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Price Discounts and Peer Effects in Information Goods: Results from An In-vivo Organic Randomized Experiment

(Authors' names blinded for peer review)

This paper looks at the interplay between price promotions and peer influence in the case of movies in Video-on-Demand (VoD), which is an example of an information good that cannot be stored. We analyze outcomes from a large-scale in-vivo organic randomized field experiment ran for 3 consecutive months using the VoD system of a large telecommunications provider offering triple-play service to roughly half a million households. 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 also use cell phone call detailed 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 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. Essentially, firms can break-even if they offer price promotions to households with enough connections to generate enough sales through peer influence to counter the undesirable effect of price promotions. We show how the ability of the firm to break-even depends on the magnitude of the effect of peer influence, the discount offered by the firm and the markup factor. At the average of the covariates observed in our setting, the firm breaks-even if it offers price promotions to households with more than 4 connections.

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

1. Introduction

Price promotions are one of the main ingredients of the traditional marketing strategies used by sellers to attract consumers (Blattberg et al. 1995). This led many researchers over the years to study how prices affect demand, in particular in the case of packaged goods (see Shoemaker (1979), Neslin et al. (1985), Schneider and Currim (1991), Chiang (1991), Bell et al. (1999)). Substitution and income effects have been studied in detail with multi-period models focusing on intertemporal substitution effects. The economic literature on storable goods has also shown that consumers formulate reference prices and that they react enthusiastically when promotions reduce prices below what they expect to pay (Klein and Oglethorpe 1987). As a consequence, sales accelerate with price promotions in the short-run but then they dip significantly when promotions are retracted (Grover and Srinivasan 1992). Models with stockpiling explain that consumers buy more when prices decrease in part because households maintain inventories of the goods that they can store for future consumption and thus may buy less after price promotions (Arrow et al. 1951, Blattberg et al. 1981). This behavior may hurt the profitability of firms in the long-run (Dodson et al. 1978, Srinivasan et al. 2004). Furthermore, consumers may associate frequent price promotions to inferior product quality, which may also decrease their loyalty towards brands in the long-run (Mela et al. 1997). However, these results may not apply to the case of information goods that cannot be stored. One such example is movies in Video-on-Demand (VoD), which consumers can typically only watch within a brief window of time after purchase.

In this paper we develop a two-period model with two products to study what happens to consumption when the price of one product changes in the first period leading consumers to adjust their beliefs about the price of this product in the second period and, consequently, their demand. This model shows that a post-promotion dip in sales can arise even with non-storable goods. This model also shows that consumers targeted with price promotions may buy less than consumers that were not targeted with price promotions when prices come back to their original levels. Whether this happens depends on how much consumers accelerate purchases with price promotions and how sharply they adjust their beliefs about future prices. Finally, this model also shows that on aggregate firms can sell less with price promotions. Whether this happens depends, essentially, on the strength of the intertemporal substitution effects, which are in part affected by how consumers update their beliefs about prices.

We test the predictions of this model empirically using outcomes from an in-vivo organic randomized experiment ran by a telecommunications provider. A new menu called "Good Opportunities" was added to the VoD system of all households with a VoD enabled set-top-box from this provider during three consecutive months. A group of households were offered movies under this new menu at the usual prices – those negotiated by the provider and the content owners. 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. The movies shown to each household under this new menu were selected at random from a set of predetermined movies that represents well the titles that this provider wants to offer under the highlights section of its VoD system. A fuller catalog of movies is also available in this VoD system that consumers can get access to by navigating away from the highlights section.

In total, 492,931 households and 135 movies were included in this experiment. Empirically, we show that on average households with price promotions buy 32% more of the movies offered under the new menu than households without price promotions during the first month of the experiment. Also, on average all households in the experiment buy a similar number of these movies in the second month of the experiment. This provides some evidence that 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 buy on average fewer of these movies than the 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. The fact that price promotions may reduce the sales of information goods that cannot be stored is troublesome for IT firms in particular in a world where increased digitization has been shifting a significant share of profits towards digital products and digital channels. The convergence between TV and Internet has been placing the movie industry at the heart of this shift and stakeholders such as content providers, content distributors and advertisers, are all trying to optimize pricing schedules, temporary discounts and offers via coupons and vouchers.

In parallel, the proliferation of social networks, recommender systems and e-commerce websites with product reviews allows consumers to more easily and more quickly access information from their friends and from the crowd to learn about product quality. More information about products reduces uncertainty, which may ultimately result in more consumption. The literature in information systems in recent years has shown that there is peer influence in the consumption of some digital products (Tucker 2008, Aral et al. 2009, Aral and Walker 2011, Bapna and Umyarov 2015). Therefore, we posit whether these peer effects can help firms counter the likely negative effects of price promotions on sales. At the outset, it is not clear whether this can happen because the magnitude of the effect of peer influence in the consumption of digital goods might not be as large as some early papers may have claimed. A number of recent studies have shown that homophily can easily lead researchers to overestimate peer effects when randomized experiments are unavailable (Aral et al. 2009, Shalizi and Thomas 2011). Yet, and applying the rational above to our case of VoD movies, if consumers buy more VoD movies when their friends do then, perhaps, peer influence can help counter the reduction in sales observed with price promotions. In fact, if this is the case then firms should consider combining strategies that lead some consumers to buy more of some products with viral strategies that may lead people to also buy more when their friends do. As our experiment shows, a strategy to increase the short-term sales of some products to some consumers is to offer price promotions. Therefore, the research question before us is whether the magnitude of the effect of peer influence in the consumption of VoD movies is enough to counter the aggregate loss in sales that arises from price discounts.

Identifying the effect of peer influence in the consumption of digital goods is a hard task from an empirical point of view due to the unknown effects of unobserved covariates. However, during our experiment we randomized the movies offered to households under the "Good Opportunities" menu. Therefore, the characteristics of these movies are random in our setup. Furthermore, we find that the average age of the movies offered under this menu is a good predictor for their sales. Hence, we use this covariate as an instrument for friends' purchases and this allows us to identify the effect of peer influence in the consumption of VoD movies. Two households are called friends in our setting if people in one of them call people in the other one on the phone. The average and median degree in the social graph of connected households are 10.23 and 7, respectively. On average, we find that when a household purchases a movie under this menu her friends purchase 2.304 additional movies elsewhere in the VoD system. This magnitude for the effect of peer influence associated to movies offered under the "Good Opportunities" menu allows the firm to break-even when she offers movies at discounted prices to households with enough friends to generate enough sales through peer influence to counter the undesirable losses associated to the reduction in the sales of movies that remain without discounts. 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 ($price/marginalcost - 1$) of 0.6 used during our experiment, the firm would have broken even if it had targeted price promotions to households with more than 4 friends. However, we also note that in our setting the firm would not break-even if the true effect of peer influence is closer to the bottom of the 95% confidence interval around the average reported above.

