Master Thesis

Review Manipulation in the Hotel Industry: The Case of One-Time Contributors

Abstract: Although**,** review manipulation has shown to have a significant adverse impact on consumer welfare, there is yet little understanding of which economic incentives drive this behavior as most of the current research has focused on the characteristics that define a fake review. The present study investigates these incentives using the innovative approach of examining one-time contributor user reviews as an alternative measure of review manipulation. With a sample comprising 450 hotels, registered on TripAdvisor, from the cities of Amsterdam and Brussels two type of studies were developed encompassing both cross-sectional and panel data analyses. The empirical results obtained show that review manipulation is sufficiently economically important since agents with different economic incentives will indulge in review fraud in a dissimilar extent. These incentives were found to include: the type of organizational structure; the total number of reviews; and the attributed user bubble rating.

Keyword: Fake Reviews; Review Manipulation; Review Fraud; eWOM; Online Consumer Reviews; Review Helpfulness; Machine Learning

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Table of Contents

1. Introduction ... 1
2. Literature Review ... 4
2.1. From WOM to EWOM ... 4
2.2. Online Consumer Reviews ... 5
2.2.1. Review Helpfulness ... 5
2.3. Review Manipulation ... 7
2.3.1. Machine Learning ... 7
2.3.2. Linkage with Economic Incentives ... 8
2.4. Hypotheses and Concept Development ... 8
2.4.1. Organizational Structure ... 9
2.4.2. Competition ... 9
2.4.3. Number of Reviews ... 10
2.4.4. Review rating ... 11
3. Methodology ... 12
3.1. Context ... 12
3.2. Sample Extraction ... 13
3.3. Measures ... 14
3.3.1. Cross-Sectional Study ... 14
3.3.2. Panel Study ... 17
3.3.3. Table of Measures ... 18
3.4. Analysis ... 19
3.4.1. Cross-Sectional Study ... 19
3.4.2. Panel Study ... 20
4. Results ... 22
4.1. Statistical Assumptions ... 22
4.1.1. Cross-Sectional Study ... 22
4.1.2. Panel Study ... 24
4.2. Descriptive Statistics ... 27
4.3. Regression Results ... 29
4.3.1. Cross-Sectional Study ... 29
4.3.2. Panel Study ... 31
5. Discussion ... 33
5.1. Organizational Structure ... 33
5.2. Competition ... 33
5.3. Number of Reviews ... 34

5.4. Review Rating 35
6. Implications 37
6.1. Theoretical 37
6.2. Practical 37
7. Limitations and further research 39
8. Conclusion 40
9. Bibliography 41

List of Tables

Table 1: Hypotheses description 11
Table 2: Measures description and code 18
Table 3: Correlation Matrix and VIF results (cross-sectional) 23
Table 4: Correlation Matrix and VIF results (panel study) 26
Table 5: Descriptive statistics for the cross-sectional study 27
Table 6: Descriptive statistics for the panel study 28
Table 7: Results of the cross-sectional regression models 29
Table 8: Results of the panel study regression models 31
Table 9: Hypotheses testing results 32

List of Figures

Figure 1: Number of reviews in the sample per day (from Jan/2010 to Aug/2016) 12
Figure 2: Rating distribution of one contributor reviews 15
Figure 3: Rating distribution of one-time contributors 15
Figure 4: Shapiro-Wilk test for normal data 23
Figure 5: Breusch-Pagan test for heteroscedasticity 24
Figure 6: Hausman test 25
Figure 7: Modified Wald test for groupwise heteroscedasticity 25
Figure 8: Wooldridge test for autocorrelation in panel data 26

1. Introduction

Online Consumer review websites such as TripAdvisor, Amazon and Yelp have become increasingly popular in the past few years. This growth can be largely attributed to the ability of these platforms to reduce uncertainty regarding unobservable characteristics of products, creating both consumer and producer surplus (Dellarocas, 2006; Chevalier and Mayzlin, 2006).

Nevertheless, as the popularity of these platforms has increased, so have concerns that the credibility of its reviews may be undermined by agents with the intent of engaging in review fraud (also known as review manipulation or fake reviews), not only to benefit themselves but also to harm competitors. This behavior is mainly driven by the desire to increase sales performance as current literature provides strong evidence of the existence of a significant connection between online reviews and consumer purchase decisions (Luca, 2011; Chevalier and Mayzlin, 2006). However, consumers may also be adversely affected by fake reviews since this cheating behavior leads them to take suboptimal decisions, regarding products or services, that can further develop into mistrust, concerning this communication channel in later purchases. (Dellarocas, 2006).

