THE EFFECTS OF PRICE PROMOTIONS ON ONLINE USER REVIEWS

by

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Dissertation for the Master in Marketing

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Biographical Sketch

Bruno Miguel Saldanha Sista was born in Vila Nova de Gaia, Portugal, on the 28th June 1991.

Showing a love for letters and a head for numbers from a very early age, he was admitted to elementary school at 5 years old and was consistently an honour roll student throughout primary, middle and high school.

At 14 he chose to attend the Socioeconomic Sciences course, driven by his increasing interest in business and finance, a trait inherited from his entrepreneur mother, manager of a local computer retailing business, where Bruno spent most of his afternoons nurturing a deep passion for technology.

Graduating high school as top of his class in 2008, he went on to attend the Bachelor in Economics at the University of Porto – Faculdade de Economia. There, he was able to further develop his understanding of business and trade markets, always complementing his classroom learning with the soft-skill development opportunities that only students' organizations can provide (as coordinator of the Marketing department at NEV/EXUP as well as team leader at eCOROmia – Choir of the Faculty of Economics of Porto).

Bruno also participated in the ERASMUS exchange programme, through which he attended courses in the Master of Business Administration at the Universitá degli Studi di Roma Tor Vergata for a semester in 2011.

He finally graduated on the 12th December 2012.

In April 2013 he was recruited by Sage Portugal, a subsidiary of Sage Group plc, to fill the role of Controller in the Financial Planning & Analysis department. His passion for numbers and complex analytical puzzles and his technological savvy have been useful since then, in his crusade for timely KPI reports and comprehensive dashboards.

In September of the same year he embraced the challenge of pursuing further education, and finally enrolled in the Master in Marketing at his alma mater, FEP-UP.

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As I look back to the two years that have passed since I attended the first class of this course, I can't go without congratulating the academic staff of the Master's degree in Marketing for the incredible learning experience they provided, as well as my colleagues for the companionship and support we shared as we approach, together, the conclusion of this chapter of our academic lives.

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Last, but certainly not least, my heartfelt thanks go to my family and friends for their continuous support and enthusiasm, for standing by me through the good times and bad, for helping me stay sane and confident in myself, and for generally making my world a sunnier place.

Abstract

The aim of this research is to analyse how pricing strategies (specifically through promotional discounts) can lead to fluctuations in user review scores of products in an online marketplace. This will hopefully shed some light on the role of price in the customers' pre-purchase expectations, and the post-purchase evaluation of their consumption experience.

To achieve that goal, we've done extensive research into the concepts of online communities, electronic word of mouth, and customer satisfaction, in an attempt to understand the mechanisms behind fluctuations in online recommendations after the occurrence of promotional discounts.

A practical application of those concepts was made through observation of consumer behaviour in users of the Steam platform, an online software distribution service, collecting review scores over the course of 2 months. Applying change point analysis methods, we confirm that promotional discounts not only had a significant effect on the volume of reviews posted, but also caused a fluctuation in the products' user ratings, disrupting the otherwise stable process of word of mouth generation, causing variations in review scores that can be either positive or negative.

Finally, we reaffirm the importance of future research on the subjects of electronic word of mouth and online recommendation systems, proposing the addition of further variables to this analysis, including product attributes and discount rates, which will allow for more definite answers on how pricing strategies, when paired with adequate online feedback management policies, can be used to generate more business in online markets.

Keywords: Online recommendations, Electronic Word of Mouth, Virtual Communities, User Reviews, Product ratings, Customer satisfaction

Resumo

O objectivo desta investigação foi o de analisar como alterações na estratégia de pricing de um produto (especificamente, promoções de preços) podem causar flutuações nas recomendações de utilizadores em plataformas de comércio online. A finalidade é trazer uma nova luz sobre o papel do preço na formação de expectativas pré-compra por parte dos consumidores, e as avaliações pós-compra das suas experiências de consumo.

Para responder a esse desafio, foi feita uma extensiva revisão bibliográfica sobre os conceitos de comunidades virtuais, electronic word of mouth e satisfação do consumidor, numa tentativa de compreender os mecanismos que estão por detrás das flutuações nos online review scores depois da ocorrência de descontos de preço.

Foi ainda feita uma aplicação prática destes conceitos através da observação do comportamento dos utilizadores da plataforma Steam, um serviço de distribuição digital de videojogos, tendo sido recolhidos dados de review scores ao longo de 2 meses. Aplicando métodos de change point analysis (Análise de pontos de mudança), confirmou-se que descontos promocionais têm não só um efeito significativo no volume de recomendações publicadas online, mas também na apreciação média dos consumidores, criando uma disrupção no processo de geração de word of mouth sob a forma de variações nos review scores que podem ser positivas ou negativas.

Finalmente, reafirmamos a necessidade de investigação futura sobre os temas de electronic word of mouth e sistemas de recomendações online, propondo a adição de mais variáveis para esta análise, incluindo atributos ao nível do produto e as taxas de desconto, que permitirão respostas mais completas e com nível de confiança superior para estas e outras questões de investigação. A finalidade será investigar a viabilidade de utilizar estratégias de pricing, combinadas com políticas eficazes de gestão de feedback online, para gerar maior volume de vendas nos mercados online.

Palavras-chave: Recomendações Online, Electronic Word of Mouth, Comunidades Virtuais, User Reviews, Product ratings, Satisfação do Consumidor.

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I. Introduction

The advent of the commercial Internet allowed for the development of new communication tools and several new forms of interaction between users online. The Web 2.0, in turn, gave its users new powers to contribute with content to the network and bringing a social component to most online experiences (Solomon & Schrum, 2007).

Several services have appeared on the web appealing to the "participatory culture", from blogs to social networks, inviting the user to take part in the creation of social, economic and cultural value (Jöckel *et al.*, 2008). e-Commerce is perhaps one of the most impactful new paradigms to emerge from this trend. The appearance of dotcoms such as Amazon.com and ebay.com, pioneers in the creation of online marketplaces that facilitate the fulfilment of transactions through the web, has come to revolutionize the way citizens of the Internet (individuals or companies) relate to trade and shopping. These marketplaces are dependent on the participation of consumers, their main selling point being the direct interaction between sellers, prospects and buyers, setting them apart from physical points of sale (Pavlou & Gefen, 2004).

Social Commerce is a relatively 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, or articles published in the specialized press, instead sourcing his information to his peers, who share first-hand opinions and reviews of their experiences with those products (Schafer et al., 1999). The creation of this collective intelligence has brought such impact on the decision-making processes for online shopping, that Electronic Word of Mouth (henceforth, eWOM) and User-Generated Content (UGC) have become two of the most discussed subjects between marketers (See-To *et al.*, 2014), who now more than ever recognize the effects of customers participating 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.

Customer feedback management and monitoring of user reviews in online platforms must be a concern addressed in any marketing plan, since these public manifestations of word of mouth can have very a positive effect on the generation of leads and business, but also a notably negative impact in the event negative buzz starts to circulate online (Chen & Xie, 2008).

Although 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 (refer to the study by Chevalier & Mayzlin, 2006), the authors of this study still found a gap in literature exploring the effects of Marketing initiatives (besides brand advertising) on the generation of word of mouth. In order to address this informational void, the aim of this article will be to analyse how pricing changes (specifically through promotional discounts) can lead to fluctuations in the user review scores of products in an online marketplace. This will hopefully shed some light on the role of price in the consumer's pre-purchase expectations, and the post-purchase evaluation of their consumption experience.

To achieve that goal, we'll first review the literature regarding the main constructs that make up the framework of social shopping, starting from the definition of community and its application to the Internet; the motivations for engaging in word of mouth and how virtual communities have made it easier to share opinions online; the phenomenon by which the Web 2.0 has led to the creation of online marketplaces and the importance of electronic word of mouth in the online shoppers' purchasing decisions; and finally, how customers form their expectations based on price, and how they take pricing initiatives into account when publishing user feedback online.

Chapter 2 starts with the concretization of our research questions and our hypotheses, after which we will explain our methodology for this study, based on the extraction and analysis of price and user review scores from products in an online marketplace (specifically, Steam, a software digital distribution platform) over the course of 2 months. On Chapter 3 we will present our findings and attempt to answer the research questions, examining any possible weaknesses in our quantitative dataset.

Finally, we will reaffirm the importance of future research on the subjects of electronic word of mouth and online recommendation systems, proposing the addition of further variables to this analysis, which will allow for more definite answers on how pricing strategies, when paired with adequate online feedback management policies, can be used to generate more business.

II. Literature review

In order to fully understand the phenomena we're trying to study, we found it important to analyse the scientific work that has been the foundation of word of mouth marketing throughout the years, and look onto the most commonly accepted and referenced articles for answers to why and how individuals make the decision of reviewing goods and services post-purchase.

i. Communities and their social value

Attempts to define the term "community" have been a source of debate among scholars of the social sciences for decades (Komito, 1998). At the heart of the disagreements lies the typology of bonds that can link individuals to form a community.

Earlier definitions put emphasis on geography and the locality of relationships (Park, 1926), defining the ideal community as "small, homogenous and having a strong sense of group solidarity" (Tonnies, 1957).

Other, more recent, research defines community as a network of social relationships between individuals, regardless of geographical limitations, who share feelings of belonging (Wild, 1981) and are sources of emotional support and companionship, emphasizing the strength of ties between nodes of the network and the different ways strong (family, friendship) and weak ties (acquaintance) can create social value – stronger ties facilitate the flow of material resources and emotional support, while weaker ties can serve as bridges of information less likely to be biased by affectional factors – influenced by the opinions of close relatives, for example (Frenzen & Nakamoto, 1993).

Finally, some community scholars argue that a community may simply be founded on a shared experience or idea, i.e., if their members can find a common interest, even if none of them share any other kind of bond or have never so much as interacted face-to-face. Here, the community serves to provide a sense of shared identity, akin to the concept of *alma mater* as a bond between *alumni* of an academic institution (Falk Moore & Myerhoff, 1975), or the virtual bond observed by Schouten & McAlexander (1995) among owners of Harley-Davidson motorcycles, which sparked the research into brand communities.

Current literature still refers to the theoretical framework laid by these authors to explain the similarities and differences between traditional communities and modern online social networks (Tayebi, 2013).

ii. Word of mouth

Word of mouth, whose many attempts at definition by academics include being an "oral, person-to-person communication between a receiver and a communicator whom the receiver perceives as non-commercial, regarding a brand, product or service" (Arndt, 1967), is considered to have one of the strongest impacts in shaping the consumer decision-making processes, among all types of communication (Tybout et al., 1981).

This all stems from the credibility of WoM versus traditional advertising. Nielsen's latest report on this subject, "Global Trust in Advertising and Brand Messages" (Nielsen, September 2013), elects word of mouth as the form of communication most trusted by consumers. To the question "To what extent do you trust this form of advertising?", 84% of respondents (#1 in the ranking) claimed to completely or somewhat trust "recommendations from people I know", while 68% of the sample showed trust in "consumer opinions posted online" (#3 in the ranking, preceded by "branded websites" with a score of 69%).

This laurel is due to the customer's search for the "truth about the product" (Dichter, 1966), and as such being more receptive to listening to advice from other users who they believe have no material interest or ulterior motive for recommending a product or brand.

It is no surprise, then, that negative word of mouth has a higher influence on the consumer than positive word of mouth (Engel et al.,1969; Tybout et al., 1981). The focus on negative aspects of the product/service has no place in traditional B2C advertising, but it is abundantly present in C2C (consumer-to-consumer) communication (Bambauer-Sachse & Mangold, 2011).

This does not mean, however, that word of mouth is a linear function of customer (dis)satisfaction. Anderson (1998) used nation-wide data from consumers of the US and Sweden to present the CS-WOM relationship as an asymmetrical U-shaped function suggesting consumers are more likely to engage in word of mouth the closer they are to either end of the satisfaction spectrum. Furthermore, the same model cast doubt on previous suppositions that unsatisfied consumers were more prone to engage in WOM, since the data showed that difference was not as statistically significant as predicted by some authors, who claimed dissatisfied customers engaged in negative word of mouth up to 10 times more frequently (Schlossberg, 1991).

In fact, the impact of word of mouth is mostly owed to its high diffusion rate. In 1969, a study proposed that 90% of customers who experimented with a new product/service had shared their experience with at least one other person, and 40% commented on their level of satisfaction with 2 or more acquaintances within a few days of the trial (Engel et al., 1969). A more recent survey (Blodgett et al., 1993) showed that 75% of consumers engage in negative word of mouth, sharing their dissatisfaction with an average of 5 other people, thus cementing the idea that negative buzz has tremendous reach and impact.

It is important, yet very difficult, for a brand to be aware of the WoM generated around its products and services, since most of the communication occurs on a level beyond its control – individuals share their consumption experiences on their day-to-day and more often than not engage in negative word of mouth in situations that don't warrant a formal complaint to the seller (Swan & Oliver, 1989).

Finally, the advent of the Internet and the emergence of new computer-mediated communication tools have contributed immensely to the engagement and diffusion of word of mouth, generating the novel concept of electronic word of mouth (eWoM). As more users gain access to the digital world, C2C communication is becoming a widespread and increasingly impactful factor in the marketing strategies of companies and brands (Chen & Xie, 2008).

iii. Motivations for word of mouth engagement

Dichter (1966) attempted to justify word of mouth by proposing four main motivations for positive communication:

- **Product involvement**, leading to product-related discussion;
- **Self-involvement**, to satisfy the buyer's own emotional needs of self-confirmation or recognition;
- **Other involvement**, or a will to help other consumers make the right purchase decisions;
- **Message involvement**, resulting from brand-originated ads or commercials.

