Price Discounts and Peer Effects in Information Goods: Results from a Randomized Experiment

This paper studies how price promotions affect the consumption of information goods that cannot be stored, and how peer influence moderates these effects by triggering spillovers to the friends of the users that receive the promotions. We analyze outcomes from a large-scale randomized field experiment ran for 3 consecutive months using the Video-on-Demand (VoD) system of a large telecommunications provider. We show that households with access to movies priced 25% lower than usual lease 11.1% more of these movies than households that never had access to movies at reduced prices. However, they also lease 3.3% fewer of the movies without price discounts during the entire experiment, which reduces aggregate sales by 2.9%, hurting the provider's profitability. We use cell phone call detail records from this same provider to infer a graph of social proximity across households. The average degree in this graph is 10.23 friends. Using this graph, we then find a positive effect of peer influence in the consumption of movies in this VoD system, which can be strategically used by the firm to issue price promotions minimizing profit losses. Firms can break-even if they offer price promotions to households with enough friends to generate enough sales through peer influence to counter the undesirable effect of price promotions. At the average of the covariates observed in our setting, our industrial partner would break-even if it targets households with more than 4 friends with price promotions, which would be easy to achieve in the market we study.

Key words: Peer Influence, Price Promotions, Randomized Experiment, Video-on-Demand

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1. Introduction

Price promotions are one of the main ingredients of the traditional marketing strategies used by firms to maintain brand awareness. Several analytical models and empirical studies have shown that, for the case of storable goods, sales accelerate during price promotions and decrease once promotions are retracted (Neslin et al. 1985, Blattberg et al. 1995). While existing and new consumers react differently to price promotions (Anderson and Simester 2004), there is evidence that these may be detrimental to the profit of the firm in the medium to long run (Grover and

Srinivasan 1992, Srinivasan et al. 2004). These results, however, are based on promotions available to all users simultaneously and, for the most part, explained by stockpiling: consumers purchase more during price promotions to consume later, namely when promotions are over. In the case of information goods, stockpiling is not always practical or feasible because consumption must occur during the promotion period. For example, in the case of a pay-for-play video-on-demand service, consumers must watch videos within 24 or 48 hours of renting. Moreover, promotions can be applied selectively to some users, and may be used strategically to benefit the bottom line of the firm. Thus, whether price discounts increase or decrease the sales of information goods is essentially an empirical question.

In parallel, several studies have shown evidence of increased consumption due to peer effects in the context of digital products (Tucker 2008, Aral et al. 2009, Aral and Walker 2011, Bapna and Umyarov 2015). Price promotions are likely to increase the sales of the products offered at discounted prices across the subset of consumers that get access to promotions but the extent to which they contribute to an increase in word of mouth and to spillovers in sales across the friends of the consumers who get the promotions is currently unknown. More interesting, and according to the literature, price promotions and peer effects may contribute to overall sales in opposite directions. Specifically, and most likely, price promotions reduce overall sales but increase the sales of the discounted products, which may then increase sales across friends. Therefore, focusing only one of these aspects, either peer effects or price promotions, may not reveal all the nuances of interest to the firm and thus offer only a partial view of the potential outcomes of price promotions in information goods.

In this paper we study (1) the effect of price promotions on own consumption of information goods that users cannot store, and (2) the effect of promotions on spillovers to friends of users that are affected by these promotions. We report results from a large-scale randomized field experiment ran using the Video-on-Demand (VoD) system of a major telecommunications provider, from which consumers can rent movies and watch them within 48 hours after purchase.

A new menu called "Good Opportunities" was added to this VoD system for 3 consecutive months. A group of households were offered movies under this new menu at the usual prices. Another group of households were offered movies under this new menu at discounted prices. A third group of households were offered movies under this new menu at discounted prices during the first two months of the experiment and at the usual prices during the last month of the experiment. Households were assigned to groups before the experiment started at random and remained in the same group throughout the whole experiment.

We find that households with price promotions bought 32% more of the movies offered under the new menu than households without price promotions during the first month of the experiment. All households in the experiment bought a similar number of these movies in the second month of the experiment and thus the effect of these price promotions was short-lived. In the third month of the experiment households that were exposed to price promotions during the first two months of the experiment bought on average fewer of these movies than households that were never exposed to price promotions. Overall, during this experiment, the sales of movies in the whole VoD system decreased by 2.9% compared to what they would have been if price promotions had not been introduced.

Next we look at whether price promotions can further induce peer effects, and whether these effects can counter, and potentially overcome, the reduction in sales observed over the users that got access to price promotions. In our particular setting, if the friends of consumers with price discounts buy more VoD movies due to price promotions then peer influence may help the firm maintain sales. Furthermore, the friends of consumers with discounts may be influenced by the latter to buy VoD movies at the original prices, which may not only increase sales but also boost the firm's profits. We use data from call detailed records to proxy a network of social proximity across households in our setting. We assume that two households are friends if people in one of them call people in the other one on the phone. The average and median degree in the resulting social graph of connected households are 10.23 and 7, respectively.

Identifying peer effects in demand is a hard empirical task due to the unknown effects of unobserved covariates that may simultaneous lead consumers to purchase and to be friends (Manski 1993, McPherson et al. 2001, Shalizi and Thomas 2011). We address this concern in our setting by leveraging our randomized experiment. Namely, the movies offered to households under the "Good Opportunities" menu during our experiment we randomly selected and thus their characteristics are also random with respect to the social network across households. In short, the social network across households did not determine which movies were offered to which households under the new menu. For example, we find that the average age of the movies offered under the new VoD menu is a good predictor for sales. Hence, we use this covariate as an instrument for friends' purchases. On average, we find that when a household purchases a movie under the "Good Opportunities" menu her friends purchase 2.304 movies elsewhere in the VoD system. This statistic contrasts with the average effect of peer influence in this VoD system, which is only 0.172. Using these results, we show that the firm can take advantage of the effect of peer influence to break-even when it offers movies at discounted prices to households with enough friends. How many friends a household must have to be targeted with price promotions to ensure break-even depends on the magnitude of the discount as well as on the markup that the firm applies to movies in the VoD system. For the average discount of 25% and average markup rate of 0.6 used during our experiment, the firm would break even if it targeted price promotions to households with more than 4 friends, which is a threshold well within the distribution of number of friends in our empirical setting, and thus a strategy that our industrial partner could easily implement in practice.

Our paper studies the interplay between price promotions and peer influence in information goods that cannot be stored. We show how firms can take advantage of peer influence to counter the potential losses that may arise from price promotions in this context. A firm that knows, or that can reasonably proxy, the social network across its consumers may use this knowledge to issue price promotions to a select set of consumers, creating brand awareness, and potentially increasing profits. Our results enlarge the space of actions available to the firm by showing how managers can actively take advantage of social network data to improve the performance of a traditional marketing strategy. The remainder of this paper is organized as follows. Section 2 provides a review of the relevant literature on the effect of price promotions on sales and on the effect of peer influence. Section 3 introduces our experimental context and our experimental design. Section 4 provides descriptive statistics and preliminary results. Section 5 analyzes the effect of price promotions on sales and section 6 analyzes the effect of peer influence on sales. Section 7 shows how the firm can issue price promotions to break-even and section 8 summarizes our findings, limitations and provides suggestions for future research.

2. Literature Review

2.1. The Effect of Price Promotions on Consumer Demand

Promotions are a fundamental marketing tool used by sellers to encourage trial and trigger brand switching. Ehrenberg et al. (1994) discuss that they are increasingly used in industries with fierce competition because they provide a quick way to respond to attacks from competitors. Thaler (1985) and Klein and Oglethorpe (1987) argue that consumers formulate a reference price for how much they expect to pay for a product, which is usually based on past prices and on the frequency of observed discounts. A product is on price promotion when it is offered at a price lower than the list price. According to Chandon et al. (2000) price discounts provide consumers with monetary savings, added value and other hedonic benefits such as exploration and self expression. The prior literature analyzed the impact of price promotions on the consumption of storable goods. We know that price promotions increase short-term sales (Woodside and Waddle 1975, Ward and Davis 1978b,a) and store traffic (Walters and Rinne 1986, Kumar and Leone 1988, Walters and MacKenzie 1988), trigger brand substitution within the same product category (Gupta 1988, Kumar and Leone 1988, Bawa and Shoemaker 1987) and increase sales in complementary products (Walters and Rinne 1986, Walters 1991, Mulhern and Leone 1991). Price promotions affect short-term sales because consumers immediately perceive a gain associated to the gap between the reference price and the reduced list price (Sawyer and Dickson

1984). This perception is shaped by the promotion message and by how the new price is communicated to consumers (Sinha and Batra 1999). Mixed results have been reported as where the increase in short-term sales come from. Chintagunta (2002) show that the additional sales come mostly from existing consumers. Gupta (1988) and Kumar and Leone (1988) find otherwise and Blattberg and Wisniewski (1989) report that this result depends on the product.

