Welfare Properties of Profit Maximizing Recommender Systems: Theory and Results from a Randomized Experiment

Recommender systems have been introduced to help consumers navigate large sets of alternatives. They usually lead to more sales, which may increase consumer surplus and firm profit. In this paper, we ask whether firms may hurt consumers when they choose which recommender systems to use. We use data from a large scale field experiment ran using the video-on-demand system of a large telecommunications provider to measure the price elasticity of demand for movies placed in salient and non-salient slots on the TV screen. During this experiment, the firm randomized the slots in which movies were recommended to consumers as well as their prices. This setting readily allows for identifying the effects of price and slot on demand and thus compute consumer surplus. We find empirical evidence that consumers are less price elastic towards movies placed in salient slots. Using the outcomes of this experiment we simulate how consumer surplus and welfare change when the firm implements several recommender system, namely one that maximizes profit. We show that this system hurts both consumer surplus and welfare relative to the systems designed to maximize the latter. We also show that, at least in our setting, the system that maximizes profit does not generate less consumer surplus than some recommender systems often used in practice, such as content-based, lists of most sold, most rated and highest rated products. Yet, how much extra rent the firm can extract from strategically placing movies in salient slots is still a function of the popularity and quality of movies used to do so. Ultimately, our results question whether recommender systems embed mechanisms that extract excessive surplus from consumers, which may call for better scrutiny.

Key words: recommender systems, profit maximization, welfare properties, randomized experiment

1. Introduction

Digitization increased significantly the number of products and services available to consumers. In this context, recommender systems became a pervasive tool to help navigate large catalogs. The very first implementations of these systems were aimed at maximizing matching using heuristics. For example, content-based recommender systems would suggest items similar to the ones that the consumers previously bought and collaborative filters would suggest items that bought by consumers with similar purchasing history. Several papers showed that the introduction of these systems allowed consumers to more easily find niche products extending and fattening the distribution of sales (Brynjolfsson et al. 2006, Anderson 2006). This effect has been empirically observed across industries, in particular in the case of experience goods (Dewan and Ramaprasad 2012, Oestreicher-Singer and Sundararajan 2010, Brynjolfsson et al. 2006, Tucker and Zhang 2007, 1
Elberse and Oberholzer-Gee 2007) and there is evidence that it increases the surplus of consumers (Brynjolfsson et al. 2003, 2010). Other works, using modeling and simulation, show that the effect of recommender systems on the distribution of sales depends essentially on how they manipulate product saliency (Fleder and Hosanagar 2009) and that the effect of these systems on consumer surplus and on welfare may be ambiguous (Choudhary and Zhang 2016, Fleder and Hosanagar 2009). Recommender systems may also affect consumer preferences through anchoring, which may hamper maximizing their surplus (Adomavicius et al. 2013).

The question of how recommender systems affect consumers becomes even more important as these systems mature and start allowing firms to introduce elements of profit maximization into the original implementations (Jannach and Adomavicius 2017). Today, firms use the suggestions from content-based and collaborative filtering recommender systems to predetermine sets of items that are highly relevant to consumers but then order them in ways that may maximize profit (Das et al. 2009) as well as ensure some level of consumer trust leading to repeated purchases. However, little is known about the welfare properties of these profit-aware recommender systems. This is not surprising because instantiating such a system requires firms to know the demand curve for their products. A firm that does not know this curve is likely to simply order suggestions to consumers in decreasing order of similarity, which is a rule of thumb often used in practice believed to work well in practice. A firm that knows the demand curve may instead use similarity measures to identify products that are likely to align with the preferences of consumers, and thus help maintain trust, and then use the demand curve to reorder suggestions to maximize profit. Our paper starts by introducing an analytical model showing conditions under which recommending items to consumers to maximize profits hurts the surplus of the latter. We then show how a firm can use a randomized control trial to econometrically identify the demand curve and, finally, we show what happens to the profit of the firm and to the surplus of consumers when the firm uses this knowledge strategically.

We estimate the demand curve for movies, which is an experience good, in the Video-on-Demand (VoD) system of a large telecommunications provider and simulate the behavior of consumers when they face suggestions from different types of recommender systems. We are primarily interested in comparing the consumer surplus obtained by the recommender system that maximizes the profit of the firm and that obtained by the recommender system that maximizes consumer surplus in order to learn whether they are different and if so by how much. We design, implement and analyze outcomes from a randomized field experiment with more than 600 thousand households over a period of half a year. We identify the price elasticity of demand in this setting, which is the parameter of interest that shapes the demand curve allowing us later to compute the appropriate counterfactuals for welfare analysis. Recommender systems operate by manipulating the saliency across products.
They highlight some products making others relatively more hidden. Therefore, in our context, we model the demand for a movie as a function of price and saliency. Specifically, saliency is associated to the slot in which movies are shown to consumers on their TV screen. People in the country that we study read from left to right and, therefore, placing movies towards the left of the TV screen primes consumers to pay more attention to them. We randomize independently both the slot and the price of each and every movie suggested to consumers during our experiment, which allows us to identify the price elasticity of demand for movies placed in salient and non-salient slots. We show empirical evidence that, in our setting, consumers exhibit a lower price elasticity of demand for movies placed in the slots towards the left of the TV screen (irrespective of the movies placed in these slots). These movies are highlighted to consumers and, as a consequence, consumers are more tolerant when their prices increase. Then, different recommender systems, operationalized by manipulating differently the slots where movies are shown to consumers, yield different levels of sales, profits and consumer surplus that we compare using simulation.

The difference in the price elasticity of demand between movies placed in slots towards the left and towards the right of the TV screen allows the firm to extract surplus from consumers. We show that under certain conditions this difference leads the firm to suggest movies to consumers to maximize profit in a way that is different from the way that consumers would like to receive recommendations in order to maximize consumer surplus. In our setting, and on average across our simulations, the consumer surplus generated by the recommender system that maximizes profit is 8.44% lower than the consumer surplus that would be attained by the recommender system that would maximize consumer surplus. Total welfare may also reduce when the firm maximizes profit. Across our simulations, and on average, when the firm maximizes profit welfare reduces 2.07% relative to the welfare that would be attained by the recommender system that would maximize welfare. We also show that for certain subsets of movies used during our experiment, these losses can be as high as 28.7% and 12.2%, respectively for consumer surplus and welfare. We also study what may happen when consumers interact repeatedly with the recommender system. We discuss that by how much recommender systems hurt consumer surplus is, in part, determined by whether or not consumers realize that sometimes they are suggested “second best” products. How exactly this occurs in real world settings is still an open question. For example, only by incurring in additional search costs can consumers know whether there are better products for them. However, not only those that search further become a self-selected sample, but also when they do so their surplus is already reduced due to the additional search costs. Firms may also use consumer feedback, such as number of likes and reviews, to learn more about consumer enjoyment, but again such signals are noisy, scant and come from self-selected samples of consumers. Finally, we also provide empirical evidence that in our setting consumers exhibit a lower price elasticity of demand towards the movies
placed in salient slots immediately after the experiment started and that this effect reduces over time. Therefore, in our setting, consumers seem to be able to learn how to discern good movies from bad movies that are placed in salient slots by our exogenous manipulations.

We expect that our measurements of the welfare inefficiency associated to profit-aware recommender systems will trigger additional research on this subject, and in particular research aimed at understanding the relative magnitude of these losses vis-a-vis those introduced by other mechanisms that firms typically use to extract surplus from consumers, such as price discrimination. This type of research is also likely to inform us better about whether recommender systems need scrutiny to protect consumers. The remainder of our paper is then organized as follows. Section 2 provides a review of the relevant literature and positions our work vis-a-vis the current knowledge. Section 3 introduces a theoretical model for demand and shows conditions under which firms recommend products to consumers in ways that hurt consumer surplus and welfare. Section 4 describes our empirical context and our experiment. Section 5 introduces our empirical strategy. Section 6 presents our results and section 7 concludes.

2. Literature Review
Digitization changed many industries by lowering production, distribution and consumption costs (Bakos 1997). This reduction in costs allowed for an unprecedented increase in product availability and variety, which is likely to attract more consumers (Brynjolfsson et al. 2003, Anderson 2006, Clemons et al. 2006). However, large sets of alternatives might increase search costs disproportionately, which may have a significant adverse impact on consumer welfare (Stigler 1961). Under some conditions, more alternatives may even lead to less choice (Kuksov and Villas-Boas 2010).

Digital recommender systems have been introduced to help consumers navigate these large sets of alternatives (Resnick and Varian 1997). At their core, these systems change product saliency. They highlight some products to consumers at the expense of others that become relatively more hidden. The early works in recommender systems have shown that, in general, these systems allow consumers to more easily find niche products online, which reduces the concentration of sales Brynjolfsson et al. (2011).

However, and ultimately, what happens to the distribution of sales depends heavily on how recommender systems affect product saliency. For example, content-based recommender systems, which increase the saliency of products similar to the products that consumers have already purchased in the past, tend to reduce the concentration of sales. Several authors find empirical evidence of this fact. For example, Oestreicher-Singer and Sundararajan (2010) find empirical evidence of this effect at Amazon’s bookstore. Tucker and Zhang (2007) provide empirical evidence of this fact in the context of wedding service vendors. Elberse and Oberholzer-Gee (2007) find that the demand
for niche home video products increased in US. Chellappa et al. (2007) discuss similar findings in music sales and Dewan and Ramaprasad (2012) show how in the music industry the shift towards niche songs arises due to the increased ability to sample. More recently, Fleder and Hosanagar (2009) show that collaborative-filtering recommender systems, which increase the saliency of the products bought by similar consumers, may instead increase the concentration of sales because they disproportionally recommend the most popular products. Self-reinforcing mechanisms that increase the popularity of already popular artists leading to a super-star effect have been proposed by Rosen (1981) and Frank and Cook (1995) and empirically observed, for example, in Salganik and Watts (2008). For in-depth reviews of the types of recommender systems currently available and how they work please refer to (Breese et al. 1998, Adomavicius and Tuzhilin 2005).

Knowing how the introduction of recommender systems changes the distribution of sales is useful from a managerial point of view, in particular for inventory management and contract negotiation. However, this tells us little about changes in the profit of firms or in consumer welfare. Brynjolfsson et al. (2003, 2010) provide some evidence that the long-tail effect at Amazon’s bookstore increased consumer surplus. However, and resorting to theoretical work, (Choudhary and Zhang 2016) show how the accurateness of the recommender system may both increase and decrease consumer surplus. Along the same lines, and resorting to simulation, Fleder and Hosanagar (2009) show that the effect of recommender systems on welfare is hard to anticipate. On the one hand, recommender systems help consumers find products that may better match their preferences, which were hard to find before. This is likely to increase consumer surplus. On the other hand, recommender systems may also lead consumers to purchasing products that otherwise they would not want. For example, (Adomavicius et al. 2013) show that ratings presented by recommender systems affect consumer preferences through anchoring. Furthermore, the authors also show that the effect of anchoring is stronger for the recommender systems that seem more reliable. All these biases may reduce consumer surplus and, overall, the effect of recommender systems on welfare is ambiguous. In more recent work, Hosanagar et al. (2014) study the impact of recommender systems on consumer fragmentation. The authors study consumer fragmentation because it may affect welfare. In particular, fragmentation may hamper the benefits associated to externalities because there is less information about products when fewer consumers buy them. This aspect may be very important in the case of experience goods, in which consumers tend to ask friends for information and opinions before purchase (Nelson 1970). The authors find that recommender systems do not seem to fragment consumers in the music industry because personalization not only tends to suggest a more similar mix of products over time but also leads consumers to buy more.

The prior literature focused on whether saliency changes the likelihood of purchase given price. For example, Salganik et al. (2006) created two virtual markets for songs from unknown bands and
randomly assigned subjects to one of these markets. Songs were ordered randomly in one of the markets and ordered according to the number of downloads in the other market. The authors found that reported popularity was self-reinforcing for all but the very best or worst songs. In a follow-up study, the same authors ran a similar experiment Salganik and Watts (2008). In the setup phase, they asked participants to listen to the songs and rate them. Then they ordered songs according to these ratings so that better songs would come last and thus seem worse. They observed that, over time, all songs (good or bad) tended to converge to their true download rank. Taken together, these studies showed that priming in these markets is constrained by the individual’s private preferences, that is, there are limitations to how much firms can prime consumers to purchase experience goods. More important, these studies look at how saliency shapes consumer behavior, but no prices were involved. The subjects could download songs for free, which hampers the generalization of results to real world settings.

More recently, Muchnik et al. (2013) examined the behavior of consumers in a social news aggregator website. In one treatment condition, users saw a positive vote on a comment; in another treatment condition, they saw a negative vote; and in the control condition no manipulation was introduced. The authors found that the probability of an “up vote” was much higher when users initially saw a positive vote than in the control condition, which suggests a priming effect, but they found no statistically significant effect when users saw a negative vote. Therefore, they concluded that priming effects are asymmetric: users seem to exhibit a desire to correct negative bias but otherwise follow the herd. Again, this is an example in which the researchers manipulated saliency, but no prices were involved, which limits the ability to learn how priming can actually be used in a profit maximizing context. In a setting closer to ours, Godinho de Matos et al. (2016) partner with a large telecommunications company to analyze the impact of peer ratings in a real-world VoD market. After experimentally changing the number of likes displayed to consumers, the authors found that likes influence consumer behavior independently from the underlying product quality. However, they also found little evidence of long-term bias as a result of priming effects, at least in their setting. Specifically, when movies were artificially promoted or demoted in peer rating lists, subsequent likes cause them to return to their true quality position relatively quickly. Again, this is an example in which the authors manipulate saliency but leave prices untouched, and thus they could not appreciate how saliency and prices tradeoff, which eventually prevented them from discussing how firms can strategically manipulate saliency to increase profits and how such behavior may hurt consumers.

The prior literature has also established that humans are not perfect at maximizing their welfare. They make mistakes when making decisions and are primed to make certain types of decisions that might not always enhance their welfare. In particular, the way messages are framed and how
they are delivered to individuals makes a difference. As a consequence, firms may use messages to strategically take advantage of the inefficiencies associated to consumer choice Richard H. Thaler (2008), Thaler and Sunstein (2003). This line of research is concerned with the design of specific nudges that steer consumer behavior. Recommender systems are a specific type of nudge. They affect the search cost of the recommended products Pathak et al. (2010) and affect individual ex-ante expectations about the ex-post enjoyment from consuming the recommended products. The fundamental contribution of our work relative to all these studies is to link saliency to the price elasticity of demand, which provides us with a clear measure of how priming consumers changes their willingness to pay, and, from there, how priming affects their well-being across several recommender systems.

