UNIVERSITY OF EASTERN FINLAND
Faculty of Social Sciences and Business Studies
Business School

THE RECIPROCAL SPILLOVER EFFECT IN ONLINE BOOK SALES

Integrated with the effect of online reviews

Master's Thesis, Innovation Management
Hien T. Nguyen 277227
April 27, 2018

ABSTRACT
UNIVERSITY OF EASTERN FINLAND
Faculty of Social Sciences and Business Studies
Master's Program in Innovation Management

NGUYEN, HIEN: The reciprocal spillover effect in online book sales. Integrated with the effect of online reviews.
Master's Thesis, 63 p. and 3 appendices (2 pages)
Mentor: Dr. Ville-Veikko Piispanen
April 2018

Keywords: Reciprocal spillover effect, online reviews, online feedback.

The purpose of this thesis is to investigate into the reciprocal spillover effect and the effect of online reviews on online book series sales. In particular, the study aims to answer whether the first book sales change during the release of a new book of its sequel and whether extension attributes e.g. new book success and sequence number as well as online reviews metrics i.e. valence and volume are associated with book sales.

According to previous literature, the consumption of parent product tends to increase when an extension is released. A number of factors related to extensions have been found to have an effect on the parent sales. Meanwhile, past research on the effect of online reviews on sales yields inconsistent results. Some found that both metrics of online word-of-mouth were significant while others provided contrasting evidence.

This study utilizes the salesrank of 171 book series and online reviews metrics collected on Amazon.com. It employs quantitative approach with the use of the linear mixed-effects models to first capture the sales pattern over 6 weeks and then analyze the relationship between other factors and book sales.

The result implied that there was a noticeable decreasing pattern of first book salesrank during the studied period. Moreover, it suggested significant associations between extension attributes i.e. extension success and sequence number and the original book sales. Interestingly, it also found that the effect of sequence number on first book sales depends greatly on the extension success. Incorporating the persuasive effect of online reviews, the study showed that the number of reviews and its interaction with ratings played a vital role in first book sales change.

Contents

List of Tables

List of Figures

1 INTRODUCTION

1.1 The book publishing industry and book as a brand

Every industry bears its own risks, even for a long-established one like book publishing. The book publishing industry is described as a complex, adaptive, semi-chaotic industry (Greco, 2013). To understand its complexity, one has to employ the Bose-Einstein gas molecule distribution to model such unpredictable customer behaviors towards book consumption (Greco, 2013). No one, not even authors, booksellers or marketers, knows for sure whether or not there be any book sold, when and where the consumption will rise again and why a group of people are interested in the same book over different periods of time. Besides that, the market for books is already a crowded one (Clark and Phillips, 2014). Hundreds of thousands of book titles are out every year, resulting in a constant growth in customer choice set (Hendricks and Sorensen, 2009). As a consequence, books fight over limited shelf space trying to garner customers' attention, and ultimately generate sales, before being shelved away to sections that customers rarely visit. Being shelved away means the kiss of death for book sales and means that it will be returned to publishers and be pulped some day (Alan, 2013). Another interesting feature of the highly occupied market is that book sales follow the "Pareto distribution" or the power law probability distribution (Greco, 2013). It means that a large proportion of total sales is dominated by only a small number of books. This may be a reflection of book qualities; yet, it may also represent the asymmetric information in an inefficient market

(Hendricks and Sorensen, 2009). Or in other words, customers are not fully aware of the majority of products available to them.

Every new book is a new product and every new product is associated with high uncertainty. The book uncertainty lies in both ends (Greco, 2013). Publishers as well as authors do not know whether their books will be a success before the publication decision. Customers are not sure that any book is of their preference before the purchase decision. Both parties seem to place their bet on their decisions (Greco, 2013) and have their own way in coping with the uncertainty. Similar to many other industries, publishing houses employ many innovative strategies in order to diversify revenue areas or reduce the risk associated with new products, and as a result, to bring down the risk of terminating operation in the highly competitive market (Eldridge, 2014). One of the strategies is the broadly used - brand extension (Keller et al., 2008). Not only can brand extension fulfill customers' desires by providing varieties under a single brand but also it can increase the book span on retailers' shelves and attract more customers every time its extension is launched (Hardie et al., 1994). Brands can be extended in many different ways either under different categories or the same category. While the former means that introducing new types of product dissimilar to the original (e.g. clothes and dolls featuring famous book characters), example of the latter can be stretching a brand by publishing new books under the same title over a period of time and ultimately forming a book series. Using the latter strategy, publishers can relive the title's life cycle and at the same time avoid over-stretching brand to excessive categories (Hardie et al., 1994). Figure 1 is an example illustrating the success of such strategy. The graph shows the Amazon salesrank pattern of the first book in *The Traitor Son Cycle* series from 2015 to 2018 during which book 3, 4 and 5 were released. It is evident that book 1's salesrank had a tendency to decrease right before and after the release of a new book. It indicates that the first book became popular and more people were buying it from the website.

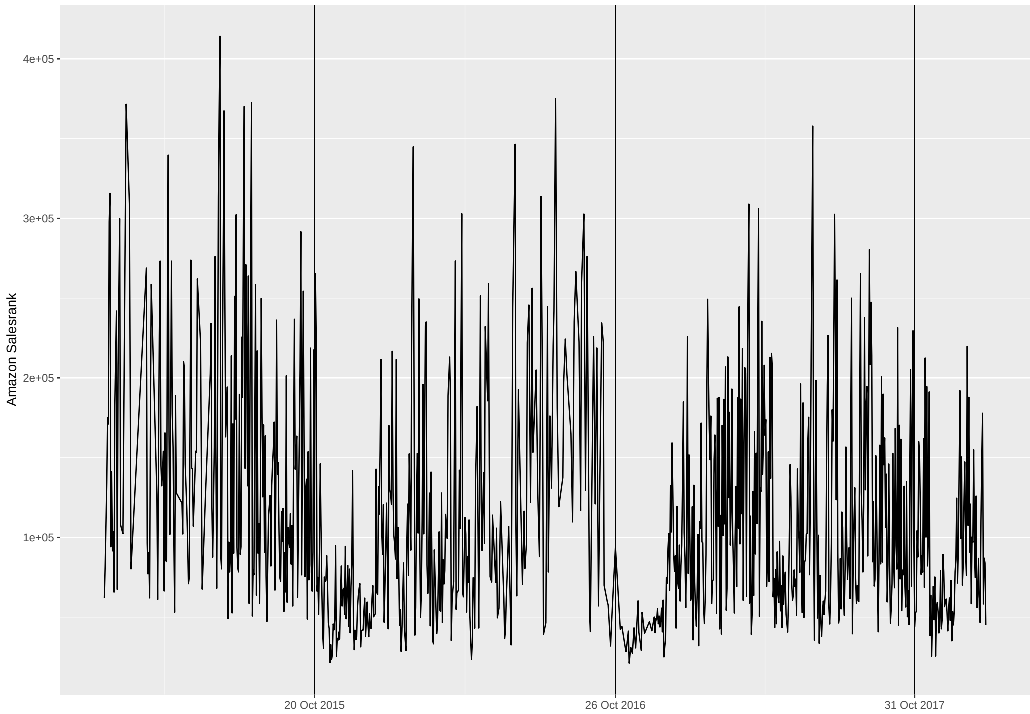


Figure 1: The salesrank pattern of The Red Knight book one in *The Traitor Son Cycle* series from February 2015 to January 2018 on Amazon.com. Vertical lines are displayed at the time when the third, fourth and fifth book was out.

1.2 Purpose of this study

Understanding the reciprocal spillover effect and its driving factors can be of great benefits for various reasons. First, due to the industry characteristics mentioned in section 1.1, so as to maintain business operation some of the publishers' activities include execute a right promotion strategy and properly forecast sales (Clark and Phillips, 2014). Recognizing that such effect exists enables a better advertising budget allocation and more accurate sales prediction. Second, it has several implication for negotiating and managing contracts with authors. Besides that, authors will have more confident in their first books knowing that the following books can spread news about the first one.

In this thesis, drawing on extant literature in brand extension theories, I first seek to understand the first book performance during six weeks of its new book release. To do this, I examine the Amazon salesrank pattern of the first book of 171 series that had a new book coming out in 2015-2017. The result confirms that the salesrank decreases during the studied period. This supports the existence of the backward spillover effect in the book publishing industry. Second, I investigate the association between a set of extension attributes, i.e. extension success and new book sequence number, and the first book sales and conclude that these extension attributes significantly contribute to the first book success.

As mentioned in the previous section, customers face an overwhelmingly large and continuously growing set of products. When they get informed a specific product, they have to deal with the uncertainty from their purchase decision. Facing such situation, people tend to turn to other buyers and learn from them (McFadden and Train, 1996). Accordingly, in the final part I look into the effect of online word-of-mouth on the first book sales. Indeed, the persuasive effect of online reviews is inspected. Given the rise of E-commerce, online reviews are found to have significant effect on customers' decision. However, past research on reciprocal effect has failed to take into account such effect. The result suggests that the number of reviews and its interaction with rating do play an important role in driving sales, while rating does not. Based on this result, it is recommended that marketers should implement the right strategy to encourage book readers/buyers to share their opinions on online platforms.

The rest of this thesis is presented as follows. Section 2 discusses the current body of literature on the reciprocal spillover effect as well as online reviews. Data and research method is mentioned in section 3. Next, I report the model building process and results in section 4. Finally, a discussion of findings, managerial implications and suggestions for future research are in the final chapter.

2 LITERATURE REVIEW

2.1 Brand Extension and Reciprocal Spillover Effect

2.1.1 Brand Extension

In any one year, typically 80 percent to 90 percent of new products launched to the market are extensions (Keller et al., 2008). Extensions come in all forms and shapes, under the same category (e.g Fazer Salmiakki ice cream, Apple iPhone X, Deadpool 2) or entirely different categories (e.g. Harry Potter movies v.s. book series). That is to say, brand extension is one of the most commonly used branding strategies in various industries ranging from FMCG (fast moving consumer goods), electronics to motion picture industry. It is a strategy where companies decide to take advantage of the existing (parent) brand name when introducing a new (child) product.

Brand extensions can be classified into line extension and category extension. The former refers to using a current brand name to a new product within the original category as in the case of Coca-Cola (regular) and Diet Coke. The latter means introducing a completely new product class under an existing brand name such as Yamaha motorcycles and Yamaha musical instruments (Aaker and Keller, 1990). Another way to categorize extensions is vertically and horizontally. The vertical brand extension is defined as "introducing a brand in the same product category as the core brand, but at a different price point and quality level" (Kim and Lavack, 1996, page 24), while extending brand horizontally is to "either apply or extend an existing product's name to a new product in the same product class or to a product category new to the company" (Pitta and Prevel Katsanis, 1995, page 60).