A number of studies examine the long-term effect of price promotions on consumption. Ehrenberg et al. (1994) showed that price promotions for established packaged grocery products do not affect long-term sales nor consumer loyalty. Nijs et al. (2001) followed 560 products for more than 4 years. They find that price promotions rarely yield any long-term effects although these effects are necessarily hard to measure empirically over such long periods of time. Pauwels et al. (2002) also show that the effects of price promotions are short lived. The idea that consumers formulate a reference price has also been used to explain the absence of positive long-term effects from price promotions. Just like consumers react enthusiastically when prices reduce they also react defensively when firms retract price promotions because they perceive a loss. This leads them to become less likely to buy the product. Strang et al. (1975) and Dodson et al. (1978) find that price promotions may end up hurting firms in the long-run. Lattin and Bucklin (1989), Kalwani et al. (1990) and Mayhew and Winer (1992) show that consumers exposed to frequent price promotions adjust their reference price downwards and are more likely to purchase the product only when it is promoted. Consumers may perceive frequent price promotions as a signal of inferior product quality, which might decisively hurt the long-term profitability of the firm. Dodson et al. (1978) argue that consumers who buy products when promotions are available can attribute this behavior to the promotions themselves rather than to increased affinity with the product. However, this decision-making mechanism does not contribute to increase sales in the long-run.

Finally, we note that all studies referred above look at storable packaged goods. The dynamics of how consumers adjust demand for this type of products when price promotions are available is closely related to stockpiling. Assuncao and Meyer (1993) discuss how stockpiling in turn results from the forward-looking behavior of consumers. Ailawadi et al. (2001) show that consumers are flexible when it comes to buying packaged goods and that sales increase as a result of promotions when consumers can stockpile. Chandon and Wansink (2002) show that stockpiling leads consumers to buy more products at a faster rate, namely products that are easy to store and convenient to consume.

2.2. The Effect of Peer Influence on Product Adoption and Consumption

Strang and Soule (1998) study the role of diffusion in innovation theory. Diffusion is the mechanism by which products and services disseminate within a social system. The latter comprises all people that may adopt the innovation as well as all the channels for information sharing about the innovation. Mahajan and Peterson (1985) and Valente (1995) discuss how diffusion can be triggered by external forces, such as mass media and policy requirements. Alternatively, diffusion can also be propelled by the fact that people adapt their behavior to that of their friends. In this context, Leenders (2002) defines peer influence as the dyadic process by which people "...shape their behavior, beliefs and attitudes according to what other people in the social system think, express and do". Peer influence can be intentional or unintentional and is not limited to direct communication but, one way or another, information about the behavior and attitudes of friends needs to be available and shared. Sociology offers a number of theories for peer influence. Most of them look at how the behavior and attitudes of friends change one's assessment of a situation. In particular, the opinions of friends are often seen as standards – frames of reference – against which people evaluate their own opinions and options.

The concept of frame of reference arises associated to two fundamental ideas: communication – people use people with whom they have direct ties as their frame of reference (Coleman et al. 1966); and comparison – people use people they feel similar to as their frame of reference (Burt 1987). In this context, communication refers to the social influence exerted through direct contact between people, for example, by discussing issues face to face. Communication allows people to exchange information about issues at hand. Uncertainty reduces as people learn from each other and thus agreement of opinions, attitudes and beliefs is more likely to arise. The classical works of (Festinger 1950, Festinger and Thibaut 1951, Berelson 1954, Katz and Lazarsfeld 1955, Lazarsfeld et al. 1968) show empirically that in fact people use personal contacts to obtain more information and to better support their arguments. According to (Leenders 2002) comparison, on the other hand, arises when "people search for social identity and ascribe to themselves the characteristics or feelings that other people would ascribe to them if they had the same information at their disposal". As discussed in (Van den Bulte and Lilien 2001), a normative view of peer influence offers the argument that people experience discomfort when other people whose approval they value adopt an innovation but they do not. A competitive view of influence would instead argue that people are concerned that other people who adopt the innovation might be able to gain a competitive edge unless they also adopt it. These mechanisms are not independent and, therefore, they are hard to identify from an empirical point of view. For example, through word-of-mouth people learn about the attitudes, beliefs and behavior of their friends but then they can align their behavior with that of their friends because of normative pressures, competitive concerns or a combination of both.

Several studies provide empirical evidence of peer effects in the consumption of IT goods Salganik et al. (2006) created virtual markets for songs and recruited students to listen and download them for free. They found that popularity was self-reinforcing, as measured by number of downloads, for all but the very best or worst songs. Tucker and Zhang (2011) found similar self-reinforcing results measuring click-through rates on an online hub for wedding service vendors. Muchnik et al. (2013) examined the behavior of consumers in a social news aggregator website finding that herding effects may be asymmetric. Users seemed to exhibit a desire to correct negative bias in responses to previous comments but otherwise followed the herd. In a setting closer to ours, Godinho de Matos et al. (2016) found that users tend to correct both negative and positive bias in the consumption of VoD movies and associate this behavior to the fact that contrary to previous research, in their setting, consumers had to organically undergo decisions that entailed financial risks. Finally, there is also evidence that peer influence may be detrimental for the firm. For example, Feinberg et al. (2002) describes how Amazon faced consumer revolt when consumers sharing information through online sources realized that the Internet store was offering different price promotions to distinct consumers.

3. Context, Datasets and Experiment

3.1. TV Provider and VoD Service

Our work was developed in partnership with a major telecommunications provider, hereinafter called TELCO. TELCO offers TV, Internet, telephony and VoD service. It is the market leader of Pay-TV in the country where it operates serving approximately 1.5 million households. According to a market report published by Screen Digest, 65% of the households in this country subscribed to Pay-TV by the end of 2012. 69% of the households with TELCO purchase triple play bundles that include TV, Internet and telephony. We had access to TELCO's VoD transactional database between January 2013 and March 2014. This dataset registers roughly 1.7 million movie leases. Roughly half of the active households subscribe VoD of which 30% paid for VoD content at least once during this 15-month period.

We have the anonymized identifier of the household requesting each VoD transaction through the anonymized identifier of the MAC address of the corresponding Set-Top Box (STB). For each transaction we have the identifier of the movie leased, the price paid and a timestamp for when the lease took place. We have characteristics for each movie offered by TELCO in this VoD system such as movie age, runtime, IMDb votes, IMDb rating and IMDb metascore (that is, ratings from movie critics). Figure 1 shows the look and feel of the TV screen for this VoD system. Consumers can access the VoD system using a hot-key in their STB remote control. Pressing this hot-key displays the entry screen of the VoD system, called highlights section. This screen contains a set of menus filled with movies chosen by an editorial team. Movies are organized into menus such as "New Movies" and "Suggestions". Each menu has a header with a name that clearly identifies the type of movies it contains. Menus are horizontal lines on the screen. Different menus are stacked vertically. Two menus fit the screen at each time and a cursor highlights a single movie cover at a time.

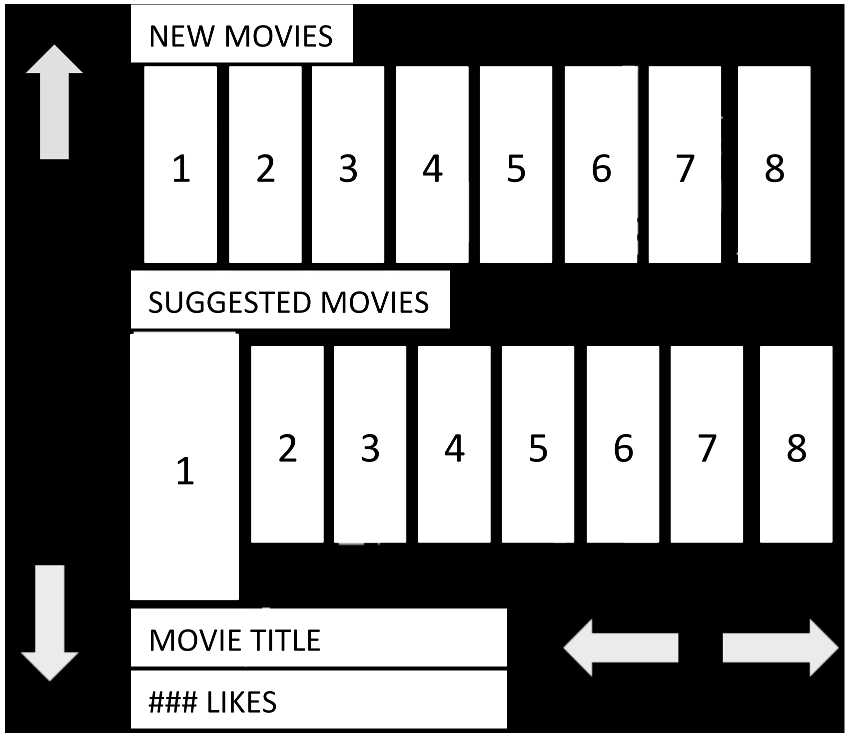

Figure 1 The Look and feel of the Video-on-Demand Interface on the TV screen.

Users can scroll up and down across menus. Upon scrolling into a new menu, a number of movie covers are visible under that menu and the cursor starts by highlighting the movie farthest to the left. Users can scroll past the last movie cover on the screen to access additional movies under the same menu. TELCO displays 15 movies per menu and 11 menus in the highlights section. The title and number of likes of the movie highlighted by the cursor are shown towards the bottom of the screen. Clicking on the cover of a movie leads to a new screen with the year of release, play length, cast and synopsis. From this screen consumers can lease the movie, use a promotional coupon to watch the movie or watch the movie trailer (if one is available). A leased movie can be watched for a period of 48 hours after purchase. Leased movies cannot be stored past this deadline.

