideally, one would want to confirm our results in the context of a pure randomized experiment. Second, our data only cover catalog movies. Newly released movies may experience different effects. Third, due to the nature of the experiment, the prices of *VOD SD* and *VOD HD* formats are fixed during the period of interest. Therefore, we are unable to estimate the own-price elasticities of *VOD SD* and *VOD HD*, and how the price changes in VOD would affect EST sales. Fourth, we only focus on different digital channels within a single online retail store. Thus, we are unable to examine how price promotions affect sales in a different retailer. We were also not able to measure the precise mechanism of information spillover. Measuring it would be an important research direction for future.

However, in spite of these limitations, we believe our research contributes to the literature by highlighting new managerial opportunities in online markets to conduct and directly measure the impact of price experiments on sales, and by suggesting new and potentially surprising interactions between presumably competing channels in online markets.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.jretai.2015.02.002.

References

Abhishek, Vibhanshu, Peter Fader and Kartik Hosanagar (2012), "Media Exposure Through the Funnel: A Model of Multi-Stage Attribution," Working Paper.

Anderson, Eric T. and Duncan Simester (2013), "Advertising in a Competitive Market: The Role of Product Standards, Customer Learning, and Switching Costs," *Journal of Marketing Research,* 50 (4), 489–504.

Balachander, Subramanian and Sanjoy Ghose (2003), "Reciprocal Spillover Effects: A Strategic Benefit of Brand Extensions," *Journal of Marketing,* 67 (1), 4–13.

Bijmolt, Tammo H.A., Harald J. van Heerde and Rik G.M. Pieters (2005), "New Empirical Generalizations on the Determinants of Price Elasticity," *Journal of Marketing Research,* 42 (2), 141–56.

Brynjolfsson, Erik, Yu Hu and Michael D. Smith (2003), "Consumer Surplus in the Digital Economy: Estimating the Value of Increased Product Variety at Online Booksellers," *Management Science,* 49 (11), 1580–96.

Brynjolfsson, Erik, Hu Yu and Mohammad S. Rahman (2009), "Battle of the Retail Channels: How Product Selection and Geography Drive Cross-Channel Competition," *Management Science,* 55 (11), 1755–65.

Cameron, Colin A. and Pravin K. Trivedi (2013), *Regression Analysis of Count Data,* 2nd ed. Cambridge: Cambridge University Press.

Chevalier, Judith and Austan Goolsbee (2003), "Measuring Prices and Price Competition Online: Amazon.com and BarnesandNoble.com," *Quantitative Marketing and Economics,* 1 (2), 203–22.

Danaher, Brett, Samita Dhanasobhon, Michael D. Smith and Rahul Telang (2010), "Converting Pirates Without Cannibalizing Purchasers: The Impact of Digital Distribution on Physical Sales and Internet Piracy," *Marketing Science,* 29 (6), 1138–51.

Deleersnyder, Barbara, Geyskens Inge and Giel Katrijn (2002), "How Cannibalistic is the Internet Channel? A Study of the Newspaper Industry in the United Kingdom and The Netherlands," *International Journal of Research in Marketing,* 19 (4), 337–48.

Dellarocas, Chrysanthos, Guodong Gao and Ritu Narayan (2010), "Are Consumers More Likely to Contribute Online Reviews for Hit Products or Niche Products?," *Journal of Management Information Systems,* 27 (2), 127–57.

Digital Entertainment Group (2014), *DEG year-end 2013 home entertainment report,* (Retrieved July 12, 2014), [http://degonline.org/wp-content/uploads/2014/01/DEG-Year-End-2013-Home-Entertainment-Report.pdf]

Dinner, Isaac M., Harald J. Van Heerde and Scott Neslin (2014), "Driving Online and Offline Sales: The Cross-Channel Effects of Digital Versus Traditional Advertising," Working Paper.

Elberse, Anita (2010), "Bye-Bye Bundles: The Unbundling of Music in Digital Channels," *Journal of Marketing,* 74 (3), 107–23.

Elberse, Anita and Felix Oberholzer-Gee (2008), "Superstars and Underdogs: An Examination of the Long Tail Phenomenon in Video Sales," Working Paper.