Therefore, the current policy of most online review platforms is to create constraints and punish this type of cheating behavior. For example, Amazon imposed a five reviews per week limit in products not bought on its online store, in an effort to clamp down paid fake reviewers (Bishop, 2016). This ruling comes after a suppression on companies that encourage incentivized reviews, that is, those that provide a free product in exchange for a positive review (Perez, 2016). Another example is TripAdvisor that maintains a list of around 30 blacklisted hotels who were caught bribing customers for positive user reviews through discounts and cut-price meals (Mirror, 2012)

Additionally, governments have been imposing stricter guidelines in order to curb review manipulation or attempts to mislead the consumer. For example, the Federal Trade Commission updated its guidelines to include online consumer reviews, hence, a user must acknowledge, if any, the connection between himself and the reviewed product or service (FTC, 2009). Relatedly, the Congress of the United States recently enacted the Consumer Review Freedom Act, which addressed the usage of reservation “gag clauses” that prevented users from expressing their opinion and allowed businesses to sue those who left a negative review (Addady,2016).

Although clearly a topic of great concern and importance, literature pertaining it has been severely undermined as most of the current research has focused on the diverse characteristics that differentiate fake reviews from the truthful ones (Mayzlin et al, 2014; Luca and Zervas, 2016). This is also the strategy pursued by many of the major online review platforms, that have developed complex built-in algorithms that aim to detect and eliminate review fraud (e.g. Yelp). Nevertheless, the task of identifying suspected fake reviews is extremely difficult, since they try to mimic the characteristics of truthful ones, therefore leaving the question whether this is the right path to address this problem.

As a consequence, in this thesis, the exercise of detecting fake reviews is sidetracked in favor of an alternative and newer approach that consists in an empirical analysis regarding the many economic incentives that characterize review fraud (Mayzlin et al., 2014). Additionally, as the relationship between reviews and sales performance is higher on experimental products (Babić Rosario et al., 2016), it is more pertaining to research this topic in such scenario, as the incentives to engage in review manipulation are higher.

Therefore, this study aims to reply to the following problem statement:

What are the economic incentives that encourage review manipulation in the hotel industry?

Furthermore, this problem statement has been divided into four sub-questions: 1. How does the ownership structure of hotels incentivize manipulative behaviors? 2. How does competition encourage review fraud in the hotel industry? 3. Does the number of reviews alter the review manipulation equilibrium of hotels? 4. Can a change on the review rating reflect a change in incentives to engage in review manipulation?

The present study contributes to the field of research by providing further insights regarding the incentives behind review manipulation and perhaps validates an alternative path to investigate this phenomenon. It also offers an empirically tested analysis in a setting more beneficial to the producer that has not been sufficiently investigated in current literature (Mayzlin et al 2014). Moreover, unlike previous research, this thesis uses a panel data set, that enables the construction of models concerning the different characteristics that may alter the incentives to engage in review manipulation through the spectrum of time.

The rest of this thesis is organized as follows: chapter two discusses the theoretical foundations underpinning the current research and present the hypothesis that will be tested in this study; chapter three describes the context and data sources; chapter four reveals the research findings per hypothesis, chapter five discusses the results and analyzes them based on the conjectured hypotheses; chapter six the theoretical and practical implications of the achieved conclusions and chapter seven discusses the limitations of the performed study and provides recommendation for future research.

2. Literature Review

2.1. From WOM to EWOM

The power of word-of-mouth (WOM, hereafter) has been widely documented in consumer literature (Herr et al., 1991; King and Summers, 1970). The importance of this C2C communication channel lies on its large influence on consumers, since it is perceived as more persuasive and trustworthy than marketer created sources of information (Bickart and Schindler, 2001).

Normally, WOM was defined as an oral communication between acquaintances (Arndt, 1967), however, the advent of the Internet and the development of Web 2.0 led to a paradigm shift that further extended WOM and created a new online communication channel, commonly designated electronic word-of-mouth (eWOM, hereafter). Hennig-Thurau et al (2004) defined eWOM as: "*any positive or negative statement made by potential, actual or former customers about a product or company, which is made available to a multitude of people and institutions via the internet*" (p.39).

An important characteristic of eWOM is the ability to make online recommendations under the guise of anonymity, allowing consumers to share feedback in a more comfortable way without geographical constraints (Goldsmith and Horowitz, 2006). This makes eWOM both more abundant and voluminous than tradition WOM which requires close ties between the consumers exchanging information and physical proximity in order to concretize the communication channel (Litvin et al., 2008).