Finally, subscribers can leave the highlights section of the VoD system and search for movies in the complete catalog, which holds more than 1,000 titles at any point in time. The catalog is hierarchically organized into content categories such as movies, music, TV-shows and documentaries. Within each of these categories, screens are organized as described above with menus for genres. In addition to browsing through the entire catalog, subscribers can use a keyword search function to look for specific movies based on movie titles, movie directors and actor names. All households see the same number of movies both in the highlights section as well as in the catalog.

3.2. Social Graph of Households

We also obtained three months of Call Detail Records (CDRs) for cell phone communications served by TELCO. Each CDR contains the anonymized phone numbers of the caller and the callee and a timestamp for when the call took place. This dataset contains over 193 million calls. We use these CDRs to define an undirected graph of communications across households. We start by matching all anonymized phone numbers to their anonymized Pay-TV accounts. In this process we discard all CDRs in which one of the calling parties is an anonymized number with no counterpart in the database of Pay-TV accounts. We also discard all anonymized phone numbers associated to accounts that do not subscribe VoD. Note that a Pay-TV account with TELCO may have cell phone service from another provider. Yet, if that anonymized phone number is listed in the Pay-TV account information of the household then we can match this Pay-TV account to all the cell phone activity of this anonymized phone number that is served by TELCO. All Pay-TV accounts at TELCO have at least one contact phone number even if this number is served by another provider.

Therefore, we have a partial view of the social network (but still one that matches Pay-TV accounts at TELCO with anonymized cell phone number serviced by other providers), as is typically the case with the type of study we pursue in this paper. For example, we do not observe phone calls between two people when both of them subscribe phone service from other providers although they may subscribe to Pay-TV at TELCO. Later in section 8 we discuss how this limitation might affect our results. An edge between two households is included in the social graph if a person in one of them calls a person in the other in our dataset of CDRs. Hereinafter, two households connected in this graph will be called friends for short. The resulting social graph contains 492,931 households and 2,013,952 edges. Figure 2 shows the degree distribution of households in this graph. The median and average degree are 7 and 10.23, respectively.

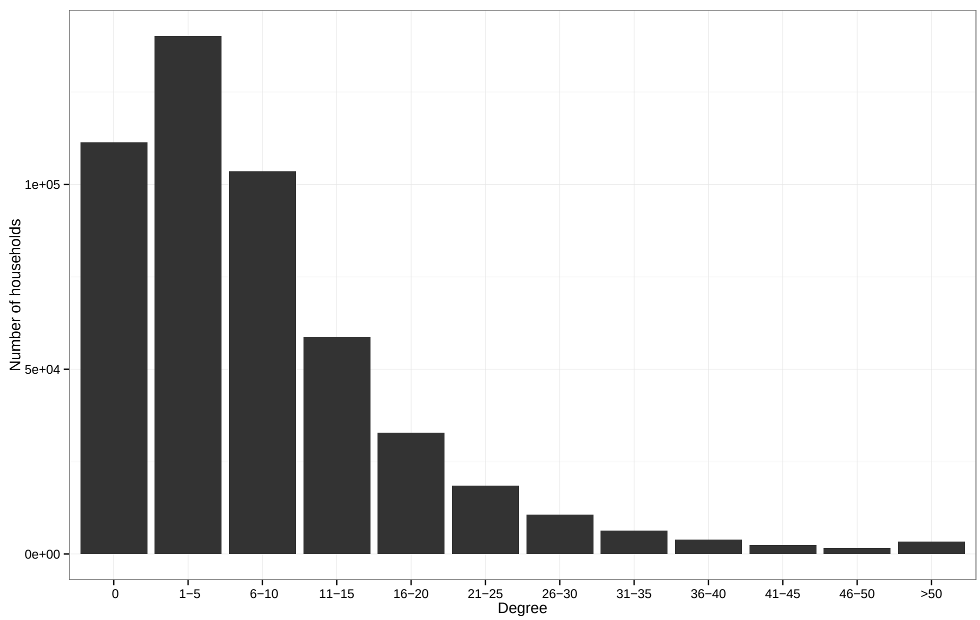

Figure 2 Degree Distribution Across Households in the Social Graph.

3.3. Experimental Design

The experiment studied in this paper consisted in introducing a new menu in the highlights section of the VoD system of this telecommunications provider. This menu, called "Good Opportunities", was available to all 492,931 households with a VoD enabled set-top-box for 12 consecutive weeks in the second half of 2013. No additional messages were provided to consumers besides the addition of the "Good Opportunities" menu to their VoD system. Also, all households experienced the same VoD interface on the TV screen. A carefully devised randomized setup was employed to allow us to empirically measure both the effect of price promotions and the effect of peer influence in the consumption of movies in this VoD system.

Before the experiment started, households were assigned to one of three experimental groups: group $G0$ (never discount): households in this group were offered movies under the new menu at the usual prices – those negotiated by TELCO and the content providers; group $G1$ (always discount): households in this group were offered movies under the new menu at reduced prices throughout the whole experiment; group $G2$ (partial discount): households in this group were offered movies under the new menu at reduced prices during the first two months of the experiment and at the usual prices during the third month of the experiment. Households were assigned to groups at random and remained in the same group throughout the whole experiment. Also before the experiment started all movies in the VoD system of TELCO that would remain available for at least the duration of the experiment were sorted according to the number of leases obtained during the previous 30 days. The top 270 movies in this list were considered for this experiment. A random ordered subset of 90 movies from this list was assigned to the first month of the experiment. Another random ordered subset of 90 movies from this list was assigned to the second month of the experiment and the ordered subset with the remaining 90 movies was assigned to the last month of the experiment. Next, the movies that TELCO had selected to introduce in other menus of the highlight section in each month were removed from the subset of movies to use in our experiment in that month. The top 45 movies that remained for each experimental month were then effectively used in that month of the experiment. Every month, each household was offered a random subset of 15 movies from the set of movies that could be effectively used in that month.

4. Descriptive Statistics and Preliminary Data Analysis

Table 1 shows summary statistics for household demographic information across groups, including degree in the social graph, total number of calls over the three months for which we have CDRs, TV tenure (number of months that the household has had TV service with the firm), whether the household is within a lock-in period and whether the household opted-in for an electronic receipt (usually used as a proxy for income in triple-play settings). This table includes average and standard deviations for each of these variables across groups as well as one-way Analysis of Variance (ANOVA) for each of the variables. ANOVA tests the null hypothesis that all three groups have the same mean. All tests provide large p-values indicating that households are on average similar across groups. Detailed definitions of all the variables used in the paper are provided in table 13 included as appendix.

Table 1 Summary statistics for household-level demographics by treatment group and one-way ANOVA for the test of similar means.

Var	Stat	G0	G1	G2	F value	Pr(>F)
Degree	Mean	10.210	10.230	10.230	0.188	0.829
	S.D.	10.240	10.220	10.120		
Total Calls	Mean	203.800	205.100	203.800	0.786	0.456
	S.D.	311.200	313.700	310.500		
TV Tenure (months)	Mean	77.530	77.530	77.130	2.380	0.093
	S.D.	60.590	60.560	60.470		
Has Contract?	Mean	0.561	0.559	0.559	0.940	0.391
	S.D.	0.496	0.496	0.496		
Electronic Receipt	Mean	0.319	0.320	0.319	0.412	0.663
	S.D.	0.466	0.466	0.466		
	N	164,458	164,090	164,383		

Figure 3 shows that households in groups $G1$ and $G2$ experienced similar prices in the first two months of the experiment as well as households in groups $G0$ and $G2$ in the last month of the experiment. This figure also shows that prices increased over time for all groups of households, in particular from the second to the third month in the experiment because the editorial team at TELCO pulled virtually no movies away from the experiment to other menus in the highlights section in the last month of the experiment.

Figure 4 shows that the observed characteristics of the movies offered under the “Good Opportunities” menu were similar across groups of households, as expected given that movies were randomly assigned to each household. During our experiment a total of 135 different movies were displayed to households with VoD service under the “Good Opportunities” menu. Another 159 different movies were offered to these households in other menus of the highlights section only and another 1,101 different movies were available to these households from the catalog of the VoD system. The latter movies were never shown in the highlights section of the VoD system and thus were never under the “Good Opportunities” menu either.

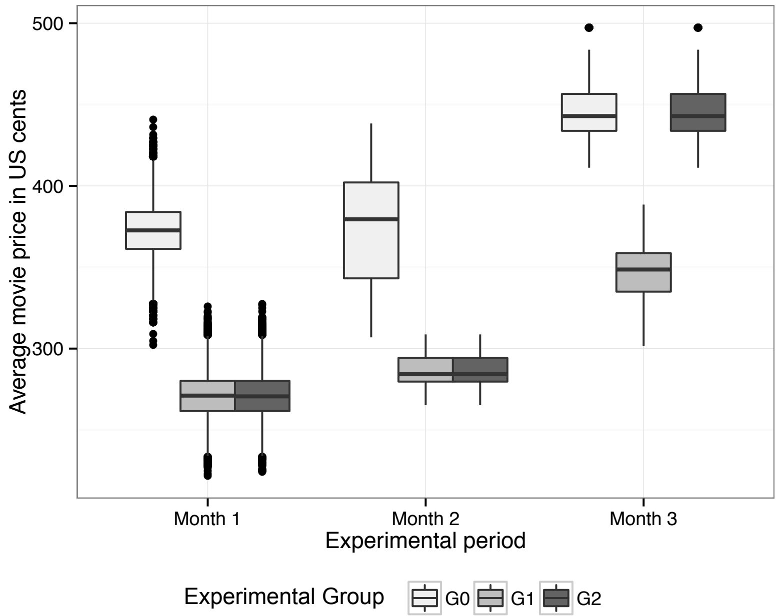

Figure 3 Average price of movies shown in the new menu to each group of households over time.