Our paper is the first to study the interplay between price promotions and peer influence in the context of information goods that cannot be stored. This is a topic of increased importance in a world that is increasingly shifting consumption towards this type of goods such as media streaming. We show how a 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. Finally, we show how the outcomes of such an experiment can be productively combined from a managerial point of view to propose a strategy that firms can follow to issue price promotions for these goods in ways that allow them to break-even. Our analysis leads us to expect that firms that combine price promotions with viral marketing strategies are likely to perform better than competitors who do not. Depending on the frequency of these well-designed campaigns, this upper edge may decisively affect long-term profitability.

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 analyzes a utility model that teases out how demand changes with changes in prices and with signals from friends about the quality of the products in the market. Section 4 introduces our experimental context and our experimental design. Section 5 provides descriptive statistics and preliminary results. Section 6 analyzes the effect of price promotion on sales and section 7 analyzes the effect of peer influence on sales. Section 8 shows how the firm issue price promotions to break-even and section 9 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 all over the the world to attract consumers. 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. Promotions come often in the form of coupons and price discounts and are used to increase sales, encourage trial and trigger brand switching. Thaler (1985) and Klein and Oglethorpe (1987) argue that consumers formulate a reference price for how much they expect to pay for a product. This reference price is usually based on past prices and on the frequency of observed discounts. The reference price assembled by consumers might naturally be different from the list price offered by the seller. A product is on price promotion when it is offered at a price lower than the list price that is signaled to consumers typically through advertising and/or store signs. 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 literature in behavioral economics has analyzed the impact of price promotions on the consumption of storable goods. The early works of Woodside and Waddle (1975) and Ward and Davis (1978b,a) show that price promotions increase short-term sales. Walters and Rinne (1986), Kumar and Leone (1988) and Walters and MacKenzie (1988) show that they also increase store traffic. Gupta (1988), Kumar and Leone (1988), Bawa and Shoemaker (1987) show that they trigger brand substitution within the same product category and Blattberg and Wisniewski (1989) and Krishnamurthi et al. (1992) show that these effects are asymmetric. Namely, during a price promotion higher quality brands attract more consumers than lower quality ones. Walters and Rinne (1986) and Walters (1991), Mulhern and Leone (1991) also find that price promotions increase sales in complementary products. Blattberg et al. (1981) find evidence that price promotions shorten inter-purchase times but Neslin et al. (1985) find that the short-term spike in sales is still the dominating effect.

Sawyer and Dickson (1984) argue that 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. Therefore, whether a price discount works depends on how consumers perceive the discount. Della Bitta et al. (1981) show evidence that in general managers believe that at least a 15% discount is needed to attract consumers. Price discounts between 10% and 40% have been used often by researchers to study effects of price promotions on the demand for packaged goods. Sinha and Batra (1999) show that the promotion message itself and the way the new price is communicated to consumers also shape perceptions and willingness to buy.

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. Chintagunta (2002) show that the additional sales observed in the short-run 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. 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 of 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 even have negative long-term effects for the firm.

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. If consumers may perceive frequent price promotions as a signal of inferior product quality then they might decisively hurt the long-term profitability of firms. 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.

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 indeed consumers are flexible when it comes to buying packaged goods and that sales increase as a result of promotions when consumers stockpile. Chandon and Wansink (2002) show that stockpiling leads consumers to buy more products at a faster rate, namely products that are convenient to consume. In addition, the ability to stockpile distorts the perceptions of consumers. Goods that consumers can store are perceived as relatively less expensive at the time of purchase, which increases their sales even further. However, Mela et al. (1998) show that the reduction in consumption in the long term may supersede the spike in consumption in the short-term propelled by stockpiling. Thus, increased sales during price promotions can be seen more as sales borrowed from the future than increased consumption.

A number of information goods cannot be stockpiled. One such example is movies for rent in Video-on-Demand (VoD), which consumers have to watch within a brief window of time after purchase. Therefore, the results summarized above may not apply in the case of these information goods. Surprisingly, there is little research on the effect of price promotions on the consumption of information goods. An exception is the work of (Gong et al. 2015) where the authors find that price promotions in digital purchases (known as the Electronic Sell Through (EST) channel) do not seem to cannibalize VoD sales. This result is inconsistent with the findings that price promotions trigger substitution across similar products, which leads the authors to argue that it may arise in their setting because of information transmission through third-party websites and blogs that may lead to information spillovers.

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, such as face to face meetings, phone conversations, email and text messages, websites and blogs. 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 it 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 (**?**); and comparison – people use people they feel similar to as their frame of reference (**?**). 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 did not. A competitive view of influence would instead argue that people are concerned that other people who adopted the innovation might be able to gain a competitive edge unless they also adopt it. These mechanisms are not independent and are therefore 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.

Finally, Zafarani et al. (2014) suggest that herding behavior occurs when people observe the actions of all other people in the social system and act in conformity with what the majority does. The key difference between herding and peer influence is the fact that in the former people make decisions based on global information – sometimes called the wisdom of the crowd – whereas peer influence arises through information cascades that spread only across direct friends.

Herding behavior was studied by Salganik et al. (2006) who 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. More recently, 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.

As discussed in Chevalier and Mayzlin (2006), Forman et al. (2008), Dellarocas et al. (2010), Geva et al. (2013), Goes et al. (2014), Godinho de Matos et al. (2016) consumers are increasingly using real-time feedback on product quality provided by their friends and by the crowd through reviews in e-commerce websites, blogs and online social networks. However, there is still little research looking at the interplay between peer influence and traditional marketing tools in the context of information goods. In particular, it seems paramount to study how peer influence and price promotions interact in the case of goods that consumers cannot stockpile. Katz and Lazarsfeld (1955), Katz and Shapiro (1994) argue that peer influence may act as a multiplier and thus increase firm profits. Moretti (2011), Bapna and Umyarov (2015) show empirical evidence of the latter. However, peer influence may also work in detriment of 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.

