The Effects of Price Promotions on Online User Reviews

Author: BRUNO SISTA - Email: brunosista@gmail.com

University: UNIVERSITY OF PORTO

Co-author(s): Beatriz Casais (University of Porto, Faculty of Economics)
/ **Nuno Moutinho** (University of Porto, Faculty of Economics)

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Abstract

As an effort to better understand the role of price in the consumers' pre-purchase expectations and post-consumption evaluations, we observe how promotional discounts can lead to fluctuations in user recommendations for discount products in an e-Commerce platform, Steam.
Applying the change point analysis method for the observation of longitudinal data, we confirm that temporary discounts can disrupt the otherwise stable process of word of mouth generation. The researchers observed a significant effect on the volume of reviews posted for a product shortly after the occurrence of a discount and also variations in review scores that can be either positive or negative.
Future research on this subject may allow for more evidences on how pricing strategies can be used to generate more business in online markets, when paired with adequate online feedback management policies.

Keywords: *Price Promotions, Electronic Word of Mouth, User Reviews*

***Pricing** track of EMAC 2016*

1. Introduction

Social Commerce is a recent concept, appearing under the umbrella of the Web 2.0 (Hajli, 2015). The modern user is no longer limited to the information producers/retailers choose to make available for their merchandise and services, articles published in the specialized press, but they tend to source for information from peers, who share first-hand opinions and reviews of their experiences with those products (Schafer, Konstan, and Riedi, 1999). The creation of this collective intelligence has brought such impact on the decision-making processes for online shopping, that Electronic Word of Mouth (eWOM) and User-Generated Content (UGC) have become two of the most discussed subjects between marketers (See-To & Ho, 2014), who now more than ever recognize the effects of customers participation in the creation of brand equity, either by increasing notoriety and reach of the brand, or through the part they play in changing other users' perception of quality of the products.

Recent literature recognizes C2C communication has a relevant impact on the purchasing decision-making of e-Commerce platform users, with the potential to affect volumes of sales (Chevalier and Mayzlin, 2006). Since that pioneer work, several studies have applied the same principles to different markets, the main consensus being that online shoppers adopt online reviews as reliable information sources in their decision making (Cui, Lui, and Guo, 2012; Filieri and McLeay, 2014).

Despite the impact of eWoM in the success of e-Commerce strategies, and the fact that Price is generally accepted as a relevant determinant of customer satisfaction (Voss, Parasuraman, and Grewel, 1998), we found a lack of research on the impact of Pricing on Online Product Reviews. Li and Hitt (2010) confirmed a correlation between price and product evaluations for cross-sectional datasets. The goal of this research is to confirm a relationship of causality between pricing initiatives activated on a given product (specifically promotional discounts) and the generation of electronic word of mouth (through the proxy of online product reviews) for that product, analysing the behaviour of user reviews after a variation in price.

This exploratory study was translated into the following hypotheses:

Hypothesis 1: The occurrence of a price reduction in a product leads to an increase in the number of user reviews published in the days following the discount.

Hypothesis 2: The occurrence of a price reduction causes a change in the average review score of a product in the days following a discount.

2. Methodology

To test these hypotheses, our study focuses on the behaviour of users of the Steam platform, a software digital distribution service which has been developing efforts in making the purchase and consumption of videogames into a social experience. The choice of a digital distribution service is justified because it allows us to eliminate as many third party intermediaries as possible between producers and consumers. Other web-services such as Amazon or ebay, because they mostly sell physical products, could lead to distortions on user review scores due to users biasing their product reviews in the light of logistical distribution problems (delivery delays, damaged products, stock ruptures, etc.). Steam users are provided with a homogeneous product, and the variations in consumption experience derive only from the different hardware setups which they use to play.

Computerized scraping methods were used to download data from the Steam storefront search engine (store.steampowered.com/search), through daily extractions between the 18th January and 30th March 2015.

The following variables were stored for over 8.000 products on sale, for each of the 71 daily observations:

- Gross price
- % of promotional discount
- Total nº of user reviews
- % of positive reviews

These variables were considered to be the most adequate for a first exploration of a relationship between pricing initiatives and word of mouth (volume and nature), mainly for their exposure in the Steam platform, being the most emphasized and readily available proxies of the constructs under analysis.

Although data was collected for all products in the Steam storefront, we opted to select a sample that we assume most closely represents the behaviour of the market under regular circumstances. For that purpose, we selected only 658 products that fulfilled a series of criteria of "normality" (e.g., not free, released before 2015, ≥ 100 reviews)

For each of the products we extracted the 29 observations that spanned the period between 14 days before and 14 days after the occurrence of the discount. In this timeline, and for the interpretation of the graphics and figures below, consider T=15 as the first day of the price discount.

To test the hypotheses we analysed the evolution of two main variables:

- **New reviews published daily**. Considering that we are able to extract the total number of reviews existing at the time of extraction:

R_T: Total number of user reviews existing on day T

r_T: Number of new reviews published on day T

(1) $R_T = R_{T-1} + r_T$

- **Average product review score** is defined by the percentage of all reviews posted up until the time of extraction that are positive:

S_T: Average review score on day T, i.e.