Brand extension is particularly appealing to companies owning to its enormous benefits. First of all, the high risk of failure associated with new products can be significantly reduced if the products are launched under a well-known brand name (Aaker and Keller, 1990; Martinez and Pina, 2003; Joshi and Mao, 2012). So, if the brand is strong enough, customers will link parent and extension products, use the parent brand as a judgmental cue and transfer relevant brand knowledge to its extensions. In other words, customer evaluation of the extension is influenced by parent brand through a process called equity transfer (Aaker and Keller, 1990; Park et al., 1991). At the end of the process, the new product will be classified into the same category as the previous one in customers' mind. Second, developing a completely new brand name for new products can be very costly because of all the branding expenses. Brand extension can considerably cut down these costs since the brand already exists (Völckner and Sattler, 2006). However, brand "stretching" is not without its risks. In fact, one of the biggest ones that makes managers cautious when it comes to the decision whether or not to adopt this strategy is brand overextension. Unsuccessful extensions can dilute the brand image. Even when extensions are successful, they can also cause equity wear-out (Loken and John, 1993). A cautionary tale is the case of Harley Davidson when the brand is extended too far from the original image (casestudyinc.com, 2012).

2.1.2 Reciprocal Spillover Effect

According to extant literature on brand extension, spillover effects happen when an extension is introduced. The definition of a spillover effect is the impact of one product on the consumption of another (Balachander and Ghose, 2003).

Spillover effects are also separated into two kinds. The first is the impact of parent brand equity on extension success, referring to as forward spillover effect. The other is the effect of extensions on sales of the parent products, which is called reciprocal spillover effect or feedback effect or also backward effect.

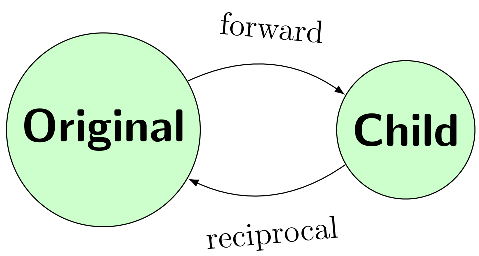


Figure 2: The spillover effect between parent and extension products

Whereas the former has been a central of numerous studies since the beginning, the latter received a decent amount of attention only recently (Knapp et al., 2014; Kim et al., 2016). This is easy to understand considering the motivation behind such strategy adoption; that is to enhance new products' success rate by leveraging the existing brand equity. However, the need to acknowledge and the ability to measure reciprocal spillover effect become more and more important in every business decision making. For instance, Balachander and Ghose (2003) investigated the spillover effects using panel data of two different product categories at two markets. The results suggested that the advertising of extensions might be equally or even more effective in gaining attention to the parent brand than the parent advertising itself. As a consequence, taking the reciprocal effect into account enables managers to allocate more precisely the advertising budget so that less money spent on parent products but still achieve the desired state of success. The second example is in case of brand extension licensing, which has been used across many industries (e.g. movies based on books). The integration of both the forward and reciprocal spillover effect into the extension right evaluation can be beneficial for both buyers and sellers (Knapp et al., 2014). In the case of movie adaptions from books, even though adding the reciprocal effect means adding complexity to the evaluation process, the extension rights can be over-evaluated if such effect is not considered because the parent brand may as well enjoy extra sales from the release of the extension (Knapp et al., 2014).

A number of factors related to extension and parent brand have been found to be significant in the reciprocal spillover effect in previous papers. Regarding extension attributes, Lane and Jacobson (1997) claimed that customer extension evaluation can enhance or jeopardize brand evaluation. Their findings are in line with those of Sheinin (2000) who also confirmed the importance of extension experience. Yet, the magnitude depends on the customer familiarity with the parent brand; in particular, the effect is greater for less popular parent brand and lesser for popular one. Zhang and Taylor (2009) investigated the feedback effect of negative information about the brand extensions on customers' attitude towards the parent brand. Using two studies and two sets of product (computers and toothbrushes), they concluded that there was a shift in participants' attitude before and after they were informed about the bad information regarding extension. Besides that, they also found the important moderating roles of information negativity and association set size in such effect. Another study by Chang (2002) once again confirmed that unfavorable extension experience threatened the parent brand equity. (Knapp et al., 2014) validated the impact of extension success on the post-extension parent brand sales in their paper.

Concerning parent brand attributes, (Martinez and De Chernatony, 2004) using a market survey found that parent brand quality had a positive influence on parent brand image after extension. Also, (Buil et al., 2009) concluded that the extension caused a more detrimental effect on parent brand equity when the parent brand equity was high than when it was medium. Besides extension and parent brand attributes, past research also examined other factors such as customer attributes and marketing efforts. For example, motivation level changed the way customers evaluated brand extension failure information and formed perception of the parent equity (Ng, 2010), or customer involvement affected the reciprocal spillover effect between line extension and parent brand (Boisvert, 2012). Additionally, attitude towards extension advertising (Dens and De Pelsmacker, 2010) and extension advertising exposure (Montaner and Pina, 2009) also influenced the brand extension feedback effect. Table 2 provides more details into findings and study context of previous papers.

On the one hand, most theories employed in earlier studies implied that the reciprocal spillover effect is fundamentally the final outcome of a categorization process (Childs, 2017). Such process describes how customers categorize new products based on their previous experience with and/or knowledge of the parent brand, and during the process customers' preference for the parent product is revealed. A few and frequently used theories are associative network theory, categorization theory and accessability-diagnosticity theory (Childs, 2017). These theories suggest that extension attributes trigger the effect (Knapp et al., 2014), and that the actual consumption of the parent products after that depends primarily upon the information, the link between the two products, and how consumers process those. Strictly speaking, the categorization process happens in a closed circle and is not influenced by any external factors from surrounding environment other than the extension information. For example, in (Balachander and Ghose, 2003) the associative network theory is conceptualized as a knowledge network in consumer memory consisting of various links of different strengths between nodes (see figure 3). The nodes represent the brand's image, the parent product, and its extension product. Since all these nodes are linked together, and since the link previously established between the brand and the parent product is very likely to be strong, spillovers happen once customers are exposed to extension advertising. Because of that, this particular node representing the parent product in the network is activated, and when it comes above a threshold level, customers are reminded of the parent product. Although using a different theory to explain the existence of the reciprocal effect, the accessibility-diagnosticity framework applied in (Knapp et al., 2014) is another example of a categorization process. Essentially, the two parent characteristics (i.e fit and backward integration[1]) are indicators of the connection between the parent and extension products, and they can be easily recognized by customers themselves. These theories arguably gave reasonable explanations in the studied contexts such as fast moving consumer goods, in which the possibility that customers have knowledge of or some experience with the parent brand before the release of extension is relatively high.

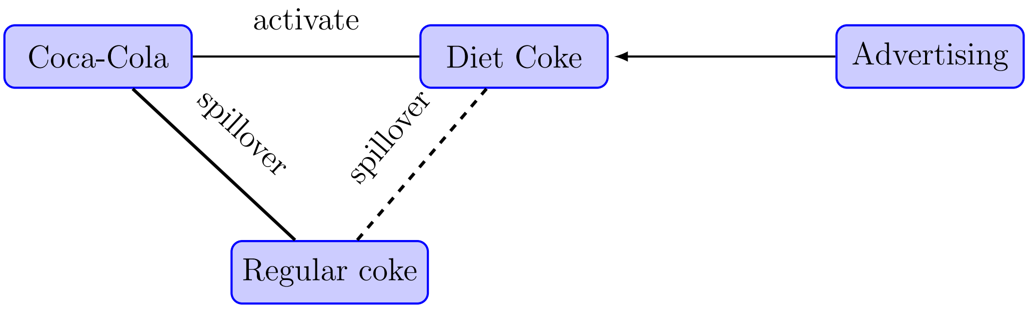


Figure 3: A simple illustration of the associate network theory

One the other hand, despite a growing body of literature on the reciprocal effect, very little is known in the context of entertainment products such as books, music albums, games and so on. There are several characteristics that distinguish entertainment products from other consumer goods. First, they have short life cycles, meaning that product sales usually peak at the beginning and gradually disappear afterward (Luan and Sudhir, 2010). Thus, at the time extension is launched, the parent sales can be very low or non-existent. Second, customers often purchase entertainment products because of the "experiential" aspects not because of the material aspects

[1]In their study, fit indicates how similar an extension(movie) is to its parent (book) (i.e. whether or not the author is in the movie production), and backward integration refers to the parent brand's support through promoting the extension (i.e. whether or not books republished in a tie-in version)

(Lacher, 1989). For that reason, another name for these products is experience products, mainly because their quality is difficult to judge before consumption and it relies heavily on personal taste. Third, those are single-purchase products, which means customers buy these only once (Zhu and Zhang, 2010) and those who own them will be less likely to pay for it again. Given these characteristics, those aforementioned theories are not applicable since they can not fully give grounds for the consumption behavior of customers who have no previous knowledge of parent products, especially in the case of line extensions of experience products (e.g. releasing a new book in a series where the consumption of extensions often requires the consumption of previous ones). On top of that, the products' quality is full of uncertainty, which makes purchase decision even riskier.

2.2 Online reviews

The pursuit of understanding what factors drive consumer behavior, which in turn leads to product sales, has never ended among researchers and practitioners. Word-of-mouth communication has always been around no matter how developed our technology is. Past research on traditional word-of-mouth observed that people sometimes weighted others' opinions more than their own judgements (Banerjee, 1992, 1993) and that it actually did influence on people's decision (McFadden and Train, 1996). This type of social learning was found to be most efficient when communication between buyers and sellers is little (Ellison and Fudenberg, 1995) and when product attributes can not be fully known in advance (McFadden and Train, 1996). Very similar findings were reported in recent research on online customer feedback, a modern form of word-of-mouth communication. Studies such as (Chevalier and Mayzlin, 2006; Maslowska et al., 2017, etc.) have confirmed online reviews affect customers' purchase decision. For experience products they are even of greater value (Chen et al., 2004) since they provide information relevant to product quality which is not simply found in the product description. Both traditional and modern forms possess the power that they are more persuasive and trustworthy than any of those by experts and celebrities since they are written by previous buyers (Willemsen et al., 2011). Both influence product sales through either increasing customers' awareness of or shaping their attitudes and behaviors towards the product (Duan et al., 2008a). However, unlike the former, the latter is more advanced in terms of speed, breadth and depth. In other words, online word-of-mouth communication is no longer limited in time and space owning to the technology advancement (Cui et al., 2012).