Finally, our work is also related to the prior literature in marketing looking at how price and non-price oriented advertising affect the sensitivity of consumers. Kaul and Wittink (1995) show results from a meta-analysis concluding that retail-oriented price advertising tends to increase price sensitivity whereas non-price advertising tends to decrease price sensitivity. As we will see below, this comes in line with our finding that strategically positioning movies in salient slots reduces price elasticity irrespective of price. Kalra and Goodstein (1998) show that such an aggregate meta-analysis hides a number of complex effects that may move price elasticity in different directions. For example, effects may be heterogeneous with respect to the brands’ baseline market shares. Mitra and Lynch (1995) note that some researchers argue that advertising decreases price elasticity because it enhances market power, while other researchers argue the opposite because advertising provides more information about substitutes. The authors provide a framework to reconcile these findings and hypothesize that advertising affects price elasticity through two mechanisms – the size of the consideration set and the relative strength of consumer preferences. On the one hand, advertising enlarges the consideration set leading consumers to consider more substitutes, which increases price elasticity. On the other hand, advertising provides additional information about the products allowing consumers to reduce uncertainty and to decisively prefer specific products for which they may be willing to pay more, thus reducing the price elasticity of demand. In our setting, the former mechanism is unlikely to be at play. All consumers saw the same number of movies under the new menu that was introduced during our experiment. Furthermore, all such movies were similar to each other. Our paper shows that placing movies in salient slots, that is, increasing their advertising, hooks up consumers to them reducing price elasticity, thus a result that comes in line with the second mechanism described in Mitra and Lynch (1995).
3. Theoretical Model

3.1. Setup

Consider a representative consumer, two products indexed by \( j \), called H and L, and two slots, a salient slot and a non-salient slot, where these products will be placed by a monopolistic firm. Let \( d_j \) represent the demand for product \( j \) and let \( s_j \) represent whether product \( j \) is placed in the salient slot. We have \((s_H, s_L) \in \{(0, 1); (1, 0)\}\). Let \( p_j \) represent the price of product \( j \) and define

\[
d_j(p_j; s_j) = p_j^{\beta_0 + \beta_1 s_j}
\]

This standard log-linear functional form is commonly used in the literature to specify the demand for digital goods, such as in the seminal work by (Brynjolfsson et al. 2003). The elasticity of demand for the product placed in the non-salient slot is \( \beta_0 \) and the elasticity of demand for the product placed in the salient slot is \( \beta_0 + \beta_1 \). Without loss of generality, let \( \beta_1 > 0 \). This entails that consumers are less price elastic with respect to products placed in the salient slot. Let \( c_H \) and \( c_L \) represent the marginal cost of products H and L, respectively. Without loss of generality, let \( 0 < c_L < c_H \). Let \( m_j = p_j(s_j) - c_j \) represent the margin associated to product \( j \). In this setup, the profit of the firm and the consumer surplus are given by

\[
\Pi(p_H, p_L; s_H, s_L) = \sum_{j=H,L} d_j(p_j; s_j)(p_j(s_j) - c_j) = \sum_{j=H,L} m_j p_j^{\beta_0 + \beta_1 s_j}
\]

\[
CS(p_H, p_L; s_H, s_L) = \sum_{j=H,L} \int_{p_j}^{+\infty} d_j(p, s_j)dp = \sum_{j=H,L} -\frac{p_j^{1+\beta_0 + \beta_1 s_j}}{1 + \beta_0 + \beta_1 s_j}
\]

3.2. Profit Maximization

For sake of simplicity assume price elasticities of demand less than \(-1\), that is, \( 1 + \beta_0 < 0 \) and \( 1 + \beta_0 + \beta_1 < 0 \). Given an allocation of products to slots the firm sets prices to maximize total profit, which yields

\[
p_j^*(s_j) = c_j \frac{\beta_0 + \beta_1 s_j}{1 + \beta_0 + \beta_1 s_j}, m_j^*(s_j) = -c_j \frac{1}{1 + \beta_0 + \beta_1 s_j}
\]

Note that in this setup, conditional on slot, the product with a higher cost yields a higher margin. The following profit arises for each allocation of products to slots:

\[
\Pi(p_H^*, p_L^*; s_H = 1, s_L = 0) = -\frac{(\beta_0 + \beta_1)\beta_0 + \beta_1}{(1 + \beta_0 + \beta_1)^{1+\beta_0 + \beta_1}} c_H^{1+\beta_0 + \beta_1} - \frac{\beta_0^0}{(1 + \beta_0)^{1+\beta_0}} c_L^{1+\beta_0}
\]
\[
\Pi(p_H^*, p_L^*; s_H = 0, s_L = 1) = -\frac{(\beta_0 + \beta_1)^{\beta_0 + \beta_1}}{(1 + \beta_0 + \beta_1)^{1+\beta_0+\beta_1}} c_L^{1+\beta_0+\beta_1} - \frac{\beta_0^{\beta_0}}{(1 + \beta_0)^{1+\beta_0}} c_H^{1+\beta_0}
\]

This leads to our first result:

**RESULT 1**: The firm places the product with the highest cost in the salient slot if both costs are lower than a threshold \( F \), i.e. if \( c_H < F \), with

\[
F = \frac{1 + \beta_0 + \beta_1}{\beta_0 + \beta_1} \left[ \frac{\beta_0 (1 + \beta_0 + \beta_1)}{(1 + \beta_0)(\beta_0 + \beta_1)} \right]^\frac{\beta_0}{\beta_1}
\]

**PROOF:**

\[
\Pi(p_H^*, p_L^*; s_H = 1, s_L = 0) - \Pi(p_H^*, p_L^*; s_H = 0, s_L = 1) = f(c_H) - f(c_L)
\]

\[
f(c) = -\frac{(\beta_0 + \beta_1)^{\beta_0 + \beta_1}}{(1 + \beta_0 + \beta_1)^{1+\beta_0+\beta_1}} c^{1+\beta_0+\beta_1} + \frac{\beta_0^{\beta_0}}{(1 + \beta_0)^{1+\beta_0}} c^{1+\beta_0}
\]

\[
f'(c) = -\left( \frac{\beta_0 + \beta_1}{1 + \beta_0 + \beta_1} \right)^{\beta_0 + \beta_1} c^{\beta_0} \left[ c^{\beta_1} - \left( \frac{1 + \beta_0 + \beta_1}{\beta_0 + \beta_1} \right)^{\beta_0 + \beta_1} \left( \frac{\beta_0}{1 + \beta_0} \right)^{\beta_0} \right]
\]

Therefore, \( f(\cdot) \) is increasing when \( c < F \) and decreasing otherwise. Consequently, \( f(c_H) > f(c_L) \) when \( c_H < F \). Thus, in this case, \( \Pi(p_H^*, p_L^*; s_H = 1, s_L = 0) > \Pi(p_H^*, p_L^*; s_H = 0, s_L = 1) \) and the firm places the product with the highest cost in the salient slot. Similarly, the firm places the product with lower cost in the salient slot when \( c_L > F \).

The intuition behind this result is as follows: \( f(c) \) can be interpreted as the extra profit originated from promoting a product with cost \( c \) from the non-salient slot to the salient slot, ceteris paribus. In other words, \( f(c) \) is the difference between the product-level profit curve in the salient slot and the product-level profit curve in the non-salient slot for the same product. This function has a maximum at \( F \), meaning that a (hypothetical) product with cost \( F \) would be the best product to promote to the salient slot. This is the product for which the difference in profits between being in the salient slot and in the non-salient slot is maximized, ceteris paribus. Note that whenever
a product is promoted to the salient slot another product needs to be demoted. In any case, promoting (demoting) any other product with a cost different than $F$ to (from) the salient slot has a lower impact on profit. Therefore, the best strategy for the firm is to place the product with cost closest to $F$ in the salient slot: when the cost of both products is lower than $F$, then the product with highest cost (closest to $F$) should be placed in the salient slot; when the cost of both products is higher than $F$, the product with lowest cost (closest to $F$) should be placed in the salient slot. More information would be required to determine the best configuration when $F$ is higher than the cost of one product but lower than the cost of the other product.

The result below relates the gain in profit from profit maximization with $\beta_1$:

**RESULT 2:** The gain in profit when profit is maximized increases with $\beta_1$.

**PROOF:**

\[
\Delta \Pi = - \left[ \frac{(\beta_0 + \beta_1)^{\beta_0 + \beta_1}}{(1 + \beta_0 + \beta_1)^{1 + \beta_0 + \beta_1}} c_H^{1 + \beta_0 + \beta_1} + \frac{\beta_0^{\beta_0}}{(1 + \beta_0)^{1 + \beta_0}} c_L^{1 + \beta_0} \right] \\
+ \left[ \frac{(\beta_0 + \beta_1)^{\beta_0 + \beta_1}}{(1 + \beta_0 + \beta_1)^{1 + \beta_0 + \beta_1}} c_L^{1 + \beta_0 + \beta_1} + \frac{\beta_0^{\beta_0}}{(1 + \beta_0)^{1 + \beta_0}} c_H^{1 + \beta_0} \right] \\
\]

\[
\frac{\partial \Delta \Pi}{\partial \beta_1} = - \frac{(\beta_0 + \beta_1)^{\beta_0 + \beta_1}}{(1 + \beta_0 + \beta_1)^{1 + \beta_0 + \beta_1}} \left[ r(c_L) - r(c_H) \right] \\
\]

\[
r(c) = \left[ \log \left( \frac{\beta_0 + \beta_1}{1 + \beta_0 + \beta_1} \right) + \log(c) \right] c^{1 + \beta_0 + \beta_1} \\
\]

\[
r'(c) = \left[ \log \left( \frac{\beta_0 + \beta_1}{1 + \beta_0 + \beta_1} \right) + \frac{1}{1 + \beta_0 + \beta_1} + \log(c) \right] (1 + \beta_0 + \beta_1)c^{\beta_0 + \beta_1} \\
\]

\[
1 + \beta_0 + \beta_1 < 0, - \frac{(\beta_0 + \beta_1)^{\beta_0 + \beta_1}}{(1 + \beta_0 + \beta_1)^{1 + \beta_0 + \beta_1}} > 0 \\
\]

Appendix 9.1 shows that $r'(c) > 0$ in the region of conflict. Therefore, $r(c_L) > r(c_H)$, which immediately results in the fact that $\Delta \Pi$ increases with $\beta_1$. 
3.3. Effect on Consumer Surplus

The following consumer surplus arises when the firm maximizes profit:

\[ CS(p^*_H, p^*_L; s_H = 1, s_L = 0) = -\frac{(\beta_0 + \beta_1)^{1+\beta_0+\beta_1}}{(1 + \beta_0 + \beta_1)^{2+\beta_0+\beta_1}}c_H^{1+\beta_0+\beta_1} - \frac{\beta_0^{1+\beta_0}}{(1 + \beta_0)^{2+\beta_0}}c_L^{1+\beta_0} \]

\[ CS(p^*_H, p^*_L; s_H = 0, s_L = 1) = -\frac{(\beta_0 + \beta_1)^{1+\beta_0+\beta_1}}{(1 + \beta_0 + \beta_1)^{2+\beta_0+\beta_1}}c_L^{1+\beta_0+\beta_1} - \frac{\beta_0^{1+\beta_0}}{(1 + \beta_0)^{2+\beta_0}}c_H^{1+\beta_0} \]

This leads to our third result:

**RESULT 3:** The consumer surplus is maximized when the firm places the product with the highest cost in the non-salient slot if \( c_L > G \) with

\[ G = \frac{1 + \beta_0 + \beta_1}{\beta_0 + \beta_1} \left[ \frac{\beta_0(1 + \beta_0 + \beta_1)}{(1 + \beta_0)(\beta_0 + \beta_1)} \right]^{1+\beta_0} \]

**PROOF:**

\[ CS(p^*_H, p^*_L; s_H = 1, s_L = 0) - CS(p^*_H, p^*_L; s_H = 0, s_L = 1) = g(c_H) - g(c_L) \]

\[ g(c) = -\frac{(\beta_0 + \beta_1)^{1+\beta_0+\beta_1}}{(1 + \beta_0 + \beta_1)^{2+\beta_0+\beta_1}}c^{1+\beta_0+\beta_1} + \frac{\beta_0^{1+\beta_0}}{(1 + \beta_0)^{2+\beta_0}}c^{1+\beta_0} \]

\[ g'(c) = -\frac{(\beta_0 + \beta_1)^{1+\beta_0+\beta_1}}{(1 + \beta_0 + \beta_1)^{2+\beta_0+\beta_1}}c^{\beta_0} \left[ c^{\beta_1} - \frac{\beta_0(1 + \beta_0 + \beta_1)}{(1 + \beta_0)(\beta_0 + \beta_1)} \right]^{1+\beta_0} \left( \frac{1 + \beta_0 + \beta_1}{\beta_0 + \beta_1} \right)^{\beta_1} \]

Therefore, \( g(c) \) is increasing when \( c < G \) and decreasing otherwise. Consequently, \( g(c_H) > g(c_L) \) when \( c_L > G \). Thus, in this case, \( CS(p^*_H, p^*_L; s_H = 0, s_L = 1) > CS(p^*_H, p^*_L; s_H = 1, s_L = 0) \) and consumer surplus is maximized when the firm places the product with the lowest cost in the salient slot. Similarly, consumer surplus is maximized when the firm places the product with highest cost in the salient slot when \( c_H < G \).
The intuition behind this result is analogous to that behind Result 1: \( g(c) \) can be interpreted as the additional consumer surplus originated from promoting a product with cost \( c \) from the non-salient slot to the salient slot, ceteris paribus. Like in the case of Result 1, \( G \) corresponds to the cost of the product that maximizes the difference in consumer surplus generated by placing that product in the salient slot and placing it in the non-salient slot. Thus, the strategy that maximizes consumer surplus places the product with cost closest to \( G \) in the salient slot.

Combining Result 1 and Result 3 leads to the following result:

**RESULT 4:** The allocation of products to slots that maximizes profit does not maximize consumer surplus when \( G < c_L < c_H < F \).

**PROOF:** It suffices to show that \( F > G \), which follows immediately from the fact that

\[
G = F \left[ \frac{\beta_0(1 + \beta_0 + \beta_1)}{(1 + \beta_0)(\beta_0 + \beta_1)} \right]^{\frac{1}{\beta_1}}, \beta_1 > 0, 1 + \beta_0 < 0, 1 + \beta_0 + \beta_1 < 0
\]

Result 4 shows that when the cost of the products fall in the \((G, F)\) region a conflict arises between the way that the firm recommends products to maximize profits and the way in which consumers would like to be recommended products to maximize consumer surplus. Figure 1 illustrates this conflict. Within the shaded area maximizing profit requires placing the product with the highest cost in the salient slot, while maximizing consumer surplus requires placing the product with the lowest cost in this slot. Outside this area there is no conflict – placing the product with the highest cost in the salient slot maximizes both profit and consumer surplus when costs are lower than \( G \), and placing the product with the lowest cost in this slot maximizes both profit and consumer surplus when costs are higher than \( F \).

It is clear that no conflict arises when \( \beta_1 = 0 \) because in this case both slots are similar. The results that follow relate the size of the conflict region and the magnitude of the loss in consumer surplus with the difference in the price elasticity of demand between slots.