As a consequence, of these characteristics eWOM finds itself as having two major advantages over traditional WOM, both in terms of speed and reachability. This is important since this communicational channel has been found to be a good predictor of sales performance (Chen, Wang, and Xie 2011; Chevalier and Mayzlin 2006; Moe and Trusov 2011) and, therefore, an indispensable tool for marketers. This connection is amplified based on the degree of uncertainty of the product, meaning that eWOM has a stronger impact on experimental (e.g. hotels, restaurants), hedonistic[1] and new goods (Dhar and Wertenbroch, 2000; Babić Rosario et al., 2016), since in these cases the assessment of the product qualities is more difficult prior to its use.

1-Goods that exploit the human senses and are used for luxury purposes (e.g. perfumes).

2.2. Online Consumer Reviews

Although eWOM communication has the ability to connect users through multiple channels (e.g .discussion forums, weblogs and news groups) (Hennig-Thurau et al., 2004), one of the most prevalent and accessible forms of communication comes from online consumer reviews (Schindler & Bickart, 2005). Unlike sellers who offer product-oriented information, such as product attributes and technical specifications, online reviews deliver consumer-oriented information that describe products in terms of usage situations and measures its performance from a user's perspective (Bickar & Schindler, 2001). As in the case of eWOM, online consumer reviews have a substantial influence on the purchase decision-making process, and therefore sales performance, as it provides information through the lenses of a consumer (Zhu and Zhang, 2010; Babić Rosario et al., 2016).

Literature pertaining this topic has been extensively covered in the past few years, however, possibly due to the sheer amount of research relating to it, certain subjects lack an overreaching consensus. One of such cases concerns the effects of review valence on sales performance. Although it seems straightforward that review valence has a positive or negative impact on sales performance, the relationship seems conflicting as this field of research is factionalized between those who argue that review valence is a good predictor of sales performance (e.g. Chevalier and Mayzlin, 2006, Dellorocas et al., 2007, Chintagunta et al., 2010) and others who contend that review volume is a more reliant predictor (Gu et al., 2012; Ho-Dac et al., 2014; Liu 2006; Xiong and Bharadwaj, 2014).

2.2.1. Review Helpfulness

As a result of these inconsistences researchers started to look less at the connection between online consumer reviews and sales performance and started to dwell more upon the concept of "helpfulness". This notion is evaluated through a peer-evaluation feature, that many major online review platforms incorporate into their website, that helps users find superior reviews. For example, TripAdvisor encourages users to provide a "Thanks" upvote if they find a particular review helpful. Hence, based on this feature, a new field of research was developed that permitted further assessment of the qualitative characteristics of reviews that ease consumer's purchase decision making process. Overall review "helpfulness" can vary across three dimensions: reviewer reputation, review rating and review depth (Chua and Banerjee, 2015).

Reviewer reputation refers to the profile description of users who have submitted a review and that many online review platforms openly display for public scrutiny. For example, TripAdvisor gives the number of previous contributions and helpful votes of each specific user registered on its website. Prior research has shown that user's response to a given review is partly influenced by the contributor's reputation (Pavlou and Dimoka, 2006). Others even contend that reviewers' reputation plays an important role on predicting sales performance (Forman et al., 2008). This characteristic is also an important source of credibility for consumers, as even the more sceptic ones can venture to read past submitted reviews and appraise the reviewer based on its ability to write a helpful review (Ghose and Ipeirotis, 2011).

Another helpful qualitative characteristic is the rating assessment. In most online review platforms users have to provide a rating appraisal of their experience, of the product or service, in order for the platform to conduct a single aggregated overall valence (Wu et al., 2011). These ratings usually comprise a five-point scale and tends to summarize, numerically, the entire content of the textual review (Chevalier and Mayzlin, 2006). Prior research has shown that extreme ratings are more helpful, as they provide a clear argument in favor or against the usage of a certain product or service (Forman et al., 2008). Alternatively, other schools of thought have reasoned that moderate rating are more helpful than extreme ones, as they present both the advantages and disadvantages of the products or services (Mudambi and Schuff, 2011).

The last dimension is review depth, which is defined as a measure of the amount of textual content that reviewers provide to justify a given rating (Mudambi and Schuff, 2010) This characteristic is deemed helpful as it demonstrates the reviewer's involvement and enthusiasm about the product, which plays an important role on the perceived quality of the review (Pan and Zhang, 2011). Reviews with substantial depth also provide a sense of adequacy and competence (Metzger, 2007; Wang, 2010). However, there is an optimal level of review depth as an overly detailed review may lead to reluctance from consumers (Otterbacher, 2009).