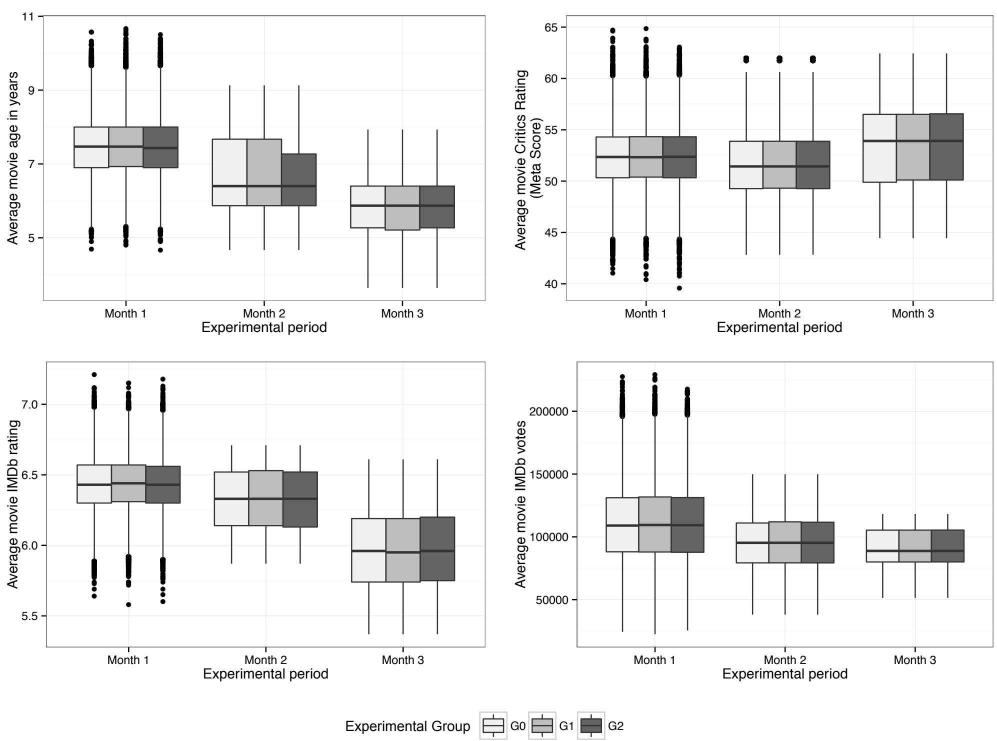

Figure 4 Characteristics of the movies shown in the new menu to each group of households over time.

Table 2 displays summary statistics and t-tests comparing movies used under the "Good Opportunities" menus, movies used in other menus of the highlights section of the VoD system and movies used in the catalog. We observe some systematic differences between movies used in the highlights section and movies used in the catalog. In particular, the former are younger, have more IMDb votes and lower IMDb metascores. There are no differences in the IMDb rating and duration. Moreover, we observe no differences between movies used in the "Good Opportunities" menus and movies in used in the other menus of the highlights section. This means that the movies offered to households under the "Good Opportunities" menus are on average similar to the other movies that the firm pulls to the other menus in the highlights section of the VoD system, which are usually the most recent and most sold ones. Therefore, our experiment generalizes to movies that a VoD provider is interested in including in the highlights section of its VoD system. We note that 78% of the leases in this VoD system are originated from movies in the highlights section.

Figure 5 shows percentage differences in the average number of leases of movies offered to households under the Good Opportunities menus between group $G1$ and $G0$ and between group $G2$ and $G0$ for each period in the experiment. Vertical bars represent 90% confidence intervals. As expected, households in groups $G1$ and $G2$ buy on average more movies under the "Good Opportunities" menu than households in group $G0$ in the first month. In the second month this difference erodes even though these households still have access to movies at discounted prices under the "Good Opportunities" menu. This provides evidence that households tend to accelerate consumption with price promotions and that the effect of the latter might be short-lived. In the third month of the experiment, households in group $G2$ lose access to movies at reduced prices under the "Good Opportunities" menu and lease fewer of them. In fact, they may even lease fewer movies than households in group $G0$ in this month from the "Good Opportunities" menu. This provides evidence that once exposed to price promotions households accelerate consumption significantly, tend to wait for future promotions to lease additional movies or both. In all cases, this behavior is likely to hurt the long-term profitability of the firm. Table 3 shows the t-tests associated to this figure.

Table 2 Summary statistics and t-tests comparing groups of movies in the "Good Opportunities" menu (EXP), in the highlights section but not in the "Good Opportunities" menu (HL) and in the catalog (CT).

Var	Test	Stat	Treat1	Treat2	Diff	T.Stat	P.Value
IMDb Metascore	Exp. - High.	Mean	52.050	50.260	1.791	0.745	0.457
		S.D.	16.910	18.760			
	Exp. - Cat.	Mean	52.050	57.790	-5.740	-3.127	0.002
		S.D.	16.910	16.410			
	High. - Cat.	Mean	50.260	57.790	-7.531	-4.139	0.0001
		S.D.	18.760	16.410			
IMDb Rating	Exp. - High.	Mean	6.266	6.198	0.068	0.473	0.637
		S.D.	1.249	1.193			
	Exp. - Cat.	Mean	6.266	6.263	0.003	0.026	0.979
		S.D.	1.249	1.109			
	High. - Cat.	Mean	6.198	6.263	-0.065	-0.649	0.517
		S.D.	1.193	1.109			
IMDb Votes	Exp. - High.	Mean	94,420	69,795	24,624	1.644	0.102
		S.D.	147,281	98,618			
	Exp. - Cat.	Mean	94,420	42,826	51,594	3.943	0.0001
		S.D.	147,281	94,643			
	High. - Cat.	Mean	69,795	42,826	26,970	3.239	0.001
		S.D.	98,618	94,643			
Release Year	Exp. - High.	Mean	2,008	2,009	-1.659	-2.309	0.022
		S.D.	5.033	7.213			
	Exp. - Cat.	Mean	2,008	2,005	2.711	5.388	0.00000
		S.D.	5.033	8.402			
	High. - Cat.	Mean	2,009	2,005	4.370	6.986	0
		S.D.	7.213	8.402			
Runtime (mins)	Exp. - High.	Mean	100.300	103.200	-2.975	-1.457	0.146
		S.D.	17.770	16.600			
	Exp. - Cat.	Mean	100.300	103.300	-3.073	-1.835	0.068
		S.D.	17.770	20.430			
	High. - Cat.	Mean	103.200	103.300	-0.098	-0.067	0.947
		S.D.	16.600	20.430			

Table 3 T-tests for average leases across groups over time during our experiment.

Month	Test	Stat	Treat1	Treat2	T.Stat	P.Value
1	G1 - G0	Mean	0.003	0.002	3.283	0.001
		S.D.	0.057	0.050		
1	G2 - G0	Mean	0.003	0.002	4.642	0.000
		S.D.	0.061	0.050		
1	G2 - G1	Mean	0.003	0.003	1.385	0.166
		S.D.	0.061	0.057		
2	G1 - G0	Mean	0.003	0.003	-0.607	0.544
		S.D.	0.059	0.061		
2	G2 - G0	Mean	0.003	0.003	-0.784	0.433
		S.D.	0.059	0.061		
2	G2 - G1	Mean	0.003	0.003	-0.174	0.862
		S.D.	0.059	0.059		
3	G1 - G0	Mean	0.003	0.003	0.810	0.418
		S.D.	0.055	0.057		
3	G2 - G0	Mean	0.002	0.003	-1.628	0.103
		S.D.	0.049	0.057		
3	G2 - G1	Mean	0.002	0.003	-2.531	0.011
		S.D.	0.049	0.055		

5. The Effect of Price Promotions on VoD Sales

5.1. Empirical Strategy

We study the effect of price promotions on the consumption of VoD movies in two steps. First, we look at their effect on VoD sales during the entire experiment. Second, we look for evidence of intertemporal substitution effects. For the former, we use the following reduced-form equation:

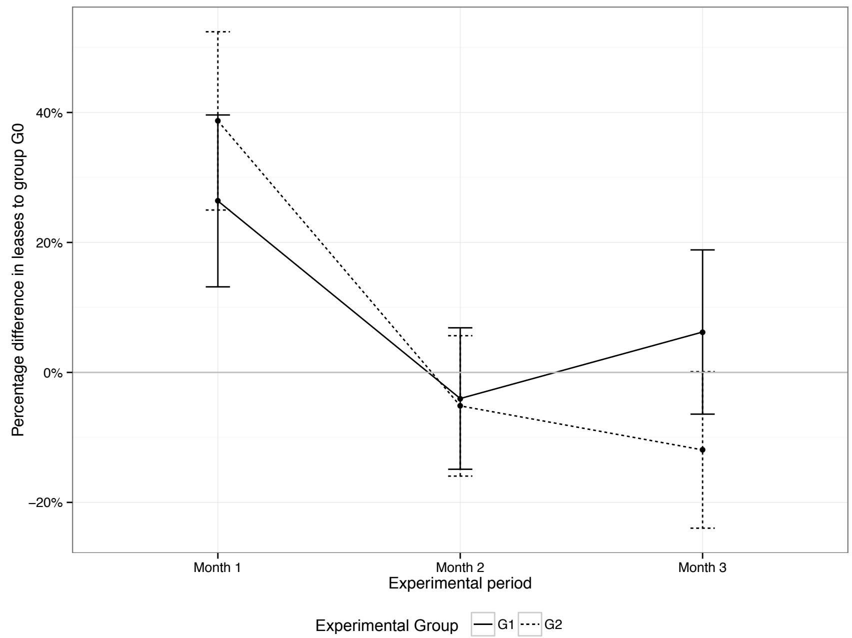

Figure 5 Differences in the sales of movies used in the experiment between groups $G1$ and $G0$ and between groups $G2$ and $G0$.