In brief, word-of-mouth is one of the most widely accepted notions in consumer behavior (Cheung et al., 2007). Despite that, none of the previous studies on the reciprocal spillover effect to the best of my knowledge has studied the persuasive effect of online opinions of others as a potential factor affecting parent sales during line extension release. It is interesting that even when the parent sales were collected from both online and offline source, the effect of online reviews was also ignored (see Knapp et al. (2014) for example). One paper using the number of online reviews on Amazon.com in their investigation on the reciprocal spillover effect is (Kim et al., 2016). However, the context is category extension (movie adaptions from books) and their focus is on its awareness effect (the number of reviews represents the number of people who are aware of the product).

2.3 Hypotheses

2.3.1 Extension attributes

As mentioned in section 2.1.2, extant literature on brand extension research has found an association between extension attributes and parent success. In a paper done by Hendricks and Sorensen (2009), they concluded that the sales patterns during the extension release period, which is an demonstration of the reciprocal spillover effect, was largely due to customers finding out the artist upon hearing the new album release. In other words, when a new product come out, via many different ways customers get informed about the previous ones. So, the information spillover effect between products during this period is confirmed. This is also consistent with the first half paper by Balachander and Ghose (2003), who stated that due to the existence of economies of information, the advertising of a product causes a "halo effect" that affects the consumption of other same branded products. In particular, through the signaling mechanism, customers will form a quality perceptions of the parent products once they are exposed to the extension quality information. Consequently, it is expected that during the release period of a new book, the level of its success, which is the outcome of its promotion strategy, raise customers' awareness of the book series and thus affects on the first book sales. Additionally, Hendricks and Sorensen (2009) also found that the spillover between album 2 and 1 is largest and between album 3 and 1 is smaller. Therefore, I expect that the higher the book sequence number, the lesser the reciprocal spillover effect. The hypotheses regarding the extension attributes are as follows.

Hypothesis 1 *The sales pattern enjoys a positive effect during new book release.*

Hypothesis 2 *The new book level of success is positively associated with the first book sales during new book release.*

Hypothesis 3 *The sequence number of the new book is associated with the first book sales during new book release.*

2.3.2 Online reviews

Valence and volume are the two metrics of online feedback and have been rigorously studied in past research. Review valence is the average number of stars rated by customers who have bought and used the product. It can be used to evaluate the overall product quality and also to recommend to customers (Cui et al., 2012). Review volume is the total number of reviews about a product. It is an indicator of the product popularity and WOM intensity (Maslowska et al., 2017).

Figure 4: An example of review valence and volume showed on Amazon.com where 4.2 stars are book ratings and 85,060 is the number of reviews.

Research on the effect of online reviews in the context of experience goods has revealed inconsistent results (see table 1 for a brief look at previous findings). For instance, many studies such as (Duan et al., 2008b; Zhang and Dellarocas, 2006) found support for the positive effect of review valence in their analysis of book salesrank and movie box office performance. Yet, using the same product categories, Chen et al. (2004), Liu (2006) and Duan et al. (2008a) found no significant effect of ratings on sales. In respect of review volume, a positive effect had been found on book sales and movie revenues (Chevalier and Mayzlin, 2006; Duan et al., 2008b); nonetheless, Chintagunta et al. (2010) claimed that valence not volume was a main driver of box office performance. Maslowska et al. (2017) whose paper examined the interaction between review volume and valence suggested that the higher the review volume, the stronger the effect of valence on purchase probability. Duan et al. (2008a) explained that the reason for such inconsistency among findings was due to the difference in their focus. Some papers focused on customer reviews' persuasive effects while the others centered on its awareness effects. According to the authors, word of mouth is not only the factor driving sales but also the end result of a purchase decision. Word-of-mouth may cause sales to increase, and vice versa an increase in user reviews can be an sign of an increase in sales.

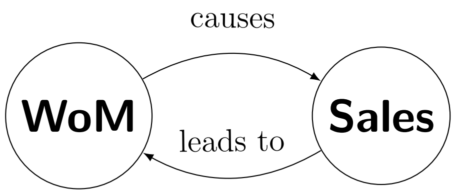


Figure 5: The causality between product sales and word-of-mouth

Therefore, it is important to distinguish its influencer and indicator roles. Since this thesis emphasizes on the persuasive effect of online reviews, only the number of reviews before the extension release is studied, and thus exclude the increasing number of reviews during the period in order to avoid the confusion between the two effects. Consequently, the next set of hypotheses is presented:

Hypothesis 4 *Ratings are positively associated with the first book sales during new book release.*

Hypothesis 5 *The number of reviews before extension release is positively associated with the first book sales during new book release.*

Hypothesis 6 *The higher ratings the greater association between the number of reviews before release and the first book sales during new book release.*

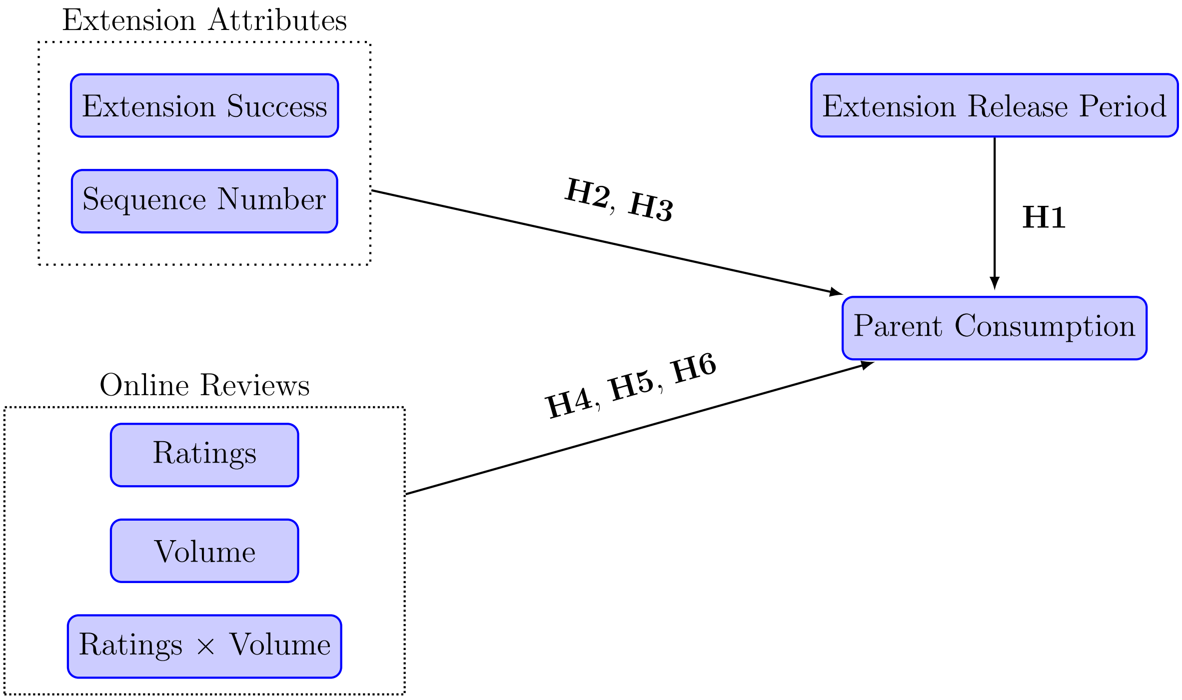


Figure 6: Summary of hypotheses

Table 1: Summary of some previous studies on the effect of online reviews in the experience product context. X indicates significance

Articles	**Product**	**Valence**	**Volume**
Chen et al. (2004)	Books		X
Liu (2006)	Movies		X
Zhang and Dellarocas (2006)	Movies	X	
Zhu and Zhang (2006)	Movies	X	X
Duan et al. (2008a)	Movies		X
Duan et al. (2008b)	Movies		X
Chintagunta et al. (2010)	Movies	X	
Amblee and Bui (2011)	Amazon short stories	X	X
Kim et al. (2016)	Movies		X

Table 2: Summary of previous studies on the reciprocal spillover effect

Factors	**Articles**	**Context**	**Findings**
Reciprocal Spillover Effect			
Extension Attributes			
Customer extension evaluation	Lane and Jacobson (1997)	FMCG	The more customers associated extension with parent brand, the greater the backward effect.
Extension experience	Sheinin (2000)	FMCG	Experience with brand extension had a more significant effect on unfamiliar parent brands than familiar ones.
Unfavorable extension experience	Chang (2002)	FMCG	Brand image was diluted by bad brand extension experience.
Negative extension information	Zhang and Taylor (2009)	FMCG & electronics	Customers changed their brand attitude and belief upon hearing negative extension information in both product categories. Also, information negativity and association set size moderated the backward effect.
Extension success	Knapp et al. (2014)	Motion picture	Financial success of a movie after its release did affect sales of its book version.

Table 2: Summary of previous studies on the reciprocal spillover effect

Factors	Articles	Context	Findings
Parent Attributes			
Pre-extension parent brand quality	Martinez and De Chernatony (2004) Buil et al. (2009)	Sportwear	The brand image was influenced by the perceived quality of parent brand prior to extension.
Customer Attributes			
Customer motivation	Ng (2010)	Electronics	Extension failures have different effects at different levels of motivation for customers in different culture.
Customer involvement	Boisvert (2012)	Financial service	Together with extension innovativeness and quality, consumer involvement imposed a mediating effect on the relationship between extension and parent brand.
Customers' attitudes towards extension	Martinez and De Chernatony (2004)	Sportwear	Attitudes regarding extended products positively affected brand image.

Table 2: Summary of previous studies on the reciprocal spillover effect

Factors	Articles	Context	Findings
Marketing Efforts			
Extension advertising	Montaner and Pina (2009)	FMCG	Extension advertising can lessen the negative feedback effect.
	Dens and De Pelsmacker (2010)	FMCG & Electronics	Advertising for extension influenced customers' choice of parent product.
Marketing support	Knapp et al. (2014)	Motion picture	Marketing support positively impacts the post-extension parent sales.

3 DATA AND RESEARCH METHOD

3.1 Data collection

The data comprises book characteristics and user review data collected from the website Amazon.com, one of the biggest online booksellers, using the API (Application Programming Interface) provided by Keepa. The sample was constructed by first identifying a list of book series which had new books released between May 2015 and November 2017. The time span was set due to data availability from Keepa and the end month was exactly 3 months before the data collection began. This first step was done by searching information on goodreads.com, a popular website for book lovers and also part of the Amazon family since 2013. The keywords used are *"book sequel"* and year (i.e. 2015, 2016, 2017) under the Listopia category. The resulting list contained 209 first books and 310 new books.

In the second step, only the newest released books were chosen out of 310 new books. For example, book 3, 4 and 5 in *The Tree of Ages series* came out in 2015, 2016 and 2017, respectively; book 3 and 4 were omitted. Doing so helps avoid adding complexity to the study since correlation is reduced to book level instead of book and series level. Consequently, this step resulted in 209 books and their sequels in the sample.