Eliashberg, Jehoshua, Anita Elberse and Mark A.A.M. Leender (2006), "The Motion Picture Industry: Critical Issues in Practice, Current Research, and New Research Directions," *Marketing Science,* 25 (6), 638–61.

Erdem, Tülin and Baohong Sun (2002), "An Empirical Investigation of the Spillover Effects of Advertising and Sales Promotions in Umbrella Branding," *Journal of Marketing Research,* 39 (4), 408–20.

Hashim, Matthew J. and Zhulei Tang (2010), "Delivery of Movies via the Internet: Uncovering Strategies for the Release of Digital Formats," Working Paper.

Hausman, Jerry A., Bronwyn Hall and Zvi Griliches (1984), "Econometric Models for Count Data With an Application to the Patents–R&D Relationship," *Econometrica,* 52 (4), 909–38.

Hendricks, Ken and Alan Sorensen (2009), "Information and the Skewness of Music Sales," *Journal of Political Economy,* 117 (2), 324–69.

Hu, Yu and Michael D. Smith (2013), "The Impact of eBook Distribution on Print Sales: Analysis of a Natural Experiment," Working Paper.

Janakiraman, Ramkumar, Catarina Sismeiro and Shantanu Dutta (2009), "Perception Spillovers Across Competing Brands: A Disaggregate Model of How and When," *Journal of Marketing Research,* 46 (4), 467–81.

Kannan, P.K., Barbara K. Pope and Sanjay Jain (2009), "Practice Prize Winner-Pricing Digital Content Product Lines: A Model and Application for the National Academies Press," *Marketing Science,* 28 (4), 620–36.

Kaul, Anil and Dick R. Wittink (1995), "Empirical Generalizations About the Impact of Advertising on Price Sensitivity And Price," *Marketing Science,* 14 (3), 151–60.

Knox, George and Jehoshua Eliashberg (2009), "The Consumer's Rent vs. Buy Decision in the Rentailer," *International Journal of Research in Marketing,* 26 (2), 125–35.

Kumar, Anuj, Michael D. Smith and Rahul Telang (2014), "Information Discovery and the Long Tail of Motion Picture Content," *Management Information Systems Quarterly,* 38 (4), 1057–78.

Kushwaha, Tarun and Venkatesh Shankar (2013), "Are Multichannel Customers Really More Valuable? The Moderating Role of Product Category Characteristics," *Journal of Marketing,* 77 (4), 67–85.

Li, Hongshuang and P.K. Kannan (2014), "Attributing Conversions in a Multichannel Online Marketing Environment: An Empirical Model and a Field Experiment," *Journal of Marketing Research,* 51 (1), 40–56.

Manchanda, Puneet, Peter E. Rossi and Pradeep K. Chintagunta (2004), "Response Modeling With Nonrandom Marketing-Mix Variables," *Journal of Marketing Research,* 41 (4), 467–78.

Montaguti, Elisa, Scott A. Neslin and Sara Valentini (2014), "Do Marketing Campaigns Produce Multichannel Buying and More Profitable Customers? A Field Experiment," Working Paper.

Mukherjee, Anirban and Vrinda Kadiyali (2011), "Modeling Multichannel Home Video Demand in the US Motion Picture Industry," *Journal of Marketing Research,* 48 (6), 985–95.

Smith, Michael D., Joseph Bailey and Erik Brynjolfsson (1999), *Understanding Digital Markets: Review and Assessment,* MIT Press.

Smith, Michael D. and Rahul Telang (2009), "Competing With Free: The Impact of Movie Broadcasts on DVD Sales and Internet Piracy 1," *MIS Quarterly,* 33 (2), 321–38.

Tellis, Gerard J. (1988), "The Price Elasticity of Selective Demand: A Meta-Analysis of Econometric Models of Sales," *Journal of Marketing Research,* 25 (4), 331–41.

Walters, Rockney G. (1991), "Assessing the Impact of Retail Price Promotions on Product Substitution, Complementary Purchase, and Interstore Sales Displacement," *Journal of Marketing,* 55 (2), 17–28.

Wierenga, Berend (2006), "Motion Pictures: Consumers, Channels, and Intuition," *Marketing Science,* 25 (6), 674–7.

Zentner, Alejandro, Michael D. Smith and Cuneyd Kaya (2013), "How Video Rental Patterns Change as Consumers Move Online," *Management Science,* 59 (11), 2622–34.