$$Y_{it} = \beta_0 + \beta_1 Promotions_{it} + d_t + u_{it} \quad (1)$$

where depending on the specification Y_{it} will represent the number of leases by household i during month t of movies under the "Good Opportunities" menu – $Leases\_EXP_{it}$ – the number of leases of movies elsewhere in the VoD system – $Leases\_Not\_EXP_{it}$ and the sum of the two – $Leases\_All_{it}$. $Promotions_{it}$ is a dummy variable indicating whether household i had access to movies at discounted prices during month t under the "Good Opportunities" menu, d_t are time dummies and u_{it} is an idiosyncratic error term including all time constant and time varying effects that affect the consumption of movies by household i in month t. We estimate this equation using OLS because in our setup identification is obtained by design – price promotions were given to households at random. In this expression, β_1 measures the average effect of price promotions during the entire experiment on the sales of VoD movies. A more elaborate reduced-form equation that we use to study the consumption of VoD movies used in the experiment is

$$Leases\_EXP_{it} = \beta_0 + \beta_1 Promotions_{it} + \beta_2 Promotions_{it} \cdot d_{t>1} + \beta_3 d_{i \in G2} \cdot d_{t=3} + d_t + u_{it} \tag{2}$$

where $d_{t>1}$ indicates the last two months of the experiment, $d_{t=3}$ indicates the last month in the experiment and $d_{i \in G2}$ indicates whether household i belongs to group $G2$. We also estimate this equation using OLS because households were assigned to groups at random and price promotions were also assigned to groups at random. In this specification, β_1 captures the average effect of price promotions during the first month of the experiment and β_2 captures how this effect changes after this month. Thus, this specification allows us to measure whether households accelerate consumption with price promotions. In addition, β_3 compares the average number of leases of households in group $G0$ to the average number of leases of households in group $G2$ in the last month of the experiment. This comparison allows us to test whether consumption returns to pre-price promotion levels once price promotions are retracted. Note that in this specification we aggregate the last two months in the experiment when we use $d_{t>1}$ in order to obtain more power than that offered by the simple t-tests shown in Table 3. We do this because on average the consumption of movies by households in groups $G0$ and $G1$ is not different from the second month to the third month in the experiment (p-value = 0.31).

Finally, note that our dependent variable is a count variable in all specifications. Therefore, and for sake of robustness, we present both OLS results as well as results using a negative binomial distribution for the dependent variable. In both cases, we cluster errors at the household level.

5.2. Empirical Results

Table 4 shows the average effect of price promotions on VoD sales during the entire experiment. The first two columns show that households with price promotions buy 11.1% more of the movies under the "Good Opportunities" menu. The next two columns show that these households buy 3.3% fewer of the movies elsewhere in the VoD system. The last two columns in this table show that these households buy 2.9% fewer movies overall. The previous three comparisons are all relative to households without price promotions. These results show that there is substitution from the consumption of movies offered at the usual prices to movies offered at discounted prices and that over a sufficiently long period of time aggregate sales can reduce with price promotions. Therefore, we find empirical evidence of substitution among similar products and of overall demand contraction.

Table 4 Effect of price promotions on the sales of movies in VoD during our experiment.

	Dependent variable:					
	Leases (Exp)		Leases (Non Exp)		Leases (All)	
	OLS	Neg.Bin	OLS	Neg.Bin	OLS	Neg.Bin
	(1)	(2)	(3)	(4)	(5)	(6)
Promotions	0.0003^{***}	0.111^{***}	-0.003^{***}	-0.033^{***}	-0.003^{**}	-0.029^{**}
	(0.0001)	(0.037)	(0.001)	(0.013)	(0.001)	(0.013)
Constant	0.003^{***}	-5.942^{***}	0.107^{***}	-2.233^{***}	0.110^{***}	-2.209^{***}
	(0.0001)	(0.037)	(0.001)	(0.011)	(0.001)	(0.011)
Month Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,478,793	1,478,793	1,478,793	1,478,793	1,478,793	1,478,793

Note: *p<0.1; **p<0.05; ***p<0.01

Cluster robust standard errors in ()

Table 5 shows the results from estimating equation (2), which allows us to analyze the average effect of price promotions on the sales of movies offered under the “Good Opportunities” menu over time. The first two columns show that households with price promotions buy roughly 32% ($exp(0.282)$) more of these movies during the first month of the experiment. However, these households also buy roughly 28% ($exp(0.251)$) fewer of these movies during the last two months of the experiment. These comparisons are relative to households without price promotions. These results show that households with price promotions anticipate consumption and that this effect seems to be short-lived. The last two columns in this table show that households with price promotions in the first two months of the experiment lease roughly 17% ($exp(0.160)$) fewer of these movies in the last month of the experiment than households that never had movies at discounted prices lease during this same month. This result shows that consumption levels may not necessarily come back to pre-promotion levels once promotions are retracted.

Households in group G2 experienced usual prices before the experiment and observe a decrease in price for movies offered under the "Good Opportunities" menu during the first two months of the experiment. Therefore, in the first month they react to the price drop with an increase in consumption caused both by a contemporaneous substitution effect (movies in the "Good Opportunities" menu became cheaper than other movies outside the menu) and an intertemporal substitution effect (movies in the "Good Opportunities" menu became cheaper than the expected price of the same movies in the following months). With low prices continuing throughout the second period, households adjust their beliefs and presume that prices in the third month will continue low, leading to a decrease of the intertemporal substitution effect, i.e., households do not anticipate consumption from the third period to the second period as much. This effect and the intertemporal substitution effect in the first month (anticipation of consumption from the second period to the first period), lead households to consume roughly as much in the second period as households that never experience promotions. In the third period, with the increase in prices, two other effects arise. On the one hand, when prices experienced under the "Good Opportunities" menu go back to usual levels in the last month of the experiment, the contemporaneous substitution effect disappears as there is no special advantage in buying movies from the "Good Opportunities" menu. On the other hand, the intertemporal substitution effect now works in the opposite direction: households believe that prices after the experiment will be lower than current prices and, therefore, will refrain from consuming as much. In other words, households anticipate potential future promotions. These effects lead to a decrease in overall consumption in the third month for households that experienced promotions, when compared with households that never experienced promotions.

Table 5 Impact of price promotions on the consumption of movies under the "Good Opportunities" menu over time.

	Dependent variable:			
	Leases (Exp)			
	OLS	Neg. Binomial	OLS	Neg. Binomial
	(1)	(2)	(3)	(4)
Promotions (β_0)	0.001^{***}	0.282^{***}	0.001^{***}	0.282^{***}
	(0.0002)	(0.062)	(0.0002)	(0.062)
Promotions * (Month > 1) (β_1)	-0.001^{***}	-0.251^{***}	-0.001^{***}	-0.287^{***}
	(0.0002)	(0.074)	(0.0002)	(0.075)
G2 * (Month = 3) (β_2)			-0.0004^{**}	-0.160^{**}
			(0.0002)	(0.071)
Constant	0.002^{***}	-6.062^{***}	0.002^{***}	-6.062^{***}
	(0.0001)	(0.052)	(0.0001)	(0.052)
Month Dummies	Yes	Yes	Yes	Yes
Observations	1,478,793	1,478,793	1,478,793	1,478,793

Note: *p<0.1; **p<0.05; ***p<0.01

Cluster-robust standard errors in parentheses

6. Peer Influence in VoD Consumption

6.1. Empirical Strategy

We want to determine whether there is peer influence in the consumption of movies in this VoD system, that is, whether a household leases more movies because her friends do. A number of effects can arise in the context of our experiment. First, a household may lease more movies from the "Good Opportunities" menu when her friends do. Second, a household may lease more movies from other menus in the VoD system when her friends lease movies from the "Good Opportunities" menu. Third, a household may lease more movies overall – that is, anywhere in the VoD system – when her friends lease movies from the "Good Opportunities" menu. Fourth, a household may lease more movies overall when her friends lease more movies overall. Finally, all the above may happen simultaneously. Each of the situations enumerated above is likely associated to different types of messages exchanged across households. Friends can talk about specific movies in the VoD system, about movies in the "Good Opportunities" menu, about the "Good Opportunities" menu itself, about the VoD system in general or they can even talk about all the above at the same time. Our randomized setup allows us to identify the four effects of peer influence enumerated above. For example, to study whether a household purchases more movies under the "Good Opportunities" menu when her friends do, we estimate

$$Leases\_EXP_{it} = \alpha + \rho Frd\_Leases\_EXP_{it} + d_t + u_{it} \tag{3}$$