In the third step, I excluded 38 books together their sequels because their information are not obtainable directly from Amazon.com. Either because the book is out-of-print (available only on the secondary market) throughout the studied time period, or because the book is published in only Kindle version whose salesrank information is not provided by Amazon. After three steps and all filtering criteria, the sampling process ends with 171 book series together with their ASINs (Amazon Standard Identification Number).

The variable data collection began with determining the desired studied time frame. Hendricks and Sorensen (2009) analysed the effect of new albums on the first album using the sales histories of 355 music artists. They noticed that sales of the first album started to increase roughly 4 weeks before the official release dates, peaked during the release week and remained approximately the same as sales percentage after that. Based on their findings and some sample observations, I chose a span of 6 weeks in total - 1 week before and 5 weeks after new book release - and used their weekly data for analysis.

Typically books are published in two formats - hardcover and paperback, and in most cases, their publication dates are different. For example, the publication date for book 7 of *the Chronicles of Nick series* in hardcover format is May 3, 2016 and in paperback is September 5, 2017. Salesranks of both formats were collected accordingly. Note that on Amazon, there is a pre-order period. Therefore, the information on salesrank is available even if the book has not been released yet. Since Amazon ranks top-selling products with small numbers (i.e. 1,2,3, etc.), so higher salesrank reflects lower sales. As a result, I made a comparison between two formats and selected more popular books (i.e. lower salesrank). This step is crucial because of two reasons. First, when the publication date of a newly released book is determined, it leads to accurately setting the studied periods in which

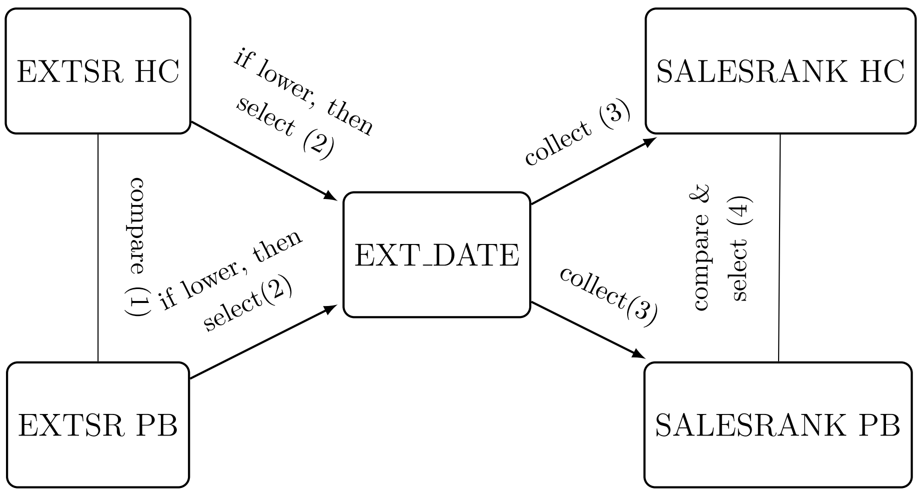


Figure 7: Steps to determine the more popular book formats (hardcover (HC) and paperback (PB)) and its release date.

the effect of a better-selling version of new book on its parent is measured. Second, a better-selling format of the first book is also captured. Figure 7 gives a more specific sequence of steps taken during this phase.

Next, sequence number in the series was acquired. Finally, first book characteristics such as ratings and the number of reviews until 28 days before new book was released as well as average price in each period were collected. Table 3 gives a description on main variables.

3.2 Data overview

Table 4 presents summary statistics of our main variables. As observed in (Chevalier and Mayzlin, 2006), book ratings on Amazon are overall positive with the average of approximately 4.25 stars. Three variables - VOLUME, EXTSR and SALESRANK - show a considerable heterogeneity in the sam-

Table 3: Description of variables used in the model

Variable	Name	Description
Fixed effects		
Time periods	$PERIOD$	Six periods coded into 0, 1, 2, 3, 4, 5
Extension attributes		
Sequence number	$SEQNUM_i$	The newly released book number in series i
Extension salesrank	$EXTSR_{ij}$	Salesrank of a new book in series i at period j
Online reviews		
Valence	$RATING_i$	The ratings of book i
Volume	$VOLUME_i$	The total number of customer reviews given to book i 28 days before extension release
Control variable		
Average price	$PRICE_{ij}$	Mean price of book i in period j
Dependent variable		
Parent book salesrank	$SALESRANK_{ij}$	Salesrank of book i at period j
Random effects		
Book identification	PAR_ID_i	Unique number for book i in the sample

ples. For instance, mean value for VOLUME is 1,264 comments (SD = 6,687), whereas median value indicates that half of the books receive under 203 reviews. This can also be recognized by the high standard deviation. One of the explanations for such great variation is that VOLUME is the accumulated number of book reviews until 28 days before extension publication date. It is inevitable that the volume of reviews might have an immense difference between the ones that released book 3 and the ones that released book 8 for example. However, eliminating older comments means making the

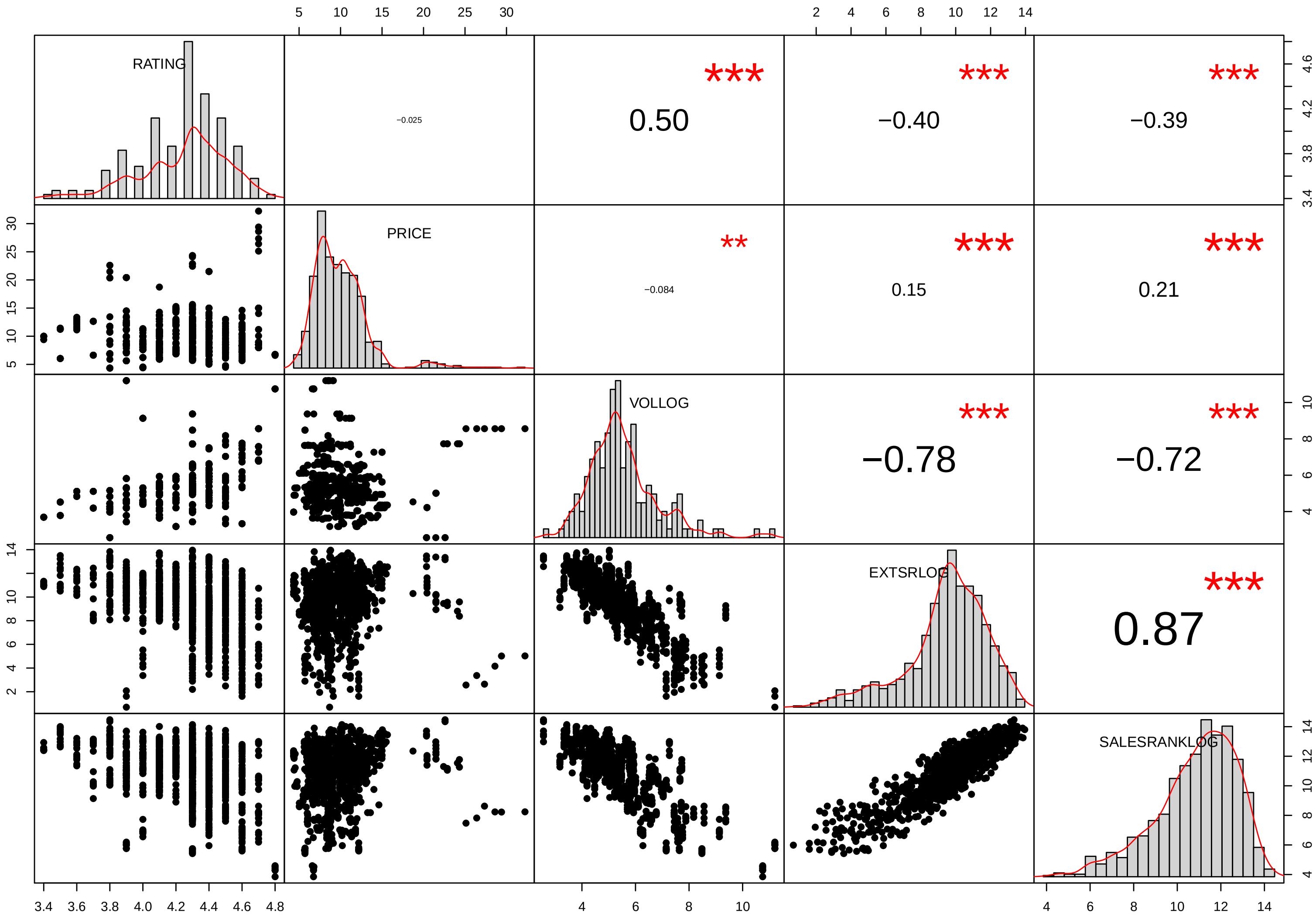
Table 4: Summary statistics

Variable	**N**	**Mean**	**St. Dev.**	**Min**	**Median**	**Max**
PERIOD	1,026	2.500	1.709	0	2.5	5
SEQNUM	1,026	3.187	1.666	2	3	11
RATING	1,026	4.25	0.26	3.4	4.3	4.8
VOLUME	1,026	1,264	6,685	13	203	73,397
PRICE	1,025	9.790	3.346	4.340	9.390	32.230
EXTSR	987	67,129	132,456	2	16,793	1,152,798
SALESRANK	1,023	153,937	220,555	47	65,632	1,920,159

assumption that older reviews are not of any importance. Meanwhile, prior studies have confirmed that customers do read reviews (Chevalier and Mayzlin, 2006) and online reviews are more influential for less popular products (Zhu and Zhang, 2010). Therefore, eliminating old reviews would hurt less popular products. Besides that, since logarithmic transformations are widely used to transform variables with highly skewed distributions into ones that are more approximately normal (Benoit, 2011), so this transformation technique is applied to those highly skewed variables[2]. This act is also consistent with the majority of previous studies (see Chen et al. (2004), Chevalier and Mayzlin (2006) for example).

Figure 8 gives a more specific visualization about the relationship between main variables of interest. Spearman's Rank-Order correlation coefficients are displayed in the upper pannel, scatter plots in the lower pannel and histograms on the diagonal. The reason for not using Pearson but Spearman's

[2] Measurement of skewness are $\gamma_{volume} = 9.21, \gamma_{extsr} = 3.77, \gamma_{salesrank} = 2.78$



*** Correlation is significant at 0.01 level.

Figure 8 Correlation chart and scatter plots of variables is because Spearman's correlation is calculated based on ranks, so the correlation does not change after variable transformation. The logarithmic transformation of VOLUME, SALESRANK and EXTSR are called VOLLOG, SALESRANKLOG and EXTSRLOG respectively from this point onwards. A negative correlation is found between VOLLOG and SALESRANKLOG; $r = -0.72; p < 0.000$, indicating that increases in VOLLOG were linked with decreases in SALESRANKLOG and vice versa. Moreover, EXTSRLOG and SALESRANKLOG are positively correlated ($r = 0.87; p < 0.000$). Interestingly, two predictors - VOLLOG and EXTSRLOG - are also highly correlated ($r = -0.78, p < 0.000$), which could be an indication of the forward spillover effect. Still, the magnitude is not greater than 0.85, a threshold suggested by (Bohrnstedt and Carter, 1971), to raise an issue of multicollinearity. The scatter plots in the lower panel show clearly the strength and direction of the relationship of these variables.