**RESULT 5:** The size of the conflict region for consumer surplus increases with \( \beta_1 \).

**PROOF:** We want to show that \( \frac{\partial F}{\partial \beta_1} > 0 \) and \( \frac{\partial G}{\partial \beta_1} < 0 \).

\[
\frac{\partial \log(F)}{\partial \beta_1} = \frac{\beta_0}{\beta_1} (\log(1 + x) - x), x = \frac{\beta_1}{\beta_0(1 + \beta_0 + \beta_1)} > 0
\]
Figure 1 Illustration of the conflict between the maximization of profit and the maximization of consumer surplus. The extra profit earned by the firm from maximizing profit, compared to the recommender system that maximizes consumer surplus, is given by \( f(C_H) - f(C_L) \). The corresponding loss in consumer surplus is given by \( g(C_H) - g(C_L) \).

\[
\log(1+0) - 0 = 0, \quad \frac{\partial \log(1+x) - x}{\partial x} = \frac{1}{1+x} - 1 < 0, \forall x > 0 \\
\log(1+x) - x < 0, \forall x > 0, \quad \frac{\partial \log(F)}{\partial \beta_1} > 0 \\
\frac{\partial \log(G)}{\partial \beta_1} = -\frac{1 + \beta_0}{\beta_1} (x + \log(1-x)), \quad x = \frac{\beta_1}{(1 + \beta_0)(\beta_0 + \beta_1)} > 0 \\
0 + \log(1 - 0) = 0, \quad \frac{\partial x + \log(1-x)}{\partial x} = 1 - \frac{1}{1-x} < 0, \forall 1 > x > 0 \\
\quad x + \log(1-x) < 0, \forall 1 > x > 0, \quad \frac{\partial \log(G)}{\partial \beta_1} < 0
\]

**RESULT 6:** The loss in consumer surplus when profit is maximized increases with \( \beta_1 \).

**PROOF:**
\[ \Delta CS = -\left\{ \frac{(\beta_0 + \beta_1)^{1+\beta_0+\beta_1}}{(1 + \beta_0 + \beta_1)^2 + \beta_0 + \beta_1} c_L^{1+\beta_0+\beta_1} + \frac{\beta_0^{1+\beta_0}}{(1 + \beta_0)^2 + \beta_0} c_L^{1+\beta_0} \right\} + \frac{\beta_0^{1+\beta_0}}{(1 + \beta_0)^2 + \beta_0} c_H^{1+\beta_0+\beta_1} + \frac{\beta_0^{1+\beta_0}}{(1 + \beta_0)^2 + \beta_0} c_L^{1+\beta_0} \]

\[ \frac{\partial \Delta CS}{\partial \beta_1} = -\frac{(\beta_0 + \beta_1)^{1+\beta_0+\beta_1}}{(1 + \beta_0 + \beta_1)^2 + \beta_0 + \beta_1} [s(c_L) - s(c_H)] \]

\[ s(c) = \log\left(\frac{\beta_0 + \beta_1}{1 + \beta_0 + \beta_1}\right) + \frac{1}{1 + \beta_0 + \beta_1} + \log(c) \left\{ c^{1+\beta_0+\beta_1} \right\} \]

\[ s'(c) = \log\left(\frac{\beta_0 + \beta_1}{1 + \beta_0 + \beta_1}\right) + \frac{1}{\beta_0 + \beta_1} + \log(c) \left\{ (1 + \beta_0 + \beta_1) c^{\beta_0+\beta_1} \right\} \]

\[ 1 + \beta_0 + \beta_1 < 0, \quad -\frac{(\beta_0 + \beta_1)^{1+\beta_0+\beta_1}}{(1 + \beta_0 + \beta_1)^2 + \beta_0 + \beta_1} > 0 \]

Appendix 9.1 shows that \( s'(c) < 0 \) in the region of conflict. Therefore, \( s(c_L) > s(c_H) \), from which the result follows immediately.

The previous results show the nuclear role that \( \beta_1 \) plays in our setting. \( \beta_1 \) measures the difference in the price elasticity of demand across slots in the recommender system and it is the reason why conflicts arise between the firm and consumers with respect to how recommendations should be issued. Furthermore, the larger this difference the more likely conflicts are to arise and the larger they are in magnitude. In sum, \( \beta_1 \) embodies the mechanism by which conflicts arise and thus our empirical application later in this paper will be used to identify this parameter.

### 3.4. Effect on Total Welfare

Define total welfare as the sum of consumer surplus and profits, that is, \( W(p_H^*, p_L^*; s_H, s_L) = \Pi(p_H^*, p_L^*; s_H, s_L) + CS(p_H^*, p_L^*; s_H, s_L) \). The following results follow:

**RESULT 7:** Total welfare is maximized when the firm places the product with the highest cost in the non-salient slot when \( c_L > H \) with

\[ H = \left[ \frac{1 + 2\beta_0}{(1 + \beta_0)(1 + 2\beta_0 + 2\beta_1)} \right] \left[ \frac{\beta_0 (1 + \beta_0 + \beta_1) \frac{\beta_0}{\beta_0 + \beta_1} (1 + \beta_0 + \beta_1)}{(1 + \beta_0)(\beta_0 + \beta_1)} \right] \]
\textbf{PROOF:}

\[
W(p_H^*, p_L^*; s_H = 1, s_L = 0) - W(p_H^*, p_L^*; s_H = 0, s_L = 1) = h(c_H) - h(c_L), h(c) = f(c) + g(c)
\]

\[
h'(c) = - \frac{1 + 2\beta_0 + 2\beta_1}{1 + \beta_0 + \beta_1} \left( \frac{\beta_0 + \beta_1}{1 + \beta_0 + \beta_1} \right)^{\beta_0 + \beta_1} c^{\beta_0}.
\]

\[
\left[ c^{\beta_1} - \frac{(1 + 2\beta_0)(1 + \beta_0 + \beta_1)}{(1 + \beta_0)(1 + 2\beta_0 + 2\beta_1)} \right] \left[ \frac{\beta_0(1 + \beta_0 + \beta_1)}{(1 + \beta_0 + \beta_1)} \right]^{\beta_0} \left( \frac{1 + \beta_0 + \beta_1}{\beta_0 + \beta_1} \right)^{\beta_1} = 0.
\]

Therefore, \( h(c) \) is increasing when \( c < H \) and decreasing otherwise. Consequently, \( h(c_H) > h(c_L) \) when \( c_L > H \). Thus, in this case, \( W(p_H^*, p_L^*; s_H = 1, s_L = 0) > W(p_H^*, p_L^*; s_H = 0, s_L = 1) \) and total welfare is maximized when the firm places the product with the lowest cost in the salient slot. Similarly, welfare is maximized when the firm places the product with lowest cost in the salient slot when \( c_H < H \).

\textbf{RESULT 8:} The allocation of products to slots that maximizes profit does not maximize total welfare when \( F > c_H > c_L > H \).

\textbf{PROOF:} It suffices to show that \( F > H \), which follows immediately from the fact that

\[
F = F \left[ \frac{(1 + 2\beta_0)(1 + \beta_0 + \beta_1)}{(1 + \beta_0)(1 + 2\beta_0 + 2\beta_1)} \right]^{\frac{1}{\beta_1}}, \beta_1 > 0, 1 + \beta_0 < 0, 1 + \beta_0 + \beta_1 < 0
\]

Result 7 shows that when the marginal cost of the products fall in the \((H, F)\) region a conflict arises between the order in which the firm recommends products to maximize profits and the order in which these products should be recommended to consumers to maximize total welfare. Therefore, the selfish behavior of the firm with respect to the order in which products are recommended to consumers may even hurt welfare besides hurting consumer surplus. We also note that this region where welfare reduces is a subset of the region previously identified where consumer surplus reduces. This arises because \( G < H \), which follows immediately from the fact that
\[ H = G^\left(1 + 2\beta_0\right)\left(\beta_0 + \beta_1\right) \frac{\beta_1}{\beta_0(1 + 2\beta_0 + 2\beta_1)} \], \beta_1 > 0, 1 + \beta_0 < 0, 1 + \beta_0 + \beta_1 < 0

This section shows that under certain conditions profit maximizing firms recommend products to consumers in ways that hurt consumer surplus. In particular, this result arises when consumers exhibit different price elasticities of demand with respect to the different slots that the firm uses to recommend products. Appendix 9.2 shows numerical examples that illustrate our results. The first example considers only one representative consumer. The second example introduces a taste parameter allowing for two types of consumers. Both cases show how loss in consumer surplus arises. The theoretical model developed in this section considers only one representative consumer, which is enough to show that a profit maximizing firm recommends products to consumers in ways that may hurt consumer surplus. This model can be easily extended to multiple consumers, which would essentially represent additional independent markets, each of which could generate loss in consumer surplus. Finally, we note that there are significant economic instances in which consumers use the recommender system only once, or only once from time to time with significantly large inter-visit times. This happens, for example, to purchase expensive products, which consumers are more likely to buy only seldom, such as cars and houses. Therefore, the results presented so far are informative for a number of important occasions. In any case, in the next subsection we analyze what happens when consumers interact repeatedly with the recommender system.

3.5. Dynamics with Repeated Interactions
Consider now two consecutive time periods in which the representative consumer interacts with the recommender system. In this case, consider \( \beta_{0,t} \) and \( \beta_{1,t} \) for period \( t \), \( \beta_{0,t+1} \) and \( \beta_{1,t+1} \) for period \( t + 1 \) and assume that \( \beta_1 \) reduces from \( t \) to \( t + 1 \) when there is loss in consumer surplus at time \( t \), that is, consumers become more flexible towards the product placed in the salient slot once they were less so in the past and lost surplus. Figure 2 shows how this reduction in \( \beta_1 \) changes the conflict region from period \( t \) to period \( t + 1 \). Result 5 implies that this region shrinks. Result 6 implies that the loss in consumer surplus in period \( t + 1 \) will be smaller than that experienced in period \( t \). Likewise, result 2 implies that the gain in profit in period \( t + 1 \) will be smaller than that enjoyed by the firm in period \( t \).

Generalizing the rationale above, \( \beta_1 \) reduces over time yielding lower profits for the firm and lower loss in consumer surplus with each interaction. Furthermore, this dynamic process embodies loss of surplus for consumers at each and every interaction. This result comes in line with the
Figure 2  Illustration of how the conflict region depicted in the previous figure changes across two consecutive time periods. The consumers that are hurt in period $t$ are either lost or rely more heavily in the non-salient slot, reducing $\beta_1$. This shrinks the conflict region, lowers the extra rent that the firm can enjoy from strategically choosing products to slots and lowers the loss in consumer surplus.

findings in (Godinho de Matos et al. 2016), where the authors experimented with a video-on-demand system and found that movies that have been promoted (or demoted) to a better (worse) slot return to their natural slot after a dynamic process during which consumers issue less (more) likes to promoted (demoted) movies. Also in this case, the process by which movies converge back to their natural slots is achieved at the expense of consumers who find that bad movies have been promoted to good slots and that good movies have been demoted to bad slots. Whether $\beta_1$ converges to zero cannot be unequivocally determined in our model. If $\beta_1$ reaches zero then the conflict region becomes inexistent. In this case, consumers enjoy the maximum surplus possible and the firm collects the profit associated to that equilibrium. If $\beta_1$ does not reach zero then the conflict region is sustained by other mechanisms such as, for example, search costs. If the non-salient slot embodies higher search costs irrespective of the quality of the products placed in both the salient and in the non-salient slot then consumers may prefer to purchase from the salient slot, even if the product placed there is of lower quality and they know about it, because they save the search cost. This would result in a positive $\beta_1$ that would likely to be sustained over time.
In practice, whether consumers perceive that they may have been shown only a “second best” product in the salient slot is far from trivial because firms are unlikely to implement recommender systems that maximize consumer surplus and thus it is hard for consumers to directly observe the ideal world for them. In addition, there might be several roughly equally good products to the consumer. The firm will choose the one with the highest margin for the salient slot but the consumer will have a hard time to tell roughly equally good products apart. This may allow the firm, in practice, to sustain extra rents over time. Finally, note that each new consumer needs to go through the adjustment process described before whereby $\beta_1$ keeps reducing. Therefore, and in a real world setting, the extra profit that the firm can collect from strategically allocating products to slots is, in part, shaped by the mix of consumers that use the recommender system in terms of new consumers (who still need to adjust and thus still exhibit a higher $\beta_1$) versus repeated consumers (who have already adjusted and thus exhibit a smaller $\beta_1$).

4. Our Work and Our Experimental Context

4.1. Research Approach

Figure 3 illustrates the research approach that we follow to study the welfare properties of recommender systems. The first step in this approach was introduced in the previous section and includes the theoretical model showing conditions under which there is a conflict between the order in which the firm wants to suggest products to consumers and the order in which consumers would like to receive these recommendations. This model shows that conflicts arise due to differences in price elasticity of demand between the salient and the non-salient slot. Therefore, the second step in our work is to run a large-scale randomized field experiment to measure these elasticities and test whether they are different. Below, we introduce our industrial partner and describe in detail the experiment that we run to accomplish this goal. Finally, in the third step of our work, we plug in the estimates for the price elasticities of demand identified using our field experiment into the expressions for profit, consumer surplus and welfare derived in our theoretical model, and provide simulation results showing how different recommender systems compare in terms of how much surplus they generate.

Our simulations compute how consumers would behave in face of different recommender systems and thus allow us to show how their welfare is affected when the firm maximizes profit vis-a-vis, for example, when the recommender system is setup to maximize consumer surplus. As discussed before, it is unlikely that, in practice, firms arrange recommendations only to maximize short-term profits because they need to maintain consumer trust across repeated interactions. Also, they are unlikely to arrange recommendations in ways that fully maximize consumer surplus. Therefore, when we compare these recommender systems we are, in fact, providing bounds for the loss in
ANALYTICAL MODEL

Price elasticities of demand:
Non-salient slot: $\beta_0$
Salient slot: $\beta_0 + \beta_1 (> \beta_0)$

Choose movie order to:
Max CS or Max $\pi$
Compute: $\Delta CS$, $\Delta \pi$
Show conditions for conflict

RANDOMIZED EXPERIMENT

Randomize:
Movie price and slot
Allows for empirically identifying $\beta_0$ and $\beta_1$
Confirm that $\beta_1 > 0$
(robustness checks with popularity and quality)

SIMULATIONS

Use estimates of elasticity to simulate consumer behavior with several recommender systems
Use analytical expressions to compute distribution of CS and $\pi$ across simulations
Compare welfare properties across recommender systems

Figure 3 Building-blocks of our analysis. The randomized field experiment is used to identify the price elasticities of demand, which according to the theoretical model are the fundamental parameters to determine if conflicts arise. Simulations plug in these estimates into the expressions obtained in the theoretical model to describe how consumers would behave in face of different recommender systems.

consumer surplus that consumers may experience in practice. This exercise is similar to that performed in economic analysis when one compares the consumer surplus associated to a monopoly (that chooses price to maximize profit) and that associated to the competitive market (in which price is set to maximize consumer surplus). Also as in such cases, our measure of consumer surplus reflects everything that may affect the consumers’ willingness to pay for the product. For example, some firms are, at times, interested in improving the “user experience” as a way to ensure that consumers keep coming back. User experience is captured by consumer surplus to the extent that consumers are willing to pay more for a better user experience. In other words, using consumer surplus as a measure of consumer well being captures everything about the latter except traits that do not affect the consumer’s willingness to pay.