P_T: Total number of positive reviews existing on day T

p_T: New positive reviews published on day T

(2) $S_T = \frac{P_T}{R_T} = \frac{P_{T-1} + p_T}{R_{T-1} + r_T}$

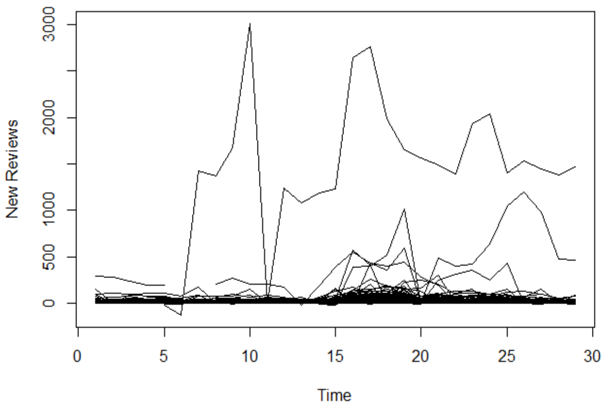
Hence, the data collected should be sufficient to detect periods in which the average score of reviews posted was higher (or lower) than the sum of all reviews posted up until that point in time.

The serially dependent nature of these variables defies the assumption of i.i.d. observations for the Change Point Analysis method that will be used to detect changes in means. This will lead to an increased vulnerability to type I errors because of the possibility of overestimation of residuals (Lund et al., 2007). However, this assumption is one that is frequently overlooked by literature in the analysis of empirical data, since real time series are rarely stationary and truly stochastic processes.

3. Results and Findings

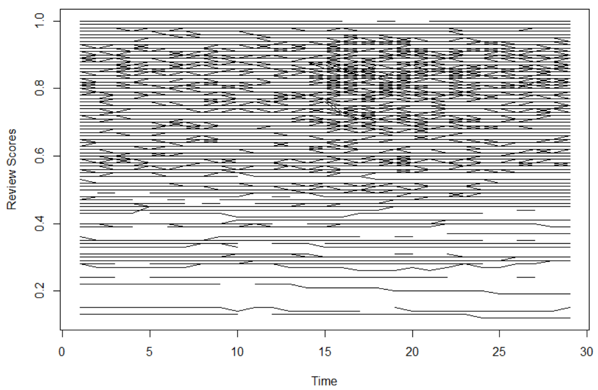
Figure 1 depicts the evolution of this variable, where it is easy to detect that an outstanding number of reviews are published in the few days after the start of a price discount (T=15), when compared with the relatively stable process of generation of user recommendations. Testing for a change point gives a positive result for a change in means in T=16 with at least 99% confidence. Thus, we **confirm Hypothesis 1**, and conclude, about the behaviour of consumers in the Steam platform, that a price reduction has a significant impact on the volume of product reviews published in the days following the pricing initiative.

Figure 1. Reviews Published Daily



For review scores, in our first attempt to explore the data in our sample we built the time series chart based on the average review scores for those products (figure 2).

Figure 2. Average Review Scores



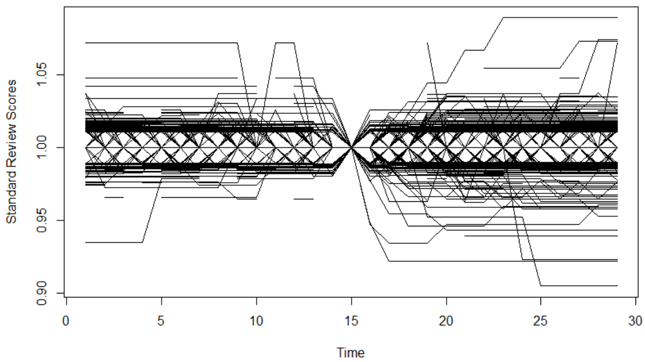
The result provided some information about the behaviour of our variables. One of the most evident interpretations of this plot is that average review scores are relatively stable for the period of analysis, which is coherent with the fact that we're analysing cumulative, serially dependent scores. Out data is also presented in a percent-point scale, which explains the predominantly parallel lines. This chart was certainly not sufficient to answer our research questions, although it was immediately apparent that review scores are subject to more frequent variations after T=15 (incidentally, the first day of the price discount), as we can observe from the higher density of segments with non-null slope in the second half of the time series plot.

Although review scores range from 12% to 100% for the period observed, they are highly concentrated around the 85% mark and the distribution is relatively stable.