Figure 9 inspects further the relationship between two variables after transformation, SALESRANKLOG and EXTSRLOG. Evidently, both EXTSRLOG and SALESRANKLOG experienced a dip in the second weeks (from 9.76 to 9.03 for the former and from 11.32 to 11.01 for the latter). Nevertheless, EXTSRLOG had a steadier and clearer increasing pattern after the second week and quickly went up to the value of the first week. Meanwhile, SALESRANKLOG enjoyed some fluctuations, but it does not appear to reach the original point of the first week any time soon in the next 5 weeks. Also, note that the shape of distributions are varied in each period. To be more specific, the minimum and maximum values rose and fell at different times.

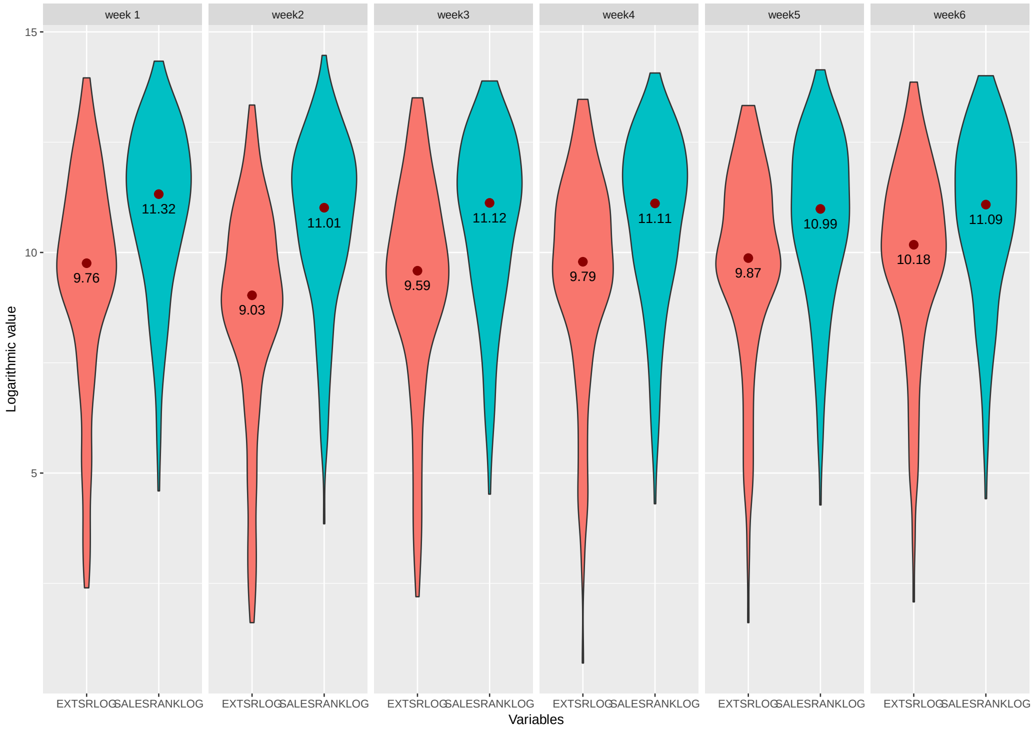


Figure 9: Violin plot shows patterns of SALESRANKLOG and EXTSRLOG in 6 weeks. Red dots display median values and the shape describes the distribution.

The peaks and shapes of the belly are also moved and changed.

3.3 Research method

The method I employ for data analysis is the linear mixed-effects models with **R**, an open source language and environment for statistical computing R Core Team (2017). The package in use is **nlme** Pinheiro et al. (2017).

As defined in (Barr et al., 2013), a model in which fixed effects, random effects and group-level errors have a linear relationship with dependent variable is called *linear mixed-effects model.* Equally important is the assumption that random group effects and group-level residuals are normally distributed and independent. Mixed-effects models allow the fixed effect to be tested against an error term that defines the variance at the group level (Barr et al., 2013). Furthermore, groups are fitted in models as random sample from a population of groups. For that reason, inference or prediction are possible beyond the groups in the sample (Mehtätalo and Lappi, 2014).

Given our longitudinal data, the use of linear mixed-effects models is appropriate and can eliminate a number of drawbacks that traditional approaches suffer from (Baayen et al., 2008). First and foremost, it increases statistical power by harnessing all repeated observations instead of averaging out across time. Also, the model can easily treat time as a continuous variable and reveal the pattern of the response variable throughout the period (Bliese and Ployhart, 2002). Second, the majority of traditional regression analysis techniques assume the constant variance and independence among variables (Kenny and Judd, 1986). These assumptions can be relaxed in linear mixed models (Mehtätalo and Lappi, 2014). In fact, they offer a superior advantage by allowing specified structure of variance-covariance matrix which accounts for auto correlation and heterogeneity of residuals. Finally, model parameters are estimated based on the available data, so missing data do not cause any problem or bias (Barr et al., 2013). For example, if one of the periods are not available for one book, the model will estimate parameters using the other two points rather than omitting the whole book from the sample.

I followed steps for *growth modeling* proposed by Bliese and Ployhart

(2002). According to them, there are two critical issues that need to be addressed in growth models. First, how time is treated as a predictor in the models, either linear or quadratic, etc.. Second, the error variance-covariance matrix should be properly modeled. Besides that, it is recommended that various statistical models are tested and compared in the building process instead of reporting a single model and parameters as a final result. Therefore, taking these into consideration, I will lay out the model building process and results in the next section.

4 MODEL BUILDING AND RESULTS

4.1 Model building

Figure 9 in previous section indicates that in earlier weeks the SALESRANKLOG tends to decrease, and later on it slightly increase (for a better view on individual books, see figure 11). Thereby, the first model starts with curvilinear PERIOD. As mentioned in 3.2, the various distribution shapes of SALESRANKLOG plotted on PERIOD demonstrate that the variable variability differs across time. Thus, heteroscedasticity is modeled in the next model. In model 3, random slopes are added. The default method for parameter estimation in **nlme** is **REML** (Restricted Maximum Likelihood). The **R** code is as below:

```
MODEL WITH RANDOM INTERCEPT
mod.1<-lme(SALESRANKLOG~PERIOD+PERIOD2, random = ~1|PAR_ID,
              data = books, na.action = na.omit)

ADDING INCONSTANT VARIANCE
mod.2 <- update(mod.1, weights = varExp(form = ~PERIOD))

ADDING RANDOM SLOPE
mod.3<-update(mod.2, random = ~1+PERIOD|PAR_ID)

CONSTRASTING THREE MODELS
anova(mod.1, mod.2, mod.3)
```

The above fitted models are compared using the generic ANOVA function and the results are shown in table 5

Table 5: Likelihood Ratio Test resulted from ANOVA function

	Model	df	AIC	BIC	logLik	Test	L.Ratio	p-value
mod.1	1	5	1743.396	1768.034	-866.6979			
mod.2	2	6	1697.575	1727.140	-842.7875	1 vs 2	47.82095	$< .0001$
mod.3	3	8	1661.891	1701.312	-822.9456	2 vs 3	39.68377	$< .0001$

The Akaike Information Criterion (AIC) estimates the relative information loss when the given model is used and the smaller value of AIC means better fit (Gałecki and Burzykowski, 2013). In this case, the model 3 has the smallest value. At the same time, the low p-values when tested the model 1 v.s. model 2 and model 2 v.s. model 3 suggest that model 2 is better than model 1 and model 3 is best among all three. That means a random slope for each individual book and inconstant variance for each period are needed. Building upon this last model, each of the independent variables is added in the next phase.

Table 6 presents the results of five models after extension attributes together with their interactions are added one by one. The coefficients for PERIOD and squared PERIOD in the model 3 is statistically significant[3]. It means that modeling curvilinear PERIOD is appropriate. Note that in the table each model does substantially better than the previous one. More

[3]The model with linear PERIOD is also fitted and the result shows insignificant coefficient for the variable

Table 6: The results of each model when adding extension attributes

	MODEL				
	(3)	(4)	(5)	(6a)	(6b)
Intercept	10.955***	6.899***	6.625***	6.747***	5.256***
	(0.146)	(0.216)	(0.284)	(0.277)	(0.449)
PERIOD	−0.185***	−0.182***	−0.181***	−0.408***	−0.376***
	(0.024)	(0.024)	(0.024)	(0.041)	(0.041)
$PERIOD^2$	0.032***	0.016***	0.015***	0.010**	0.010**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
EXTSRLOG		0.447***	0.456***	0.454***	0.614***
		(0.022)	(0.022)	(0.023)	(0.045)
SEQNUM			0.062	0.030	0.455***
			(0.046)	(0.043)	(0.114)
PERIOD×EXTSRLOG				0.025***	0.022***
				(0.004)	(0.004)
EXTSRLOG×SEQNUM					−0.047***
					(0.012)
SD(Intercept)	1.876	0.931	0.913	0.914	0.883
	(1.684, 2.091)	(0.800, 1.08)	(0.789, 1.058)	(0.789, 1.059)	(0.766, 1.018)
SD(PERIOD)	0.079	0.082	0.082	0.072	0.065
	(0.064,0.098)	(0.066, 0.101)	(0.066, 0.101)	(0.056, 0.092)	(0.049, 0.087)
SD(Residual)	0.428	0.380	0.381	0.383	0.382
	(0.386, 0.475)	(0.341, 0.425)	(0.342, 0.425)	(0.344, 0.427)	(0.343, 0.425)
Exp	−0.114	−0.069	−0.068	−0.065	−0.062
	(-0.150, -0.077)	(−0.107, −0.031)	(−0.106, −0.031)	(−0.102, −0.028)	(−0.099, −0.026)
Observations	1,023	984	984	984	984
Log Likelihood	−822.946	−681.326	−682.691	−674.038	−670.074
Akaike Inf. Crit.	1,661.891	1,380.652	1,385.381	1,370.077	1,364.149
Bayesian Inf. Crit.	1,701.312	1,424.640	1,434.247	1,423.818	1,422.762

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

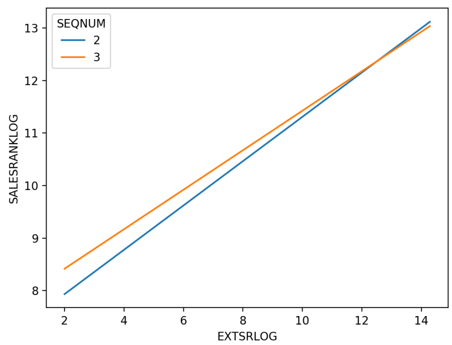
Approximate standard errors for fixed effects and 95% confidence intervals for covariance parameters are in parentheses particularly, adding the extension success results in a remarkable reduction in the AIC as well as BIC and Log Likelihood of model 4. These criteria also reduce gradually after that when additional variables are added.