4.2. Our Industrial Partner
Our industrial partner, hereinafter called TELCO, is a major multinational telecommunications provider that offers TV, Internet, telephony and Video-on-Demand (VoD). It serves more than 1 million households, 69% of which purchase triple play bundles. Households subscribe either
standard or premium service. The latter is more expensive. It includes more TV channels and better Internet connection speeds. We had access to TELCO’s VoD database between June 2013 and March 2014. Roughly half of the active households subscribe VoD, of which a fifth paid for VoD content at least once during this 9-month period. During this period we observe roughly 800 thousand movie leases. We have the anonymized identifier of the household requesting each 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 of the movie and a timestamp for when the lease took place. We also have a number of covariates for each movie in TELCO’s database such as title, director, studio, play length, synopses, cast and genre.

Figure 4 shows the look and feel of the TV screen in this VoD system, which consumers can access using a hot-key in their STB remote control. This screen, called the Highlights Section, contains a set of menus filled with movies chosen by an editorial team. Movies are organized into menus such as Promotions, Suggestions, Dramas, Comedies. Each menu has a header with a name that clearly identifies the type of movies it contains. Menus are horizontal lines stacked vertically on the TV screen. Two menus fit the TV screen at any time and users can scroll up and down across menus. Upon scrolling to a new menu the cursor highlights the movie farthest to the left. Users can scroll left and right across movies under the same menu. They can also scroll past the last movie cover on the right of the TV screen to unveil hidden movies. TELCO displays 15 movies per menu and 11 menus in the highlights section. The title of the movie highlighted by the cursor is shown towards the bottom of the screen. The number of likes of the movie is shown close to the title for premium consumers. Clicking on the cover of a movie leads to a new screen with the year of release, play length, cast and synopsis. A number of actions are available from this new screen such as lease the movie, use a promotional coupon to lease the movie or watch the movie trailer (if one is available). Leased movies can be watched for a period of 48 hours and cannot be stored past this deadline. Premium consumers can also issue likes for movies.

Figure 4 also illustrates the fact that under each menu slots towards the left of the TV screen are more salient than slots towards the right of the screen. This is a known fact in countries where consumers read from left to right (Godinho de Matos et al. 2016). These movies are more prominent at the eyes of consumers and, for example, consumers may be more tolerant when their prices increase. Finally, users can leave the highlights section of the VoD interface and search for movies in the complete catalog. The catalog is hierarchically organized into content categories such as movies, documentaries and TV shows. Within each of these categories, screens are organized as described above with menus for genres. All households see the same number of movies both in the Highlights Section as well as in the full catalog. TELCO’s full VoD catalog offers access to more than 2,000 pieces of content at any point in time.
Figure 4 Illustration of the TV screen for the Video-on-Demand system at TELCO. Menus are stacked vertically on the screen and movies are shown horizontally under each menu. The title of the movie highlighted by the cursor shows on the bottom of the screen (alongside with the number of likes for premium consumers).

4.3. Randomized Experiment

The experimental design followed in our study is illustrated in figure 5. All households at TELCO with VoD service were included in the experiment. A new menu, called “Good Deals” was introduced into the highlights section of the VoD system. This menu was accessible to both standard and premium households with 3 clicks down on the remote control. At the beginning of the experiment, households were randomly named “original” or “discount”. During the experiment, the former households got movies under the new menu at their original price, which was decided by TELCO. The latter households got movies under the new menu at discounted prices. The discounted price was the marginal cost of the movie for TELCO, which was negotiated between TELCO and content owners. The average discount was 25% across the movies used during this experiment.

Before the experiment started, all movies in TELCO’s VoD catalog were ordered according to sales during the previous 30 days and the 270 movies at the top of this list were used in
the experiment. This is represented by step 1 in figure 5. This set of 270 movies was randomly
subsetted into 6 non-overlapping sets of 45 movies each of them to be used during each month
of the experiment. This is represented by step 2 in figure 5. Therefore, a different subset of the
most sold movies in TELCO’s VoD catalog during the 30 days before our experiment started was
used each month in our experiment. Let $M_t$ represent the subset of movies used in month $t$. Then
a number of operations were repeated on a monthly basis. For month $t$ the movies in $M_t$ that
were not shown in other VoD menus (to avoid double counting) were randomly ordered. This is
represented by step 3 in figure 5. Let $OM_t$ represent this randomly ordered list of movies. Then,
and for each household separately, a random subset of 15 movies in $OM_t$ were shown under the
“Good Deals” menu on the TV screen. This is represented by step 4 in figure 5. Therefore, each
household in our experiment was shown a different (randomized) subset of movies in a randomized
order. The set of 15 movies allocated to each household remained in the “Good Deals” menu for the
entire month until this procedure was repeated in the next month with a different set of 45 movies.
That is, the recommender system that we study in this paper does not shift nor replaces movies
once consumers buy them. If a consumer buys a movie from the “Good Deals” menu this movie
remains in the menu until the end of the month. This is the common practice in VoD systems.
However, a recommender system that would dynamically adjust items to refresh those shown to
consumers in salient slots would likely register even more sales for the movies placed in these slots,
yield even a larger difference in the price elasticity of demand between salient and non-salient slots.
Finally, the movies under the “Good Deals” menu were shown, for each household, either at their
original price or at discounted prices, as represented by step 5 in the figure 5.

5. **Empirical Strategy and Identification**

We want to estimate the demand curve for movies as a function of their price and the slot where they
are placed on the TV screen for both standard and premium households following the functional
form used in equation 1. Let $i$ represent a movie, let $m \in \{s, p\}$ represent the type of household ($s$
for standard and $p$ for premium), let $l \in \{d, o\}$ represent the type of price for the movies offered
under the “Good Deals” menu ($d$ for discounted and $o$ for original) and let $t$ represent a week. Let
$d_{imlt}$ represent the demand for movie $i$ from households of type $m$ with prices of type $l$ in week $t$,
let $p_{imlt}$ represent the price of movie $i$ in week $t$ for households of type $m$ with prices of type $l$ and
let $s_{imlt}$ represent the average slot on the TV screen in which movie $i$ is placed in week $t$ across
households of type $m$ with prices of type $l$. We estimate the following reduced form equation:

\[
\log(d_{imlt}) = \beta_0 + \beta_0 p \log(p_{imlt}) + \beta_1 p \log(p_{imlt}) 1(s_{imlt} < R)
\]
Figure 5 Illustration of our experimental design. All VoD-enabled households at TELCO were included in the experiment as well as the 270 movies with more sales during the 30 days before the experiment started. Households were exposed to movies in random orders on the TV screen under the new menu and were randomly assigned the original price or discounted price.

\[ + \beta_0 \log(p_{\text{imt}}) \mathbb{1}(m = s) + \beta_1 \log(p_{\text{imt}}) \mathbb{1}(s_{\text{imt}} < R) \mathbb{1}(m = s) \]

\[ + i + m + t + \tau_{im} + \epsilon_{imt} \]  

(2)

where \( i, m \) and \( t \) represent dummies for movies, household types and weeks, respectively, \( \tau_{im} \) are dummies to control for the different sampling probabilities of movies across different types of households and \( \epsilon_{imt} \) is the idiosyncratic error term. There are standard and premium households in our setting. Therefore, we control for household type. We use 270 movies during our experiment and thus the need for movie fixed effects. These fixed effects capture the effect of the different characteristics that these movies have (e.g., different genre, year of release). Given the layered structure in our setting, i.e., movies are shown to different households types, we also include an interaction fixed effect (\( \tau \) in our model) to control for the fact that there is a different number of standard and premium households in our experiment from where different movies may end up having different exposure. Finally, and given that our experiment developed over several weeks, we also include week dummies to control for common time.

Refer to figure 6 for an illustration of our setup. Slots before \( R \), which are farther to the left of the TV screen, represent, on aggregate, the salient slot in our theoretical model (that is, when \( s_j \)}
is one in equation 1). In other words, slot $k$ on the TV screen is salient if $k < R$ and non-salient otherwise (in this definition, slot 1 is the one farther to the left on the TV screen). Therefore, in the reduced form above $\beta_{0p}$ and $\beta_{0p} + \beta_{0s}$ represent the price elasticity of demand of premium and standard consumers with respect to movies placed in the non-salient slots. Similarly, $\beta_{0p} + \beta_{1p}$ and $\beta_{0p} + \beta_{1p} + \beta_{0s} + \beta_{1s}$ represent the price elasticity of demand of premium and standard consumers with respect to movies placed in the salient slots. We expect $\beta_{0p} < 0$, $\beta_{0s} + \beta_{0p} < 0$, $\beta_{0p} + \beta_{1p} < 0$ and $\beta_{0p} + \beta_{1p} + \beta_{0s} + \beta_{1s} < 0$ given that these coefficients measure price elasticities of demand. Our research hypotheses are that $\beta_{1p} > 0$ and $\beta_{1p} + \beta_{1s} > 0$, that is, households are less price elastic with respect to movies placed farther to the left of the TV screen (which, in our setting, are more salient). Finally, we may also expect standard consumers to be more price elastic than premium consumers, that is, $\beta_{0s} < 0$ and $\beta_{0s} + \beta_{1s} < 0$, because their income is likely lower.

![Figure 6 Illustration of different price elasticities of demand for movies under the new menu towards the left and towards the right of the TV screen for standard and premium consumers. Our hypothesis is that consumers are less price elastic towards movies shown to the left of the TV screen.](image)
We estimate our reduced form equation using a Poisson regression because our dependent variable is a count and thus this regression provides direct and unbiased estimates for the price elasticities of demand that we are interested in. Both the price and the slot of each movie have been randomly assigned during our experiment. Therefore, we expect no correlation between our independent covariates and the idiosyncratic error term.

6. Results
6.1. Descriptive Statistics and Balance Across TV Slots
We analyze 45 movies per month in our experiment and we aggregate our data on a weekly basis. Our experimental dataset comprises 26 weeks, two types of households, standard and premium, and two levels of prices, discounted and original. Therefore, we analyze, 4,680 observations. We register 2,238 sales from the “Good Deals” menu during our experiment for a total revenue of $7,663. Table 1 shows that prices, age, IMDb ratings and IMDb votes are similar across movies placed in different slots on the TV screen during our experiment. These results are obtained using ANOVA showing that the slots in which movies are placed do not explain these covariates. This is expected, given the random assignment of movies to TV slots under the “Good Deals” menu during our experiment and provides evidence of the good balance that our randomized schedule achieved to identify the price elasticity of demand across TV slots. Appendix 9.4 shows Tukey plots comparing all pairs of TV slots. This appendix provides additional evidence that the movies placed in different slots were similar during our experiment. Furthermore, the movies placed in the “Good Deals” menu are similar to the movies placed under other menus of TELCO’s VoD system (results available upon request) and thus the sample of movies that we use in our experiment represents well the set of movies that this provider uses under its highlights section.

Table 2 shows the average price per slot for the movies used placed in the “Good Deals” menu during our experiment. This table also shows the average price for when the price was low and high, which allows us to confirm the average discount of 25% during our experiment. This table also shows sales per slot, and cumulative sales up to each slot, for the movies placed in this menu during our experiment. We observe that movies with the higher price sell more up to slot 4, which gives us some preliminary evidence that despite the higher price these movies still sell more when placed towards the left of the TV screen. Finally, this table also shows the average IMDb rating, average IMDb votes and average year of release per slot for these movies. The average for these covariates across all movies placed in the “Good Deals” menu during our experiment are 6.25, 79869 and 2008.14, respectively.
Table 1  Evidence of balance across slots for movie prices, ages, IMDb ratings and IMDb votes.

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<td>2986451</td>
<td>7231</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>IMDb Rating</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Slot</td>
<td>7</td>
<td>4.18</td>
<td>0.597</td>
<td>0.434</td>
<td>0.88</td>
</tr>
<tr>
<td>Residuals</td>
<td>192</td>
<td>263.97</td>
<td>1.375</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>IMDb Votes</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Slot</td>
<td>7</td>
<td>1.153e+11</td>
<td>1.647e+10</td>
<td>1.015</td>
<td>0.422</td>
</tr>
<tr>
<td>Residuals</td>
<td>192</td>
<td>3.116e+12</td>
<td>1.623e+10</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Movie Age</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Slot</td>
<td>7</td>
<td>251</td>
<td>35.8</td>
<td>0.77</td>
<td>0.613</td>
</tr>
<tr>
<td>Residuals</td>
<td>182</td>
<td>8464</td>
<td>46.5</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 2  Prices (in cents), sales and movie characteristics per slot for the movies under the “Good Deals” menu during our experiment.

<table>
<thead>
<tr>
<th>Covariate</th>
<th>Stat</th>
<th>Slot: 1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price</td>
<td>Mean</td>
<td>290.7</td>
<td>302.8</td>
<td>281.5</td>
<td>275.8</td>
<td>285.5</td>
<td>291.0</td>
<td>291.4</td>
<td>302.2</td>
</tr>
<tr>
<td>Price</td>
<td>price=low</td>
<td>Mean</td>
<td>246.2</td>
<td>252.1</td>
<td>245.3</td>
<td>236.8</td>
<td>237.7</td>
<td>249.6</td>
<td>241.9</td>
</tr>
<tr>
<td>Price</td>
<td>price=high</td>
<td>Mean</td>
<td>332.0</td>
<td>340.4</td>
<td>316.3</td>
<td>314.8</td>
<td>325.6</td>
<td>329.2</td>
<td>336.4</td>
</tr>
<tr>
<td>Sales</td>
<td>price=low</td>
<td>Sum</td>
<td>89</td>
<td>94</td>
<td>71</td>
<td>76</td>
<td>86</td>
<td>98</td>
<td>101</td>
</tr>
<tr>
<td>Cumulative sales</td>
<td>price=low</td>
<td>Sum</td>
<td>89</td>
<td>183</td>
<td>254</td>
<td>330</td>
<td>416</td>
<td>514</td>
<td>615</td>
</tr>
<tr>
<td>Sales</td>
<td>price=high</td>
<td>Sum</td>
<td>109</td>
<td>86</td>
<td>62</td>
<td>80</td>
<td>72</td>
<td>53</td>
<td>65</td>
</tr>
<tr>
<td>Cumulative sales</td>
<td>price=high</td>
<td>Sum</td>
<td>109</td>
<td>195</td>
<td>257</td>
<td>337</td>
<td>409</td>
<td>462</td>
<td>527</td>
</tr>
<tr>
<td>IMDb rating</td>
<td>Mean</td>
<td>6.34</td>
<td>6.48</td>
<td>6.49</td>
<td>6.07</td>
<td>6.21</td>
<td>6.03b</td>
<td>6.30</td>
<td>6.37</td>
</tr>
<tr>
<td>IMDb votes</td>
<td>Mean</td>
<td>69485</td>
<td>65545</td>
<td>89221</td>
<td>67213</td>
<td>62480</td>
<td>68613</td>
<td>101790</td>
<td>96039</td>
</tr>
</tbody>
</table>

6.2. Empirical Findings

Table 3 shows the results obtained from estimating the reduced form equation presented in section 3 using the data collected during our randomized experiment. Each column instantiates a different value for $R$ as indicated on the top of the corresponding column. The price elasticities of demand for movies in slots $R$ and beyond are $-0.29$ and $-0.75$ for premium and standard consumers, respectively. In addition, standard consumers are more elastic than premium consumers ($p-values < 0.0004$). More important, we confirm our hypothesis that consumers, both standard
and premium, are less price-elastic towards movies placed in slots farther to the left of the TV screen, that is, slots prior to $R$, as shown by the interaction between price elasticity and $\text{slot} < R$ for the cases of $R = 2$ and $R = 3$. One could also expect this interaction to become less significant as $R$ increases, that is, as one blurs the definition of left of the TV screen. Empirically, we find that both premium and standard consumers exhibit a smaller price elasticity of demand for the first two slots under the new menu. Figure 7, illustrates our results for a particular movie and $R=2$. Price in the horizontal axis varies between $1.19$ and $3.99$, which are the minimum and maximum that we observe in our dataset. As expected, we observe more sales for the salient slot and for standard consumers (there are more standard consumers than premium consumers at TELCO and in our experiment). The price elasticity of demand can be glanced by looking at how much the lines in this figure drop. Therefore, we observe that standard consumers are much more price elastic and that both standard and premium consumers exhibit (similarly) a lower price elasticity of demand for movies placed in the salient slot.