Identifying peer influence is empirically challenging because unobserved homophily makes it hard to separate decisions originating from shared preferences from those caused by information spillovers (McPherson et al. 2001). Aral et al. (2009), Aral (2010), Shalizi and Thomas (2011) discuss some of the theoretical and empirical challenges that researchers typically face to identify peer influence and offer some solutions. Identifying how peer influence may change the effects of price promotions is even a harder task. First, data on product consumption and social network connections are not always available hand in hand. Second, both price promotions and social networks are endogenously determined in most practical settings making it difficult to identify the effect of each of them separately much less the potential effects of their interaction. Models of peer influence, such as (Bramoullé et al. 2009, Oestreicher-Singer and Sundararajan 2012), and matching in high resolution panels, such as in (Aral et al. 2009), have been used to control for unobservables to prevent overestimating the effect of peer influence. Other approaches include using structural models (Ma et al. 2014), randomization (Anagnostopoulos et al. 2008) and instrumental variables (Tucker 2008, Godinho de Matos et al. 2014).

In this paper we show how a randomized field experiment can be used to obtain identification and thus measure the effect of the interplay between price promotions and peer influence. As Bapna and Umyarov (2015) put it, randomized experiments are the gold-standard in social sciences research to tease out causal effects because they allow for controlling for unobserved time-varying effects that challenge identification in observational studies. A number of studies use randomized experiments to identify the effect of peer influence. For example, Aral and Walker (2011) show evidence of contagious adoption of a Facebook application that allows users to share comments related to the movie industry. Bapna and Umyarov (2015) awarded free premium subscriptions to a random set of LastFM subscribers and showed that people connected to users that subscribe the premium service are more likely to acquire this service themselves.

3. A Two-Period Model of Consumer Demand with Price Uncertainty

3.1. Contemporaneous and Intertemporal Substitution Effects and Income Effects

Consider two goods (later in our experimental setting movies under the "Good Opportunities" menu and movies elsewhere in the VoD system) sold over two time periods to one representative consumer. Let x_{jt} represent the quantity of good j in period t and p_{jt} the (positive) price of this good, with $j=1,2$ and $t=1,2$. Prices p_{11}, p_{21} and p_{22} are fixed and exogenously given (later we will study how changing the price of the first good in the first period, that is, how reducing the price of the movies offered under the "Good Opportunities" menu, affects sales). However, the price of the first good in the second period (p_{12}) is unknown to the consumer. In this case, the consumer solves

$$\begin{array}{ll} \underset{\mathbf{x},y}{\text{Max}} & U(x_{11},x_{21})+\beta E[U(x_{12},x_{22})]+v(y) \\ \text{subject to} & w=x_{11}p_{11}+x_{21}p_{21}+E[x_{12}p_{12}+x_{22}p_{22}]+y \end{array}$$

in which $v(y)$ is the utility from the discounted consumption of the outside good, y, with $v(\cdot)$ increasing and concave. The price of the outside good is price normalized to 1. For sake of simplicity we assume that $U(x_1,x_2)$ is separable in its arguments with $U(x_1,x_2)=u(x_1)+u(x_2)$ and that $u(\cdot)$ is increasing and concave. The first order conditions, which are given by

$$\frac{u'(x_{11}^*)}{p_{11}}=\frac{u'(x_{21}^*)}{p_{21}}=\beta E\left[\frac{u'(x_{12}^*)}{p_{12}}\right]=\beta E\left[\frac{u'(x_{22}^*)}{p_{22}}\right]=v'(y^*)$$

define implicitly the consumption of these two goods as a function of their prices and their marginal utility in each time period. These conditions guarantee that (1) the contemporaneous price-adjusted marginal utilities are the same for both goods – contemporaneous substitution effect; and that (2) the price-adjusted marginal utility of a good in one period is proportional to the expected price-adjusted marginal utility of a good in the next period with the discount rate as the proportional factor – intertemporal substitution effect. We now perform a comparative statics analysis to study the effect of changing the price of the first good in the first period on consumption. The Slutsky equations for the first period yield:

$$\frac{\partial x_{11}^*}{\partial p_{11}} = \frac{\partial h_{11}^*}{\partial p_{11}} - \frac{\partial x_{11}^*}{\partial w} x_{11}^*; \frac{\partial x_{21}^*}{\partial p_{11}} = \frac{\partial h_{21}^*}{\partial p_{11}} - \frac{\partial x_{21}^*}{\partial w} x_{21}^*$$

where h_{j1}^* is the Hicksian demand for good j in the first period. Assume that income effects $(\partial x_{j1}^*/\partial w)$ are small relative to substitution effects $(\partial h_{j1}^*/\partial p_{11})$. Following **?** this is a standard assumption for goods that represent a small portion of the consumer's budget, such as digital goods. Therefore, and assuming normal goods, we immediately have

$$\frac{\partial x_{11}^*}{\partial p_{11}} < 0; \frac{\partial x_{21}^*}{\partial p_{11}} > 0$$

and, therefore, when the price of the first good decreases in the first period the consumer buys more of it and less of the second good in the first period.

We now analyze what happens to consumption in the second period. For sake of simplicity assume that the price of the first good in the second period can take one of two values: low price, p_{12L}, and high price, p_{12H}. Also, the consumer attaches probability α to the fact that this price will be p_{12H} given the observed price of this good in the first period, that is, $\alpha = P[p_{12} = p_{12H}|p_{11}]$ (that is, upon observing that movies offered under the "Good Opportunities" menu sell for a lower price, consumers may adjust their beliefs about the prices of the movies that will be offered under this menu in the future. Note that for sake of simplicity we also assume that consumers know the prices of the movies offered elsewhere in the VoD system in the future, namely we assume that observing prices of movies offered under the "Good Opportunities" menu is uninformative about prices of other movies in the VoD system in the future). Let x_{j2H}^* represent the consumption of good j in the second period when the price of the first good is high in this period and let x_{j2L}^* represent the consumption of good j in the second when the price of the first good is low in this period. Expanding the expected values we obtain:

$$E[x_{12}^*] = \alpha x_{12H}^* + (1-\alpha) x_{12L}^*; E[x_{22}^*] = \alpha x_{22H}^* + (1-\alpha) x_{22L}^*$$