where $Frd\_Leases\_EXP_{it}$ is the number of leases of movies offered under the "Good Opportunities" menu by friends of household i in month t. In this equation ρ measures the effect of peer influence associated with the consumption of movies offered under the "Good Opportunities" menu. However, in this case, we cannot use OLS to estimate ρ because $Frd\_Leases\_Exp_{it}$ may be correlated to u_{it}. For example, homophily is likely to lead to correlation in unobserved covariates across friends (McPherson et al. 2001), such as in preferences across movie types or even in network outages that may prevent using the VoD system (friends may live close by and thus be served by the same network node). We use an instrumental variable to identify ρ. We instrument $Frd\_Leases\_EXP_{it}$ with the average age of the movies offered under the "Good Opportunities" menu to friends of household i in month t, which we represent by $Frd\_Avg\_Age\_EXP_{it}$. This covariate is random in our setup because during our experiment the movies that were offered to households under the "Good Opportunities" menu were selected at random. This ensures that there is no correlation between $Frd\_Avg\_Age\_EXP_{it}$ and u_{it}. Table 6 shows that the average age of the movies suggested to households and to households' friends are unrelated to household characteristics such as TV tenure (number of months that the household has TV service with the firm), whether the household is within a lock-in period and whether the household opted-in for an electronic receipt. In addition Table 7 shows that these household characteristics do not explain average movie age. In fact the explanatory power of the models in this table is virtually zero. Table 8 shows that the average age of the movies offered to friends under the "Good Opportunities" menu is a good predictor for how many movies these households lease both under the "Good Opportunities" menu (column 1) as well as overall in the VoD system (column 2). Essentially, this table shows our first stage results and that our instrument is not weak in line with definitions in Stock and Yogo (2005). Therefore, we estimate ρ using 2SLS as follows:

Table 6 Results from t-tests of average movie age and average friends movie age by available demographic household information.

			Group 1	Group 2	Diff.	t-stat	p-value
Contract vs. No Contract	Avg Movie Age	avg	6.669	6.671	-0.002	-0.800	0.424
		sd	1.161	1.162			
		n	643,785	500,946			
	Avg Friend Movie Age	avg	6.671	6.672	-0.002	-1.139	0.255
		sd	0.792	0.797			
		n	643,785	500,946			
Elec. Receipt vs. No Elec. Receipt	Avg Movie Age	avg	6.669	6.671	-0.001	-0.509	0.611
		sd	1.161	1.161			
		n	371,787	772,935			
	Avg Friend Movie Age	avg	6.671	6.672	-0.0003	-0.204	0.838
		sd	0.781	0.801			
		n	371,787	772,935			
TV Tenure High vs. TV Tenure Low	Avg Movie Age	avg	6.670	6.670	0.0001	0.045	0.964
		sd	1.161	1.161			
		n	572,190	572,541			
	Avg Friend Movie Age	avg	6.671	6.672	-0.0003	-0.220	0.826
		sd	0.785	0.803			
		n	572,190	572,541			

Table 7 Results from regressions of average movie age and average friend movie age on available demographic households information.

	Dependent variable:							
	Avg Movie Age			Avg Friend Movie Age				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Has Contract?	−0.002			−0.002	−0.002			−0.002
	(0.002)			(0.002)	(0.001)			(0.002)
Electronic Receipt		−0.001		−0.001		−0.0003		−0.0001
		(0.002)		(0.002)		(0.002)		(0.002)
TV Tenure (months)			0.00000	0.00000			−0.00000	−0.00001
			(0.00002)	(0.00002)			(0.00001)	(0.00001)
Constant	6.671***	6.671***	6.670***	6.671***	6.672***	6.672***	6.672***	6.673***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
Observations	1,144,731	1,144,722	1,144,731	1,144,722	1,144,731	1,144,722	1,144,731	1,144,722
R^2	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
Adjusted R^2	−0.00000	−0.00000	−0.00000	−0.00000	0.00000	−0.00000	−0.00000	−0.00000
Note:						*p<0.1; **p<0.05; ***p<0.01		

$$1^{st}\ Stage: Frd\_Leases\_EXP_{it} = \delta_0 + \delta_1 Frd\_Avg\_Age\_EXP_{it} + d_t + v_{it} \tag{4}$$

$$2^{nd}\ Stage: \quad Leases\_EXP_{it} \quad = \alpha + \rho \widehat{Frd\_Leases\_EXP}_{it} + d_t + u_{it} \tag{5}$$

The same identification strategy is used to identify ρ in the other specifications that we are interested in, namely when the dependent variable becomes $Leases\_Not\_EXP_{it}$ or $Leases\_All_{it}$ and also when the endogenous variable becomes $Frd\_Leases\_All_{it}$, which represents the number of movies leased anywhere in the VoD system by friends of household i in month t. Finally, we note that ρ in equation (5) identifies the aggregate of a number of effects that arise from micro-mechanisms that we cannot empirically distinguish. Some of these micro-mechanisms might push up the effect of peer influence while others will pull it down. For example, positive appraisals about the quality of the movies offered under the "Good Opportunities" menu will contribute positively to the effect of peer influence, while negative appraisals will likely have the opposite effect. Envy among friends may also contribute positively or negatively to the effect of peer influence. Some people may feel jealous when their friends watch a movie and talk about it and will react by watching it too (recall the ideas around competitive and normative pressures introduced in section 2.2). Furthermore, in our randomized setup the same movie is unlikely to have the same search costs to households that are friends. Therefore, some people may also feel jealous when their friends watch a movie that they cannot find easily in the VoD system and, as a consequence, they end up watching fewer movies. While we acknowledge that we are unable to empirically distinguish among all these micro-mechanisms that may affect the effect of peer influence in our setting, we believe that ultimately what the firm cares about is the aggregate effect of peer influence and whether this is sufficiently strong to counter the negative effects of price promotions identified in section 5.

6.2. Empirical Results

Column (1) in Table 9 shows the results obtained from estimating equation 4. We do not find evidence that households lease more of the movies offered under the "Good Opportunities" menu when her friends do. The other columns in this table show results for the other specifications that we are interested in. Column (2) shows that a household buys 2.187 movies elsewhere in the VoD system when her friends buy 1 movie under the "Good Opportunities" menu due to the effect of peer influence. Column (3) shows that a household buys 2.304 movies overall in the VoD system when her friends buy 1 movie under the "Good Opportunities" menu due to the effect of peer influence. Finally, Column (4) shows that a household buys overall 0.172 movies in this VoD system when her friends buy 1 movie in the VoD system due to the effect of peer influence. Therefore, we find evidence of peer influence in the consumption of movies in this VoD system and we have some evidence that the message that registers with households through peer influence is not necessarily associated to specific movies or even to the "Good Opportunities" menu itself but rather a message about the VoD system as a whole. Our results also show that the effect of peer influence associated to movies offered under the "Good Opportunities" menu dominates the effect of peer influence associated to other movies in the VoD system. This may help the firm maintain sales with price promotions if she can strategically use the effect of peer influence generated by offering movies under the "Good Opportunities" menu.

Table 8 **Friends' leases as a function of the average age of the movies offered to them under the "Good Opportunities" menu.**

	Dependent variable:	
	Friend Leases (Exp)	Friend Leases (All)
	OLS	OLS
	(1)	(2)
Avg Friend Movie Age	-0.001^{***}	-0.015^{***}
	(0.0003)	(0.003)
Promotions	-0.0001	0.002
	(0.0004)	(0.007)
Constant	0.041^{***}	1.357^{***}
	(0.002)	(0.025)
Month Dummies	Yes	Yes
Kleibergen-Paap rk Wald F-stat	18.451	21.963
Observations	1,144,731	1,144,731
Note:	*p<0.1; **p<0.05; ***p<0.01	
	Cluster robust standard errors in ()	

6.3. Robustness checks on the effect of peer influence

We perform a number of robustness checks that show that the results we report in this paper are unlikely an artifact of functional form. In an alternative specification we regress the log of our dependent variables on our independent variables. In another alternative specification we regress the log of our dependent variables on the log of our endogenous variable (using also the log of our IV). Appendix B shows the results obtained. Our first stages work as expected, instruments are not weak and the second stages remain unchanged.

Table 9 Effect of peer influence on the leases of VoD Movies during our experiment.

	Dependent variable:			
	Leases (Exp)	Leases (Not Exp)	Leases (All)	
	2SLS	2SLS	2SLS	2SLS
	(1)	(2)	(3)	(4)
Friend Leases (Exp)	0.117	2.187^{**}	2.304^{**}	
	(0.113)	(1.114)	(1.147)	
Friend Leases (All)				0.172^{**}
				(0.084)
Promotions	0.0003^{**}	-0.003^{**}	-0.003^{*}	-0.004^{**}
	(0.0001)	(0.002)	(0.002)	(0.002)
Constant	-0.001	0.032	0.030	-0.108
	(0.004)	(0.037)	(0.038)	(0.104)
Month Dummies	Yes	Yes	Yes	Yes
Wald test	6.536***	3.321***	2.876**	3.07**
Observations	1,144,731	1,144,731	1,144,731	1,144,731

Note: *p<0.1; **p<0.05; ***p<0.01

Cluster robust standard errors in ()

Table 10 shows results from a quite demanding falsification test. Columns (1) and (2) replicate the results obtained in columns (3) and (4) of table 9 to facilitate comparison. Columns (3) and (4) show results when we use VoD leases in January, February and March of 2013, thus 6 months before the experiment started, for our dependent variable. We use exactly the same endogenous variables (that is, friends' leases during our experiment) and the same instruments as before to test the adequacy of the latter. Note that before the experiment started there were no leases of movies offered under the "Good Opportunities" menu because this menu was not available in the VoD system, and thus we cannot replicate columns (1) and (2) in table 9 in this exercise. This falsification test shows that our instruments work appropriately, namely households' leases before the experiment started are not affected by friends' leases during the experiment. These results provide evidence that our results are unlikely to be picking up spurious correlations in our data.