Table 3

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>sales</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>R=2</td>
</tr>
<tr>
<td>log(price)</td>
<td>$-0.298^{**}$</td>
</tr>
<tr>
<td>(0.135)</td>
<td>(0.135)</td>
</tr>
<tr>
<td>log(price)*slot&lt;$R$</td>
<td>$0.122^{***}$</td>
</tr>
<tr>
<td>(0.042)</td>
<td>(0.033)</td>
</tr>
<tr>
<td>log(price)*standard</td>
<td>$-0.463^{***}$</td>
</tr>
<tr>
<td>(0.130)</td>
<td>(0.131)</td>
</tr>
<tr>
<td>log(price)*slot&lt;$R$*standard</td>
<td>$-0.023$</td>
</tr>
<tr>
<td>(0.030)</td>
<td>(0.022)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.093</td>
</tr>
<tr>
<td>(1.042)</td>
<td>(1.037)</td>
</tr>
</tbody>
</table>

Sampling Probability Dummies: Yes Yes Yes Yes Yes Yes Yes Yes
Movie Dummies: Yes Yes Yes Yes Yes Yes Yes Yes
Time Dummies: Yes Yes Yes Yes Yes Yes Yes Yes
Household Type Dummies: Yes Yes Yes Yes Yes Yes Yes Yes

Note: $^*$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01
Figure 7   Illustration of the price elasticity of demand for premium and standard consumers for movies placed in the salient and non-salient slots. Standard consumers are more price elastic than premium consumers and all consumers are less price elastic for movies placed in the salient slots.

Table 4 shows how the estimates for the price elasticity of demand for premium and standard consumers differ for time periods right after the introduction of the “Good Deals” menu compared to later time periods. As in the previous table, each column instantiates a different value of $R$ as indicated at the top of the column. We create a dummy variable that indicates whether observations pertain to the first 4 months during the experiment, represented in the table by $period < P$, or else to the last 3 months during the experiment. Therefore, the results in this table show that the difference in the price elasticity of demand between the salient and non-salient slots arises during the time periods immediately after the introduction of this menu, thus providing some evidence that parameter $\beta_1$ in the theoretical model introduced in section 3 attenuates over time in our setting, as could be expected in light of the discussion in that section. These results are obtained controlling for movie age to avoid potential confounding effects as time goes by.

6.3. The Role of Movie Popularity, Movie Quality and Movie Age

The previous results show that consumers exhibit a lower price elasticity of demand for movies placed towards the left of the TV screen. This is a result obtained on average across all the movies
Table 4 Estimates for the price elasticity of demand for premium and standard consumers for movies placed in slots prior to \( R \) and in slot \( R \) and beyond for months 1-4 (\( \text{period}<P \)) versus months 5-7. The difference in the price elasticity of demand for slots prior to \( R \) arises from time periods right after the introduction of the “Good Deals” menu.

<table>
<thead>
<tr>
<th>sales</th>
<th>R=2</th>
<th>R=3</th>
<th>R=4</th>
<th>R=5</th>
<th>R=6</th>
<th>R=7</th>
<th>R=8</th>
<th>R=9</th>
</tr>
</thead>
<tbody>
<tr>
<td>log(price)</td>
<td>-0.285**</td>
<td>-0.298**</td>
<td>-0.303**</td>
<td>-0.318**</td>
<td>-0.330**</td>
<td>-0.312**</td>
<td>-0.332**</td>
<td>-0.340**</td>
</tr>
<tr>
<td>log(price)*standard</td>
<td>-0.444***</td>
<td>-0.427***</td>
<td>-0.416***</td>
<td>-0.400***</td>
<td>-0.388***</td>
<td>-0.372***</td>
<td>-0.369***</td>
<td>-0.356***</td>
</tr>
<tr>
<td>log(price)*slot&lt;( R )</td>
<td>0.073</td>
<td>-0.040</td>
<td>-0.028</td>
<td>-0.035</td>
<td>-0.087</td>
<td>-0.042</td>
<td>-0.012</td>
<td>0.003</td>
</tr>
<tr>
<td>log(price)*slot&lt;( R )*standard</td>
<td>-0.154</td>
<td>-0.107*</td>
<td>-0.153***</td>
<td>-0.124***</td>
<td>-0.115***</td>
<td>-0.105***</td>
<td>-0.100***</td>
<td>-0.114***</td>
</tr>
<tr>
<td>log(price)*slot&lt;( R )*period&lt;( P )</td>
<td>0.112</td>
<td>0.174*</td>
<td>0.136*</td>
<td>0.141*</td>
<td>0.194**</td>
<td>0.086</td>
<td>0.085</td>
<td>0.071</td>
</tr>
<tr>
<td>log(price)*slot&lt;( R )*period&lt;( P )*standard</td>
<td>0.146</td>
<td>0.128*</td>
<td>0.177***</td>
<td>0.133***</td>
<td>0.135***</td>
<td>0.117***</td>
<td>0.105***</td>
<td>0.115***</td>
</tr>
<tr>
<td>Constant</td>
<td>0.684</td>
<td>0.729</td>
<td>0.743</td>
<td>0.772</td>
<td>0.661</td>
<td>0.566</td>
<td>0.241</td>
<td>0.325</td>
</tr>
</tbody>
</table>

Note: \(^*p<0.1; \quad **p<0.05; \quad ***p<0.01\)

used during our experiment. Table 5 shows that this result is heterogeneous across movie popularity. We define a dummy variable indicating whether the number of votes on IMDb falls within the first 3 quartiles of the distribution of IMDb votes across the movies used in our experiment or else on the top quartile of this distribution. We observe that the difference in the price elasticity of demand for movies placed towards the left of the TV screen is driven by popular movies both for standard and premium consumers. This means that while on average the firm is able to hook
up consumers to movies placed towards the left of the TV screen this is not necessarily true for all movies. In fact, this does not seem to be the case for unpopular movies. The firm is only able to hook up consumers to movies that are sufficiently known, otherwise placing unpopular movies towards the left of the TV screen does not seem to affect the price elasticity of demand. In other words, the firm is only able to profitably increase the price of movies placed towards the left of the TV screen if these movies are sufficiently well known.

Table 6 provides similar heterogeneous results for the case of movie ratings. We define a dummy variable indicating whether IMDb rating falls within the first 3 quartiles of the distribution of IMDb ratings across the movies used in our experiment or else on the top quartile of this distribution. We observe that the difference in the price elasticity of demand for movies placed towards the left of the TV screen is also driven by better movies both for standard and premium consumers. Similarly to the case of movie popularity, placing worse movies towards the left of the TV screen does not seem enough to hook up consumers. The firm is only able to profitably increase the price of the movies placed towards the left of the TV screen if these movies are sufficiently good.

Finally, table 7 provides similar heterogeneous results for the case of movie age. In this analysis, movie age is measured in years elapsed since the release of the movie in TELCO’s VoD system and the beginning of our experiment. We observe that the difference in the price elasticity of demand for movies placed towards the left of the TV screen is also driven by more recent movies both for standard and premium consumers. Similarly to the cases of movie popularity and movie quality, placing older movies towards the left of the TV screen does not seem enough to hook up consumers. The firm is only able to profitably increase the price of the movies placed towards the left of the TV screen if these movies are sufficiently new.

6.4. Effect on Consumer Tastes

Tables 8 and 9 show the results obtained from estimating the reduced form equation presented in section 3 only for premium consumers using the likes issued by households in our experiment during the experiment. These results are shown only for premium households because standard ones did not see the number of likes on the TV and could not issue likes. The dependent variables in these regressions are the number of likes and the number of likes per lease, respectively (the latter is set to zero when there are no leases). The results in both these tables show that our exogenous manipulations of movies into slots during the experiment did not change the number of likes issued by consumers. This provides some evidence that doing so did not seem to change their preferences, which lessens the concerns that potential losses in consumer surplus could be confounded with the fact that preferences may change as a result of recommendations. Tables 10 and 11 show similar results interacting slot with movie quality, providing additional evidence that
Table 5  The role of popularity on the estimates for the price elasticity of demand for premium and standard consumers for movies placed in slots prior to $R$ and in slot $R$ and beyond. Consumers are less elastic to popular movies placed in slots towards the left of the TV screen.

<table>
<thead>
<tr>
<th></th>
<th>$R=2$</th>
<th>$R=3$</th>
<th>$R=4$</th>
<th>$R=5$</th>
<th>$R=6$</th>
<th>$R=7$</th>
<th>$R=8$</th>
<th>$R=9$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\log(\text{price})$</td>
<td>0.078</td>
<td>0.068</td>
<td>0.052</td>
<td>0.058</td>
<td>0.072</td>
<td>0.078</td>
<td>0.074</td>
<td>0.052</td>
</tr>
<tr>
<td></td>
<td>(0.238)</td>
<td>(0.239)</td>
<td>(0.240)</td>
<td>(0.240)</td>
<td>(0.239)</td>
<td>(0.239)</td>
<td>(0.240)</td>
<td>(0.240)</td>
</tr>
<tr>
<td>$\log(\text{price})*\text{bottom quartiles}$</td>
<td>$-0.527^{**}$</td>
<td>$-0.514^{**}$</td>
<td>$-0.494^*$</td>
<td>$-0.496^*$</td>
<td>$-0.498^*$</td>
<td>$-0.507^{**}$</td>
<td>$-0.505^*$</td>
<td>$-0.504^*$</td>
</tr>
<tr>
<td></td>
<td>(0.258)</td>
<td>(0.258)</td>
<td>(0.259)</td>
<td>(0.258)</td>
<td>(0.258)</td>
<td>(0.258)</td>
<td>(0.259)</td>
<td>(0.259)</td>
</tr>
<tr>
<td>$\log(\text{price})*\text{slot}&lt;R$</td>
<td>0.249***</td>
<td>0.182***</td>
<td>0.185***</td>
<td>0.142***</td>
<td>0.105**</td>
<td>0.078</td>
<td>0.078</td>
<td>0.090</td>
</tr>
<tr>
<td></td>
<td>(0.073)</td>
<td>(0.063)</td>
<td>(0.062)</td>
<td>(0.055)</td>
<td>(0.051)</td>
<td>(0.048)</td>
<td>(0.048)</td>
<td>(0.055)</td>
</tr>
<tr>
<td>$\log(\text{price})<em>\text{slot}&lt;R</em>\text{bottom quartiles}$</td>
<td>$-0.443^{***}$</td>
<td>$-0.454^{***}$</td>
<td>$-0.456^{***}$</td>
<td>$-0.456^{***}$</td>
<td>$-0.450^{***}$</td>
<td>$-0.444^{***}$</td>
<td>$-0.437^{***}$</td>
<td>$-0.429^{***}$</td>
</tr>
<tr>
<td></td>
<td>(0.133)</td>
<td>(0.133)</td>
<td>(0.133)</td>
<td>(0.132)</td>
<td>(0.132)</td>
<td>(0.133)</td>
<td>(0.133)</td>
<td>(0.135)</td>
</tr>
<tr>
<td>$\log(\text{price})*\text{standard}$</td>
<td>$-0.175^{**}$</td>
<td>$-0.146^{**}$</td>
<td>$-0.181^{***}$</td>
<td>$-0.152^{**}$</td>
<td>$-0.139^{**}$</td>
<td>$-0.100^*$</td>
<td>$-0.094^*$</td>
<td>$-0.077$</td>
</tr>
<tr>
<td></td>
<td>(0.083)</td>
<td>(0.070)</td>
<td>(0.070)</td>
<td>(0.061)</td>
<td>(0.056)</td>
<td>(0.055)</td>
<td>(0.055)</td>
<td>(0.058)</td>
</tr>
<tr>
<td>$\log(\text{price})<em>\text{bottom quartiles}</em>\text{standard}$</td>
<td>$-0.003$</td>
<td>$-0.001$</td>
<td>$-0.001$</td>
<td>0.001</td>
<td>$-0.007$</td>
<td>$-0.008$</td>
<td>$-0.011$</td>
<td>$-0.006$</td>
</tr>
<tr>
<td></td>
<td>(0.020)</td>
<td>(0.022)</td>
<td>(0.022)</td>
<td>(0.023)</td>
<td>(0.024)</td>
<td>(0.025)</td>
<td>(0.027)</td>
<td>(0.029)</td>
</tr>
<tr>
<td>$\log(\text{price})<em>\text{slot}&lt;R</em>\text{standard}$</td>
<td>$-0.100$</td>
<td>0.0003</td>
<td>0.004</td>
<td>$-0.006$</td>
<td>$-0.017$</td>
<td>$-0.026$</td>
<td>$-0.030$</td>
<td>$-0.026$</td>
</tr>
<tr>
<td></td>
<td>(0.089)</td>
<td>(0.049)</td>
<td>(0.043)</td>
<td>(0.041)</td>
<td>(0.038)</td>
<td>(0.037)</td>
<td>(0.035)</td>
<td>(0.035)</td>
</tr>
<tr>
<td>$\log(\text{price})<em>\text{slot}&lt;R</em>\text{bottom quartiles}*\text{standard}$</td>
<td>0.087</td>
<td>0.011</td>
<td>0.004</td>
<td>$-0.002$</td>
<td>0.023</td>
<td>0.026</td>
<td>0.025</td>
<td>0.012</td>
</tr>
<tr>
<td></td>
<td>(0.095)</td>
<td>(0.056)</td>
<td>(0.048)</td>
<td>(0.046)</td>
<td>(0.043)</td>
<td>(0.042)</td>
<td>(0.040)</td>
<td>(0.040)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.816</td>
<td>0.864</td>
<td>0.856</td>
<td>0.716</td>
<td>0.758</td>
<td>0.826</td>
<td>0.845</td>
<td>0.835</td>
</tr>
<tr>
<td></td>
<td>(1.095)</td>
<td>(1.093)</td>
<td>(1.094)</td>
<td>(1.096)</td>
<td>(1.096)</td>
<td>(1.096)</td>
<td>(1.097)</td>
<td>(1.100)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
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<th>$R=6$</th>
<th>$R=7$</th>
<th>$R=8$</th>
<th>$R=9$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sampling Probability Dummies</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Movie Dummies</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Time Dummies</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Household Type Dummies</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
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<td>4,592</td>
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<td>4,592</td>
</tr>
<tr>
<td>Akaike Inf. Crit.</td>
<td>7,295.296</td>
<td>7,298.779</td>
<td>7,298.885</td>
<td>7,301.295</td>
<td>7,302.435</td>
<td>7,305.033</td>
<td>7,305.126</td>
<td>7,305.158</td>
</tr>
</tbody>
</table>

*p<0.1; **p<0.05; ***p<0.01

consumer preferences did not seem to change during our experiment even when better movies were placed in salient slots.
Table 6  The role of quality on the estimates for the price elasticity of demand for premium and standard consumers for movies placed in slots prior to $R$ and in slot $R$ and beyond. Consumers are less elastic to better movies placed in slots towards the left of the TV screen.