Therefore, using the total derivatives we have:

$$\frac{dE[x_{12}^*]}{dp_{11}} = (x_{12H}^* - x_{12L}^*)\frac{\partial \alpha}{\partial p_{11}} + \alpha \frac{\partial x_{12H}^*}{\partial p_{11}} + (1-\alpha)\frac{\partial x_{12L}^*}{\partial p_{11}}$$

$$\frac{dE[x_{22}^*]}{dp_{11}} = (x_{22H}^* - x_{22L}^*)\frac{\partial \alpha}{\partial p_{11}} + \alpha \frac{\partial x_{22H}^*}{\partial p_{11}} + (1-\alpha)\frac{\partial x_{22L}^*}{\partial p_{11}}$$

where $\partial \alpha/\partial p_{11}$ represents how the consumer updates her beliefs about the price of the first good in the second period upon observing the price of this good in the first period. If the consumer does not update her beliefs, i.e., if $\partial \alpha/\partial p_{11} = 0$, only the second and third terms of these equations are at play, and a change in the price of the first good in the first period affects consumption in the second period through two mechanisms: intertemporal substitution and income effects, both of them embedded in the consumer's optimization problem leading to x^*_{12H} and x^*_{12L}. Assuming normal goods immediately implies

$$\frac{\partial x^*_{j2H}}{\partial p_{11}} > 0; \frac{\partial x^*_{j2L}}{\partial p_{11}} > 0$$

for $j = 1, 2$ and, therefore, when the price of the first good decreases in the first period the expected consumption of both goods in the second period increases. Assume now that the consumer updates her beliefs about the price of the first good in the second period once the price of this good in the first period is observed. In particular, let us assume that the higher the price of the first good in the first period the more the consumer believes that the price of this good in the second period will be high, i.e., $\partial\alpha/\partial p_{11} > 0$. This effect counterbalances the intertemporal substitution effect discussed above for the case of the first good because $(x^*_{j1H} - x^*_{j1L}) < 0$, which results from using the Slutsky equation for this good in the second period and from assuming that the substitution effect dominates the income effect. Therefore, the intertemporal substitution effect is stronger for this good in the second period when the consumer does not update her beliefs about future prices. The opposite conclusion arises for the case of the second good because $(x^*_{j2H} - x^*_{j2L}) > 0$, which also results from using the Slutsky equation for this good in the second period and from assuming that the substitution effect dominates the income effect. Finally, we note that the consumer may buy less overall when the aggregate of the substitution effects (contemporaneous and intertemporal) dominates the effect on the consumption of the first good in the first period.

3.2. The Effect of Signals From Friends About Product Quality on Consumption

We augment the model introduced before to include the effect of signals from friends about their perceived product quality. Assume that the two goods in our model are experience goods, i.e., consumers only ascertain product fit after consumption, and that the utility of consumer i accounting for product fit is of the form

$$U_i(x_1, x_2, \theta_i) = g_i(\theta_i)[u_i(x_1) + u_i(x_2)]$$

where $g_i(\cdot)$ is increasing and concave and $\theta_i > 0$ represents the product fit (for sake of simplicity, similar to both goods in the market). Let $\hat{\theta}_i \equiv \frac{1}{n}\sum_j^n \theta_j$ represent the accumulation of signals about product quality that consumer i obtains from n of her friends after they have purchased goods in the market. Assume that signals from friends good predictors for θ_i due to homophily. Assuming a large enough n the Central Limit Theorem yields $\hat{\theta}_i \xrightarrow{dist} N(\theta_i, \sigma^2/n)$. With uncertainty about product fit consumer i solves

$$\begin{array}{ll} \underset{\mathbf{x},y}{\text{Max}} & E[U_i(x_{11},x_{21},\theta_i)|\hat{\theta}_i,n]+\beta E[U_i(x_{12},x_{22},\theta_i)|\hat{\theta}_i,n]+v_i(y) \\ \text{subject to} & w=x_{11}p_{11}+x_{21}p_{21}+E[x_{12}p_{12}+x_{22}p_{22}]+y \end{array}$$

which leads to the following first order conditions:

$$\frac{u_i'(x_{11}^*)}{p_{11}}=\frac{u_i'(x_{21}^*)}{p_{21}}=\beta E\left[\frac{u_i'(x_{12}^*)}{p_{12}}\right]=\beta E\left[\frac{u_i'(x_{22}^*)}{p_{22}}\right]=\frac{v_i'(y^*)}{E[g_i(\theta_i)|\hat{\theta}_i,n]}$$

We show how the effect of signals about product quality affects the consumption of both goods in the first period. Similar arguments can be used to show similar results for the effect of these signals on the expected consumption of these goods in the second period. The first order conditions above imply

$$E[g_i(\theta_i)|\hat{\theta}_i,n]=\frac{v_i'(y^*)}{u_i'(x_{j1}^*)}p_{j1}$$

for $j=1,2$, and thus, when the expected product fit increases, the ratio between the marginal utility of the outside good and that of good j in this period increases. This leads to a decrease in the consumption of the outside good and to an increase in the consumption of good j in this period. The latter derives from the budget constraint and from the concavity of both $u_i(\cdot)$ and $v_i(\cdot)$. Therefore, the consumption of good j increases with the number of signals received, $\partial x_{j1}^*/\partial n>0$, as long as the expected fit increases with the number of signals received:

$$\frac{dE[g_i(\theta_i)|\hat{\theta}_i,n]}{dn}>0 \implies \frac{\partial x_{j1}^*}{\partial n}>0$$

.

This, however, follows immediately from the fact that

$$E[g_i(\theta_i)|\hat{\theta}_i,n]\approx g_i(\hat{\theta}_i)+g_i''(\hat{\theta}_i)\sigma^2/2n$$

and $g_i(\cdot)$ is concave. To see this use the Taylor expansion of $g_i(\theta_i)$ around $\hat{\theta}_i$ to obtain $g_i(\theta_i)\approx g_i(\hat{\theta}_i)+(\theta_i-\hat{\theta}_i)g_i'(\hat{\theta}_i)+(\theta_i-\hat{\theta}_i)^2 g_i''(\hat{\theta}_i)/2$. The result follows immediately from $E[g_i(\theta_i)|\hat{\theta}_i,n]\approx g_i(\hat{\theta}_i)+E[(\theta_i-\hat{\theta}_i)|\hat{\theta}_i,n]g_i'(\hat{\theta}_i)+E[(\theta_i-\hat{\theta}_i)^2|\hat{\theta}_i,n]g_i''(\hat{\theta}_i)/2$ but $E[(\theta_i-\hat{\theta}_i)|\hat{\theta}_i,n]=0$ and $E[(\theta_i-\hat{\theta}_i)^2|\hat{\theta}_i,n]=\sigma^2/n$. Similar arguments lead immediately to $\partial E[x_{j2}^*]/\partial n>0$ for $j=1,2$.