These dimensions, within the concept of review "helpfulness", additionally provide a glimpse of how consumers discern information, regarding the characteristics of the user and the review, in order to distinguish fake reviews from truthful ones. However, this argument is severely undermined, as the accuracy of human deception detection is low due to people's truth bias[2], lack of physical deception cues from online consumer reviews (e.g. facial expression, body gesture and tone of voice) (Lim et al., 2010; Zhou and Zhang, 2008; Wu et al., 2010) and the fact that many fake reviews are crafted in order to mimic the characteristics of unbiased ones (Lappas, 2012).

2.3. Review Manipulation

Frequently, fake reviews are published by agents with the intent of benefiting their own business or of harming competition. However, this behavior also provides adverse consequences to the consumers. This is supported by Mayzlin (2006) which states that review fraud results in welfare loss since lower quality products have further incentives to expend more on fake reviews than higher quality products, which may cause the consumer to make suboptimal decisions. Similarly, Dellarocas (2006) argues that if the manipulation on online forums was not possible, society as a whole would be better off since agents would develop a non-biased perception of firms and always pursue the optimal choice. However, it is also possible to minimize the negative effects of review manipulation by inciting a wider participation of unbiased reviewers or by developing filtering mechanisms that detect and completely remove agents with the intent of manipulation from participating in this communication channel (Mayzlin 2006; Dellarocas, 2006).

2.3.1. Machine Learning

Currently, most of the research within this field of study has been focused on this last solution since machine learning has been shown to considerably surpass human's deception detection ability (Fuller et al., 2011; Fuller et al., 2013). Normally, a set of input features are generally used in order to explain the process of review fraud detection. One of such is the review content input features, which are based on the textual content of an online review. Although authentic and manipulated reviews are not easily distinguishable from each other, there might be delicate linguistic indications that sets them apart (e.g. number of nouns, verbs, adjectives, typos) (Hu and Liu, 2004; Ott et al. 2011). Another feature concerns the consumers' ratings of products or services and the patterns of these assessments. This consists of the usage of certain general rating deviation metrics (e.g. the difference between a reviewer's rating and the average rating) and rating deviation scores (e.g. the variance of a reviewer's rating across products) (Mukherjee et al 2013a; Xu et al 2013). The last input feature relates to reviewers' characteristics which encompasses nonverbal attributes of the behavior of the reviewers. These include the average number of reviews submitted, review votes cast, ratio of first time product reviews compared with total number of reviews and the presence of an avatar picture (Mukherjee et al 2013a; Mukherjee et al 2013b).

2.3.2. Linkage with Economic Incentives

Although machine learning literature provides strong contributes to the process of identifying fake reviews, a more recent nonmachine learning approach has been getting some traction. In this new field research, the identification of manipulated reviews is sidetracked, with the focus being given to the economic incentives behind the increase of review manipulation activity. This connection was first hypothesized by Mayzlin et al. (2014) which performed a cross-platform analysis, between Expedia and TripAdvisor, to derive the economic incentives behind review manipulation. Unlike TripAdvisor which allows anyone with a registered account to submit a review, Expedia requires proof of reservation which makes it costlier to engage in a behavior with the intent of manipulation. Hence, by exploiting this key difference between platforms, it was possible to demonstrate which market and organization factors account for a potential increase in review manipulation activity. Similarly, Luca and Zervas (2016) pursued the same goal of underlining the economic incentives behind review manipulation, however based on the assumption that reviews filtered by Yelp's built-in algorithm are considered fake reviews. This key difference permitted the construction of a panel dataset, which allowed the implementation of a variety of new analyses, including the growth of review fraud over time and the role of changes in reputation.

2.4. Hypotheses and Concept Development

This thesis follows closely the reputational incentives model of the previously mentioned literature on review fraud, such as, Mayzlin et al. (2014) and Luca and Zervas (2016). In this model, it is assumed that firms follow an optimal level of review manipulation, therefore, an increase in the costs or benefits[2] of review manipulation decreases or increases, respectively, the amount of manipulation in equilibrium and vice versa. This equilibrium is an important concept as it dictates the intensity of review manipulation activity in each hotel.

2- The benefits are associated with the gains in sales and the costs with the possibility of getting caught.