<table>
<thead>
<tr>
<th></th>
<th>R=2</th>
<th>R=3</th>
<th>R=4</th>
<th>R=5</th>
<th>R=6</th>
<th>R=7</th>
<th>R=8</th>
<th>R=9</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>log(price)</strong></td>
<td>-0.154</td>
<td>-0.158</td>
<td>-0.165</td>
<td>-0.164</td>
<td>-0.147</td>
<td>-0.149</td>
<td>-0.144</td>
<td>-0.187</td>
</tr>
<tr>
<td></td>
<td>(0.235)</td>
<td>(0.235)</td>
<td>(0.236)</td>
<td>(0.238)</td>
<td>(0.237)</td>
<td>(0.237)</td>
<td>(0.238)</td>
<td>(0.240)</td>
</tr>
<tr>
<td>**log(price)***bottom quartiles</td>
<td>-0.219</td>
<td>-0.218</td>
<td>-0.209</td>
<td>-0.207</td>
<td>-0.211</td>
<td>-0.209</td>
<td>-0.223</td>
<td>-0.192</td>
</tr>
<tr>
<td></td>
<td>(0.257)</td>
<td>(0.257)</td>
<td>(0.257)</td>
<td>(0.259)</td>
<td>(0.258)</td>
<td>(0.258)</td>
<td>(0.258)</td>
<td>(0.260)</td>
</tr>
<tr>
<td>**log(price)***slot $&lt; R$</td>
<td>0.244***</td>
<td>0.137**</td>
<td>0.138***</td>
<td>0.053</td>
<td>0.038</td>
<td>0.036</td>
<td>0.027</td>
<td>0.074</td>
</tr>
<tr>
<td></td>
<td>(0.072)</td>
<td>(0.058)</td>
<td>(0.057)</td>
<td>(0.045)</td>
<td>(0.042)</td>
<td>(0.039)</td>
<td>(0.041)</td>
<td>(0.048)</td>
</tr>
<tr>
<td>**log(price)***slot $&lt; R$*bottom quartiles</td>
<td>-0.472***</td>
<td>-0.476***</td>
<td>-0.475***</td>
<td>-0.463***</td>
<td>-0.462***</td>
<td>-0.456***</td>
<td>-0.437***</td>
<td>-0.400***</td>
</tr>
<tr>
<td></td>
<td>(0.134)</td>
<td>(0.135)</td>
<td>(0.134)</td>
<td>(0.134)</td>
<td>(0.135)</td>
<td>(0.135)</td>
<td>(0.136)</td>
<td>(0.137)</td>
</tr>
<tr>
<td>**log(price)***standard</td>
<td>-0.175**</td>
<td>-0.095</td>
<td>-0.128**</td>
<td>-0.052</td>
<td>-0.066</td>
<td>-0.059</td>
<td>-0.033</td>
<td>-0.067</td>
</tr>
<tr>
<td></td>
<td>(0.083)</td>
<td>(0.067)</td>
<td>(0.068)</td>
<td>(0.059)</td>
<td>(0.051)</td>
<td>(0.048)</td>
<td>(0.049)</td>
<td>(0.053)</td>
</tr>
<tr>
<td>**log(price)**<em>bottom quartiles</em>standard</td>
<td>0.006</td>
<td>0.016</td>
<td>0.017</td>
<td>0.009</td>
<td>-0.002</td>
<td>-0.001</td>
<td>-0.014</td>
<td>-0.041</td>
</tr>
<tr>
<td></td>
<td>(0.022)</td>
<td>(0.023)</td>
<td>(0.024)</td>
<td>(0.025)</td>
<td>(0.026)</td>
<td>(0.027)</td>
<td>(0.030)</td>
<td>(0.032)</td>
</tr>
<tr>
<td>**log(price)***slot $&lt; R$*standard</td>
<td>-0.053</td>
<td>0.014</td>
<td>0.015</td>
<td>-0.014</td>
<td>-0.028</td>
<td>-0.031</td>
<td>-0.049</td>
<td>-0.083**</td>
</tr>
<tr>
<td></td>
<td>(0.053)</td>
<td>(0.049)</td>
<td>(0.040)</td>
<td>(0.039)</td>
<td>(0.038)</td>
<td>(0.036)</td>
<td>(0.036)</td>
<td>(0.037)</td>
</tr>
<tr>
<td>**log(price)***slot $&lt; R$<em>bottom quartiles</em>standard</td>
<td>0.048</td>
<td>-0.004</td>
<td>-0.009</td>
<td>0.010</td>
<td>0.039</td>
<td>0.033</td>
<td>0.059</td>
<td>0.085**</td>
</tr>
<tr>
<td></td>
<td>(0.066)</td>
<td>(0.049)</td>
<td>(0.046)</td>
<td>(0.043)</td>
<td>(0.042)</td>
<td>(0.041)</td>
<td>(0.041)</td>
<td>(0.042)</td>
</tr>
<tr>
<td><strong>Constant</strong></td>
<td>0.415</td>
<td>0.531</td>
<td>0.539</td>
<td>0.531</td>
<td>0.522</td>
<td>0.541</td>
<td>0.637</td>
<td>0.587</td>
</tr>
<tr>
<td></td>
<td>(1.101)</td>
<td>(1.098)</td>
<td>(1.100)</td>
<td>(1.107)</td>
<td>(1.107)</td>
<td>(1.105)</td>
<td>(1.107)</td>
<td>(1.104)</td>
</tr>
</tbody>
</table>

Sampling Probability Dummies: Yes Yes Yes Yes Yes Yes Yes Yes
Movie Dummies: Yes Yes Yes Yes Yes Yes Yes Yes
Time Dummies: Yes Yes Yes Yes Yes Yes Yes Yes
Household Type Dummies: Yes Yes Yes Yes Yes Yes Yes Yes

Observations: 4,592 4,592 4,592 4,592 4,592 4,592 4,592 4,592
Akaike Inf. Crit.: 7,298.450 7,304.044 7,304.797 7,310.008 7,309.277 7,309.570 7,309.485 7,305.329

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

7. Effect of Recommender Systems on Consumer Surplus and Welfare

7.1. Setup for Simulations

The previous subsections show that in our setting both premium and standard consumers are less price elastic for movies placed in the slots towards the left of the TV screen under the new menu. According to the theoretical model presented in section 3 this is likely to lead TELCO to place
Table 7 The role of movie age on the estimates for the price elasticity of demand for premium and standard consumers for movies placed in slots prior to \( R \) and in slot \( R \) and beyond. Consumers are less elastic to more recent movies placed in slots towards the left of the TV screen.

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>billing</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td>log(price)</td>
<td>−0.747***</td>
</tr>
<tr>
<td></td>
<td>(0.235)</td>
</tr>
<tr>
<td>log(price)*movieage</td>
<td>0.059**</td>
</tr>
<tr>
<td></td>
<td>(0.026)</td>
</tr>
<tr>
<td>log(price)*slot&lt;(R)</td>
<td>0.072</td>
</tr>
<tr>
<td></td>
<td>(0.093)</td>
</tr>
<tr>
<td>log(price)*slot&lt;(R)*movieage</td>
<td>−0.413***</td>
</tr>
<tr>
<td></td>
<td>(0.143)</td>
</tr>
<tr>
<td>log(price)*standard</td>
<td>0.009</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
</tr>
<tr>
<td>log(price)<em>standard</em>movieage</td>
<td>0.002</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
</tr>
<tr>
<td>log(price)*slot&lt;(R)*standard</td>
<td>−0.014</td>
</tr>
<tr>
<td></td>
<td>(0.039)</td>
</tr>
<tr>
<td>log(price)*slot&lt;(R)<em>standard</em>movieage</td>
<td>−0.002</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
</tr>
<tr>
<td>Constant</td>
<td>−0.386</td>
</tr>
<tr>
<td></td>
<td>(1.079)</td>
</tr>
</tbody>
</table>

Sampling Probability Dummies: Yes Yes Yes Yes Yes Yes Yes Yes
Movie Dummies: Yes Yes Yes Yes Yes Yes Yes Yes
Time Dummies: Yes Yes Yes Yes Yes Yes Yes Yes
Household Type Dummies: Yes Yes Yes Yes Yes Yes Yes Yes
Observations: 4,312 4,312 4,312 4,312 4,312 4,312 4,312 4,312

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

movies in these slots in a way that hurts consumer surplus and that may also hurt total welfare. As customary, we resort to policy simulations to understand the potential magnitude of these losses. Our randomized experiment allowed us to empirically identify the relevant parameters of the demand curve. Therefore, we can use them now to determine the appropriate counterfactuals, that is, how would consumers behave if they faced different sets of movies on the TV screen that
Table 8  Absence of effect of slot on the number of likes received, indicating that during our experiment households did not seem to change their preferences for media.

<table>
<thead>
<tr>
<th>Dependent variable: number of likes</th>
<th>R=2</th>
<th>R=3</th>
<th>R=4</th>
<th>R=5</th>
<th>R=6</th>
<th>R=7</th>
<th>R=8</th>
<th>R=9</th>
</tr>
</thead>
<tbody>
<tr>
<td>log(price)</td>
<td>−0.327</td>
<td>−0.325</td>
<td>−0.325</td>
<td>−0.321</td>
<td>−0.317</td>
<td>−0.322</td>
<td>−0.317</td>
<td>−0.318</td>
</tr>
<tr>
<td></td>
<td>(0.287)</td>
<td>(0.287)</td>
<td>(0.287)</td>
<td>(0.287)</td>
<td>(0.287)</td>
<td>(0.287)</td>
<td>(0.287)</td>
<td>(0.287)</td>
</tr>
<tr>
<td>slot&lt; R</td>
<td>0.507</td>
<td>−0.092</td>
<td>−0.281</td>
<td>−0.232</td>
<td>−0.486</td>
<td>−0.415</td>
<td>−0.596*</td>
<td>−0.527</td>
</tr>
<tr>
<td></td>
<td>(0.618)</td>
<td>(0.460)</td>
<td>(0.417)</td>
<td>(0.359)</td>
<td>(0.343)</td>
<td>(0.316)</td>
<td>(0.342)</td>
<td>(0.411)</td>
</tr>
<tr>
<td>Constant</td>
<td>−17.722</td>
<td>−17.547</td>
<td>−17.540</td>
<td>−17.416</td>
<td>−17.328</td>
<td>−17.415</td>
<td>−17.418</td>
<td>−17.271</td>
</tr>
<tr>
<td></td>
<td>(3,257.668)</td>
<td>(3,256.901)</td>
<td>(3,256.813)</td>
<td>(3,259.311)</td>
<td>(3,262.483)</td>
<td>(3,259.296)</td>
<td>(3,261.095)</td>
<td>(3,262.955)</td>
</tr>
</tbody>
</table>

Sampling Probability Dummies Yes Yes Yes Yes Yes Yes Yes Yes
Movie Dummies Yes Yes Yes Yes Yes Yes Yes Yes
Time Dummies Yes Yes Yes Yes Yes Yes Yes Yes
Observations 2,340 2,340 2,340 2,340 2,340 2,340 2,340 2,340
Log Likelihood −928.518 −928.837 −928.629 −927.820 −927.974 −927.270 −928.008

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

were suggested to them by different recommender systems. We use the empirical results obtained in Table 3 with $R = 3$ (which yields higher log-likelihood than those obtained with $R = 2$) to run these simulations. In any case, the results for $R = 2$ are similar to the ones presented below and available upon request.

Consider a subset of 15 movies out of all the movies used during our experiment. In addition, assume that once the experiment is over TELCO sells these movies to consumers in a new menu in its VoD system at the prices originally negotiated with content providers. TELCO’s goal is to place these movies into the 15 slots under the new menu to maximize profit. These movies may be ordered differently from left to right on the TV screen for standard and premium consumers because these consumers have different preferences. Therefore, we compute separately for standard and premium consumers the order of recommendations that maximizes TELCO’s profits. For the allocation of movies to slots that maximizes profit we compute total profits, consumer surplus and total welfare. Likewise, for the order of movies that maximizes consumer surplus and welfare. We compute consumer surplus, profit and welfare for each type of recommender system and compare them. Finally, note that there are more than $8 \times 10^{23}$ ways to choose a set of 15 movies out of
Table 9  Absence of effect of slot on the number of likes received per lease, indicating that during our experiment households did not seem to change their preferences for media.

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>number of likes / number of leases</th>
</tr>
</thead>
<tbody>
<tr>
<td>R=2</td>
<td>R=3</td>
</tr>
<tr>
<td>log(price)</td>
<td>−0.040</td>
</tr>
<tr>
<td></td>
<td>(0.034)</td>
</tr>
<tr>
<td>slot&lt; R</td>
<td>0.045</td>
</tr>
<tr>
<td></td>
<td>(0.055)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.131</td>
</tr>
<tr>
<td></td>
<td>(0.210)</td>
</tr>
</tbody>
</table>

Sampling Probability Dummies: Yes Yes Yes Yes Yes Yes Yes Yes
Movie Dummies: Yes Yes Yes Yes Yes Yes Yes Yes
Time Dummies: Yes Yes Yes Yes Yes Yes Yes Yes
Observations: 2,340 2,340 2,340 2,340 2,340 2,340 2,340 2,340
R²: 0.164 0.164 0.164 0.164 0.164 0.164 0.164 0.164
Adjusted R²: 0.044 0.043 0.043 0.043 0.043 0.043 0.043 0.043
Residual Std. Error (df = 2045): 0.278 0.278 0.278 0.278 0.278 0.278 0.278 0.278
F Statistic (df = 294; 2045): 1.364∗∗∗ 1.362∗∗∗ 1.361∗∗∗ 1.361∗∗∗ 1.361∗∗∗ 1.361∗∗∗ 1.361∗∗∗ 1.361∗∗∗

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

Table 10  Absence of effect of slot on the number of likes received as a function of movie quality measured by IMDb ratings), indicating that during our experiment households did not seem to change their preferences for media.