Therefore, the first order conditions tell us that (1) the higher the expected quality of the goods in the market the higher their consumption in both periods; and (2) the higher the uncertainty about their quality the lower their consumption in both periods. These results show the mechanisms at work when friends provide signals about the quality of the products in the market. The better the quality signals and the lower the uncertainty about quality the higher the consumption. Hence, overall consumption increases with signals from friends about the quality of the products and this may counter the potential reduction in consumption from price promotions discussed above.

4. Our Experimental Context and Experimental Design

4.1. 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 "Promotions" 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.

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.

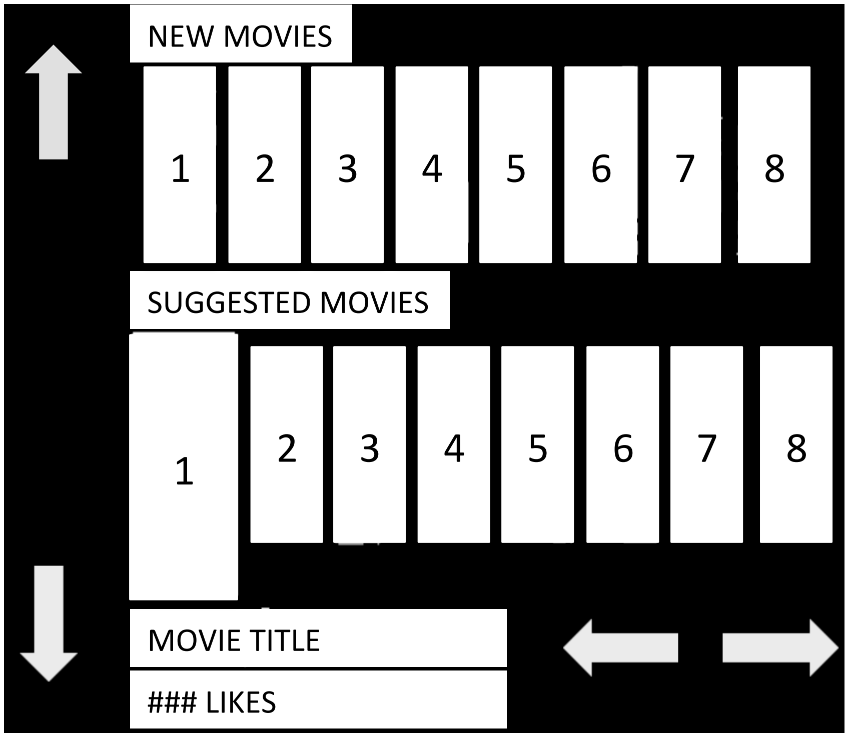

Figure 1 **The Look and feel of the Video-on-Demand Interface on the TV screen.**

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.

4.2. Social Graph of Connected Households

We also had access to Call Detail Records (CDRs) for cell phone communications served by Telco between August and October 2015. 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 anonimized number with no counterpart in the database of Pay-TV accounts. We also discard all anonimized 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 anonimized 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 anonimized 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 anonimized 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 9 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.

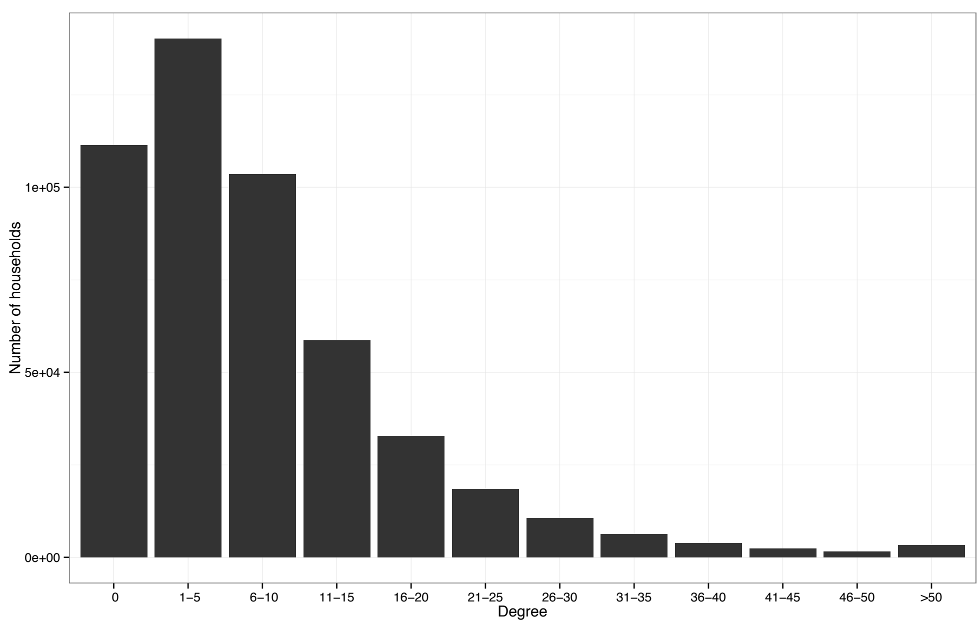

Figure 2 **Degree Distribution Across Households in the Social Graph.**

4.3. Experimental Design to Study the Effect of Price Promotions

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.

5. 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. 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. The test for TV tenure offers a p-value slightly below 10%. Still, the difference in the average TV tenure from group G2 (the lowest one) to group G0 (the highest one) is economically insignificant – a mere 12 days out of 77 months (0.5%). Detailed definitions of all the variables used in the paper are provided in table 11 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.