Table 10 Falsification test for peer influence on leases of VoD movies using leases before our experiment started for our dependent variable.

	Dependent variable:			
	Leases (All)		Past Leases (All)	
	2SLS	2SLS	2SLS	2SLS
	(1)	(2)	(3)	(4)
Friend Leases (Exp)	2.304^{**}		0.519	
	(1.147)		(1.164)	
Friend Leases (All)		0.172^{**}		0.039
		(0.084)		(0.087)
Promotions	-0.003^{*}	-0.004^{**}	-0.002	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)
Constant	0.030	-0.108	0.103^{***}	0.072
	(0.038)	(0.104)	(0.038)	(0.108)
Month Dummies	Yes	Yes	Yes	Yes
Wald test	2.876**	3.07**	217.981***	220.466***
Observations	1,144,731	1,144,731	1,144,731	1,144,731

Note: *p<0.1; **p<0.05; ***p<0.01

Cluster robust standard errors in ()

Finally, we use the number of calls between each pair of households in the social graph to proxy the strength of the tie between them and rerun our analysis. Table 11 shows that our results remain qualitatively unchanged when we do so, which provides additional evidence that we are capturing an effect that is mediated by the strength of the ties among households such as one would expect in the case of peer influence. Table 12 shows that the corresponding first stages work as expected with weighting.

Table 11 Peer effects using number of calls to proxy tie strength.

	Dependent variable:			
	Leases (Exp)	Leases (Not Exp)	Leases (All)	
	2SLS	2SLS	2SLS	2SLS
	(1)	(2)	(3)	(4)
Friend Leases (Exp)	0.073	1.361*	1.434**	
	(0.070)	(0.703)	(0.725)	
Friend Leases (All)				0.221*
				(0.134)
Promotions	0.0001	−0.006***	−0.006***	−0.003
	(0.0002)	(0.002)	(0.002)	(0.003)
Constant	0.0004	0.063***	0.064***	−0.160
	(0.002)	(0.021)	(0.022)	(0.162)
Month Dummies	Yes	Yes	Yes	Yes
Wald test	5.904***	2.59**	2.223*	1.14
Observations	1,144,731	1,144,731	1,144,731	1,144,731

Note: *p<0.1; **p<0.05; ***p<0.01

Cluster robust standard errors in ()

Table 12 First stages using number of calls to proxy tie strength.

	Dependent variable:	
	Friend Leases (Exp)	Friend Leases (All)
	OLS	OLS
	(1)	(2)
Avg Friend Movie Age	-0.002^{***}	-0.012^{**}
	(0.0004)	(0.005)
Promotions	0.001^{*}	-0.003
	(0.001)	(0.012)
Constant	0.043^{***}	1.292^{***}
	(0.003)	(0.038)
Month Dummies	Yes	Yes
Observations	1,144,731	1,144,731
Note:	*p<0.1; **p<0.05; ***p<0.01	
	Cluster robust standard errors in ()	

7. Using Peer Influence with Price Promotions to Keep Profits

The previous sections show that on average households with access to movies at discounted prices under the "Good Opportunities" menu lease 11.1% more of these movies but 3.3% less of movies elsewhere in the VoD system. We also showed that overall sales reduced 2.9% during our experiment. Let $\beta_d = 0.111$ and $\beta_{nd} = 0.033$ in the discussion below. This means that the increase in sales of the movies offered at discounted prices under the "Good Opportunities" menus did not cover the loss in sales of the remaining movies. In addition, we also know that a household leases 2.304 more movies anywhere in the VoD system when her friends lease a movie under the "Good Opportunities" menu and that a household leases 0.172 more movies anywhere in the VoD system when her friends lease a movie anywhere in the VoD system. Let $\rho_{exp,all} = 2.304$ and $\rho_{all,all} = 0.172$ in the discussion below. The additional sales of movies offered at discounted prices under the "Good Opportunities" menu generated additional sales through peer influence. Therefore, the firm might avoid the overall reduction in sales if it targets price promotions under the "Good Opportunities" menu to households with enough friends (instead of random households as done during the experiment). The percentage of movies sold at discounted prices is typically small with price promotions but their sales still generate less profit compared to what they would generate if sold without discounts. Therefore, the question from the firm's perspective is whether she can break-even in terms of profits when she offers movies at discounted prices under the "Good Opportunities" menu. Whether this is the case depends on the average discount that the firm offers to households under the "Good Opportunities" menu as well as on the average markup that the firm applies to movies in the VoD system.

Assume that $\gamma\%$ of the profits at TELCO come from movies that TELCO will offer at discounted prices. Assume also that TELCO will offer movies under the "Good Opportunities" menu with an average discount of $d\%$ to a household with N_Frd friends and that none of the latter get this menu. Let p represent the average price of movies before discounts, c represent the average marginal cost of movies in the VoD system and define $m = p/c - 1$ as the markup factor. The marginal cost of a movie is the amount of money paid by TELCO to the content owner every time a movie is purchased in the VoD system. Before price promotions the average profit of the firm per movie sold to a focal household is given by $p - c$. When price promotions are introduced the average profit reduces to $p(1-d) - c$ for the movies offered at discount, which in turn sell $1 + \beta_d$ times more, and remains $p - c$ for the remainder of the movies in the VoD system, which in turn sell $1 - \beta_{nd}$ time less with price promotions. Therefore, with price promotions the profits on the focal household change by $\gamma((1+\beta_d)(p(1-d)-c) - (p-c)) - (1-\gamma)\beta_{nd}(p-c)$. Without price promotions the average profit on friends per movie sold to the focal household due to peer influence is given by $\rho_{all,all} N\_Frd(p-c)$. When price promotions are introduced this average profit reduces $1-\beta_{nd}$ times for movies offered without discounts, due to the shift in the consumption of the focal household to movies offered at discounted prices. This shift, in turn, changes the average profit on the friends associated to the movies offered at discounted prices to $\rho_{exp,all} N\_Frd(p(1-d)-c)(1+\beta_d)$. Therefore, with price promotions the profits on the friends of the focal household change by

$N\_Frd[\gamma(\rho_{exp,all}(p(1-d)-c)(1+\beta_d)-\rho_{all,all}(p-c))-(1-\gamma)\rho_{all,all}(p-c)\beta_{nd}]$. Therefore, the firm breaks-even iff $N\_Frd > N^*$ with:

$$N^* = -\frac{\gamma((1+\beta_d)((1+m)(1-d)-1)-m)-(1-\gamma)\beta_{nd} m}{\gamma(\rho_{exp,all}((1+m)(1-d)-1)(1+\beta_d)-\rho_{all,all} m)-(1-\gamma)\rho_{all,all} m \beta_{nd}} \quad (6)$$

Figure 6 shows how N^* changes with the price discount and with the markup factor using $\gamma = 2.8\%$ as observed in our empirical setting. N^* increases with the size of the discount offered, because it is more difficult to break-even when better discounts are offered, and decreases with the markup factor, because it is easier to break-even with more profit per movie sold. For the average discount of 25% and average markup rate of 0.6 observed during our experiment the firm would need to target price promotions to households with at least 4 friends to break-even.

8. Conclusions

The marketing and economics literature has been rich in models that explain how consumers adjust demand when prices change and stockpiling is available. Consumers typically anticipate consumption but buy significantly less once price promotions are retracted, which may hurt the long-term profitability of firms. However, consumers may behave differently with information goods that cannot be stored. Namely, without stockpiling only the mechanisms associated to intertemporal substitution are at play and whether price promotions increase or decrease sales might become ambiguous. There is little empirical evidence of the effect of price promotions with non-storable goods despite their prevalence in today's markets. Our paper addresses this gap in the literature by providing empirical evidence of the effect of price promotions in the consumption of movies in Video-on-Demand (VoD), which is a setting where consumers cannot store movies to watch later.

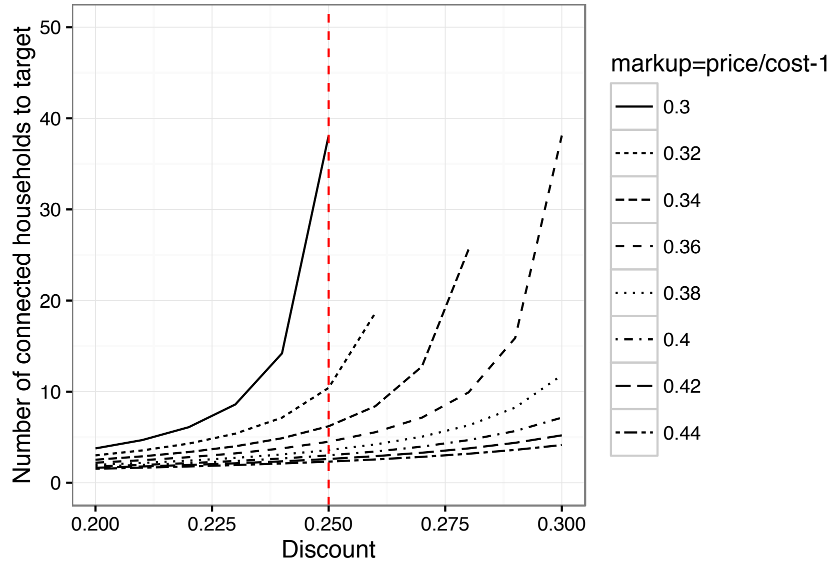

Figure 6 **Number of friends that a targeted household must have for price promotions to yield profit break-even as a function of the price discount and of the markup factor.**

We explore outcomes from an in-vivo organic randomized field experiment using the VoD system of a large telecommunications provider during which a new menu of movies – called “Good Opportunities” – was added to the highlights section of this VoD system for 3 consecutive months. A random set of households were always offered movies at the usual prices under this menu. Another random set of households were always offered movies at discounted prices under this menu. The remainder of the households were offered movies at discounted prices under this menu during the first two months of the experiment and at the usual price during the last month of the experiment. The exact movies that were offered to each household under this menu were also selected at random from a pool of movies that represents well the titles that this provider would want to push into the highlights section of the VoD system.