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>number of likes</th>
</tr>
</thead>
<tbody>
<tr>
<td>R=2</td>
<td>R=3</td>
</tr>
<tr>
<td>log(price)</td>
<td>−0.374</td>
</tr>
<tr>
<td></td>
<td>(0.289)</td>
</tr>
<tr>
<td>slot&lt; R</td>
<td>0.527</td>
</tr>
<tr>
<td></td>
<td>(1.136)</td>
</tr>
<tr>
<td>slot&lt; R*bottom quantiles</td>
<td>−0.027</td>
</tr>
<tr>
<td></td>
<td>(1.328)</td>
</tr>
<tr>
<td>Constant</td>
<td>−17.514</td>
</tr>
</tbody>
</table>

Sampling Probability Dummies: Yes Yes Yes Yes Yes Yes Yes Yes
Movie Dummies: Yes Yes Yes Yes Yes Yes Yes Yes
Time Dummies: Yes Yes Yes Yes Yes Yes Yes Yes
Observations: 2,296 2,296 2,296 2,296 2,296 2,296 2,296 2,296
Log Likelihood: −909.506 −909.632 −909.574 −909.396 −908.815 −908.718 −908.255 −908.955

Note:  
*p<0.1; **p<0.05; ***p<0.01
Table 11  Absence of effect of slot on the number of likes received per lease as a function of movie quality measured by IMDb ratings), indicating that during our experiment households did not seem to change their preferences for media.

<table>
<thead>
<tr>
<th></th>
<th>number of likes / number of leases</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>R=2</td>
</tr>
<tr>
<td>log(price)</td>
<td>−0.044</td>
</tr>
<tr>
<td>slot&lt;R</td>
<td>0.156</td>
</tr>
<tr>
<td>slot&lt;R*bottom quantiles</td>
<td>−0.136</td>
</tr>
<tr>
<td>Constant</td>
<td>0.147</td>
</tr>
</tbody>
</table>

Sampling Probability Dummies   Yes Yes Yes Yes Yes Yes Yes Yes
Movie Dummies                  Yes Yes Yes Yes Yes Yes Yes Yes
Time Dummies                   Yes Yes Yes Yes Yes Yes Yes Yes
Observations                   2,296 2,296 2,296 2,296 2,296 2,296 2,296 2,296
R²                            0.165  0.164  0.164  0.164  0.165  0.165  0.165  0.165
Adjusted R²                   0.045  0.044  0.044  0.044  0.045  0.045  0.045  0.045
Residual Std. Error (df = 2007) | 0.279   | 0.279    | 0.279    | 0.279    | 0.279    | 0.279    | 0.279    | 0.279    |

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

the movies that we used throughout the experiment. We choose 1,000 of these sets at random and average out our results. Our findings do not change if instead of we choose 10,000 of these sets at random. The results for the latter case are available upon request.

7.2. Comparing Different Recommender Systems

Figure 8 shows the relationship between consumer surplus when consumer surplus is maximized (y-axis) and consumer surplus when profit is maximized (x-axis). Each dot in this figure is a simulation for a random set of 15 movies. As expected, all dots lie (weakly) above the 45 degree line and there is some variance in terms of their distance to this line, which measures the magnitude of the loss in consumer surplus introduced by the fact that the firm maximizes profit. On average, across our simulations, this loss is 8.44%. Figure 9 shows the relationship between profit when profit is maximized (x-axis) and profit when consumer surplus is maximized (y-axis). This figure shows how much profit the firm loses when consumer surplus is maximized. The average loss across our simulations is 7.17%.

Figure 10 shows the relationship between total welfare when profit is maximized (x-axis) and total welfare when total welfare is maximized (y-axis). On average across our simulations, this
Figure 8  Loss in consumer surplus when profit is maximized (simulations over random subsets of 15 movies used in the experiment). The average loss in consumer surplus is 8.44%.

loss is 2.07%. Figure 11 shows the relationship between total welfare when consumer surplus is maximized (x-axis) and total welfare when total welfare is maximized (y-axis). On average across our simulations, this loss is 1.62%. Therefore, maximizing consumer surplus does not hurt total welfare as much as maximizing profit ($p-value < 0.0001$). The figures in Appendix 9.3 show the distribution of losses for the four cases presented before. We observe that some sets of movies yield significant losses in consumer surplus and welfare. The largest losses in consumer surplus and welfare across our simulations when profit is maximized are 28.7% and 12.2%, respectively.

7.3. Consumers’ Trust in Recommender Systems
The previous subsection shows that losses in welfare, and particularly in consumer surplus, can arise when the firm chooses the order in which products are recommended to consumers in order to maximize profits. These losses are likely to arise when consumers exhibit different price elasticities of demand for different slots and the firm takes advantage of this knowledge to maximize profit. Still,
the simulations presented in the previous subsection are for a one-shot game, in which consumers buy only once from the recommender system. Our results show that the recommender system that maximizes profits leads consumers to lose surplus. However, consumers may also lose trust in a recommender system that induces consumer loss every time they use it. This may lead consumers to come more seldom to the market, which may result in less profit for the firm and less total welfare in the long-run.

Figure 12 compares the consumer surplus obtained from ten different recommender systems. As before, each simulation is for a random subset of 15 movies used during the experiment and we report results across 1,000 simulations. The three recommender systems farther to the left maximize profit, consumer surplus and welfare, respectively from left to right. The fourth recommender system is a content-based algorithm for movie genre. We identify two sets of TELCO consumers that have different tastes for movie genres as indicated by sales data during the 30 days prior our experiment. One set of consumers prefers drama movies while the other set of consumers prefer
action movies. The fourth recommender system shown in this figure places movies of the genre that
the consumer prefers in the salient slot (if there are fewer movies of the required genre than salient
slots then the algorithm randomizes the movies placed in the extra salient slots; if, on the other
hand, there are more movies of the required genre than slots then the algorithm randomizes the
movies of the require genre that are shown in the salient slots). The three recommender systems
on the far right of this figure place the most sold movies (in TELCO’s VoD system during the
experiment), the most rated movies (i.e., the most popular movies according to IMDb) and the
highest rated movies (i.e. the movies with the highest rank according to IMDb) towards the left of
the TV screen. These recommender systems are simple to implement and thus very often used in
practice. Examples of firms that use these types of recommender systems include Amazon, Expedia,
Netflix, to name a few.

We observe that the recommender system that maximizes profit yields as much consumer surplus
as the content based recommender system. The latter also generates as much consumer surplus

Figure 10  Loss in total welfare when profit is maximized (simulations over random subsets of 15 movies used in
the experiment). The average loss in total welfare is 2.07%.
Total Welfare when Consumer Surplus is Maximized (USD)
Total Welfare when Total Welfare is Maximized (USD)

Figure 11  Loss in total welfare when consumer surplus is maximized (simulations overs random subsets of 15 movies used in the experiment). The average loss in total welfare is 1.62%.

as the recommender systems that highlights the most sold, the most rated and the highest rated movies to consumers. Figure 13 presents the same type of information for the case of total welfare. In this case, the recommender system that maximizes profit yields more total welfare than the other recommender systems in the figure. Therefore, our analysis provides some empirical evidence that, at least in our context, consumers are unlikely to lose trust in a recommender system that maximizes profit every time they use it. Such a recommender system generates lower consumer surplus than a recommender system that maximizes consumer surplus but the latter is unlikely available to consumers and the former seems to yield as much consumer surplus (as well as much total welfare) as that generated by the other recommender systems that we refer above. Therefore, consumers are unlikely to notice, or at least unlikely to complain, if the company moves from those systems to a system that recommends products to maximize profit.

Yet, it may still be the case that firms may want to maintain consumer trust by recommending only good movies that would speak for the reputation of their VoD system. We model this behavior
by considering recommender systems that maximize profit, consumer surplus or welfare that can only use movies included in our experiment that belong in the top quartile of the distribution of IMDb ratings. These three recommender systems are represented towards the far right of figures 12 and 13. As expected such a system generates less consumer surplus and less welfare given that it operates only over a constrained set of movies. More important, maximizing profit conditional on showing only these movies to consumers reduces the loss in consumer surplus relative to the maximum consumer surplus that could be generated. Columns (1) and (2) in figure 14 shows this result. The former column shows that when all movies are available the recommender system that maximizes profit generates 90.3% of the maximum consumer surplus. The latter column shows that when only movies in the top quartile of the distribution of IMDb ratings are available the recommender system that maximizes profit generates 92.3% of the maximal consumer surplus and these statistics are different ($p-value < 0.001$). Columns (3) and (4) in this figure provide similar statistics for when welfare is maximized and show that in this case limiting the set of movies that can be shown to consumers does not make a significant difference. Overall, these results show that the loss in consumer surplus reduces when the firm recommenders only good movies in an attempt to maintain its reputation and earn consumers’ trust.

8. Conclusions

Resorting to recommendations from friends and from the crowd to learn more about products is not new (Dellarocas 2003). However, the complexity of recommender systems increased significantly in recent times with the advent of big data. Furthermore, recommender systems are now ubiquitous and used to find restaurants (e.g. yelp), shoes (e.g. zappos), cars (e.g. autotrader), households (e.g. zillow), doctors (e.g. healthgrades), love partners (e.g. match). It is therefore important to study the welfare properties of these systems as they evolve and become increasingly entrenched in our daily life activities. Recommender systems were introduced to help consumers navigate large catalogs of products to find the ones that better match their preferences. But can firms also use recommender systems to extract surplus from consumers? Recommender systems generate more sales compared to markets without them, and this may increase both firm and consumer surplus, but do firms hurt consumers when they choose which type of recommender system to use? In this paper, we compare the welfare properties of different recommender systems. We compare the recommender system that maximizes profit with the recommender system that maximizes consumer surplus and with the recommender system that maximizes total welfare. The former is different from the latter two because under certain conditions firms have incentives to suggest products to consumers in ways that are different from how consumers would like to receive suggestions from the firm. We
Figure 12  Comparison of the consumer surplus obtained using different recommender systems (simulations over random subsets of 15 movies used in the experiment). The 3 recommender systems to the left maximize profit, consumer surplus and welfare using all movies included in the experiment. The fourth recommender system is a content-based recommender system for movie genre. The next 3 recommender systems are the lists for most sold, most rated and highest rated movies. The last 3 recommender systems maximize profit, consumer surplus and welfare conditional on using only movies in the top quartile of the distribution of IMDb ratings.

We confirm our theoretical results empirically using outcomes from a randomized experiment in the Video-on-Demand (VoD) system of a large telecommunications provider. For half a year, this provider randomized the order in which movies were suggested to consumers on the TV screen and whether they were sold at the original prices negotiated with the content providers or at discounted prices. Using data from this experiment we estimate the demand for movies in this VoD system as a function of both price and slot on the TV screen. Then, we simulate how consumers would have behaved when presented movie recommendations from different recommender systems. These systems place different movies in different slots on the TV screen, thus manipulating their saliency,
which yields different levels of sales, profit, consumer surplus and welfare. We show that when the firm recommends movies to consumers in an order that maximizes profit, consumers lose surplus relative to the maximum surplus that they could enjoy – 8.44% in our setting, on average across our simulations. Welfare also reduces when the firm maximizes profit – 2.07%, on average across our simulations. Our simulations also show that for certain subsets of the movies used during our experiment these losses can be significantly larger than these means. We also compare the welfare properties of the recommender systems that maximize profit, consumer surplus and welfare to those of simpler recommender systems often used in practice today, such as lists of the most sold, the most rated and the highest rated movies. We find that the former three recommender systems generate more consumer surplus and more welfare than the latter three. Furthermore, we

Figure 13  Comparison of the welfare obtained using different recommender systems (simulations over random subsets of 15 movies used in the experiment). The 3 recommender systems to the left maximize profit, consumer surplus and welfare using all movies included in the experiment. The fourth recommender system is a content-based recommender system for movie genre. The next 3 recommender systems are the lists for most sold, most rated and highest rated movies. The last 3 recommender systems maximize profit, consumer surplus and welfare conditional on using only movies in the top quartile of the distribution of IMDb ratings.
Figure 14  Comparison of the loss in consumer surplus when the firm maximizes profit using all movies used in the experiment versus using only the ones in the top quartile of the distribution of IMDb ratings (CR models) (simulations over random subsets of 15 movies). The latter yield relatively lower loss in consumer surplus.

simulate a content-based recommender system based on movie genre and we show that this system generates as much consumer surplus as the recommender system that maximizes profit. Firms use this type of system to match consumers with products that they are likely to prefer, which may increase their welfare. However, a firm that does so is also likely to be able to charge more for these products, which may then reduce consumer surplus. Therefore, how these systems change consumer well-being is difficult to anticipate and most likely a subject of empirical analysis on a case-by-case basis.

We also study what may happen when consumers interact repeatedly with the recommender system. Analytically, we show that over time the firm is unlikely to maintain extra rents if consumers perceive that they were suggested only “second best” movies in the salient slots. Empirically, we provide evidence that in our setting consumers exhibit a lower price elasticity of demand towards movies placed in the salient slots immediately after the experiment started and that this effect
dampens over time. In addition, we show that the preferences of consumers in our experiment did not seem to change over time as a function of the movies suggested to them, thus lessening the concern that recommendations were only allowing consumers to change their preferences instead of lowering their surplus. We also model recommender systems that maximize profit, consumer surplus and welfare conditional on showing only good movies to consumers. Such recommender systems could be used by the firm to maintain reputation. We show that these system yields lower loss in consumer surplus when compared to the ones that use all the movies included in our experiment.

The contribution of our paper is threefold. First, we develop a model to show how firms can use recommender systems to extract surplus from consumers. Using this model, we identify a mechanism underlying recommender systems that firms can exploit to do so – namely that consumers are less price elastic towards products under highlight. Second, we show empirical evidence that this difference in the price elasticity of demand between products under highlight and not, arises in real world settings. In particular, we devise a randomized field experiment to identify this difference empirically. The fact that we use data from a randomized experiment to measure demand is a step forward vis-a-vis the observational work done to date to study how recommender systems affect the distribution of sales. Also, our experiment is large scale with organic consumers, which obviates the usual lack of statistical power and potential biases in the results that arise from small lab-based experiments. Third, we use simulation to compute the appropriate counterfactuals to show how recommender systems compare in terms of welfare properties. To the best of our knowledge, our paper is the first to effectively measure the consumer surplus generated by these systems.