Later, Richins (1984) proposed the search for "vengeance" could be a motivation for negative word of mouth, since dissatisfied consumers might feel the need to vent frustration after a negative experience by harming the brand. On the other hand, giving a good review on a product is often the way consumers find to give something in return to the company for a positive experience (Sundaram & Hills, 1998).

Remuneration is sometimes a driver for word of mouth, even if that defies the notion of a "non-commercial communication". Referral systems that reward consumers for convincing others to adhere to the brand are some of the most commonly used methods for spreading the word about a new product, with proven success in market penetration efforts.

Finally, but perhaps most relevant to our study, Price et al., (1995) also suggested "marketplace involvement" as a motivator for word of mouth, which relates to the altruism concept derived from Dichter's original proposal, implying that the consumer feels the need to contribute to the marketplace community by sharing their personal experience and product expertise, improving the decision-making and purchase processes for other actors in the network. This was supported by Balasubramanian & Mahajan (2001), who coined the term "focus-related utility" to describe the satisfaction individuals derive from "adding value to the community".

Specifically for eWoM, most authors agree that the above motivations are also the main drivers for participating in online product-related discussion, with Cheung & Lee (2012) pointing out egoism, collectivism, altruism and principlism as the primary reasons for publishing online reviews.

iv. Online communities

The typical Internet community is seen as voluntary in nature and self-selective, i.e., community members opt in (and out) of the community as they feel the need to gather and exchange information (Ridings & Gefen, 2004), which holds especially true in communities created for discussion of specific topics (Herring, 2001).

Walther (1996) spoke at length about the power of computer-mediated communication and how the impersonal nature of online communications is often optimal in order to diffuse information and create group consensus, by minimizing the interpersonal affectional and social influences in conversations, and creating emphasis on the objectivity of contents and participatory democracy (Kiesler et al., 1984).

From earlier concepts of e-mail mailing lists and discussion groups to more modern bulletin boards and online social platforms, there are several tools online that fuel the exchange of information and communication between individuals. This exchange gives way to the formation of ties, no matter how weak or strong, that constitute computer-supported social networks with their own sets of norms and structures (Wellman, 1997).

While traditional communication is typically synchronous (in real time) and characterized by contextual cues (tone of voice, facial expressions, etc.), online communications can be asynchronous or a mix of the two (Rafaeli & Sudweeks, 1997). Asynchronous exchange of messages through forums and bulletin boards, for example, leads to the creation of information depositories that other users may find while looking for information on a given subject. This makes virtual communities a mix of social and informational networks (Burnett, 2000).

Porter (2004) suggested a typology of virtual communities with two levels of definition: On the first level, a community can be member-initiated or organization-sponsored, depending on the actor(s) that established it. The second level categorizes a community according to the orientation of the relationships between its users. Member-initiated groups can be social or strictly professional (e.g. communities of practice), while organization-sponsored communities can be commercially driven, non-profit, or governmental in nature (see **Figure 1**).

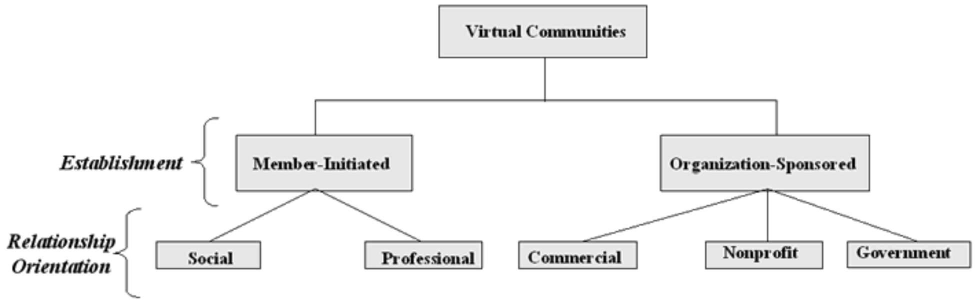


Figure 1 *- Typology of Virtual Communities proposed by Porter (2004)*

Regardless of types, Porter goes on to list 4 common attributes of all virtual communities:

- **Purpose** – the common goal or interest shared by the community members (Jones & Rafaeli, 2000)
- **Place** – not necessarily a physical space, so much as a sense of co-presence of members of a community and which can be metaphorically attributed to the "website" or "electronic address" (Harrison & Dourish, 1996)
- **Platform** – defined by the technological mediums and infrastructures that allow individuals to communicate within a community.
- **Population** – the social structure and pattern of interaction between members – communities can be small groups or networks, and the ties between members can vary in strength and nature.

Another concept highly relevant in this study is that of virtual publics, "computer-mediated spaces, whose existence is relatively transparent and open, that allow groups of individuals to attend and contribute to a similar set of computer-mediated interpersonal interactions" (Jones & Rafaeli, 2000).

While in the earlier stages of adoption these technologies were reserved to demographics who had enough disposable income to afford the cost of entry – resulting in a network of individuals homogeneous in economic standing and education (Barlow, 1995) – as the equipment and services become more and more accessible, the number of Internet groups and the diversity of virtual publics have increased exponentially.

Online communities have been a hot topic in recent marketing and management publications, as companies focus their research on how to effectively harness the power of online communities and social media (Nambisan & Watt, 2011;Weinberg *et al.*, 2013).

v. Online marketplaces and online user reviews

We have already discussed the evolution of the Internet as a revolutionary channel of communication that paved the way to discussions unchained by geographic restrictions or the traditional social network paradigm.

Initially, the Internet allowed the circulation of word of mouth through 1 to 1 media (e-mail messages) or 1 to many (via mailing lists and later through the proliferation of personal webspaces). But the revolution of Web 2.0 was game-changing in the way individuals interact online, allowing the development of tools for many-to-many communication, either through the modern social networks, forums or notice boards, and the broadcasting of user-generated content through social platforms such as blogs and YouTube or similar media-streaming websites (Solomon & Schrum, 2007).

Product-related content can, in turn, be publically published through specialized platforms like epinions.com, or through online marketplaces (Lee & Youn, 2009).

e-Commerce has been a part of the Internet for as long as it has been open to for-profit organizations, who immediately started pursuing opportunities to generate business leads via the new technology. Today, with an Internet penetration over 40% worldwide and growing (internetlivestats.com, June 2015), and PwC's Global Total Retail Consumer Survey (PwC, February 2015) reporting over 50% of their respondents shop Online at least on a monthly basis, e-Commerce has proven to be essential for any business to reach out to their full market potential.

But the backbone of e-Commerce is no longer exclusively comprised of companies reaching out to potential customers through their proprietary websites. The new reality of the Internet is oriented towards the creation of third-party platforms that serve as hubs for supply and demand, meeting points for buyers and sellers, who are provided with infrastructure and tools to communicate with each other and close deals (Pavlou & Gefen, 2004). Such is the case of ebay.com and Amazon, two of the largest online marketplaces today.

In these platforms, sellers can post their products, including more or less detailed descriptions, specifications, prices and even promotions. Buyers can contact the seller, engage in negotiation and close deals, and provide feedback on several aspects of the purchase/consumption experience, such as the quality of products, price, the quality of the interaction with the seller, and the efficiency of delivery (Schafer et al., 1999).

Online marketplaces have recognized the potential of having recommendations systems and public review systems, where consumer opinions are gathered and often condensed in the form of review scores, or ratings, giving the customer a greater range of information about the products on sale without having to visit other websites (Chen & Xie, 2008).

Besides users perceiving value in verbalizing their opinions online for the same motives we've discussed earlier, Hennig-Thurau (2004) also studied why users read those opinions. The most common goals are to "save decision making-time and make better decisions", but there are other factors such as remuneration or the sense of belonging to a community, that drive users to consume word of mouth.

Furthermore, the fact that communication in online platforms is durable and information is stored and visible for most visitors to read, brings a new light to the "community involvement" motivation for engaging in eWoM. Here, more than in traditional discussions, that contribution is not completely altruistic. By sharing their opinions through the Internet, users of web-based opinion platforms hope to motivate others to do the same, increasing the flux of information. That way, for example, if they encounter some problem with their product, they're more likely to find someone who has encountered the same issue before and knows how to solve it. And, in turn, that is more likely to happen once the platform has reached a critical mass of users and interactions (Peddibhotla & Subramani, 2007).

Users who share their opinion in search of recognition, self-enhancement or social benefit, can also see the Internet as a facilitator. Online marketplaces often recognize a user's frequency of activity through reputation systems, letting shoppers access other users' review history, which ultimately allows the perception of expertise and how helpful they have been in the past (Hu et al., 2008). Shen et al. (2012) even studied the competition for attention between online reviewers and their strategic perspective on content creation.

Several other, more recent, studies have confirmed that online reviews have an influence on the process of information adopters by future buyers (Cheung, 2014), going as far as arguing that herd behaviour can lead shoppers to bias their opinions on others' compelling arguments and credibility, leading to a tendency for imitation on the generation of Word of Mouth (Shen *et al.*, 2014).

vi. Implications of online recommendations and review scores

The idea that online reviews influence the consumer's decision making process has been proven true by several studies. Senecal and Nantel (2004) conducted an online experiment that presented subjects with several combinations of brand websites, user-generated recommendation sources, and products, reaching the conclusion that online recommendations acted as reliable information sources in the pre-purchase information seeking phase. As a consequence, "subjects who consulted product recommendations selected recommended products twice as often as subjects who did not consult recommendations." (Senecal & Nantel, 2004, p.1)

Based on those and similar results, online word of mouth has been suggested by several authors as a promising variable in forecasting future sales, particularly in the film industry (Dellarocas et al., 2007). One particular study, regarding daily box office performance for recently released movies, concluded that online review ratings had no influence in future daily revenues, suggesting that the evaluations of other users had no persuasive effect over consumers' picks of movie(s) to watch. However, the same study confirmed that the increased volume of online posting alone had a positive impact on revenues due to the awareness effect, as online reviews are an indicator of intensity of word of mouth, which is a significant driver for movie sales (Duan et al., 2008).

Chevalier and Mayzlin (2006) deserve a special mention for their pioneer analysis of user reviewing behaviour, through the observation of aggregate review scores and sales figures across 2 different online book stores (Amazon.com and Barnes and Noble's website bn.com) over the course of a year. They concluded that changes in user reviews had a significant effect on sales, not only if you consider fluctuations in average review scores, but also based on the percentage of negative opinions. The study went as far as analysing the length of commentaries in user reviews to support the idea that consumers read and respond to user generated content and take it into account in the decision-making process.

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 – see Filieri & McLeay (2014) for an application to travel and accommodation markets, and Cui *et al.*, (2012) for research on consumer electronics and videogames.

vii. Customer satisfaction theories

Yi's (1990) review on the constructs behind customer satisfaction theory is commonly referenced for presenting multiple propositions for the measurement and evaluation of consumer (dis)satisfaction. Most of those studies revolve around the disconfirmation theory, according to which consumers evaluate their products by comparing their pre-purchase expectations with the actual performance perceived during the consumption experience (Oliver, 1980). When that experience is as pleasurable as, or more pleasurable than, their expectations, consumers are left with a sense of satisfaction; whereas if the emotional outcome of consumption is subpar to expectations, then consumers will be dissatisfied.

Two of the most commonly accepted theories differ only on the basis by which those standards or expectations are created:

- the **Comparison level theory** is built on the idea that expectations are influenced by three basic sources: the consumer's past experiences with similar products; the situational context in which a product is offered, be it advertising or promotional efforts by manufacturers; and their knowledge of other consumers' experiences with the product under evaluation. Each instance of consumption will "force" the consumers to adapt their expectations by altering their comparison level (LaTour & Peat, 1979)
- the **Value perception disparity theory** implies that pre-formed expectations for products are an insufficient referential for customer satisfaction measurement, since expectations may not accurately represent an individual's needs, wants and desires. For example, individuals may create expectations for specific functions/features of a product but not others, while in practice those "extra" functions add to the consumer's perceived value of the product and therefore can increase purchase satisfaction. Therefore, the goodness of fit between the consumer's values and the objective performance of the product should instead be used to evaluate CS (Westbrook & Reilly, 1983).

Despite there being studies that support the validity of both hypotheses, neither comparison levels nor value perception disparities are sufficient to fully explain the phenomenon of consumer satisfaction by themselves (Yi, 1991). Instead, those and other constructs, such as transactional equity (Fisk & Young, 1985) and normative expectations (Woodruff et al., 1983), should be used complementarily.

Whereas satisfaction is thought of as an affective outcome of consumption, and as such being in essence a post-purchase construct, more recent studies focus on the cognitive process by which consumers assess the utility, or value, of a product, based on the sacrifices and rewards associated with its purchase and/or consumption (Zeithaml, 1988).

The customer perceived value theory has at its core the idea of a trade-off between quality and price, and proposes that consumers make their purchasing decisions based on the goal of maximizing the value-for-money ratio (Cravens *et al.*, 1988).

To evaluate the factors that contribute to the perception of value by customers, Sweeney & Soutar (2001) developed PERVAL, a four-dimensional scale that accounts for the effects of:

- **Emotional value** – feelings and affectional states derived from consumption;
- **Social value** – the product's potential to enhance the individual's notion of its own social standing;
- **Price** – perception of sacrifices incurred on the acquisition of products, either through objective costs or costs of opportunity;
- **Quality** – functional value as measured by the product's performance.