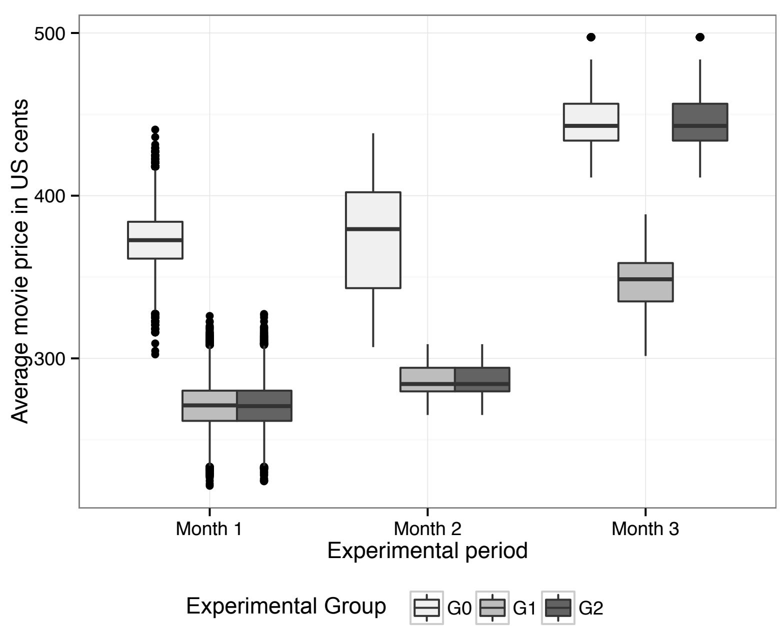

Figure 3 Average price of movies shown in the new menu to each group of households over time.

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.

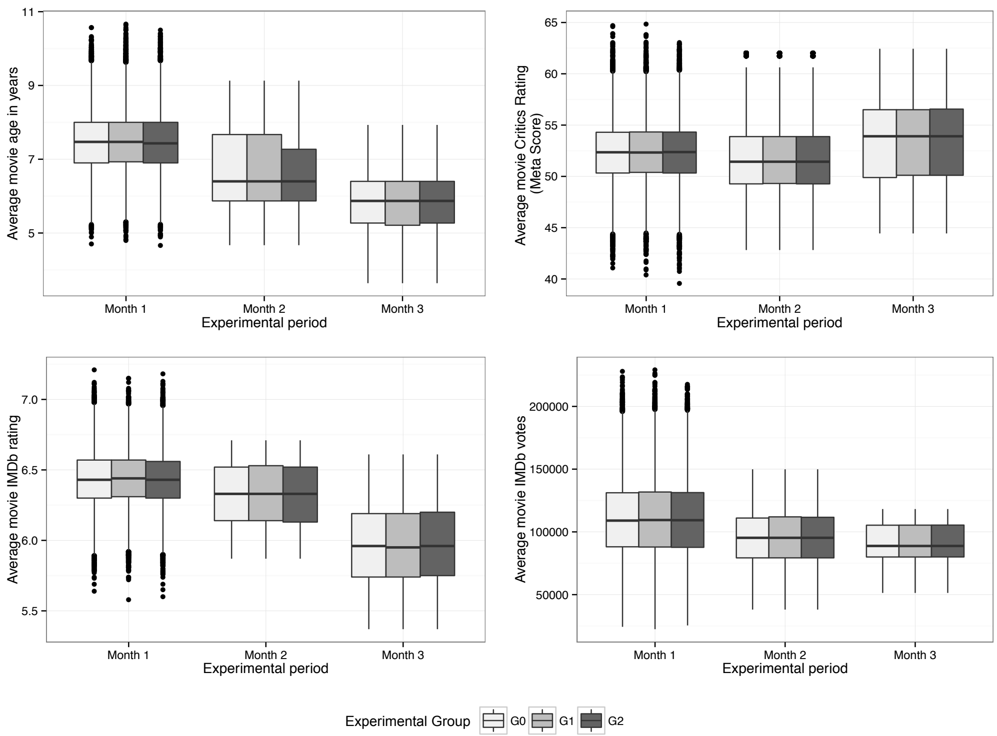

Figure 4 Characteristics of the movies shown in the new menu to each group of households over time.

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.

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			

Figure 5 shows the 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 for the percentage differences in leases to group $G0$. 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.

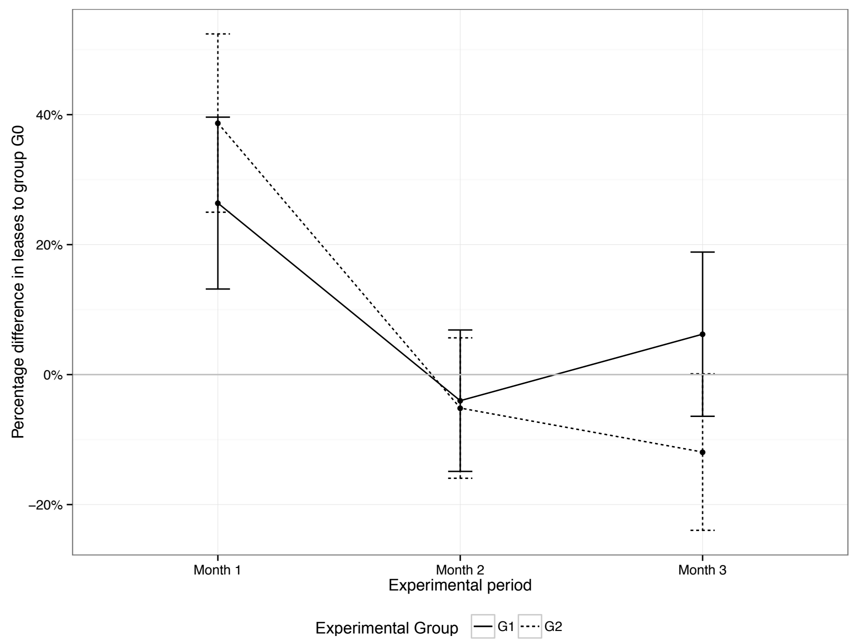

Figure 5 Differences in the sales of movies used in the experiment between groups $G1$ and $G0$ and between groups $G2$ and $G0$.

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		

6. The Effect of Price Promotions on VoD Sales

6.1. 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:

$$Y_{it} = \beta_0 + \beta_1 Promotions_{it} + d_t + u_{it} \tag{1}$$

where depending on the specification Y_{it} will represent the number of leases 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 – $Leases\_All_{it}$ – by household i during month t. $Promotions_{it}$ 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 to identify the effect of retracting price promotions to households in group $G2$ in the last month of the experiment. 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.

6.2. 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.