We note that our paper does not come without limitations. For example, in our empirical work we aggregate our data across slots on the TV screen, namely for the slots prior to slot $R$ and for slots $R$ and beyond. A larger and longer experiment could perhaps provide enough statistical power to identify a different price elasticity of demand for each slot separately, which in practice would allow the firm to further increase its profits. Whether this increased level of personalization results in more loss of consumer surplus is still an open research question. Our work also suggests that future research could compare the loss in consumer surplus that arises from maximizing profit to that generated by other strategies that firms typically use to do so such as price discrimination schedules. In addition, one may also compare the welfare properties of recommender systems that maximize profit or that maximize consumer surplus to those of pure content-based recommender systems and of pure collaborative filtering recommender systems. The latter are employed by firms that do not know the demand curve and thus use similarity across items and across users as heuristics to issue reasonable recommendations. Understanding better the relationship between these systems and those that directly maximize welfare properties may be of interest in order to know more about how
these heuristics correlate to profit and consumer surplus. Also, our theoretical approach models a pure profit maximizer, i.e. a recommender system that maximizes profit irrespective of how similar the items suggested are to the ones previously bought. However, and in practice, firms may be more likely to use two-stage profit-aware recommender systems, where in the first stage they determine a set of items that are reasonably similar to the ones bought before and then in the second stage they order such set of items in a way that maximizes profit. Our approach in this paper models such a system with a loose threshold for similarity, which does not allow us to characterize the trade-offs between profit and similarity that managers can affect in practice by how they set the similarity threshold. Future research may also study in more detail how consumers adjust their demand over time when they realize that they might have been suggested only “second best” products. This question is far from trivial because consumers are unlikely to be shown recommendations in a way that maximize consumer surplus and thus they have no direct observation of the ideal world for them unless they invest the additional search costs, which then may offset the benefit from easily finding the ideal product for them. However, whether and how consumers realize this is fundamental to understand how firms need to manage their recommender systems to maintain reputation and consumer trust in settings with repeated interactions. Finally, future research may also focus on formalizing the potential effects of content-based and collaborative filtering recommender systems on profit, consumer surplus and welfare. This line of research could focus on studying in detail the tension between showing consumers products that they are more likely to buy, which should increase their surplus, and charging more for them, given that these products match the preferences of consumers better, which should then decrease their surplus.

The contribution of our paper to managers and practitioners is significant. With our paper, managers are also exposed to the appropriate experimental protocol that they should implement to measure how they can increase profit in their setting vis-a-vis their current practice. In addition, our paper also challenges the current state of regulation in online industries that resort to recommender systems to sell products. A significant body of legislation prevents firms from extracting excessive surplus from consumers. For example, mechanisms such as price discrimination are highly scrutinized. Our paper shows that recommender systems may embed a different way of extracting surplus from consumers – one not tied to pricing but rather to how recommendations are presented to consumers in the first place. We provide estimates for the loss in consumer surplus associated to this practice in the specific case of the recommender system for movies in VoD that we study in this paper but our findings may not generalize across the Internet or even to other experience goods. Therefore, additional empirical studies may be needed to lend robustness and generalizability to this line of work. Our hope is that our paper propels other researchers to develop additional research on the topic to better inform us of how recommender systems are likely to shape welfare in online commerce.
References


Tucker, C., J. Zhang. 2007. Long tail or steep tail? a field investigation into how online popularity information affects the distribution of customer choices.

9. Appendices

9.1. Loss in Consumer Surplus as Function of $\beta_1$

Section 3 shows that

$$\frac{\partial \Delta CS}{\partial \beta_1} = -\frac{(\beta_0 + \beta_1)^{1+\beta_0+\beta_1}}{(1 + \beta_0 + \beta_1)^{2+\beta_0+\beta_1}} [s(c_L) - s(c_H)]$$

$$s(c) = \log\left(\frac{\beta_0 + \beta_1}{1 + \beta_0 + \beta_1}\right) + \frac{1}{(1 + \beta_0 + \beta_1)(\beta_0 + \beta_1)} \log(c) c^{1+\beta_0+\beta_1}$$

$$s'(c) = \log\left(\frac{\beta_0 + \beta_1}{1 + \beta_0 + \beta_1}\right) + \frac{1}{\beta_0 + \beta_1} \log(c) (1 + \beta_0 + \beta_1) c^{\beta_0+\beta_1}$$

The loss in consumer surplus increases with $\beta_1$ if $s'(c) < 0$ in the region of conflict. In this region $c > G$, with:

$$G = \frac{1 + \beta_0 + \beta_1}{\beta_0 + \beta_1} \left[ \frac{\beta_0(1 + \beta_0 + \beta_1)}{(1 + \beta_0)(\beta_0 + \beta_1)} \right]^{\frac{1+\beta_0}{\beta_1}}$$

Therefore, the result follows from:

$$\log(c) > \frac{1 + \beta_0}{\beta_1} \log\left(\frac{\beta_0(1 + \beta_0 + \beta_1)}{(1 + \beta_0)(\beta_0 + \beta_1)} \right) - \log\left(\frac{\beta_0 + \beta_1}{1 + \beta_0 + \beta_1} \right)$$
\[ s'(c) < \frac{(1 + \beta_0)(1 + \beta_0 + \beta_1)}{\beta_1} c^{\beta_0 + \beta_1} \log(1 - w) + w, \quad 1 > w = \frac{\beta_1}{(1 + \beta_0)(\beta_0 + \beta_1)} > 0 \]

\[ \log(1 - w) + w < 0, \forall 1 > w > 0, \quad \frac{(1 + \beta_0)(1 + \beta_0 + \beta_1)}{\beta_1} > 0 \]

Section 3 shows that

\[ \Delta \Pi = - \left[ \frac{(\beta_0 + \beta_1)^{\beta_0 + \beta_1}}{(1 + \beta_0 + \beta_1)^{1 + \beta_0 + \beta_1}} c_H^{1 + \beta_0 + \beta_1} + \frac{\beta_0^{\beta_0}}{(1 + \beta_0)^{1 + \beta_0}} c_L^{1 + \beta_0} \right] + \left[ \frac{(\beta_0 + \beta_1)^{\beta_0 + \beta_1}}{(1 + \beta_0 + \beta_1)^{1 + \beta_0 + \beta_1}} c_L^{1 + \beta_0 + \beta_1} + \frac{\beta_0^{\beta_0}}{(1 + \beta_0)^{1 + \beta_0}} c_H^{1 + \beta_0} \right] \]

\[ \frac{\partial \Delta \Pi}{\partial \beta_1} = - \frac{(\beta_0 + \beta_1)^{\beta_0 + \beta_1}}{(1 + \beta_0 + \beta_1)^{1 + \beta_0 + \beta_1}} [r(c_L) - r(c_H)] \]

\[ r(c) = \left[ \log \left( \frac{\beta_0 + \beta_1}{1 + \beta_0 + \beta_1} \right) + \log(c) \right] c^{1 + \beta_0 + \beta_1} \]

\[ r'(c) = \left[ \log \left( \frac{\beta_0 + \beta_1}{1 + \beta_0 + \beta_1} \right) + \frac{1}{1 + \beta_0 + \beta_1} + \log(c) \right] (1 + \beta_0 + \beta_1) c^{\beta_0 + \beta_1} \]

In the conflict region \( F > c \), with:

\[ F = \frac{1 + \beta_0 + \beta_1}{\beta_0 + \beta_1} \left( \frac{\beta_0(1 + \beta_0 + \beta_1)}{1 + \beta_0} \right)^{\frac{\beta_0}{\beta_1}} \]

Therefore:

\[ \log(c) < -\frac{\beta_0}{\beta_1} \log \left( \frac{1 + \beta_0}{\beta_0(1 + \beta_0 + \beta_1)} \right) - \log \left( \frac{\beta_0 + \beta_1}{1 + \beta_0 + \beta_1} \right) \]

\[ r'(c) > \frac{\beta_0(1 + \beta_0 + \beta_1)}{\beta_1} c^{\beta_0 + \beta_1} [w - \log(1 - w)], \quad 1 > w = \frac{\beta_1}{\beta_0(1 + \beta_0 + \beta_1)} > 0 \]

\[ w - \log(1 - w) > 0, \forall 1 > w > 0, \quad \frac{\beta_0(1 + \beta_0 + \beta_1)}{\beta_1} > 0 \]

Thus, \( r'(c) > 0 \) in this conflict region.
9.2. Numerical Examples of Loss

Figure 15 shows a numerical example in which two products, A and B are shown to one representative consumer in two slots. The representative consumer exhibits different price elasticities of demand for these slots. The assignment of products to slots that maximizes consumer surplus places product B in the first slot and product A in the second slot. The assignment of products to slots that maximizes profit does the opposite and doing so reduces consumer surplus. This case also shows that maximizing profit may also reduce total welfare.

\[ \text{Demand: } d_j = p_j - 2 + 0.8 \times \{\text{slot} = 1\} \]

\[ \text{Costs: } c_A = 2, c_B = 1 \]

<table>
<thead>
<tr>
<th>Slot assignments</th>
<th>Maximize Consumer Surplus</th>
<th>Maximize Profits</th>
</tr>
</thead>
<tbody>
<tr>
<td>Optimal prices</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( p_A = 4 ); ( p_B = 6 )</td>
<td>( p_A = 12 ); ( p_B = 2 )</td>
<td></td>
</tr>
<tr>
<td>Demand</td>
<td></td>
<td></td>
</tr>
<tr>
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<td>( d_A = 0.05 ); ( d_B = 0.25 )</td>
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<tr>
<td>Consumer Surplus</td>
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<td>$3.54</td>
</tr>
<tr>
<td>Welfare</td>
<td>$4.45</td>
<td>$4.30</td>
</tr>
</tbody>
</table>

Figure 15   Example of loss in consumer surplus with one representative consumer.

Figure 16 shows a numerical example in which two products, A and B are shown to two representative consumers in two slots. A setting with two representative consumers mimics a taste parameter and introduces the opportunity for personalization, that is, the order in which the firm shows the products to one consumer is different from the order in which it shows them to the other consumer. As before, consumers exhibit different price elasticities of demand for the two slots. The assignment of products to slots that maximizes consumer surplus places product A in the first slot.
and product B in the second slots for both consumers. The assignment of products to slots that maximizes profit does not. Instead, it assigns product B to the first slot and product A to the second slot for one of the consumers, keeping the same assignment of products to slots as before for the other consumer, thus taking advantage of personalization. This, reduces consumer surplus. In this case, maximizing profit increases welfare.

- Demand: \( d_j = p_j - 2 + 0.3 \{\text{slot}=1\} + 0.6 \{\text{consumer}=1\} \)
- Costs: \( c_A = $2, c_B = $1 \)

<table>
<thead>
<tr>
<th>Consumer</th>
<th>Maximize Consumer Surplus</th>
<th>Maximize Profits</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>Slot assignments</td>
<td>A</td>
<td>B</td>
</tr>
<tr>
<td>Optimal prices</td>
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<td>( p_A = $13.0; p_B = $2.9 )</td>
</tr>
<tr>
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<td>( d_A = 0.07; d_B = 0.39 )</td>
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<tr>
<td>Profit</td>
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<td>Consumer Surplus</td>
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<tr>
<td>Welfare</td>
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<td>$15.02</td>
</tr>
</tbody>
</table>

Figure 16 Example of loss in consumer surplus with two representative consumers.
9.3. Distributions of Loss

The following figures show the distribution of losses across our 1,000 simulations. The first figure shows the loss in consumer surplus when profit is maximized and the second figure shows the loss in profit when consumer surplus is maximized. The third figure shows the loss in welfare when profit is maximized and the fourth figure shows the loss in welfare when consumer surplus is maximized. The average loss in consumer surplus when profit is maximized is 8.44% and the loss in welfare when profit is maximized is 2.07%. The loss in welfare when consumer surplus is maximized is 1.62% and this statistic is smaller than the latter. These figures also show that the loss in consumer surplus and the loss in welfare when profit is maximized can be substantial.

![Distribution of loss in consumer surplus when profit is maximized.](image)
9.4. Balance for Movie Characteristics Across TV Slots

This appendix uses Tukey family-wise plots to provide additional evidence that the movies placed in different TV slots under the “Good Deals” menu during our experiment were similar on observables, namely price, age, IMDd ratings and IMDb votes. The figures below show comparisons for all pairs of slots.
9.5. Movie Allocation Across Households

This appendix provides evidence on observables that movies were randomly allocated across households during the experiment. The first figure below shows that indeed the sampling probability was different across movies, with some movies obtaining more exposure than others. The other figures in this section show that the characteristics of the households that got these movies under the new menu are similar in a number of fundamental observables across movies.
9.6. Robustness Check for Different Levels of Price Elasticity of Demand

Finally, Figure 31 and Figure 32 show that this finding does not arise because TELCO charges consumers in the inelastic portion of the demand curve. Figure 31 shows the distribution of t-stats obtained from testing whether the recommender system that maximizes profit generates lower consumer surplus than the recommender systems that suggest the most sold, the most rated and the highest rated movies to consumers. Results are obtained for a set of 300 simulations varying $\beta_0$ between $-1$ and $-2$ and $\beta_1$ between $0$ and $-(1 + \beta_0)$. For each of these simulations, we perform 1000 simulations each with a random subset of 15 movies used during the experiment. In each of these simulations the firm now chooses both the order in which movies are recommended to consumers as well as their price in order to maximize profit. In all cases, we conclude that the recommender system that maximizes profit does not generate lower consumer surplus. Figure 32 replicates the analysis for the case of welfare. In this case, we conclude that the recommender system that maximizes profit does not generate lower welfare than other three recommender systems referred above. Therefore, the fact that the recommender system that maximizes profit does not seem to
hurt consumers and welfare too much when compared to simpler recommender systems does not seem to be an artifact of the low prices charged by TELCO to consumers.

Acknowledgments
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Figure 22  Tukey plot for covariate IMDb rating. All contrasts across all movie slots are not statistically different from zero.
Figure 23 Tukey plot for covariate IMDb votes. All contrasts across all movie slots are not statistically different from zero.
Figure 24  Tukey plot for covariate age. All contrasts across all movie slots are not statistically different from zero.
Figure 25  Number of households exposed to each movie in the experiment.
Figure 26 Average household ARPU for all movies used in the experiment.
Figure 27 Proportion of households with active contract for all movies used in the experiment.
Figure 28  Proportion of households with premium sports channels for all movies used in the experiment.
Figure 29  Proportion of households with premium movie channels for all movies used in the experiment.
Figure 30  Proportion of premium households for all movies used in the experiment.
Figure 31  Distribution of t-stats from comparing whether the consumer surplus generated by the recommender system that maximizes profit is lower than that generated by the recommender systems that suggest the most sold, the most rated and the highest rated movies (simulations for $-2 < \beta_0 < -1$ and $0 < \beta_1 < -(1 + \beta_0)$.
Figure 32  Distribution of t-stats from comparing whether the welfare generated by the recommender system that maximizes profit is lower than that generated by the recommender systems that suggest the most sold, the most rated and the highest rated movies (simulations for $-2 < \beta_0 < -1$ and $0 < \beta_1 < -(1 + \beta_0)$.