The weight of each of these dimensions is implied to vary from consumer to consumer (Zeithaml, 1988), product to product (Sheth, 1991) and even at different decision levels – buy/not buy, choice of brand, choice of product. Therefore, multi-dimensional scales of product performance, quality and satisfaction are common, both for retail products and for services (SERVQUAL – Parasuraman et al., 1988).

These theoretical foundations still guide current literature and hold true for recent empirical applications of consumer satisfaction constructs (Flint *et al.*, 2011; Malik 2012).

viii. Systems for Online User Reviews

Online product reviews happen when consumers articulate their thoughts on product quality and post-purchase satisfaction through the Internet. To accurately portray the results of online WoM, several different types of reviewing systems can be used.

Amazon.com's model, exemplified in **Figure 2**, allows users to rate the products they purchased on a 5-point scale, and results are most readily presented as the average score, as well as the absolute frequency of each discrete evaluation.

***Figure 2** - Example of Amazon product review summary*

Booking.com, a prominent accommodation booking website, encourages its customers to evaluate hotels based on several dimensions (location, comfort, price-quality relation, staff, etc.) and agglomerates those results into a simple average score as seen in **Figure 3**.

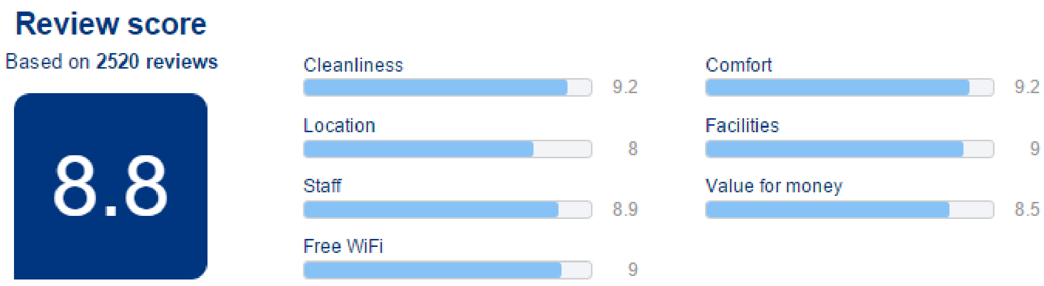


***Figure 3** - Example of booking.com review system*

Buyers and sellers on **ebay.com** evaluate each other by the quality of their interaction during a transaction, on a 3-option scale: the experience was either negative, neutral or positive. The seller's reputation is based on its past buyers' feedback and is presented in the product page as an aggregate feedback score, as well as the percentage of positive feedback, in an effort to inspire trust in future buyers – see **Figures 4 and 5**.

Figure 4 *- ebay.com seller panel on a product page (example)*

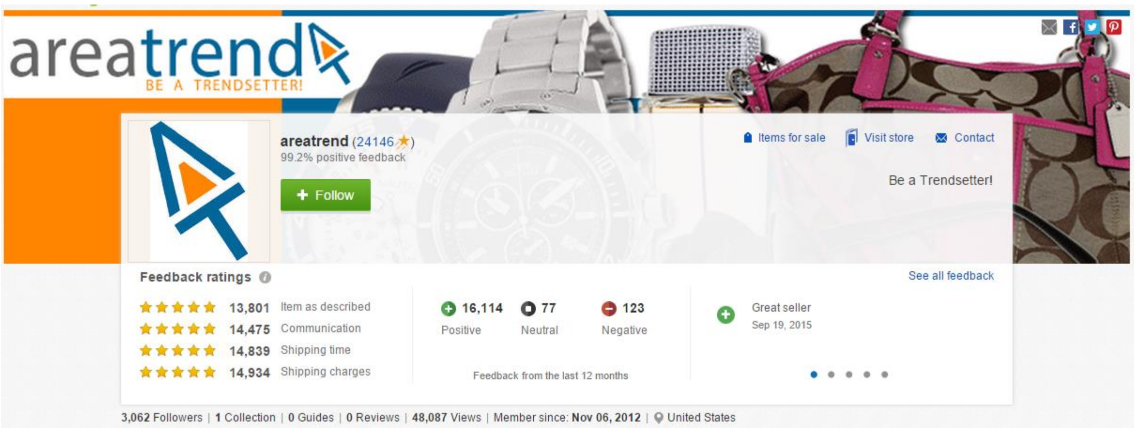


Figure 5 *- ebay.com page for the same seller as in* ***Figure 4***

In the first two cases, as well as the seller page for ebay.com, customers are asked to evaluate their perception of quality in the products purchased or the seller trustworthiness, not unlike the traditional method of measuring satisfaction through Likert scales. These reviewing systems allow future buyers to select the products or sellers that best fit their own values, or in other words, the features they value the most.

In other cases, such as the **Steam platform**, consumer reviews are made on a two-option scale: users either recommend a product they purchase, or recommend against it. The outcome is then aggregated and translated into a 9-point scale, ranging from

"Overwhelmingly Negative" to "Overwhelmingly Positive" based on the total number of reviews and the percentage of reviews that are positive. This percentage is also shown on the platform's product search engine and can be used as a sorting criteria to order products from the most recommended to least recommended. The absolute number of positive and negative reviews can also be seen on the product page – see **Figure 6**.

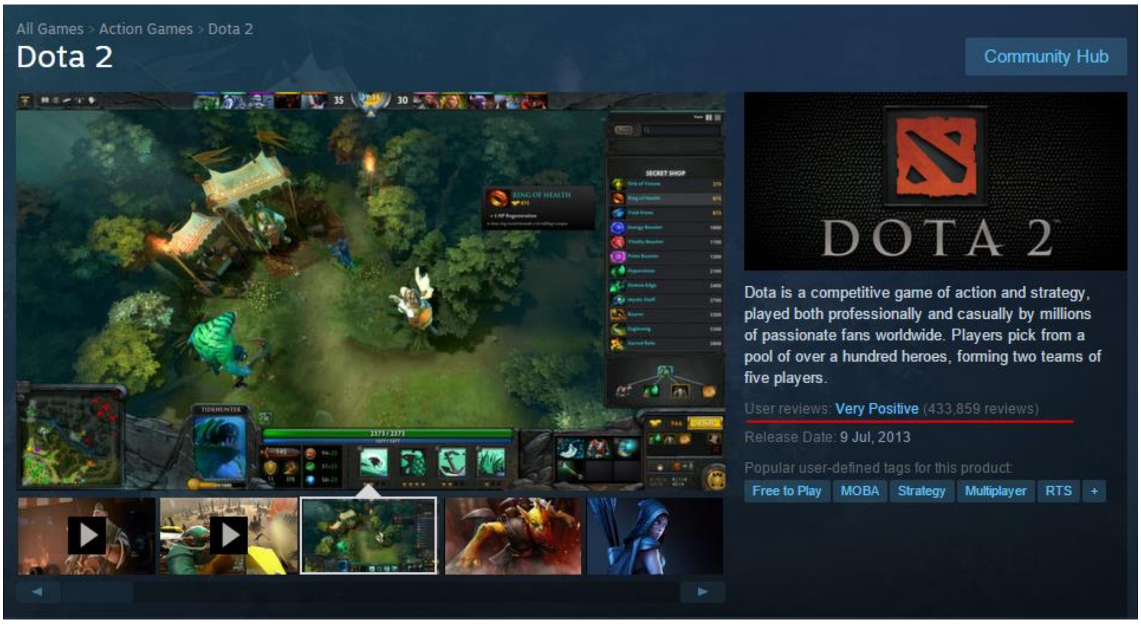


Figure 6 - Example of Steam Store Product Page, with the Product Reviews information highlighted

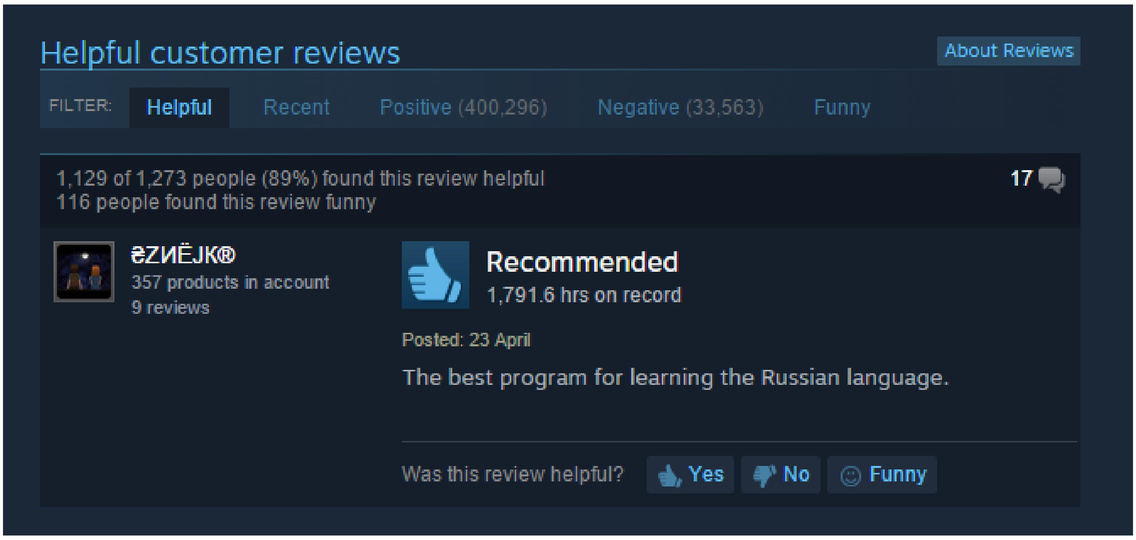


Figure 7 *- Example of Customer Reviews section in a Steam product page*

Users can also rate customer reviews on their helpfulness and/or humorous nature, which allows the platform to highlight the posts with the best feedback on each of those criteria, as well as order them by publication date – **Figure 7** shows an example of a Product review where these attributes can be seen.

The Steam reviewing system invokes the notion of a certain standard of quality that is pre-formed by consumers based on price and quality perceptions and that generate feelings of satisfaction or discomfort when compared to the actual perceived quality of products post-consumption. To understand this mechanism, it is particularly useful to analyse the thesis by Voss et al. (1998) which, although primarily focused on service exchanges, is among the first articles to emphasize the role of pricing in predicting customer satisfaction.

III. Research proposal and Methodology

The authors of this study have detected a lack of literature exploring the practical effects of marketing initiatives on the sphere of online word of mouth. To our knowledge, no other authors have tried to observe the impact of pricing actions on one of the most fundamental forms of C2C communication – user review scores.

Therefore, this research will be a first foray into this particular subject, and as such the research questions are kept sufficiently comprehensive, without going into much detail about the factors that cause and shape that impact:

- Does a price reduction on a product lead to a noticeable increase in the number of user evaluations?
- Does a price reduction on a product influence its user review score?
    - If yes, what is the direction of variation on review scores?

These research questions can be 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

i. Research object

To answer these questions, our study will focus 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.

Despite there being no official figures on the market share of the platform, estimates point to an order of magnitude of 70% of all digital sales of games (Forbes, 2011) being made through Steam. Valve, the developer of this software, reports a peak of 8,5 million simultaneous active users, with over 100 million accounts created on their servers.

The choice of a digital distribution service is also 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 (and the Steam platform does a good job of enforcing strict hardware requisites are posted in the product page, in order to prevent negative feedback and product returns).

Finally, Valve recently launched the Steam Greenlight project, a feature that invites independent developers to present their projects and prototypes to the community, allowing these to vote on ("green light") their favourite proposals and secure those a place on the Steam Storefront once they're released. By crowdsourcing the prospection of new games and developers, Valve are also able to guarantee a constant flow of new products, which gives us more data to work with, and more indie titles to analyse.

In order to fully understand the role of Steam as a facilitator of product-related word of mouth, it is again useful to resort to Porter's typology of virtual communities and their common attributes:

- **Purpose** – Steam is a digital distribution platform for video games. Users are required to register an account in order to purchase products, play Steamexclusive free-to-play titles or access user-generated contents. Upon registry, users must enter a valid e-mail address.

- **Place** – The Steam storefront and community features can be accessed directly through the website (main landing page: store.steampowered.com), although in order to launch their games users must download and install the desktop client. A mobile app is also available with access to most social features.
- **Platform** – There are several points of interaction between members of the community. First and foremost, each user has a profile which may be set to public or private, where they can publish text posts, screen captures and video clips of their gaming experiences through Steam, as well as showcase their in-game achievements and collections. Players can add other users to their Friends list, which allows them to communicate through Steam Messenger. There is also the option to create and join Steam Groups, which function as discussion forums. Finally, each product on Steam has an associated Community Hub, where Steam users can publish multimedia contents and engage in conversation about those games. The main focus of this research will be in the User Reviews section of the storefront, where only consumers who purchased a certain product can express their opinions on its quality and performance, through a recommendation/complaint.
- **Population** – Every user can access public profiles for other members of the community, as well as all content in public groups. The Friendship connection allows players to use Steam chat, and receive notifications of each other’s activity on Steam through the Friend Activity screen.

ii. Data collection

In practice, 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 – see an example of the data extracted in **Table 1**:

- 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 – as seen in **Figure 8**.