To visually interpret our data, we found it useful to compare the review score of each product at a certain moment in time, S_t, to the review score it had on the moment of occurrence of the discount.
For that matter, we create yet another construct – the Standard Score (S'_T):

(3) $$S'_T = \frac{S_T}{S_{15}}$$

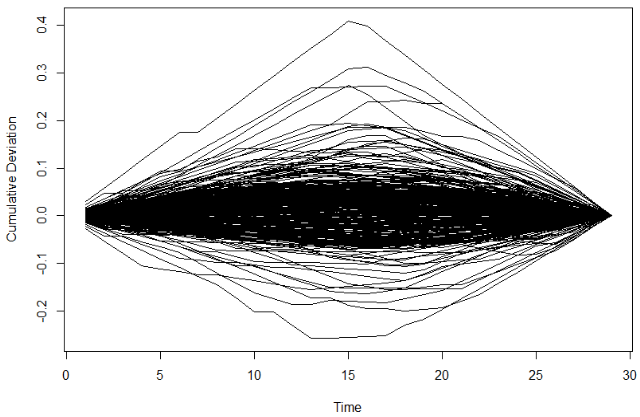
Figure 3. Standard Review Scores



Results in this new time series chart (figure 3) seems to confirm that after the occurrence of a discount (T=15) there is a higher volatility in customer reviews scores than before, and that in that case the signal of variation can be either positive or negative.

The first step towards applying our change point analysis methodology was to build the CUSUM chart (figure 4) for the evolution of review scores.

Figure 4. CUSUM Control Chart for Review Scores



It is easy to recognize a pattern for a considerable number of time series (products) coherent with the existence of a change point. In fact, testing for a change point of the distributional means with the ecp package returns positive results for a first-level change point at T=17 with at least 99% confidence, equivalent to dividing the time series into two clusters, T=[1, 17[and T=[17, 29] with statistically significant differences in means.

This result is coherent with the previous analysis of the CUSUM control chart, which is noticeably skewed towards the end of the time series (and to the right of T=15, the first observation with presence of a price discount). This can easily be justified because of: a) the delay between the moment a discount is activated and the moment a consumer finally publishes his review, after experiencing and evaluating the product; b) the serial dependence of the variable in cause, paired with some rigidity in the scale (percentages with no decimal places) which provides resistance and causes a delay in variations of average review scores.

The confirmation of a statistically significant change point in the time series around the occurrence of a price discount is deemed sufficient to **accept Hypothesis 2**. Thus we conclude that, regarding review scores for products in the Steam Storefront, the occurrence of a price discount causes a shift in the means of the distribution.

Regarding the signal of that shift, analysing a sub-sample of products that have review information available for both T=14 (last observation before a discount) and T=29:

- 103 products for which $S_{14} > S_{29}$
- 325 products for which $S_{14} = S_{29}$
- 83 products for which $S_{14} < S_{29}$

4. Conclusions

Applying the change point analysis method for the observation of longitudinal data, we confirm that temporary discounts can disrupt the otherwise stable process of word of mouth generation. They have not only a significant effect on the volume of reviews posted for a product shortly after the occurrence of a discount, but also cause variations in review scores that can be either positive or negative.

Regardless of the direction of variation of review scores, it is implied by several studies that online word of mouth and customer feedback are significant factors in the long-term generation of business, and can be used to forecast future sales. If a price promotion has a durable effect in the review scores, and future buyers use those scores as quality cues in the information gathering phase of their purchasing process:

- a temporary price reduction made with the intent to generate a durable raise in online review scores could have a positive return in the long-term;
- a temporary price reduction made with the intent of generating a short-term increase in sales and/or awareness (by volume of word of mouth) could generate a decrease in review scores that has a negative impact on the long run and in the price that customers are willing to pay in the future due to the decrease in value perceptions.

Further exploration of how online word of mouth is generated and which factors contribute to an increase or decrease of review scores in the presence of pricing initiatives could lead to developments in the paradigms of e-commerce and social commerce.

5. Limitations and future research

This study should be interpreted considering that Steam is a software digital distribution service, a typical supply-side market with a posted-price context. When the seller determines a price reduction, there is an increase in the total consumer surplus leading to an increase in the volume of sales with no decrease in quality – there is an infinite supply of homogeneous product (Kleinberg *et al.*, 2003) – which isn't always the case for retailers of physical goods.

As for review scores, our study showed that the effect of price promotions in review scores isn't linear, and understanding which factors can influence the signal of variation in user ratings should serve as the motto for future research. Using sentiment analysis methods to identify differences in the contextual cues of product reviews published before and after a price promotion can be key to understanding the consumers' though processes when making a purchasing decision online.

New customers may account for the temporary nature of the reduction when creating their reviews and still evaluate their purchased products based on the gross (non-discounted) price instead of the price at which they acquired them. This would lead to "false-positive"/"false-negative" reviews, which present a conditional evaluation based on price (Li & Hitt, 2010). According to Darke & Chung (2005), price promotions have negative effects in the consumers' value perceptions of products. Introducing a price reduction could undermine a customer’s appreciation of quality and online feedback. Festinger's (1957) dissonance theory implies that consumers tend to raise their evaluations of products when their cost of acquisition is higher.

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