Another *ANOVA* function is used to compare the refitted[4] model 6a and 6b (see appendix A). The two models differ in that the interaction between EXTSRLOG and SEQNUM is included in the latter. The result shows that model 6b with the interaction is necessary even though it is not one of the testing hypotheses. The inclusion of such interaction between EXTSRLOG $\times$ SEQNUM gives better estimated values because the term acts as a factor fostering the main effects of EXTSRLOG and SEQNUM for popular books and diminishing their effects for less popular ones.

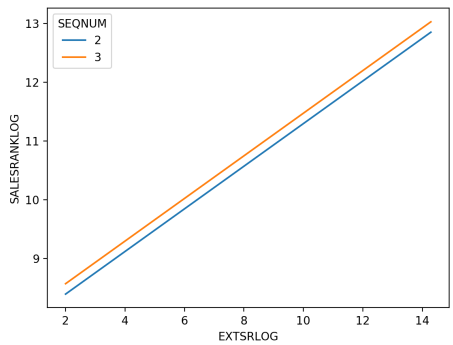
Let us consider multiple possible scenarios of two series and predicted values from model 6a and model 6b for an illustration. Firgure 10 (i) and (ii) show the prediction lines from two models, and observed values and their linear regression lines are plotted in (iii). Provided that except for EXTSRLOG, all other possible factors of two series are the same at the time of releasing its new book - book 2 and book 3. During the week before release ($PERIOD = 0$), whilst the two new books enjoy the same level of success, their effects on the first book are different in two ways. First, for books with lower salesrank (i.e. more popular), the effect is more profound for those that releases book 2 that for those that releases book 3. However, when EXTSRLOG value runs to the right, meaning lesser popularity, not only do the effects reduce but at some point there is not any difference in the

[4]using Maximum Likelihood method

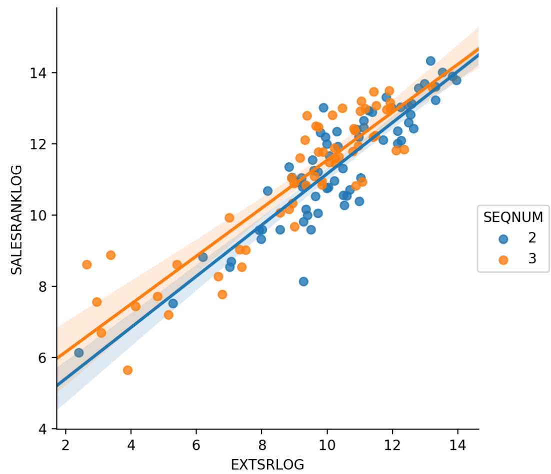
reciprocal effect between releasing book 2 and book 3. Second, between book 2 and book 3, the slope for book 2 is steeper, meaning that releasing book 2 causes a greater effect. Compared to that, the result from model 6a indicates that even though the release of book 2 produces more significant effect than that of book 3, their effects are the same for popular and non-popular books. With results from our sample, this is very unlikely to be the case.



(i) Model 6b with the interaction



(ii) Model 6a without the interaction



(iii) Observed values and two linear regression lines for sample book 2 and book 3

Figure 10: A further investigation into the interaction between *EXTSRLOG* and *SEQNUM* .

Table 7 shows more model results when online reviews characteristics are added, in which these information criteria also continue to go down. It is interesting to notice that RATINGCEN is statistically significant in model 8b, yet insignificant in model 8c. At this point, another *ANOVA* function for both refitted models is used, and the result shows that the model 8c is a slightly better fit with greater degree of freedom (p-value =0.089) (see appendix B).

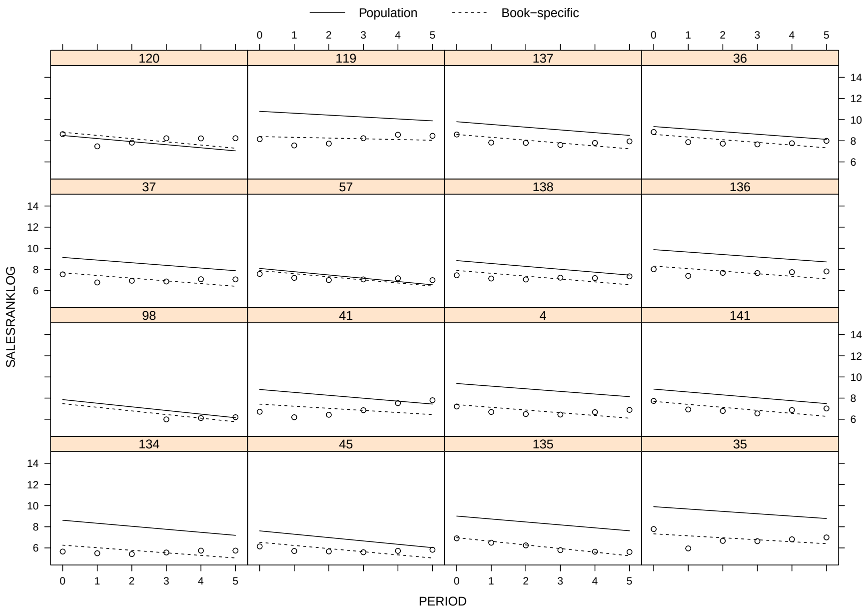
Figure 11 provides a visual representation of the two models - model 6b and model 8c. The solid line represents the predictions at the population level, which is the same for every book in the sample. The dashed line is predicted at book specific level, and is various for each individual. The observed SALESRANKLOG measurements is plotted in points. A very noticeable difference between two models is the gap between the population prediction line and the sample observed measures. For example, the fitted line of book 4, 119 and 135 follow more closely the observed values in model 8c than in model 6b. In other words, model with full extension and parent characteristics explains better the trend in SALESRANKLOG and gives more accurate predictions. After all the model observations and assessments, model 8c is chosen and reported in the next section.

Table 7: The results of each model when adding predictors and their interactions each turn

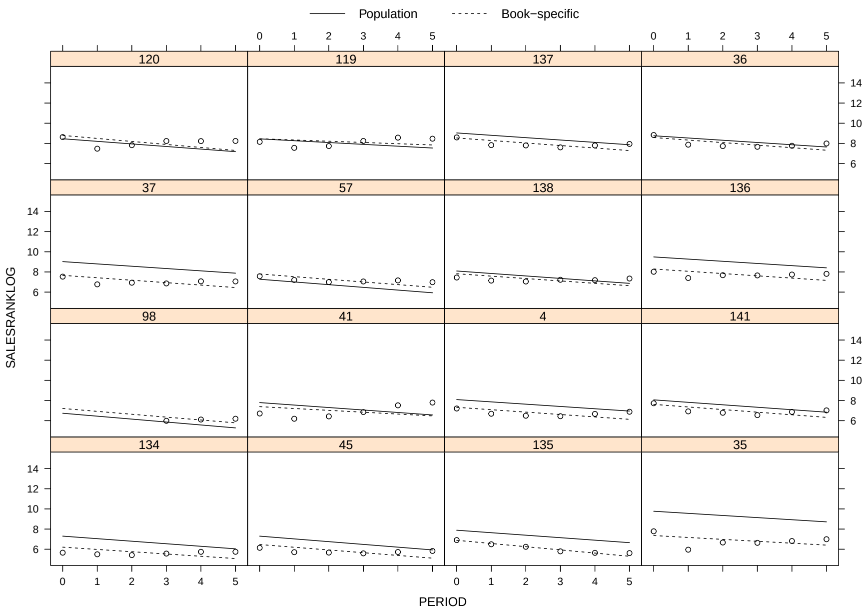
	MODEL			
	(7)	(8a)	(8b)	(8c)
Intercept	5.104^{***}	9.205^{***}	8.953^{***}	9.022^{***}
	(0.434)	(0.621)	(0.626)	(0.626)
PERIOD	-0.371^{***}	-0.311^{***}	-0.314^{***}	-0.313^{***}
	(0.040)	(0.039)	(0.039)	(0.039)
$PERIOD^2$	0.009^{**}	0.016^{***}	0.016^{***}	0.016^{***}
	(0.004)	(0.004)	(0.004)	(0.004)
EXTSRLOG	0.621^{***}	0.482^{***}	0.481^{***}	0.480^{***}
	(0.043)	(0.044)	(0.044)	(0.044)
SEQNUM	0.492^{***}	0.551^{***}	0.556^{***}	0.567^{***}
	(0.110)	(0.104)	(0.104)	(0.104)
PERIOD×EXTSRLOG	0.022^{***}	0.015^{***}	0.015^{***}	0.015^{***}
	(0.004)	(0.004)	(0.004)	(0.004)
EXTSRLOG×SEQNUM	-0.048^{***}	-0.044^{***}	-0.044^{***}	-0.045^{***}
	(0.012)	(0.011)	(0.011)	(0.011)
PRICECEN	0.074^{***}	0.081^{***}	0.082^{***}	0.085^{***}
	(0.014)	(0.014)	(0.013)	(0.014)
VOLLOG		-0.576^{***}	-0.531^{***}	-0.537^{***}
		(0.064)	(0.066)	(0.066)
RATINGCEN			-0.565^{**}	0.965
			(0.250)	(0.909)
RATINGCEN×VOLLOG				-0.294^{*}
				(0.168)
SD(Intercept)	0.841	0.777	0.773	0.768
	(0.723, 0.979)	(0.680, 0.889)	(0.676,0.884)	(0.673, 0.876)
SD(PERIOD)	0.059	0.058	0.058	0.058
	(0.043, 0.081)	(0.043, 0.079)	(0.042, 0.079)	(0.042, 0.079)
SD(Residual)	0.383	0.370	0.370	0.370
	(0.344, 0.425)	(0.333, 0.411)	(0.333, 0.411)	(0.333, 0.411)
Exp	−0.063	−0.064	−0.064	−0.064
	(−0.099, −0.028)	(−0.100, −0.028)	(−0.100, −0.028)	(−0.100, −0.028)
Observations	984	984	984	984
Log Likelihood	−660.313	−623.470	−621.422	−620.768
Akaike Inf. Crit.	1,346.627	1,274.940	1,272.844	1,273.537
Bayesian Inf. Crit.	1,410.112	1,343.294	1,346.066	1,351.623

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

Approximate standard errors for fixed effects and 95% CIs for covariance parameters are in parentheses



(i) MODEL 6b



(ii) MODEL 8c

Figure 11: A visual comparison between two models. Observations of several books are plotted in points and their prediction lines at two levels