The framework introduced in section 3 can help us understand the average consumption of households in group G2 in the last month of the experiment. These households experienced usual prices before the experiment started and observe a decrease in the price of the movies offered under the "Good Opportunities" menu during the first two months of the experiment. Therefore, they decide to anticipate consumption to the first two months in the experiment, which translates to a decrease in consumption in the third month of the experiment. This effect is stronger when these households do not update their beliefs about future prices. When these households update their beliefs about future prices two other effects arise. On the one hand, they do not anticipate consumption as much because they believe that prices after the experiment will be higher than prices in the current period but still lower than the usual prices. On the other hand, when the prices they experience under the "Good Opportunities" menu go back to usual levels in the last month of the experiment they will believe that prices after the experiment will be lower than current prices and, therefore, will refrain from consuming as much.

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

7. Peer Influence in VoD Consumption

7.1. 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. For example, a household may lease more movies from the "Good Opportunities" menu when her friends do. A household may also lease more movies from other menus in the VoD system when her friends lease movies from the "Good Opportunities" menu. A household may also lease more movies overall – that is anywhere in the VoD system – when her friends lease movies from the "Good Opportunities" menu. A household may also 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. Unfortunately, our setting does not allow us to exactly pin-pointing the messages that households exchange with each other. Still, we can determine whether there is peer influence in the consumption of VoD movies, which requires some communication to occur. We measure the effect of peer influence among households in our setup by estimating a traditional peer effects reduced-form equation. 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 represented 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}. Furthermore, Table 6 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).

Therefore, we estimate ρ using 2SLS as follows:

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

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

Effectively, Table 6 shows our first stage results and that our instrumental variable is not weak in line with definitions in **?**. 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 envious when their friends watch a movie and will react by watching it too (recall the ideas around competitive and normative pressures introduced in section 2.2). However, recall that in our setup of personalized offers under the "Good Opportunities" menu the same movie is unlikely to have the same search costs to households that are friends. Therefore, some people may also feel envious 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. It may also happen that people invite friends over to watch movies. If people apportion a fixed amount of time to watch movies in this VoD system then it might be the case that they end up watching fewer movies on their own when they go watch a movie at their friends. This type of behavior is likely to contribute negatively to the effect of peer influence. We believe that our inability to empirically distinguish among all these micro-mechanisms that affect the effect of peer influence in our setting is not a significant limitation of our work because ultimately what the firm cares is the aggregate effect of peer influence and whether this is sufficiently strong to counter the negative effects of price promotions identified in section 6.

Table 6 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) OLS	Friend Leases (All) 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 ()	

7.2. Empirical Results

Column (1) in Table 7 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 households buy more of the movies elsewhere in the VoD system when her friends buy movies under the "Good Opportunities" menu. Column (3) shows that households buy more movies overall in the VoD system when her friends buy movies under the "Good Opportunities" menu. Finally, column (4) shows that households buy more movies overall in the VoD system when her friends buy movies overall in the VoD system. 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.

The result 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 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 and thus it might help the firm maintain the level of sales with price promotions if she can strategically use the effect of peer influence generated by offering movies under the "Good Opportunities" menu to her advantage.

Table 7 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 ()

7.3. 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). In all cases, the first stages work as expected, instruments are not weak and the second stages remain unchanged. These results are available upon request.

Table 8 shows results from a falsification test. Columns (1) and (2) replicate the results obtained in columns (3) and (4) of table 7 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 variables. We use exactly the same endogenous variables (that is 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). This falsification test shows that our instruments work appropriately, namely one household's 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 8 **Falsification test for peer influence on leases of VoD movies using leases before our experiment started for our dependent variables.**

	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 9 shows that our results remain unchanged when we do so, which provides some additional evidence that in fact 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. We acknowledge that we lose some statistical power in columns (2) and (4) but the effect of peer influence is still clearly positive in these cases. Furthermore, the coefficients for the effects of peer influence in this table are statistically similar to those reported in Table 7. Table 10 shows that the corresponding first stages work as expected with weighting.

8. Trade-off Between Peer Influence and Price Promotions

The previous sections show that on average households with access to movies at discounted prices under the "Good Opportunities" menu lease 11% 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 $\beta_d = 0.11$ and $\beta_{nd} = 3.3$ 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, perhaps, the firm might avoid

Table 9 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 10 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 ()

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 must depend on the average discount that the firm offers to households under the "Good Opportunity ' 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:

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

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.

We note that this result is sensitive to how many movies are purchased in the VoD system as consequence of the peer influence induced by price promotions. In this VoD system, and due to peer influence, a household buys 2.304 movies for every movie that her friends purchase under the "Good Opportunities" menu but the standard error associated to this estimate is 1.147. Therefore, the 95% confidence interval for this effect of peer influence ranges from 0.06 to 4.55. It is easy to show that the firm cannot break-even with an effect of peer influence of 0.06. With an average price discount of 25% and an average markup rate of 0.6, the lowest effect of peer influence that would allow the firm to break-even with price promotions is 1.01. Even so, in this case the firm would only break-even if it offered movies at discounted prices to households with more than 5,000 friends. However, in our social graph, households in the top quartile of the distribution of the number of friends are connected to 11 (or more) other households. For the average price discount of 25% a markup factor of 0.6, the firm would only break-even offering price promotions to households with more than 11 friends if the effect of peer influence is, at least, 1.45. This means that in practice, in our setting, price promotions are unprofitable for a significant part of the confidence interval for the effect of peer influence identified in table 7.

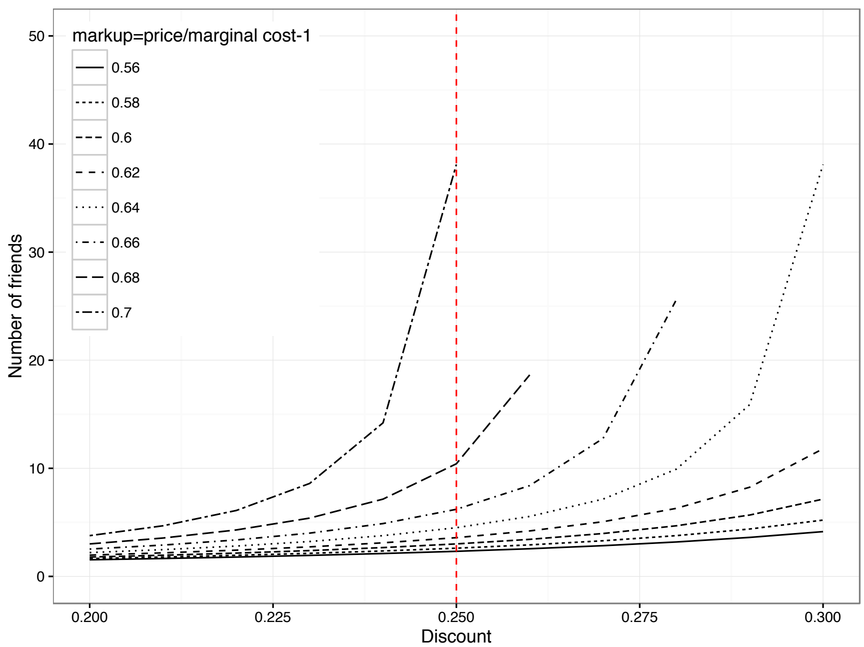

Figure 6 Number of friends that a targeted household must have for price promotions to yield profit break-even as a function of the price discount and of the markup factor.