We find empirical evidence that households offered movies at discounted prices under the “Good Opportunities” menu anticipate purchases and buy more of these movies than households without price promotions in the first month of the experiment – intertemporal substitution. This difference erodes in the second and third months of the experiment. Therefore, the anticipation effect of price promotions was short-lived in our setting. Furthermore, we find that households with price promotions under the “Good Opportunities” menu bought fewer of the movies that were not offered to them at discounted prices in other menus of the VoD system during the experiment – due to both contemporaneous and intertemporal substitution.

We also investigate whether there are peer effects in the consumption of movies in VoD. We use call detailed records to establish a social network across households. Two VoD-enabled households are friends in this graph if people in one of them call people in the other one on their cell phones. We leverage our randomized design and use the average age of the movies offered under the “Good Opportunities” menu to friends as an instrument for their leases. This covariate is random in our setup and explains well the number of movies that friends lease. We do not find evidence that households buy more movies under the “Good Opportunities” menu because their friends do. We find evidence that households buy movies elsewhere in the VoD system because their friends buy movies under the “Good Opportunities” menu. We also find evidence that overall – that is, under the “Good Opportunities” menu and elsewhere in the VoD system – households buy movies because their friends buy movies under the “Good Opportunities” menu and we also find that overall households buy movies because overall their friends buy movies. Finally, we note that the effect of peer influence triggered by a household that buys movies under the “Good Opportunities” menu is much larger than the average usual effect of peer influence in this VoD system

Finally, we combine the effect of price promotions with the effect of peer influence and show that the firm can break-even if it targets discounts to households strategically. The firm loses profit when it offers movies at discounted prices under this menu to households – because, at least in the first month of price promotions, these movies sell more but the remaining movies sell less – but the friends of these households buy more movies in the VoD system due to the effect of peer influence. Therefore, the firm breaks-even if it offers price promotions to households with enough friends to the point that these two effects cancel out. How many friends a household targeted with price promotions must have for the firm to break-even depends on the discount offered by the firm and on the markup factor that the firm applies. The higher the price discount the more friends the targeted households must have for the firm to break-even. Conversely, for the markup factor. In our setting, and for the average discount offered by the firm on movies under the “Good Opportunities” menu and for the average markup factor that the firm applies to VoD movies, the threshold for the number of friends that a household must have to receive price promotions lies well within the distribution of degree in our social graph.

In sum, our paper shows how outcomes from a large-scale randomized field experiment can be used to measure both the effect of price promotions on sales as well as the effect of peer influence among households on sales. We also show how the outcomes of such an experiment can be productively combined from a managerial point of view to propose a new strategy that firms can follow to issue price promotions in ways that allow them to minimize the undesirable losses in profit that may arise from price promotions. Our analysis shows how and why firms that use social network information to shape promotional campaigns and determine consumers to target are likely to perform better than competitors who do not. Yet, our paper does not come without limitations. First, we use a partial view of the social network across households to estimate the effect of peer influence in the second part of our paper. This introduces measurement error in our dependent covariates and thus attenuates the effect of peer influence that we measure. Still, we are able to show that there is peer influence in our setting and that it can be used to counter the losses associated to price promotions. Second, we do not measure non-linear nor heterogeneous effects in peer influence, which may arise with hedonic information goods. Finally, we acknowledge that our results may not generalize beyond the VoD system used in our experiment, namely to the case of other information goods.

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Appendix A: Variable definitions

Appendix B: Robustness: Log-linear and log-log specifications

Table 14 shows our main results using a log-linear specification, i.e., we log the endogenous variable (and our instrument) and keep the linear specification for the dependent variable. Table 15 shows results using a log-log specification, that is, we log both the endogenous variable and the dependent variable. In addition, Table 16 shows the log versions of the corresponding first stages regressions. The average age of the movies offered to friends under the “Good Opportunities” menu is a predictor of the log of the number of friends’ leases and is not a the weak instrument. In sum, these three tables show that our results are robust to functional form providing us with additional evidence of the existence of peer influence in our setting.

Table 13 Variable Overview

Variable	Periodicity	Description
Household level:		
Leases (Exp)	Monthly	Leases under the "Good Opportunities" menu
Leases (Not Exp)	Monthly	Leases not under "Good Opportunities"
Leases (All)	Monthly	Leases in the entire VoD system
Past Leases (All)	Monthly	Leases before the experiment started (01-03/2013)
Friend Leases (Exp)	Monthly	Friends' leases in the "Good Opportunities" menu
Friend Leases (All)	Monthly	Friends' leases in the entire VoD system
Promotions	Monthly	=1 if household given movies with discounts
Avg Friend Movie Age	Monthly	Avg age of friends' movies in "Good Opportunities"
Degree	Once	Number of friends of a household in the social graph
Total Calls	Once	Number of calls of a household in our CDR dataset
Household level when experiment started:		
Has Contract ?	Once	Whether the household is in lock-in period
Electronic Receipt	Once	Whether the household subscribed electronic receipt
TV Tenure	Once	Months that household had TV service from TELCO
Experimental conditions:		
G0	Once	= 1 for households that were always offered movies at the usual prices in the "Good Opportunities" menu
G1	Once	= 1 for households that were always offered movies at discounted prices in the Good Opportunities Menu
G2	Once	= 1 for households that were offered movies at discounted prices in the "Good Opportunities Menu" in months 1 and 2, and at the usual prices in month 3
Movie level:		
IMDb Metascore	Once	Rating score at www.metacritic.com
IMDb Rating	Once	IMDb Rating at www.imdb.com
IMDb Votes	Once	Number of IMDb votes at imdb.com
Release Year	Once	Year of release
Duration (mins)	Once	Duration in minutes

Table 14 Peer influence in VoD movie leases using a log-linear specification.

	Dependent variable:			
	Log Leases (Exp)	Log Leases (Non Exp)	Log Leases (All)	
	2SLS	2SLS	2SLS	2SLS
	(1)	(2)	(3)	(4)
Friend Leases (Exp)	0.080	0.980^{**}	1.026^{**}	
	(0.071)	(0.462)	(0.472)	
Friend Leases (All)				0.077^{**}
				(0.034)
Promotions	0.0002^{**}	-0.001^{*}	-0.001	-0.001^{*}
	(0.0001)	(0.001)	(0.001)	(0.001)
Constant	-0.001	0.023	0.023	-0.039
	(0.002)	(0.015)	(0.016)	(0.043)
Month Dummies	Yes	Yes	Yes	Yes
Wald test	6.712***	3.096**	2.335*	2.517**
Observations	1,144,731	1,144,731	1,144,731	1,144,731

Note: *p<0.1; **p<0.05; ***p<0.01

Cluster robust standard errors in ()

Table 15 Peer influence in VoD movie leases using a log-log specification.

	Dependent variable:			
	Log Leases (Exp)	Log Leases (Non Exp)	Log Leases (All)	
	2SLS	2SLS	2SLS	2SLS
	(1)	(2)	(3)	(4)
Log Friend Leases (Exp)	0.125	1.538^{**}	1.610^{**}	
	(0.112)	(0.731)	(0.747)	
Log Friend Leases (All)				0.224^{**}
				(0.100)
Promotions	0.0002^{**}	-0.001^{*}	-0.001	-0.001
	(0.0001)	(0.001)	(0.001)	(0.001)
Constant	-0.001	0.021	0.021	-0.057
	(0.002)	(0.016)	(0.017)	(0.051)
Month Dummies	Yes	Yes	Yes	Yes
Wald test	6.673***	3.049**	2.298*	2.867**
Observations	1,144,731	1,144,731	1,144,731	1,144,731

Note: *p<0.1; **p<0.05; ***p<0.01

Cluster robust standard errors in ()

Table 16 First Stages for the effect of peer influence on VoD movielLeases (log specification)

	Dependent variable:	
	Log Friend Leases (Exp)	Log Friend Leases (All)
	OLS	OLS
	(1)	(2)
Avg Friend Movie Age	-0.001^{***}	-0.005^{***}
	(0.0002)	(0.001)
Promotions	-0.0001	-0.001
	(0.0003)	(0.002)
Constant	0.027^{***}	0.545^{***}
	(0.001)	(0.008)
Month Dummies	Yes	Yes
Kleibergen-Paap rk Wald F-stat	17.278	21.030
Observations	1,144,731	1,144,731

Note: *p<0.1; **p<0.05; ***p<0.01

Cluster robust standard errors in ()