4.2 Results

The formula for the chosen model is specified as below:

$$SALESRANKLOG_{ij} = \beta_0 + \beta_1 \times PERIOD_{ij} + \beta_2 \times PERIOD_{ij}^2 + \beta_3 \times EXTSRLOG_{ij}$$
$$+\beta_4 \times SEQNUM_i + \beta_5 \times (EXTSTLOG_{ij} \times SEQNUM_i)$$
$$+\beta_6 \times (EXTSTLOG_{ij} \times PERIOD_i) + \beta_7 \times PRICECEN_{ij} + \beta_8 \times RATINGCEN_i$$
$$+\beta_9 \times VOLLOG_i + \beta_{10} \times (RATINGCEN_i \times VOLLOG_i) + b_{0i} + b_{1i} \times PERIOD_{ij} + \epsilon_{ij}$$

where $SALESRANKLOG_{ij}$ denotes the logarithmic values of Amazon salesrank for book i (i = 1,..,171) at period j (j = 0, 1, ..., 6 according with six weeks including one week before and week 5 after the extension chronologically ordered). $PERIOD_{ij}$ is the time of measurements, coresponding to j. $EXTSRLOG_{ij}$ is the logarithmic values of extension salesrank, $SEQNUM_i$ represents the extension sequence number and their interaction $EXTSRLOG_{ij} \times SEQNUM_i$ as well as $EXTSRLOG_{ij} \times PERIOD_{ij}$. $PRICECEN_{ij}$ and $RATINGCEN_{ij}$ are the average price and rating of book i after centering [5]. $VOLLOG_i$ is the pre-extension number of online reviews for book i. $\beta_1, \beta_2, \ldots$ and β_{10} are their corresponding coefficients. The term b_{0i} is a book-specific random intercept, b_{1i} is a random slope for $PERIOD$ and ϵ_{ij} is residual random error. The variance - covariance structure for each individual book i is presented the appendix C

The model estimated coefficients is shown in the last column of table 7 (model 8c). The significant coefficients for $PERIOD$ and $PERIOD^2$ suggest that book salesrank during the studied period have an overall tendency to

[5] Centering means subtracting the mean value. It does not affect the slope and it is for better model interpretation

decrease. One might argue that since the data was collected from one week before extension, the trend detected is downward. However, I have run the analysis without the first week and received the same results even though the magnitudes are smaller. Thereby, the first hypothesis is supported.

Both coefficients for *EXTSRLOG* and *SEQNUM* are statistically significant at 99% significance level; therefore, their associations with book salerank are of great importance. Thereby, both H2 and H3 are supported. Furthermore, the term *EXTSRLOG* $\times$ *PERIOD* and the control variable *PRICECEN* are also significantly linked with the response variable. An interesting finding is the negative sign of the interaction between *EXTSRLOG* and *SEQNUM*, which indicates that the effect of *EXTSRLOG* and *SEQNUM* do not always stay constant but it will be diminishing as the two variables increase.

Out of all coefficients of main variables, *RATINGCEN* has the largest magnitude of 0.965 yet insignificant. As a result, the null hypothesis on the association between book rating and book salesrank (H4) is rejected. Three variables - *EXTSRLOG*, *SEQNUM* and *VOLLOG* are statistically significant ($p < 0.01$) and place approximately the same weight on *SALESRANKLOG*; however, the directions of influence are quite opposite. *VOLLOG*'s coefficient of -0.481 indicates that a 10% increase in the number of review volume 28 days before extension will reduce the book salesrank by 4.48%[6]. Therefore, H5 is supported. The interaction between *RATINGCEN* and *VOLLOG* is significant at a 90% significance level. That means even though book rating

[6] $e^{-.481 \times log(1.1)}$

itself do not have any significant impact on book salesrank, it does have a moderating role in the effect of *VOLLOG* on the dependent variable. Rating moderates the effect in a way that the higher average stars, the greater the number of volume affects book sales. Thus, H6 is supported. This is reasonable considering the effect of a book that has 5 stars and 1 review and of a book that has 4 stars with 300 reviews.

5 CONCLUSION AND DISCUSSION

5.1 Research Implications

The model result discussed in the previous section offers valuable insights into the reciprocal spillover effect for line extension of experience products in general, and for new book release on the first book sales in particular. First, the decreasing pattern found in the first book's salesrank, indicating increasing sales, once again confirms the existence of the backward spillover effect and gives additional support for previous studies such as (Balachander and Ghose, 2003; Hendricks and Sorensen, 2009; Knapp et al., 2014). This study also found empirical evidence for the tremendous role of extension attributes i.e. extension success and sequence number in the sales pattern during the studied period. To be more specific, the consumption of the first book is significantly associated with the level of a newly released book success. The reason is best explained in (Hendricks and Sorensen, 2009). That is an extension release causes new customers to learn about the parent product of which they were unaware earlier. Thus, the more successful the extensions, the greater the reciprocal effect. At the same time, the decreasing salesrank also relies on the number of times a series has released its extensions before. For example, the first book enjoyed higher sales during the second book release than during the third book, which is consistent with the observation for the effect of album 2 and album 3 on the first album in (Hendricks and Sorensen, 2009). Still, such effect is not always the same for every book. For popular books, the effect of the second book success on the first book sales is more significant than that of the third book. However, for less popular ones there is not much difference in the effect of those two books on the first book.

Different from previous studies, this thesis integrates the persuasive effects of online word-of-mouth communication during extension release. The effect of online reviews on product sales has been rigorously studied in past research. Nevertheless, none of previous studies on the reciprocal spillover effect have considered online reviews as external factors influencing the parent sales. Some might argue that online customer reviews can be classified as the parent attributes because after all they are what revolve around the parent product. However, given current theories giving grounds for the reciprocal effect, it can be difficult to validate such reasoning that online reviews stand for a node in consumer knowledge networks or customers' previous experience with the parent brand that is activated when they are exposed to extensions. It is rather straightforward if online feedback is considered as an influential factor from other buyers in terms of shaping customers' attitudes and behaviors, one of the two roles it has been played throughout its history of existence either in traditional or modern form. It is external information source where customers turn to when facing difficulties in making decision. That said, it is critical to find a valid theory for the reciprocal effect other than categorization process related theories (Childs, 2017), a theory that can be applied also when customers themselves have no experience or knowledge of the two products as in the context of this study.

Back to the findings, the result shows that the number of online reviews is positively associated with the first book's sales. Despite of the insignificance of book ratings, its interaction with the logarithmic value of review volume is found to be significant. It can be said that these findings give a potential positive reconciliation of the inconsistent results from previous studies on the effect of online reviews. However, as discussed in subsection 2.3.2 the inconsistency in findings is resulted from the lack of concern for the differentiation between the two effects of online reviews - awareness and persuasiveness. Therefore, before jumping into conclusion on which side the findings contribute to, justifications are needed regarding past research, and this could be a suggestion for future study.

5.2 Managerial Implications

The study also have several managerial implications for the book publishing industry. First, low sales and high book return rate have always been a concern for those publishers who want to survive in the highly competitive, yet dynamic, industry. Therefore, two of critical strategies, the right advertising strategy and accurate sales forecast, have always been in their basket (Clark and Phillips, 2014). Whenever a new book is out, publishers will need to spend a large expenditure on book promotion. The existence of the backward spillover effect and the role of extension success mean that the promotion budget should be allocated more on the new book as suggested in (Balachander and Ghose, 2003). Consequently, not only the new book is benefited but also the first book gains its "loss" sales resulting from information asymmetry. At the same time with advertising activities, increasing the stock of the first book and paying more cash to secure its availability in book stores are also necessary. However, excessive stock, which may not sell at all, results in money being tied up (Clark and Phillips, 2014). As a result, book sales prediction is essential. With the model proposed, sales forecast can be done in a manner that the forward effect of the new book is predicted from known success of the previous book. After that, the results of the forward effect is used to anticipate the backward effect.

Another implication is for negotiating and managing author contracts. Publishers need to carefully evaluate important decisions such as whether or not signing with a particular writer a single-book with potential series or multi-book contract, and if it is a multi-book, should it be a duology (two book series), trilogy (three book series) or saga (four book and more series)? This research may not give a full answer to the question to what extent publishers should risk. However, the finding that the interaction between extension success and its sequence number dictate their main effects on parent sales can be of great contribution to the decision making process. It indicates that at some point the market for the first book will be saturated no matter how many more extensions are launched, and that when the new book is popular and its sequence number is closer to the first book, the reciprocal effect is more intense. Taking these into consideration and based on experience as well as expectations, publishers can decide whether a series should be prolonged, and as a result which contract to sign. Regarding the authors, they gain more confidence in the first book knowing that the potential for it can still be explored.

Second, this study once again emphasizes the significant part of online reviews in shaping customers' attitudes and behaviors towards first book consumption during a new book release. By encouraging book readers to share their experience on online platforms, publishers/sellers can gain many benefits not only for the time being but also for the future. There are many ways to motivate this sharing behavior. For instance, Amazon has their Top Reviewer Rankings and Hall of Fame Reviewers to showcase their best contributors and honors those who have contributed. Another example is the case of Jolse.com on which customers are given 50 cents for every review on products that they have previously purchased. This way customers are motivated to share their opinions and thus product sales are increased. Therefore, publishers are advised to do this in the same manner. For example, discounts are given for the next book if customers write reviews.

5.3 Limitations and Future Research

Like many other studies, this thesis inevitably contains a number of limitations. First of all, given the rise of digital publishing, ebooks offer convenience and an increasing number of people are buying them instead of paper versions. Omitting e-book sales means leaving out a remarkable segment of the book consumption. If the trend continues to increase, the proposed model will ultimately give a false estimation of the sales of paper version. Therefore, if possible, further studies should include the ebook sales.

With the attempt to give a simplistic view on reality, this study investigates into two small sets of attributes - extension and online reviews while neglecting many other potential factors. Factors such as marketing/promotion effort (Knapp et al., 2014), author reputation, book genres, recommendation (Chen et al., 2004), consumer characteristics (Zhu and Zhang, 2010), best-seller list (Sorensen, 2007), and so on are also found to have remarkable effects on product sales. Thus, this study can be extended in a way that other determined drivers of sales are embraced. Besides, this study examines solely the first book. Thus, another possible area for further investigation is to measure the backward effect on all previous books in a series.

Finally, since I was not aware of any prior similar literature as regards the book release, the studied period is determined based on findings in the music industry done by Hendricks and Sorensen (2009) and sample observations of several books. In particular, the assumption that the duration of the reciprocal effect for books might be equal or less than that of albums is made. For that reason, it is suggested that future studies will shed some light on this matter.

References

Aaker, D. A. and Keller, K. L. (1990). Consumer evaluations of brand extensions. *The Journal of Marketing*, pages 27–41.