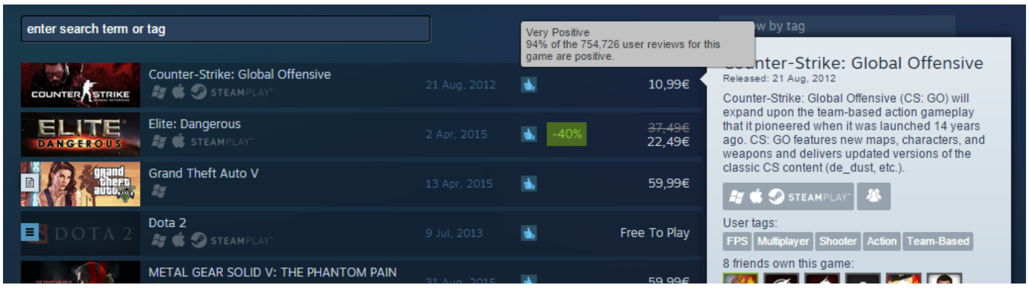


Figure 8 - Screenshot from the Steam Storefront product Search, illustrating the main attributes of a product, including product reviews and discounts

AppID	Product Name	Release Date	Gross Price	Discount	% posititve reviews	# Reviews
app/254880	MoonBase Commander	Feb 6, 2014	$5.99		85%	41
app/316840	The Sacred Tears TRUE	Sep 25, 2014	$9.99		85%	20
app/319560	Reprisal Universe	Sep 15, 2014	$9.99		86%	30
app/328920	F-117A Nighthawk Stealth Fighter 2.0	Oct 30, 2014	$6.99		92%	13
app/47730	Dragon Ageâ„¢: Origins Awakening	Mar 16, 2010	$19.99		93%	45
app/336280	Chronicles of a Dark Lord: Episode 1 Tides of Fate Complete	Dec 19, 2014	$4.99		100%	6
app/285980	Kromaia	Oct 23, 2014	$19.99		89%	28
app/329320	QbQbQb	Oct 29, 2014	$4.99	-40%	91%	46
app/319400	Disney Winnie the Pooh	Oct 6, 2014	$5.99		93%	45
...	...	...	...	...	...	...

Table 1 - Example of data extracted from the Steam Storefront

To collect this information, we used import.io's visual extractor, a manually activated page crawler tool, which presents some limitations on the quality of data extracted:

- Due to software errors and/or connection interruptions, information for some products is missing for the dates: 5th February, 26th February, 1st March.
- The time-distance between observations is not a constant (extractions were activated between 7 PM and 1 AM). In addition, because the extraction process has a duration of up to one hour, data for all products does not refer to the same moment in time – For each observation, there can be a delay of up to an hour between the first and last entries of the product database.
- For each observation, there can be duplicate data for each product, as well as products missing. To attenuate these flaws, we considered only the first record of each product in each observation, and assumed missing (null) data for missing pairs of date-product.

iii. Sample Selection and Data Treatment

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 the products that fulfilled the following requirements:

- Are not Free
- Have available information on review scores
- Have been released to the market before 2015 – Special discounts are common on the first weeks after the release of new products. Since our data extraction started in 18th January, this criteria ensures we don't analyse products that have been released too recently, since their behaviour might be irregular.
- Have at least 100 reviews on January 18 – this ensures we don't overestimate the variations in review scores. Products with a very low number of reviews would show a much higher volatility in review scores.
- Had a price discount between February 1st and March 17th.

These criteria resulted in a sample of 658 products.

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.

We then created a new construct, the "standard date" t. In practice, our standard date t=1 corresponds to the time-ordered observation made 14 days before the discount. t=29 corresponds to the observation made 14 days after the discount. And finally, t=15 always represents the discount date, allowing us to centre all occurrences of price promotions in a single standardized point in time, which will prove useful to graphically represent and visually interpret our data further on.

iv. Main variables for research

To test the hypotheses presented at the start of this chapter, we will be analysing the evolution of two main variables over a period of 29 daily observations (14 days before to 14 days after the first occurrence of a price discount):

- **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

Then:

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

- **Average product review scores**: 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., percentage of all reviews on day T that are positive

P_T: Total number of positive reviews existing on day T

p_T: New positive reviews published on day T

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

Given the simplicity in the nature of these variables, Expression 2 means that, mathematically, in order for there to be an increase in the review scores on day T, i.e.,

$$S_T > S_{T-1}$$

it must be true that:

$$\frac{p_T}{r_T} > \frac{P_{T-1}}{R_{T-1}}$$

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 (tests for autocorrelation can be found in Appendix I). 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.

v. Change Point Analysis and CUSUM charts

Change point analysis is a statistical method commonly used in several fields, from Biology to Finance, which tests for the occurrence of changes in the parameters of a distribution in a series of time-ordered observations (Matteson *et al.*, 2012).

This method has its bases on Page's (1955) proposition of a new method for detecting changes in the mean of an observation through Cumulative Sum Control Charts. By comparing each T observation with the average value of the series, Page proposed a function:

C_T: Cumulative sum of the differences to the series' average

(3) $$C_T = \begin{cases} 0, & T = 0 \\ C_{T-1} + (X_T - \overline{X}), & T > 0 \end{cases}$$

that can be represented by a CUSUM chart. In segments of the time series where the values of the observations are above the overall series average, the chart will have a positive slope. If a change point occurs, and the parameter of the distribution that is being tested for suddenly changes, then the slope of the function will change as well (Taylor, 2000). In the occurrence of a change point, it is to be expected that the time series is arranged in such a way that the CUSUM chart is similar to a U or V-shape, or its inverse.

The method of change point analysis takes this concept one step further. Firstly, we calculate $C_{diff} = C_{max} - C_{min}$, which gives us the difference between the highest and lowest values of the CUSUM function. Then, a set of bootstrap samples are generated by randomly rearranging the time series observations, in order to simulate what the CUSUM function should look like if no change point is present in the series.

The hypothesis of the occurrence of a change point is tested by comparing the original series with the bootstraps generated, with the confidence level of the test being equivalent to the percentage of bootstraps with C_{diff} higher than the original series' C_{diff}.

The same method can be used to test for changes in variation.

This test is also robust in the presence of outliers, which is particularly useful given the existence of missing data entries in our sample dataset.

Because of the exploratory nature of this study and the lack of sufficiently proved knowledge on how our variables behave in nature, we opted for a nonparametric method of change point analysis for our tests, making as little assumptions about the distribution as possible.

Additionally, because we're testing for multiple time series (specifically, one for each of the products of our sample), we needed a test capable of multivariate time series analysis.

The statistical package that presented the best fit for our needs was the ecp R package – see James & Matteson (2014) for an explanation of the computational process for the hierarchical divisive estimation tests.

IV. Results and Findings

i. New reviews published daily by product

Graphically representing and analysing a data set of 658 x 29 entries is not an easy task without the recourse to statistical software packages such as R.

The plot for reviews published daily, however, is a simple one to reproduce and, to an extent, interpret. **Figure 9** 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.

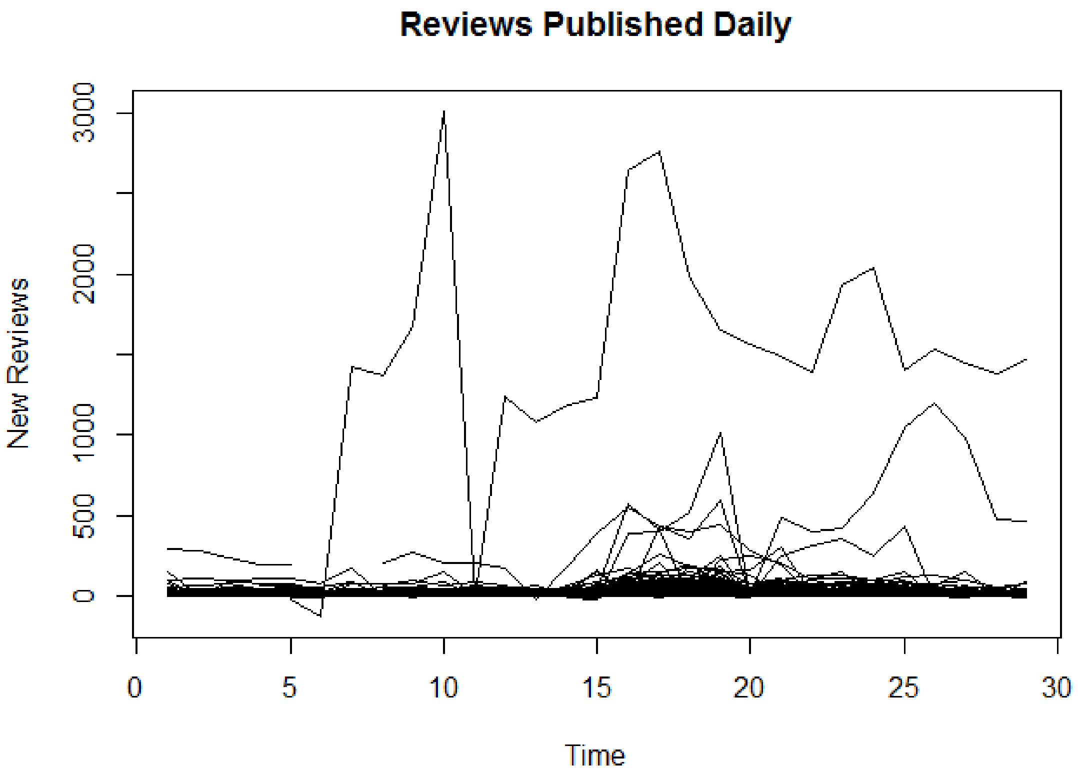


Figure 9 - Reviews Published Daily by Product

Testing for a change point (see **Appendix II** for the computer-assisted statistical test) 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.

ii. Average review scores by product

For review scores, the visualization of data was a more complex challenge.

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. The result, shown in **Figure 10**, provided some information about the behaviour of our variables.

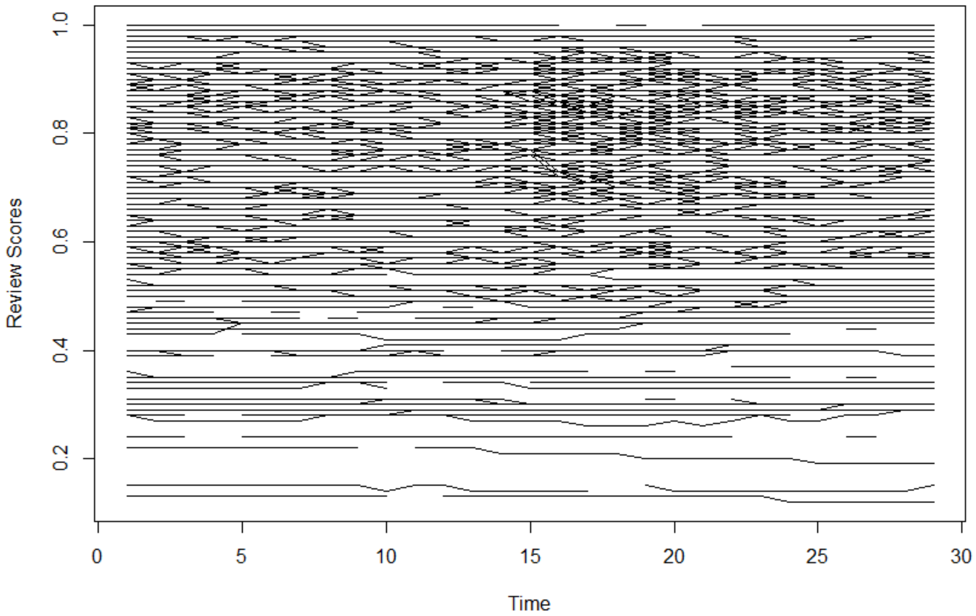
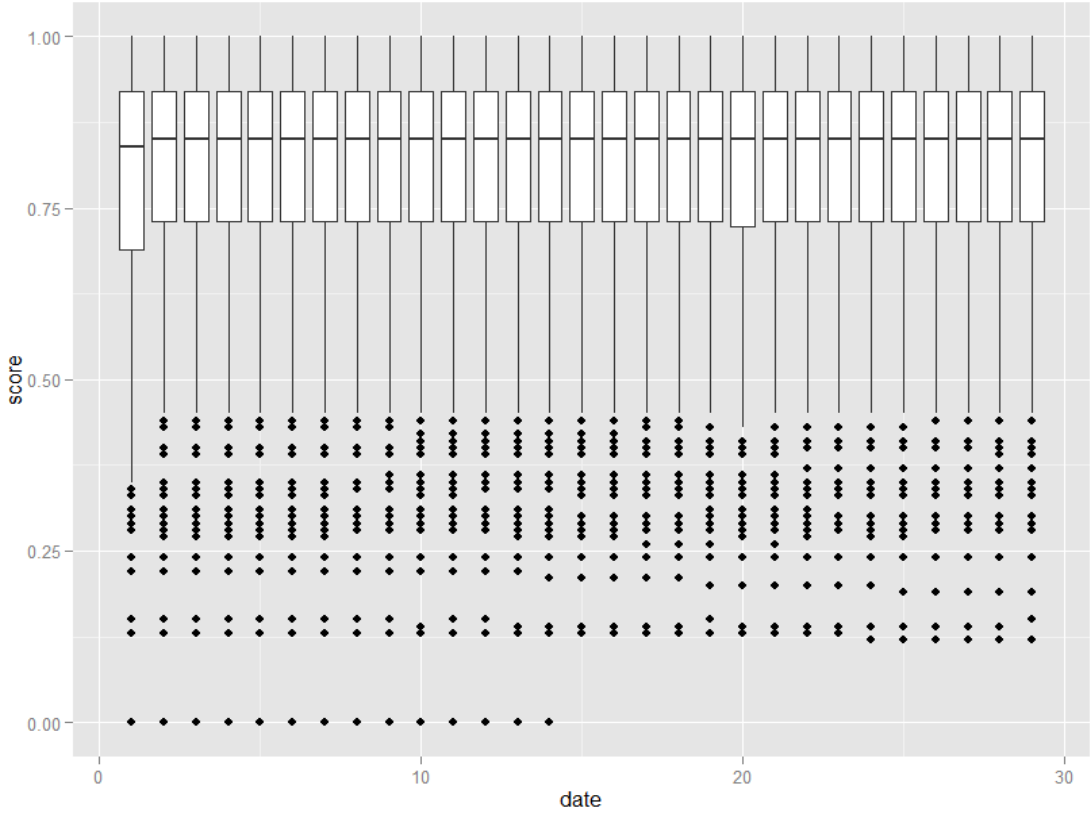


Figure 10 *– Time Series plot for Review Scores*

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, as we can observe through the time series boxplot in **Figure 11** and the statistical data in **Table 2.**




```
*t=1 affected by missing values
```

Figure 11 *- Time Series Boxplot for Product Review Scores*

	DISTRIBUTION OF REVIEW SCORES		
Stats	**t=1**	**t=15**	**t=29**
10th Percentile	59%	58%	59%
25th Percentile	73%	73%	73%
50th Percentile	85%	85%	85%
75th Percentile	92%	92%	92%
90th Percentile	95%	95%	95%
$\overline{X}$	80,493%	80,234%	80,365%
σ^2	0,0239	0,0239	0,0234
σ	0,1546	0,1546	0,1531

```
*revised to account for missing values
```

Table 2 *- Distributional statistics for Product Review Scores*

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 (S_{15}, which is its score for our standard date t=15; see the definition of this concept in Section III.iii – Sample Selection and Data Treatment).