9. Conclusions

Digitization has been shifting a significant portion of entertainment revenues towards hedonic non-storable goods such as streaming. However, there is still little research looking at the interplay between the effect of traditional marketing tools, such as price promotions, and the effect of peer influence in the consumption of this type of products. The previous literature in behavior economics and information system has been rich in producing models aimed at explaining how consumers adjust demand when prices change and stockpiling is available. In short, consumers trade-off the benefits from price reductions with the costs associated with storage and typically anticipate consumption but buy significantly less once price promotions are retracted, which may in turn hurt the long-term profitability of firms. However, the results from these models may not apply to the case of information goods that cannot be stored, such as Video-on-Demand (VoD) movies. In this paper, we explore a two-period model with two products in which consumers adjust beliefs about the price of one of the products in the second period once they observe the price of that product in the first period. We show that even without stockpiling consumers are likely to anticipate consumption during price promotions and buy less right after promotions are retracted potentially leading to a reduction in aggregate sales. Whether this happens depends on how quickly consumers anticipate demand, which is in part affected by how sharply they adjust their beliefs about future prices.

We test the predictions of this model using outcomes from an in-vivo organic randomized experiment ran at the VoD system of a large telecommunications provider. The experiment consisted in adding a new menu of movies – called "Good Opportunities" – to the highlights section of the VoD system of all households with a VoD enabled set-top-box for a period of three 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 VoD enabled 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 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. Furthermore, we find that households with price promotions bought fewer of the movies that were not offered to them at discounted prices during the experiment – contemporaneous and intertemporal substitution – and, overall, the firm sold fewer movies during the experiment compared to what would have happened if price promotions had not been introduced.

In the second part of this paper we identify the effect of peer influence in the consumption of VoD movies. Our goal was to know whether one household buys more VoD movies because her friends do and whether this effect could help the firm counter the negative effect of price promotions on VoD sales. Two VoD-enabled households are friends if people in one of them call people in the other one on their cell phones. We use a dataset of cell phone call detailed records provided by our industrial partner to infer a graph of social proximity across households.

We 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. While we cannot necessarily pinpoint the exact messages that friends exchange we can certainly show that there is peer influence in the consumption of movies in this VoD system.

We combine the effect of price promotions with the effect of peer influence and we 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 for the former two effects to cancel out. How many friends a household targeted with price promotions must have for the firm to break-even depends on the price discount offered by the firm on movies under the "Good Opportunities" menu and on the markup factor that the firm applies to VoD movies. The higher the price discount the more friends the targeted households must have for the firm to break-even. Conversely, for the markup factor. We show that our industrial partner can break-even if it strategically targets households with price promotions but this result is sensitive to the magnitude of the effect of peer influence. In particular, the firm is unlikely to break-even if the true effect of peer influence is closer to the bottom of the 95% confidence interval obtained for our estimates.

In sum, our paper shows how outcomes from a 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 strategy that firms can follow to issue price promotions in ways that allow them to minimize the undesirable losses in profit that arise from price promotions. Our analysis leads us to expect that in the long run firms that use social network information to shape promotional campaigns and determine target consumers are likely to perform better than competitors who do not.

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 are unable to identify the exact micro-mechanisms that might be at play in our setting that leads one household to lease movies when her friends do. A number of simultaneous effects might arise that we cannot empirically disentangle. Still, the firm cares with the aggregate effect of peer influence on sales so that it can test whether strategically offering price promotions to households allows for reaching profit break-even. Third, 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.

Finally, we note that research in peer influence over large social networks can further benefit from two major types of contributions. One is to study in more detail efficient designs for network-centric experiments, such as placing egos in treatment and control and, independently, placing their friends into treatment and control too. This type of design may result in a more robust setting to study the conditions under which peer influence arises. The other is to study in more detail how different messages affect peer influence, for example, by shaping the message that users exchange with their friends through carefully designed referral programs.

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Appendix. Variable definitions

Table 11 Variable Overview

Variable	Periodicity	Description
Household level:		
Leases (Exp)	Monthly	Number of leases from movies under the "Good Opportunities" menu
Leases (Not Exp)	Monthly	Number of leases from movies not under "Good Opportunities"
Leases (All)	Monthly	Number of leases in the entire VoD system
Past Leases (All)	Monthly	Number of leases before the experiment started (applies to January, February and March 2013)
Friend Leases (Exp)	Monthly	Number of leases by friends of movies under the "Good Opportunities" menu
Friend Leases (All)	Monthly	Number of leases by friends in the entire VoD system
Avg Friend Movie Age	Monthly	Average age of movies displayed in the experimental line of connected households
Promotions	Monthly	Whether a household has movies under the "Good Opportunities" menu with discounted prices
Degree	Once	Number of friends of a household in the social graph
Total Calls	Once	Total number of calls of a household in our CDR dataset
Has Contract ?	Once	Whether the household was in a lock in period when the experiment started
Electronic Receipt	Once	Whether the household had subscribed to electronic receipt when the experiment started
TV Tenure	Once	Number of months that the household had subscribed to TV service when the experiment started
G0	Once	Dummy variable $=1$ for households that were always offered movies at the usual prices in the "Good Opportunities" Menu
G1	Once	Dummy variable $=1$ for households that were always offered movies at discounted prices in the Good Opportunities Menu
G2	Once	Dummy variable $=1$ 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
IMDb Votes	Once	Number of IMDb votes
Release Year	Once	Year of release
Runtime (mins)	Once	Duration in minutes