Alan, R. (2013). Shelf wars: What authors need to know about bookstore visibility.

Amblee, N. and Bui, T. (2011). Harnessing the influence of social proof in online shopping: The effect of electronic word of mouth on sales of digital microproducts. *International Journal of Electronic Commerce*, 16(2):91–114.

Baayen, R. H., Davidson, D. J., and Bates, D. M. (2008). Mixed-effects modeling with crossed random effects for subjects and items. *Journal of memory and language*, 59(4):390–412.

Balachander, S. and Ghose, S. (2003). Reciprocal spillover effects: A strategic benefit of brand extensions. *Journal of Marketing*, 67(1):4–13.

Banerjee, A. V. (1992). A simple model of herd behavior. *The quarterly journal of economics*, 107(3):797–817.

Banerjee, A. V. (1993). The economics of rumours. *The Review of Economic Studies*, 60(2):309–327.

Barr, D. J., Levy, R., Scheepers, C., and Tily, H. J. (2013). Random effects structure for confirmatory hypothesis testing: Keep it maximal. *Journal of memory and language*, 68(3):255–278.

Benoit, K. (2011). Linear regression models with logarithmic transformations. *London School of Economics, London*, 22(1):23–36.

Bliese, P. D. and Ployhart, R. E. (2002). Growth modeling using random coefficient models: Model building, testing, and illustrations. *Organizational Research Methods*, 5(4):362–387.

Bohrnstedt, G. W. and Carter, T. M. (1971). Robustness in regression analysis. *Sociological methodology*, 3:118–146.

Boisvert, J. (2012). The reciprocal impact of vertical service line extensions on parent brands: The roles of innovativeness, quality, and involvement. *Managing Service Quality: An International Journal*, 22(6):546–564.

Buil, I., de Chernatony, L., and Hem, L. E. (2009). Brand extension strategies: perceived fit, brand type, and culture influences. *European Journal of Marketing*, 43(11/12):1300–1324.

casestudyinc.com (2012). A brand extension mistake by Harley Davidson.

Chang, J. W. (2002). Willa family brand image by diluted by an unfavorable brand extension? a brand trial-based approach. *ACR North American Advances*.

Chen, P.-Y., Wu, S.-y., and Yoon, J. (2004). The impact of online recommendations and consumer feedback on sales. *ICIS 2004 Proceedings*, page 58.

Cheung, M.-S., Anitsal, M. M., and Anitsal, I. (2007). Revisiting word-of-mouth communications: a cross-national exploration. *Journal of Marketing Theory and Practice*, 15(3):235–249.

Chevalier, J. A. and Mayzlin, D. (2006). The effect of word of mouth on sales: Online book reviews. *Journal of marketing research*, 43(3):345–354.

Childs, M. (2017). Brand extension feedback effects: What do we know and where should we go? *Journal of Product & Brand Management*, 26(7):671–689.

Chintagunta, P. K., Gopinath, S., and Venkataraman, S. (2010). The effects of online user reviews on movie box office performance: Accounting for sequential rollout and aggregation across local markets. *Marketing Science*, 29(5):944–957.

Clark, G. and Phillips, A. (2014). *Inside book publishing*. Routledge.

Cui, G., Lui, H.-K., and Guo, X. (2012). The effect of online consumer reviews on new product sales. *International Journal of Electronic Commerce*, 17(1):39–58.

Dens, N. and De Pelsmacker, P. (2010). Attitudes toward the extension and parent brand in response to extension advertising. *Journal of Business Research*, 63(11):1237–1244.

Duan, W., Gu, B., and Whinston, A. B. (2008a). Do online reviews matter? — an empirical investigation of panel data. *Decision support systems*, 45(4):1007–1016.

Duan, W., Gu, B., and Whinston, A. B. (2008b). The dynamics of online word-of-mouth and product salesan empirical investigation of the movie industry. *Journal of retailing*, 84(2):233–242.

Eldridge, D. (2014). Publishers Diversify Their Businesses with Innovative Brand Extensions.

Ellison, G. and Fudenberg, D. (1995). Word-of-mouth communication and social learning. *The Quarterly Journal of Economics*, 110(1):93–125.

Gałecki, A. and Burzykowski, T. (2013). *Linear mixed-effects models using R: A step-by-step approach*. Springer Science & Business Media.

Greco, A. N. (2013). *The book publishing industry*. Routledge.

Hardie, B. G. S., Lodish, L. M., Kilmer, J. V., Beatty, D. R., Farris, P., Biel, A. L., Wicke, L. S., Balson, J. B., and Aaker, D. (1994). The Logic of Product-Line Extensions.

Hendricks, K. and Sorensen, A. (2009). Information and the sknewness of music sales. *Journal of political Economy*, 117(2):324–369.

Joshi, A. and Mao, H. (2012). Adapting to succeed? leveraging the brand equity of best sellers to succeed at the box office. *Journal of the Academy of Marketing Science*, 40(4):558–571.

Keller, K. L., Apéria, T., and Georgson, M. (2008). *Strategic brand management: A European perspective*. Pearson Education.

Kenny, D. A. and Judd, C. M. (1986). Consequences of violating the independence assumption in analysis of variance. *Psychological Bulletin*, 99(3):422.

Kim, C. K. and Lavack, A. M. (1996). Vertical brand extensions: current research and managerial implications. *Journal of Product & Brand Management*, 5(6):24–37.

Kim, S.-H., Yi, J.-S., and Ohm, J. (2016). Do sales of an extended brand affect popularity of its original? *ASIA MARKETING JOURNAL*, 18(2):45–61.

Knapp, A.-K., Hennig-Thurau, T., and Mathys, J. (2014). The importance of reciprocal spillover effects for the valuation of bestseller brands: introducing and testing a contingency model. *Journal of the Academy of Marketing Science*, 42(2):205–221.

Lacher, K. T. (1989). Hedonic consumption: Music as a product. *ACR North American Advances*.

Lane, V. and Jacobson, R. (1997). The reciprocal impact of brand leveraging: Feedback effects from brand extension evaluation to brand evalution. *Marketing Letters*, 8(3):261–271.

Liu, Y. (2006). Word of mouth for movies: Its dynamics and impact on box office revenue. *Journal of marketing*, 70(3):74–89.

Loken, B. and John, D. R. (1993). Diluting brand beliefs: when do brand extensions have a negative impact? *The Journal of Marketing*, pages 71–84.

Luan, Y. J. and Sudhir, K. (2010). Forecasting marketing-mix responsiveness for new products. *Journal of Marketing Research*, 47(3):444–457.

Martinez, E. and De Chernatony, L. (2004). The effect of brand extension strategies upon brand image. *Journal of consumer marketing*, 21(1):39–50.

Martinez, E. and Pina, J. M. (2003). The negative impact of brand extensions on parent brand image. *Journal of Product & Brand Management*, 12(7):432–448.

Maslowska, E., Malthouse, E. C., and Viswanathan, V. (2017). Do customer reviews drive purchase decisions? the moderating roles of review exposure and price. *Decision Support Systems*, 98:1–9.

McFadden, D. L. and Train, K. E. (1996). Consumers' evaluation of new products: Learning from self and others. *Journal of Political Economy*, 104(4):683–703.

Mehtätalo, L. and Lappi, J. (2014). *Forest biometrics with examples in R.*

Montaner, T. and Pina, J. M. (2009). Extending the brand: controllable drivers of feedback effects. *Journal of Product & Brand Management*, 18(6):394–403.

Ng, S. (2010). Cultural orientation and brand dilution: Impact of motivation level and extension typicality. *Journal of Marketing Research*, 47(1):186–198.

Park, C. W., Milberg, S., and Lawson, R. (1991). Evaluation of brand extensions: The role of product feature similarity and brand concept consistency. *Journal of consumer research*, 18(2):185–193.

Pinheiro, J., Bates, D., DebRoy, S., Sarkar, D., and R Core Team (2017). *nlme: Linear and Nonlinear Mixed Effects Models*. R package version 3.1-131.

Pitta, D. A. and Prevel Katsanis, L. (1995). Understanding brand equity for successful brand extension. *Journal of consumer marketing*, 12(4):51–64.

R Core Team (2017). *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria.

Sheinin, D. A. (2000). The effects of experience with brand extensions on parent brand knowledge. *Journal of Business Research*, 49(1):47–55.

Sorensen, A. T. (2007). Bestseller lists and product variety. *The journal of industrial economics*, 55(4):715–738.

Völckner, F. and Sattler, H. (2006). Drivers of brand extension success. *Journal of marketing*, 70(2):18–34.

Willemsen, L. M., Neijens, P. C., Bronner, F., and De Ridder, J. A. (2011). highly recommended! the content characteristics and perceived usefulness of online consumer reviews. *Journal of Computer-Mediated Communication*, 17(1):19–38.

Zhang, L. and Taylor, R. D. (2009). Exploring the reciprocal effect of negative information of brand extensions on parent brand. *Marketing Management Journal*, 19(1).

Zhang, X. and Dellarocas, C. (2006). The lord of the ratings: is a movie's fate is influenced by reviews? *ICIS 2006 proceedings*, page 117.

Zhu, F. and Zhang, X. (2006). The influence of online consumer reviews on the demand for experience goods: The case of video games. *ICIS 2006 Proceedings*, page 25.

Zhu, F. and Zhang, X. (2010). Impact of online consumer reviews on sales: The moderating role of product and consumer characteristics. *Journal of marketing*, 74(2):133–148.

APPENDIX

A Likelihood Ratio Test for model 6a and model 6b

	Model	df	AIC	BIC	logLik	Test	L.Ratio	*p*-value
mod.6a	1	11	1329.996	1383.804	-653.9979			
mod.6b	2	12	1316.814	1375.514	-646.4072	1 vs 2	15.18131	$< .0001$

B Likelihood Ratio Test for model 8b and model 8c

	Model	df	AIC	BIC	logLik	Test	L.Ratio	*p*-value
mod.8b	1	15	1212.967	1286.342	-591.4836			
mod.8c	2	16	1211.848	1290.114	-589.9238	1 vs 2	3.11966	0.0774

C Variance Covariance Matrix

$$\hat{var}(SALESRANKLOG_i) = \begin{bmatrix} 0.63966 & 0.54773 & 0.55994 & 0.53551 & 0.54162 & 0.52941 \\ 0.54773 & 0.64153 & 0.55050 & 0.53942 & 0.54219 & 0.53665 \\ 0.55994 & 0.55050 & 0.64567 & 0.53161 & 0.54105 & 0.52216 \\ 0.53551 & 0.53942 & 0.53161 & 0.66947 & 0.54333 & 0.55114 \\ 0.54162 & 0.54219 & 0.54105 & 0.54333 & 0.65141 & 0.54390 \\ 0.52941 & 0.53665 & 0.52216 & 0.55114 & 0.54390 & 0.69592 \end{bmatrix}$$