For that matter, we create yet another construct – the Standard Score (S'_t):

$$(4) \quad S'_t = \frac{S_t}{S_{15}}$$

The graphical representation for this modified variable, results in time series chart in **Figure 12**:

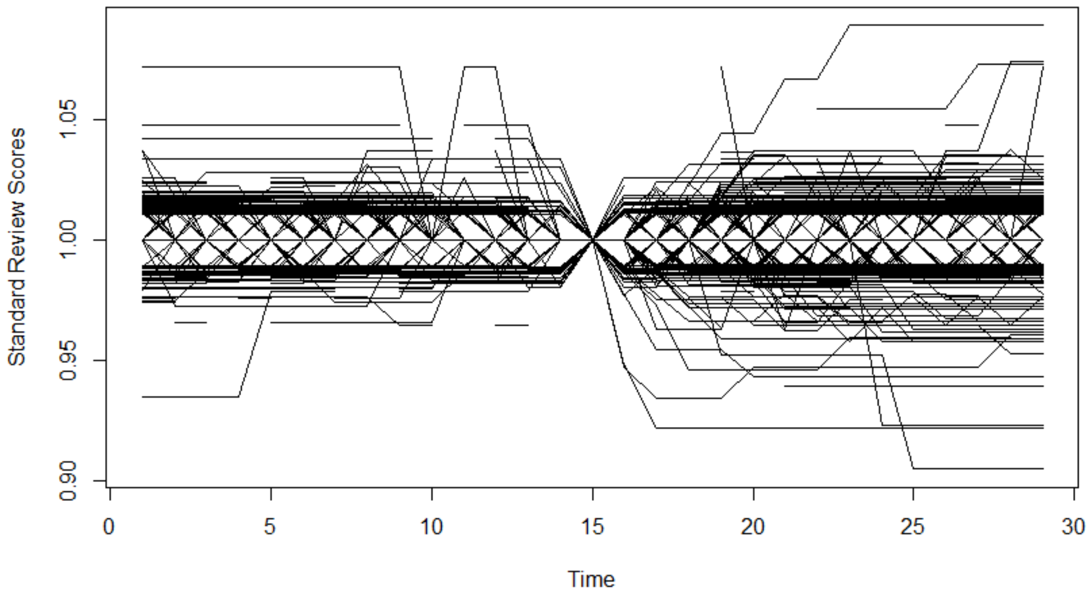


Figure 12 *- Standardized Review Scores plot*

This new plot 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 for the evolution of review scores, reproduced in **Figure 13**.

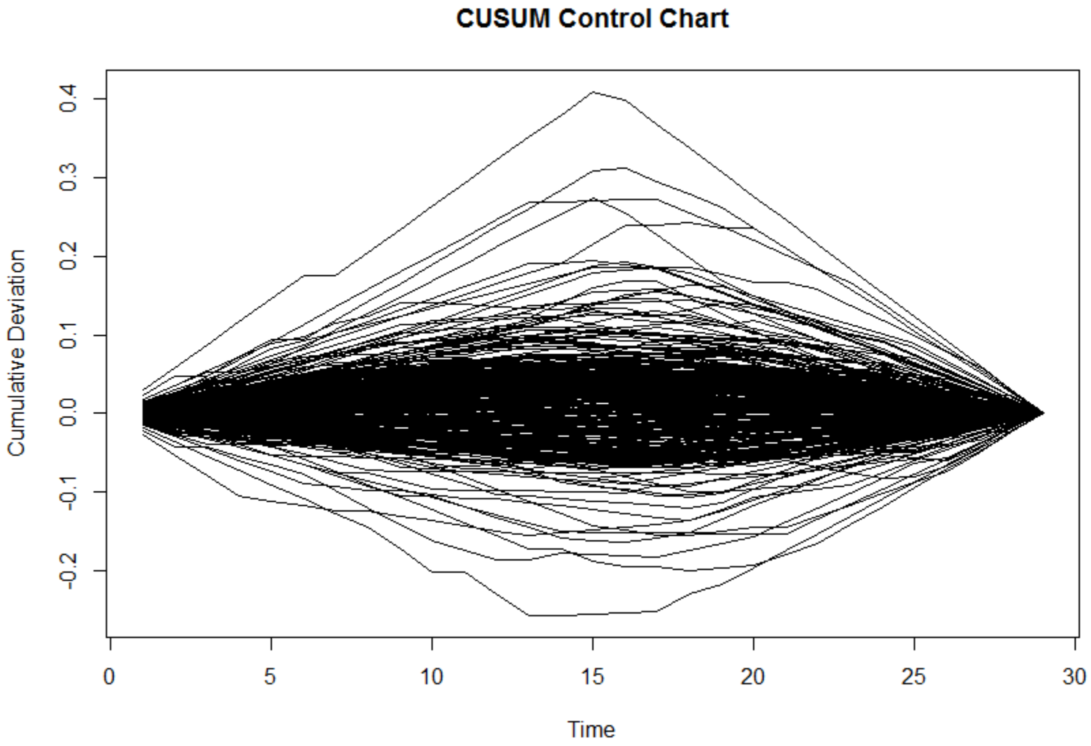


Figure 13 *- CUSUM Chart for Review Scores (Means)*

In section III.v we described what a CUSUM control chart would look like for a time series where a change point is present – a U or V shape (or its inverse) with the maximum absolute value located in or around the change point. Looking at our data it is easy to recognize a similar pattern for a considerable number of time series (products).

The final step is to run the test for a change point of the distributional means with the ecp package – see **Appendix III** for the programmatic testing process – which 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 effectively acquiring and having a first experience with the product, which we detected in the section regarding the analysis of new reviews to be at least 1 day;

b) The serial dependence of the variable in cause, paired with some rigidity in the scale (product ratings are presented in 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:

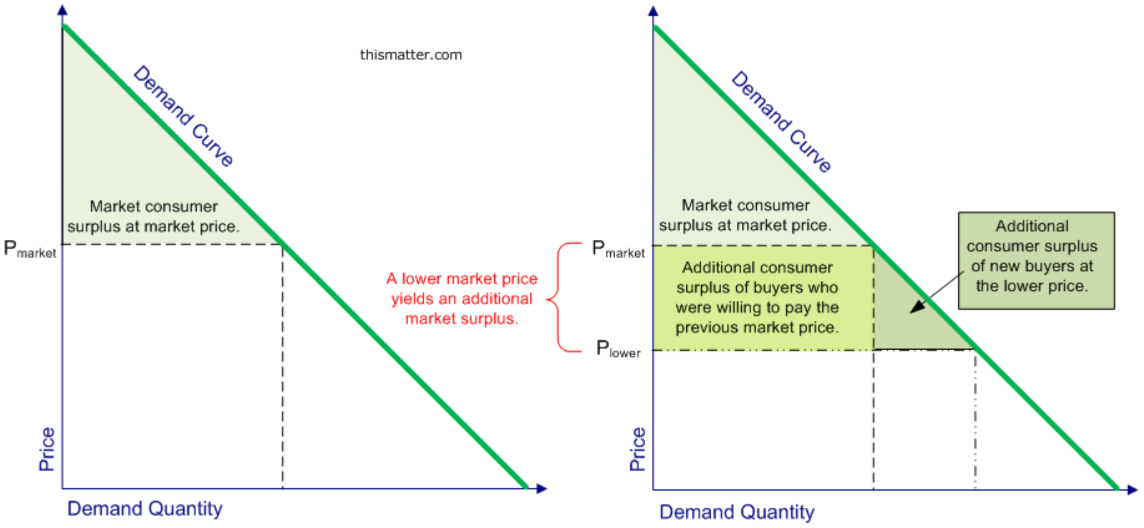
- 103 products for which $S_{14} > S_{29}$
- 325 products for which $S_{14} = S_{29}$
- 83 products for which $S_{14} < S_{29}$

V. Discussion

The two research questions this study proposed had the main objective of shedding some light into the general principles that guide electronic word of mouth generation in the context of an online marketplace, through the examination of how product reviews are affected by price promotions. We answered those questions using a set of longitudinal data extracted from the Steam platform over a course of two months, and came to the conclusion that the occurrence of a discount has a positive impact on the number of product reviews posted in the days following the pricing initiative, and that a significant impact is also felt at the level of review scores (although, for this sample, that impact could be either positive or negative).

The first conclusion is an easy one to explain, and is as simple as considering that Steam is a software digital distribution service, a typical supply-side market with a posted-price context. This means that for a fixed price determined by the seller, there is an infinite supply of homogeneous goods and each potential buyer faces a take-it-or-leave-it offer when making a purchasing decision (Kleinberg & Leighton, 2003).

In this type of context, by simplification, supply is considered perfectly elastic for a set price and the supply curve is commonly depicted as horizontal (actual supply of digital goods takes into consideration the costs of providing the service - Ke-Wei & Sundararajan, 2011). When the seller determines a price reduction, there is an increase in the total consumer surplus accompanied by an increase in the volume of sales – **Fig. 14**



Source: http://thismatter.com/economics/consumer-surplus.htm

***Figure 14** – Illustration of Supply and Demand in a Posted-Price market*

As the number of units sold increases for a certain product, an increase in the number of product reviews is also to be expected. Based on Duan et al. (2008), this increase in word of mouth alone has the potential to generate awareness and confidence in the quality of products, which could translate into future revenue, even after the promotional period.

Besides, if indecisive buyers can be won through a temporary price reduction and receive a pleasurable enough experience that they become loyal and/or can be persuaded to repeat their purchase, then a reduction in profitability in the short-term could be compensated by returns in the long run (Jacoby & Kyner, 1973).

As for review scores, we initially expected that the price reduction would induce lower expectations of quality from consumers, as suggested by Voss et al. (1998), which in turn should translate into higher customer satisfaction and more positive user feedback. However, that was not the case for our research sample.

Although there was a disruption in the process of word of mouth generation, leading to a destabilization of the review scores for a significant number of products, the direction of that shift was not linear across all products. Based on our literature review, we can rationalize that conclusion through a series of mechanisms, which could serve as the motto for future research:

- Although price discounts lead to an increase in sales through the expansion of the potential market, new buyers generally have lower reservation prices than previous buyers. These 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 like the one in **Figure 15**, which present a conditional evaluation based on price (Li & Hitt, 2010);

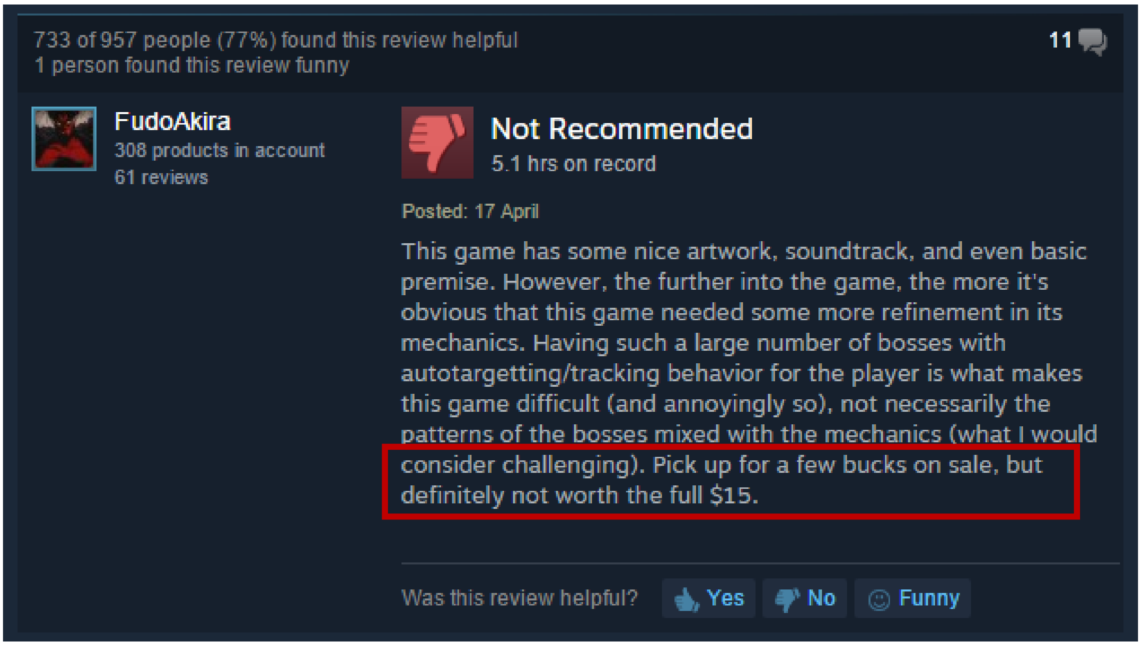


Figure 15 *- Negative product review published after a price reduction*

- According to Darke *et al.*, (2005) price promotions have negative effects in the consumers' value perceptions of products. This could mean that introducing a price reduction could undermine a customer's appreciation of quality and have detrimental effects on their online feedback;
- Festinger's (1957) dissonance theory implies that consumers tend to raise their evaluations of products when their cost of acquisition is higher. This effect could potentially bias (by excess) the reviews of customers who pay full price for a product, while the same pressure may not be as present in customers who buy at discounted prices. Eryarsoy *et al.*, (2014) explored this phenomenon for the case of online product reviews;
- Finally, and specifically for the Steam context, customers who purchase products for a higher price could likely be individuals with higher disposable income. More powerful hardware setups can easily be associated with more pleasurable and immersive experiences of video games consumption. Therefore, there could be a correlation between availability to pay more and better consumption conditions.

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 take those inflated/deflated scores into account as quality cues in the information gathering phase of their purchasing process, it could, again, be argued that:

- 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.

Either way, 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.

VI. Conclusion

i. Conclusions

The main goal of this research was to ascertain a relationship between pricing changes and the process of generation of word of mouth in online marketplaces which, given the relevance of social commerce and the power of the consumers' intervention in the creation of brand value and awareness, could reveal a new path in the development of e-business strategies.

Our research questions were formulated with the intent of proving that pricing initiatives online are met with direct responses from customers, in the form of online product reviews or recommendations.

Our first hypothesis stated that a price reduction should lead to an increase in product reviews, and it was proven true through the application of change point detection methods to a series of longitudinal data from a prominent software digital distribution service. We then proposed, based on the literature review, that the increase in awareness and buzz from those product reviews could positively influence future sales.

Our second and third hypotheses were centred on product review scores, and using the same statistical methods we proved that customer feedback is affected by price reductions not only in volume but also in nature. We also confirmed that price reductions could influence consumer evaluations negatively or positively, with plausibly durable effects in future returns.

Our main conclusion, therefore, is the urgency of further research into the subjects of online word of mouth and Pricing strategies in online marketplaces, which could demystify the mechanisms by which online buyers perceive product value, create expectations, and manifest their opinions, so that marketing science can benefit of a better understanding of social commerce, and develop new and improved strategies to realise the full potential of online and long tail markets.

ii. Limitations and future research

The purpose of our research was first and foremost of exploratory nature, utilizing empirical data to observe the behaviour of our research variables in their natural state of existence. Therefore, most decisions were made with the intent of keeping assumptions to a minimum (we overlooked the assumption of independent time series, for example, accepting the risk of being more susceptible to inference errors).

Our analysis was made with recourse to relatively basic tools and methods for data extraction and interpretation, which led to a sacrifice of statistical formality in favour of simplicity and ease of interpretation. Future research should be preoccupied with the improvement of our statistical processes, testing different methods for the detection of distributional shifts caused by pricing actions.

Besides, the empirical analysis in this study refers to a very particular social commerce platform. Steam, as a software digital distribution service, exists in a market of posted-price supply, which presumably functions in a different way to marketplaces where physical goods are traded, where marginal costs must be taken into consideration. The same base concepts could be applied to other digital goods, such as Amazon e-books or iTunes, but this study would benefit from replication in other contexts.

Steam also has a 2-point review scale – positive or negative feedback – which could possibly behave differently to other review systems (like the ones based on Likert scales) and therefore have a different impact in the consumers' formation of expectations and perceptions of value. The hypotheses in this research should be tested for other types of recommendation platforms, to assess if more flexible scales are affected differently by pricing initiatives.

Independently of the choice of online marketplace or reviewing system, there were several other variables that would have added immense value to this study. Although it wasn't one of the objectives of our research, we were unable to explain the non-linearity in the evolution of reviews before and after a discount. We present the challenge to future researchers to pinpoint the factors that define whether a product receives positive or negative feedback after a price promotion. We suggest the following starting points for that exploration:

- The possibility of a correlation between discount rates and the impact of the discount in product reviews could allow for more precise pricing actions, making it easier to forecast increases in sales in function of the percentage of price reduction.
- Understanding if different attributes of products can potentially be correlated with review scores (and the variations in review scores caused by pricing changes) could potentially identify clusters of products that are more or less susceptible to customer backlash. Understanding, for example, if a certain genre of video game has higher price-review elasticity would allow for the design of specific pricing strategies for those products.
- The timing of occurrence of a discount could also influence its effectiveness. As we've seen in this study, there is a higher volume of product reviews published on weekend than weekdays. Understanding that dynamic could lead to more cost-effective pricing actions.

Furthermore, it could prove useful to use discourse analysis methods to observe changes in the emotional and affectional cues in textual product reviews. The interpretation of online shoppers' verbalizations of product quality and satisfaction could allow for a deeper understanding of the consumer's behavioural processes, revealing factors and variables that can't be observed exclusively through review scores.

In sum, we believe that our research was a comprehensive first step for setting the foundations of an innovative and exciting approach of e-commerce strategies and electronic word of mouth marketing. In the form of an extensive literature review on the constructs behind social commerce and online recommendation systems, and an empirical examination of online marketplace behaviour, our main contribution was to offer a basis and directions for future research on a topic that is increasingly relevant and impactful.

VII. References

Anderson, E. W. (1998), "Customer Satisfaction and Word of Mouth", *Journal of Service Research*, Vol. 1, Nr. 1, pp. 5–17.

Arndt, J. (1967), "Role of Product-Related Conversations in the Diffusion of a New Product", *Journal of Marketing Research*, Vol. 4, Nr. 3, pp. 291.

Balasubramanian, S. and V. Mahajan (2001), "The Economic Leverage of the Virtual Community", *International Journal of electronic Commerce*, Vol. 5, Nr. 3, pp. 103–138.

Bambauer-Sachse, S. and S. Mangold (2011), "Brand equity dilution through negative online word-of-mouth communication", *Journal of Retailing and Consumer Services*, Vol. 18, Nr. 1, pp. 38–45.

Barlow, J. P. (1995), "Is There a There in Cyberspace?", *Utne Reader*, pp. 53–56.

Blodgett, J. G. D. H. Granbois and R. G. Walters (1993), "The effects of perceived justice on complainants' negative word-of-mouth behavior and repatronage intentions", *Journal of Retailing*, Vol. 69, Nr. 4, pp. 399–428.

Burnett, G. (2000), "Information exchange in virtual communities: A typology", *Information Research*, Vol. 5, Nr. 4.

Chen, Y. and J. Xie (2008), "Online Consumer Review: Word-of-Mouth as a New Element of Marketing Communication Mix", *Management Science*, Vol. 54, Nr. 3, pp. 477–491.

Cheung, C. M. K. and M. K. O. Lee (2012), "What drives consumers to spread electronic word of mouth in online consumer-opinion platforms", *Decision Support Systems*, Vol. 53, Nr. 1, pp. 218–225.

Cheung, R. (2014), "The Influence of Electronic Word-of-Mouth on Information Adoption in Online Customer Communities.", *Global Economic Review*, Vol. 43, Nr. 1, pp. 42–57.

Chevalier, J. and D. Mayzlin (2006), "The Effect of Word of Mouth on Sales: Online Book Reviews", *Journal of Marketing Research*, Vol. 43, Nr. 3, pp. 345–354.

The Nielsen Company (2013), *Global Trust in Advertising and Brand Messages Is Key in Advertising*, September 2013.

Cravens, D. W., C. W. Holland, C. W. Lamb and W. C. Moncrief (1988), "Marketing's role in product and service quality", *Industrial Marketing Management*, Vol. 17, Nr. 4, pp. 285–304.

Cui, G., H. Lui and X. Guo (2012), "The Effect of Online Consumer Reviews on New Product Sales", *International Journal of Electronic Commerce*, Vol. 17, Nr. 1, pp. 39–58.

Darke, P. R. and C. M. Chung (2005), "Effects of pricing and promotion on consumer perceptions: It depends on how you frame it", *Journal of Retailing*, Vol. 81, Nr. 1, pp. 35–47.

Dellarocas, C., X. Zhang and N. F. Awad (2007), "Exploring the value of online product reviews in forecasting sales: The case of motion pictures", *Journal of Interactive Marketing*, Vol. 21, Nr. 4, pp. 23–45.

Dichter, E. (1966), "How Word of Mouth Advertising Works", *Harvard Business Review*, pp. 147–166.

Duan, W., B. Gu and A. B. Whinston (2008), "Do online reviews matter? - An empirical investigation of panel data", *Decision Support Systems*, Vol. 45, Nr. 4, pp. 1007–1016.

Engel, J. F., R. J. Kegerreis and R. D. Blackwell (1969), "Word-of-mouth Communication by the Innovator.", *Journal of Marketing*, Vol. 33, Nr. 3, pp. 15–19.

Eryarsoy, E. and S. Piramuthu (2014), "Experimental evaluation of sequential bias in online customer reviews", *Information & Management*, Vol. 51, Nr. 8, pp. 964–971.

Falk Moore, S. and B. Myerhoff (1975), "Prologue", in *Symbol and Politics in Communal Ideology*, pp. 13–23, Ithaca, Cornell University Press.

Festinger, L. (1957), "A theory of cognitive dissonance", *Scientific American*, Vol. 207.

Filieri, R. and F. McLeay (2014), "E-WOM and Accommodation: An Analysis of the Factors That Influence Travelers’ Adoption of Information from Online Reviews", *Journal of Travel Research*, Vol. 53, pp. 44–57.

Fisk, R. and C. Young (1985), "Disconfirmation of Equity Expectations: Effects on Consumer Satisfaction With Services", *Advances in Consumer Research*, Vol. 12, pp. 340–345.

Flint, D. J., C. P. Blocker and P. J. Boutin (2011), "Customer value anticipation, customer satisfaction and loyalty: An empirical examination", *Industrial Marketing Management*, Vol. 40, Nr. 2, pp. 219–230.

Frenzen, J. and K. Nakamoto (1993), "Structure, Cooperation, and the Flow of Market Information", *Journal of Consumer Research*, Vol. 20, Nr. 3, pp. 360.

Hajli, N. (2015), "Social commerce constructs and consumer's intention to buy", *International Journal of Information Management*, Vol. 35, Nr. 2, pp. 183–191.

Harrison, S. and P. Dourish (1996), "Re-Place-ing Space : The Roles of Place and Space in Collaborative Systems", Proceedings of the 1996 ACM conference on Computer supported cooperative work, pp. 67–76.

Hennig-Thurau, T., K. P. Gwinner, G. Walsh and D. D. Gremler (2004), "Electronic word-of-mouth via consumer-opinion platforms: What motivates consumers to articulate themselves on the Internet?", *Journal of Interactive Marketing*, Vol. 18, Nr. 1, pp. 38–52.

Herring, S. C. (2001), "Computer-Mediated Discourse", Discourse, January issue, pp. 1–24.

Hu, N., L. Liu and J. J. Zhang (2008), "Do online reviews affect product sales? The role of reviewer characteristics and temporal effects", *Information Technology and Management*, Vol. 9, Nr. 3, pp. 201–214.

Jacoby, J. and D. B. Kyner (1973), "Brand Loyalty Vs. Repeat Purchasing Behavior", *Journal of Marketing Research*, Vol. 10, Nr. 1, pp. 1–9.

James, N. A. and D. S. Matteson (2014), "ecp: An R Package for Nonparametric Multiple Change Point Analysis of Multivariate Data", *Journal of Statistical Software*, Vol. 62, Nr. 7.

Jöckel, S., A. Will and F. Schwarzer (2008), "Participatory Media Culture and Digital Online Distribution—Reconfiguring the Value Chain in the Computer Game Industry", *International Journal on Media Management*, Vol. 10, Nr. 3, pp. 102–111.

Jones, Q. and S. Rafaeli (2000), "Time to Split , Virtually: "Discourse Architecture" and "Community Building" Create Vibrant Virtual Publics", *Electronic Markets*, Vol. 10, Nr. 4, pp. 214–223.

Ke-Wei, H. and A. Sundararajan (2011), "Pricing Digital Goods: Discontinuous Costs and Shared Infrastructure", *Information Systems Research*, Vol. 22, Nr. 4, pp. 721–738.

Kiesler, S., J. Siegel and T. W. McGuire (1984), "Social psychological aspects of computer-mediated communication.", *American Psychologist*, Vol. 39, Nr. 10, pp. 1123–1134.

Kleinberg, R. and T. Leighton (2003), "The value of knowing a demand curve: bounds on regret for online posted-price auctions", Proceedings of the 44th Annual IEEE Symposium on Foundations of Computer Science, 2003.

Komito, L. (1998), "The Net as a Foraging Society: Flexible Communities", *The Information Society*, Vol. 14, Nr. 2, pp. 97–106.

LaTour, S. A. and N. C. Peat (1979), "Conceptual and Methodological Issues in Consumer Satisfaction Research", *Advances in Consumer Research*, Vol. 6, Nr. 1, pp. 431–437.

Lee, M. and S. Youn (2009), "Electronic word of mouth (eWOM): How eWOM platforms influence consumer product judgement", *International Journal of Advertising*, Vol. 28, Nr. 3, pp. 473–499.

Li, X. and L. M. Hitt (2010), "Price Effects in Online Product Reviews: An Analytical Model and Empirical Analysis", *MIS Quarterly*, Vol. 34, Nr. 4, pp. 809.

Lund, R., X. L. Wang, Q. Q. Lu, J. Reeves, C. Gallagher and Y. Feng (2007), "Changepoint detection in periodic and autocorrelated time series", *Journal of Climate*, Vol. 20, Nr. 20, pp. 5178–5190.

Malik, S. U. (2012), "Customer Satisfaction, Perceived Service Quality and Mediating Role of Perceived Value", *International Journal of Marketing Studies*, Vol. 4, Nr. 1, pp. pp. 68–76.

Matteson, D. S. and N. A. James (2012), "A nonparametric approach for multiple change point analysis of multivariate data", *Journal of the American Statistical Association*, Vol. 109, Nr. 505, pp. 334-345.

Nambisan, P. and J. H. Watt (2011), "Managing customer experiences in online product communities", *Journal of Business Research*, Vol. 64, Nr. 8, pp. 889–895.

Page, E. S. (1955), "A Test for a Change in a Parameter Occurring at an Unknown Point", *Biometrika*, Vol. 42, Nr. 3, pp. 523–527.

Parasuraman, A., V. A. Zeithaml and L. L. Berry (1988), "SERVQUAL : A Multiple-Item Scale for Measuring Consumer Perceptions of Service Quality", *Journal of Retailing*, Vol. 64, Nr. 1, pp. 12–40.

Pavlou, P. A. and D. Gefen (2004), "Building effective online marketplaces with institution-based trust", *Information Systems Research*, Vol. 15, Nr. 1.

Peddibhotla, N. B. and M. R. Subramani (2007), "Contributing to Public Document Repositories: A Critical Mass Theory Perspective", *Organization Studies*, Vol. 28, Nr. 3, pp. 327–346.

Porter, C. E. (2004), "A Typology of Virtual Communities: A Multi-Disciplinary Foundation for Future Research", *Journal of Computer-Mediated Communication*, Vol. 10.

Price, L. L., L. F. Feick and A. Guskey (1995), "Everyday Market Helping Behavior", *Journal of Public Policy & Marketing*, Vol. 14, Nr. 2, pp. 255–266.

PwC Global (2015), "Total Retail 2015:", February 2015.

Rafaeli, S. and F. Sudweeks (1997), "Networked Interactivity", *Journal of Computer-Mediated Communication*, Vol. 2, Nr. 4.

Richins, M. L. (1984), "Word of Mouth Communication as Negative Information", *Advances in Consumer Research*, pp. 697–702.

Ridings, C. M. and D. Gefen (2004), "Virtual Community Attraction: Why People Hang Out Online", *Journal of Computer-Mediated Communication*, Vol. 10.

Schafer, J. B., J. Konstan and J. Riedi (1999), "Recommender systems in e-commerce", Proceedings of the 1st ACM conference on Electronic commerce EC 99, 2001, pp. 158–166.

Schlossberg, H. (1991), "Customer Satisfaction: Not a fad, but a way of life", *Marketing News*, Vol. 25, Nr. 20, pp. 18.

Schouten, J. W. and J. H. McAlexander (1995), "Subcultures of Consumption: An Ethnography of the New Bikers", *Journal of Consumer Research*, Vol. 22, Nr. 1, pp. 43.

See-To, E. and K. Ho (2014), "Value co-creation and purchase intention in social network sites: The role of electronic Word-of-Mouth and trust – A theoretical analysis", *Computers in Human Behavior*, Vol. 31, pp. 182–189.

Senecal, S. and J. Nantel (2004), "The influence of online product recommendations on consumers' online choices", *Journal of Retailing*, Vol. 80, Nr. 2, pp. 159–169.

Shen, W., Y. J. Hu and J. Rees (2015), "Competing for Attention : An Empirical Study of Online Reviewers ' Strategic Behaviors", *MIS Quarterly*, Vol. 39, Nr. 3, pp. 683-696.

Shen, X. L., K. Zhang and S. J. Zhao (2014), "Understanding information adoption in online review communities: The role of herd factors", Proceedings of the Annual Hawaii International Conference on System Sciences, 2014, pp. 604–613.

Sheth, J. N., B. I. Newman and B. L. Gross (1991), "Why we buy what we buy: A theory of consumption values", *Journal of Business Research*, Vol. 22, Nr. 2, pp. 159–170.

Solomon, G. and L. Schrum (2007), *Web 2.0: New Tools, New Schools*, ISTE, pp. 7–24.

Sundaram, D. S. and B. Hills (1998), "Word-of-Mouth Communications : A Motivational Analysis", *Advances in Consumer Research*, Vol. 25, pp. 527–531.

Swan, J. E. and R. L. Oliver (1989), "Postpurchase Communications by Consumers", *Journal of Retailing*, Vol. 65, Nr. 4, pp. 516–533.

Sweeney, J. C. and G. N. Soutar (2001), "Consumer perceived value: The development of a multiple item scale", *Journal of Retailing*, Vol. 77, Nr. 2, pp. 203–220.

Tayebi, A. (2013), "“Communihood:” A Less Formal or More Local Form of Community in the Age of the Internet", *Journal of Urban Technology*, Vol. 20, Nr. 2, pp. 77–91.

Taylor, W. A. (2000), "Change-point analysis: a powerful new tool for detecting changes", available at http://www. variation. com/cpa/, accessed 15 September 2015.

Tonnies, F. (1957), *Community and Association*, London, Routledge and Kegan Paul.

Tybout, A. M., B. J. Calder and B. Sternthal (1981), "Using Information Processing Theory to Design Marketing Strategies", *Journal of Marketing Research*, Vol. 18, Nr. 1, pp. 73–79.

Voss, G. B., A. Parasuraman and D. Grewal (1998), "The Roles of Price, Performance, and Expectations in Determining Satisfaction in Service Exchanges", *Journal of Marketing*, Vol. 62, Nr. 4, pp. 46–61.

Walther, J. B. (1996), "Computer-Mediated Communication: Impersonal, Interpersonal, and Hyperpersonal Interaction", *Communication Research*, Vol. 23, Nr. 1, pp. 3–43.

Weinberg, B. D., K. Ruyter, C. Dellarocas, M. Buck and D. I. Keeling (2013), "Destination social business: exploring an organization’s journey with social media, collaborative community and expressive individuality", *Journal of Interactive Marketing*, Vol. 27, Nr. 4, pp. 299–310.

Wellman, B. (1997), "An Electronic Group is Virtually a Social Network", in *Culture of the Internet*, Kiesler, S., New Jersey: Lawrence Erlbaum, pp. 179–205.

Westbrook, R. and M. Reilly (1983), "Value-percept Disparity: an Alternative to the Disconfirmation of Expectations Theory of Consumer Satisfaction", *Advances in Consumer Research*, Vol. 10, pp. 256–261.

Wild, R. (1981), *Australian Community Studies and Beyond*, Sydney: Allen & Unwin.

Woodruff, R. B., E. R. Cadotte and R. L. Jenkins (1983), "Modeling consumer satisfaction processes using experience-based norms", *Journal of Marketing Research*, Vol. 20, pp. 296–304.

Yi, Y. (1990), "A critical review of consumer satisfaction", *Review of Marketing*, Vol. 4, Nr. 1, pp. 68–123.

Zeithaml, V. A. (1988), "Consumer Perceptions of Price, Quality, and Value: A Means-End Model and Synthesis of Evidence", *Journal of Marketing*, Vol. 52, July issue, pp. 2–22.

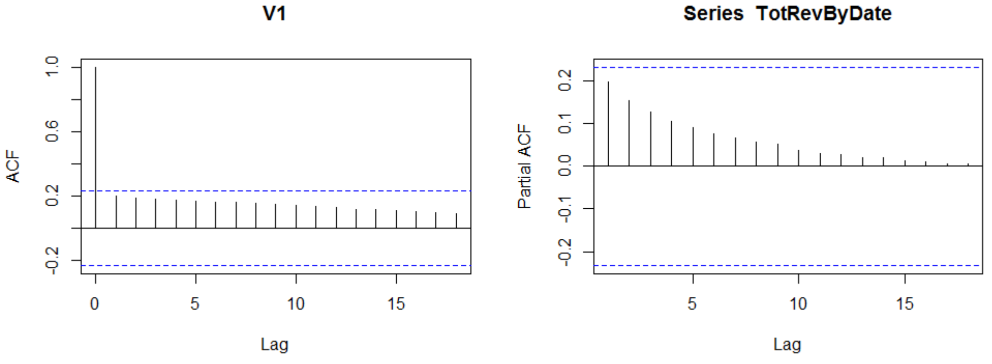
VIII. Appendices

Appendix I – Autocorrelation Factors for Number of Reviews

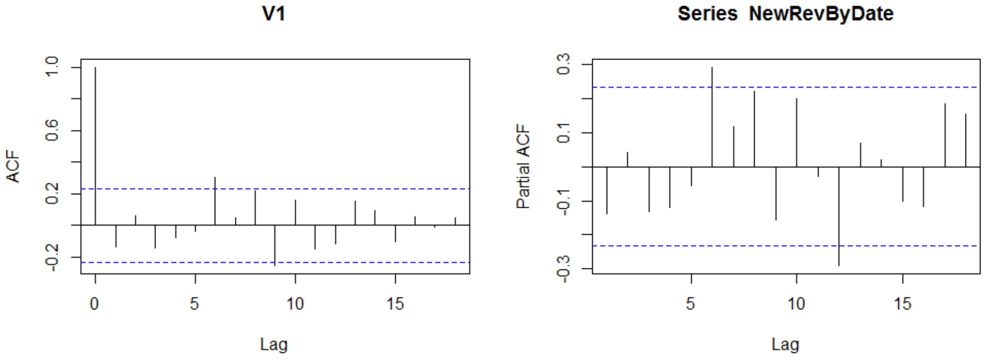
R script

```
# Loading Time Series
TotRevByDate = read.xls("TotRevByDate.xlsx", header=F)
NewRevByDate = read.xls("NewRevByDate.xlsx", header=F)

## Convert Data into Time Series
ts(TotRevByDate)
ts(NewRevByDate)

### Test for Autocorrelation on Total Reviews
par(mfrow=c(1,2))
acf(TotRevByDate)
pacf(TotRevByDate)

### Test for Autocorrelation on New Reviews
par(mfrow=c(1,2))
acf(NewRevByDate)
pacf(NewRevByDate)
```

Autocorrelation factors – ACF/PACF plots



1 – ACF and PACF tests for Total Reviews by Date, showing a significant first degree lag in the observations, indicating high levels of autocorrelation.



2 – ACF and PACF tests for New Reviews by Date, showing significant first degree lag in the observations, indicating high levels of autocorrelation, as well as a significant periodicity, likely referring to the higher number of reviews posted on weekends in comparison to weekdays (6 days partial lag).

Time series – Total Reviews By Date (“TotRevByDate.xlsx”)

```
> ts(TotRevByDate)
Time Series:
Start = 1
End = 71
Frequency = 1
           V1
 [1,] 2854016
 [2,] 2864083
 [3,] 2866254
 [4,] 2872106
 [5,] 2873828
 [6,] 2884733
 [7,] 2891389
 [8,] 2899837
 [9,] 2906390
[10,] 2914368
[11,] 2919066
[12,] 2926101
[13,] 2934424
[14,] 2934623
[15,] 2946753
[16,] 2950592
[17,] 2959433
[18,] 2967977
[19,]  133620
[20,] 2965740
[21,] 2988006
[22,] 2998956
[23,] 3005991
[24,] 3012173
[25,] 3015864
[26,] 3014618
[27,] 3023517
[28,] 3019920
[29,] 3040268
[30,] 3049826
[31,] 3055296
[32,] 3069293
[33,] 3069293
[34,] 3076561
[35,] 3086038
[36,] 3091155
[37,] 3097408
[38,] 3112225
[39,] 3112225
[40,] 3126267
[41,] 3132158
[42,] 3146781
[43,] 3148806
[44,] 3137864
[45,] 3152318
[46,] 3162114
[47,] 3170345
[48,] 3187136
[49,] 3187136
[50,] 3193085
[51,] 3198398
[52,] 3201511
[53,] 3198829
[54,] 3210809
[55,] 3226889
[56,] 3208214
[57,] 3240210
[58,] 3225212
[59,] 3264419
[60,] 3271357
[61,] 3278192
[62,] 3288676
[63,] 3252233
[64,] 3298631
[65,] 3304130
[66,] 3295189
[67,] 3319577
[68,] 3328329
[69,] 3332906
[70,] 3333364
[71,] 3339912
```

Time Series - New Reviews By Date (“NewRevByDate.xlsx”)

```
> ts(NewRevByDate)
Time Series:
Start = 1
End = 71
Frequency = 1
           V1
 [1,]     0.0
 [2,]  6798.0
 [3,]  1679.5
 [4,]  4144.5
 [5,]  4390.5
 [6,]  3389.5
 [7,]  4359.0
 [8,]  5003.0
 [9,]  4083.0
[10,]  5792.0
[11,]  2436.0
[12,]  4696.0
[13,]  3854.0
[14,]  4387.5
[15,]  4518.5
[16,]  4322.5
[17,]  3876.5
[18,]  3703.0
[19,]   143.0
[20,]   170.0
[21,]  4545.5
[22,]  5782.5
[23,]  4428.0
[24,]  5557.0
[25,]  4198.0
[26,]  -123.0
[27,]  4435.0
[28,]  6016.0
[29,]  6757.0
[30,]  4881.0
[31,]  5014.0
[32,]  9366.0
[33,]     0.0
[34,]  5356.0
[35,]  5528.0
[36,]  6190.0
[37,]  4948.5
[38,]  7880.5
[39,]     0.0
[40,]  8703.0
[41,]  3880.0
[42,] 11282.0
[43,]   135.0
[44,]  -344.0
[45,]  5277.0
[46,]  5174.5
[47,]  6284.5
[48,] 11727.0
[49,]     0.0
[50,]  4584.0
[51,]  3914.0
[52,]  4135.0
[53,]  4763.0
[54,]  8057.5
[55,]  8896.0
[56,]  6038.5
[57,]  4834.0
[58,]  4733.5
[59,]  4470.5
[60,]  4452.0
[61,]  5712.0
[62,]  6191.0
[63,]  4219.0
[64,]  4152.0
[65,]  3980.0
[66,]  3732.0
[67,]  4369.0
[68,]  6727.0
[69,]  3224.0
[70,]  4189.0
[71,]  4414.5
```

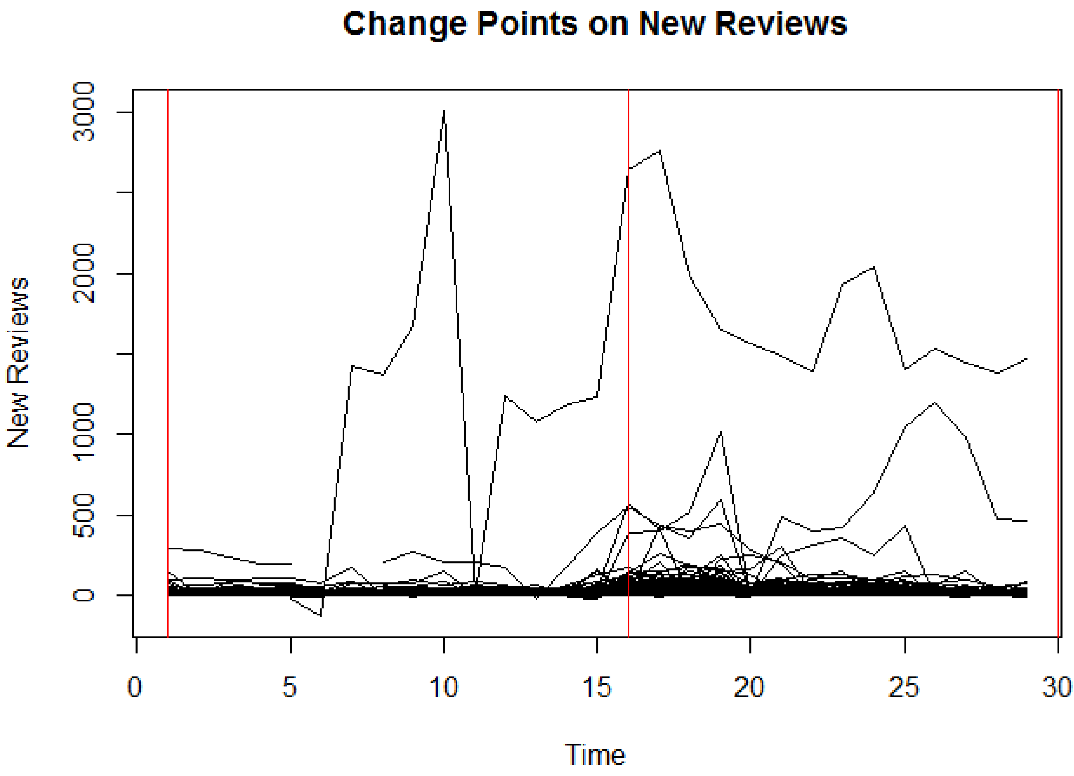
Appendix II – Change Point Detection test for New Reviews

R script for Means

```
#Load New Reviews data
NewReviews = read.xls("NewReviews.xlsx", header=F)

##Ignore missing values
NewReviews[NewReviews==""]<-NA

###Define parameters for the test:
#sig.lvl      = Level of significance to accept a change point
#k            = number of significant change points to retrieve
#min.size     = min. distance between 2 change points (in n° of observations)
#alpha        = moment index to test (mean=1; variation=2)
#R            = number of bootstraps to generate
ECPNewReviews <- e.divisive(NewReviews, min.size=2, sig.lvl=.01, k=1, alpha=1,
R=500)

####Show results
ECPNewReviews

#####Show data charts with lines on the significant change points
par(mfrow=c(1,1))
ts.plot(NewReviews, ylab="New Reviews", main="Change Points on New Reviews")
abline(NewReviews, v=ECPNewReviews$estimates, col="red")
```

R Output for Means

```
$k.hat
[1] 2

$order.found
[1]  1 30 16

$estimates
[1]  1 16 30

$considered.last
[1] 16

$p.values
[1] 0

$permutations
[1] NA

$cluster
 [1] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2
```


Change Points on New Reviews
New Reviews
0
500
1000
2000
3000
0
5
10
15
20
25
30
Time

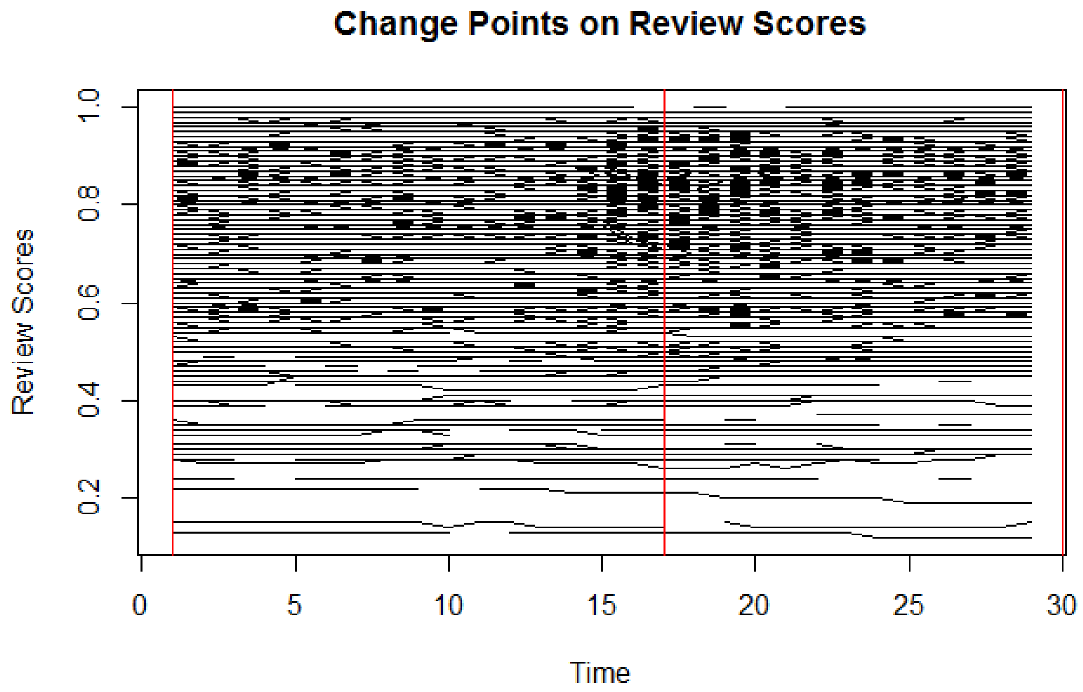
Appendix III – Change Point Detection test for Review Scores

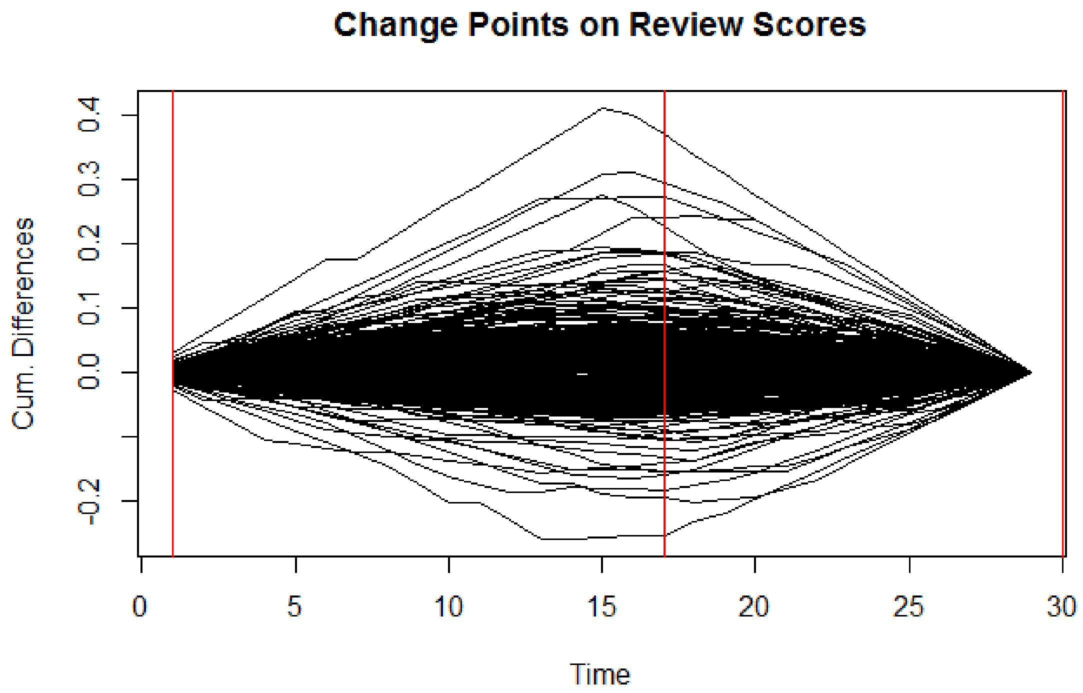
R script for Means

```
#Load Review Scores data
RevScores = read.xls("RevScores.xlsx", header=F)

##Ignore missing values
RevScores[RevScores==""]<-NA

###Define parameters for the test:
#sig.lvl      = Level of significance to accept a change point
#k            = number of significant change points to retrieve
#min.size     = min. distance between 2 change points (in n° of observations)
#alpha        = moment index to test (mean=1; variation=2)
#R            = number of bootstraps to generate
ECPRevScores <- e.divisive(RevScores, min.size=2, sig.lvl=.01, k=1, alpha=1,
R=500)

####Show results
ECPRevScores

#####Show data charts with lines on the significant change points
par(mfrow=c(2,1))
ts.plot(RevScores, ylab="Review Scores", main="Change Points on Review
Scores")
abline(RevScores, v=ECPRevScores$estimates, col="red")
ts.plot(CUSUMDev, ylab="Cum. Differences", main="Change Points on Review
Scores")
abline(RevScores, v=ECPRevScores1CP$estimates, col="red")
```

R Output for Means

```
> ECPRevScores
$k.hat
[1] 2

$order.found
[1]  1 30 17

$estimates
[1]  1 17 30

$considered.last
[1] 17

$p.values
[1] 0

$permutations
[1] NA

$cluster
 [1] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2
```


Change Points on Review Scores
Review Scores
Time
0.2
0.4
0.6
0.8
1.0
0
5
10
15
20
25
30


Change Points on Review Scores
Cum. Differences
Time
-0.2
0.0
0.1
0.2
0.3
0.4
0
5
10
15
20
25
30

R script for Variation

```
#Load Review Scores data
RevScores = read.xls("RevScores.xlsx", header=F)

##Ignore missing values
RevScores[RevScores==""]<-NA

###Define parameters for the test:
#sig.lvl      = Level of significance to accept a change point
#k            = number of significant change points to retrieve
#min.size     = min. distance between 2 change points (in n° of observations)
#alpha        = moment index to test (mean=1; variation=2)
#R            = number of bootstraps to generate
ECPRevScoresV <- e.divisive(RevScores, min.size=2, sig.lvl=.01, k=1, alpha=2,
R=500)

####Show results
ECPRevScoresV

#####Show data charts with lines on the significant change points
par(mfrow=c(1,1))
ts.plot(RevScores, ylab="Review Scores", main="Change Points on Review
Scores")
abline(RevScores, v=ECPRevScoresV$estimates, col="red")
```

R Output for Variation

```
> ECPRevScoresV
$k.hat
[1] 2

$order.found
[1]  1 30 18

$estimates
[1]  1 18 30

$considered.last
[1] 18

$p.values
[1] 0

$permutations
[1] NA

$cluster
 [1] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 2 2 2 2 2 2 2 2 2 2 2
```