2.4.1. Organizational Structure

In this regard, it is safe to assume that firms' organizational structure will affect the manipulation equilibrium. This statement is supported by prior reputational literature, for example Jin and Leslie (2009) argue that chain restaurants have higher hygiene standards due to stronger reputational incentives. Pierce and Snyder (2008) found that larger mechanical shops are less likely to adopt a cheating behavior and more likely to pass a given vehicle compared with independent shops. Similarly, the case manifested in this thesis, is between chain-affiliated and an independent organizational structures in the hotel industry. Therefore, as argued, chain affiliated hotels are less likely to engage in a cheating behavior as they face higher costs due to reputational constraints. This is due to the negative effect of getting caught that can possibly spillover across the entire brand. For example, after executives of a Lynch Hotel Group chain-affiliated hotel in Dublin were caught buying fake reviews, TripAdvisor decided to punish the entire chain through a consumer alert display in every hotel affiliated with this chain, warning users of their illicit practices (McDonagh, 2012). Moreover, chain-affiliated hotels have less positive incentives to publish fake reviews since it would only yield positive effects to one single hotel and not to the entire chain (Mayzlin et al, 2014). Therefore, the following is the first conjecture hypothesis of this thesis:

H1a: *Chain-hotels have less incentives to publish fake reviews than independent hotels.*

Consistent with the previous developed hypothesis it is also argued that independent hotels have less costs associated with the submission of self-inflicted positive fake reviews, in their TripAdvisor page, since there are no possible spillover effects, hence:

H1b: *Independent hotels have more positive fake reviews.*

2.4.2. Competition

Another important incentive that may alter the equilibrium of review manipulation is spatial competition. As stated in Mayzlin et al. (2014), besides publishing positive fake reviews in order to garner a higher rating, it is also feasible to downwardly manipulate the rating from a competitor by way of publishing a negative review. This cheating behavior, however, will only yield beneficial results if the fake review is aimed at a nearby hotel since it will increase the attractiveness of the manipulating agent in detriment of the competitor (Mayzlin et al, 2014). As previously stated, independent hotels have more incentives to engage in review fraud, due to lower costs, therefore it is hypothesized that they will be prolifically active in this type of cheating behavior, henceforth:

H2a: *Hotels near independent hotels will have more negative fake reviews.*

Based on the previous hypothesis, it is additionally argued that hotels with a nearby competitor will have a larger review manipulation activity. The reasoning behind this statement comes from Luca (2011) which stated that a decreasing rating decreases sales performance. This means that after receiving a large influx of negative reviews, from competitors, the average rating will fall, increasing the benefits to engage in self-inflicted positive review manipulation, in order to recoup the lost rating. This tit for tat conduct will increase the total amount of fake reviews, hence:

H2b: *A hotel with a nearby competitor will have more fake reviews.*

2.4.3. Number of Reviews

An additional incentive to adopt a behavior with the intent of manipulation is the total amount of reviews a hotel has obtained. TripAdvisor aggregates the reviews based on an average user review rating. The usage of such measure greatly increases the benefits of publishing early on a fake review when the total amount of reviews is low as it will have a greater effect on the average rating. However, the impact of this effect diminishes as the number reviews increases, due to the essence of the employed measure to aggregate the overall rating. Therefore, the following hypothesis is constructed:

H3: *As the amount of reviews increases the incentives to leave a fake review decreases.*

2.4.4. Review rating

As previously mentioned, the attributed review rating plays an important role in predicting sales performance (Luca, 2011). Gauging by this assumption, negative reviews provide incentives to engage in positive review fraud as by doing so they avert the possible negative consequences of a diminishing negative rating. On the other hand, positive reviews diminish these incentives as they will keep the average rating in a good standing. Therefore, the following hypothesis is conjectured:

H4: *A negative rating increases incentives for positive review fraud and a positive rating decreases them.*

Table 1: Hypotheses description

Hypothesis	Description
H1a	Chain-hotels have less incentives to publish fake reviews than independent hotels.
H1b	Independent hotels have more positive fake reviews.
H2a	Hotels near independent hotels will have more negative fake reviews.
H2b	A hotel with a nearby competitor will have more fake reviews.
H3	As the amount of reviews increases the incentives to leave a fake review decreases.
H4	A negative rating increases incentives for positive review fraud and a positive rating decreases them.

3. Methodology

The following section elaborates the procedures employed to test the proposed hypotheses. Starting first with a description of the context of the problem statement and moving on to the measures and the constructed models used to achieve meaningful results.

3.1. Context

According to a survey conducted by TripAdvisor (2016a), 81% of the travelers regard user generated online reviews important and 49% would not book a hotel without reviews. This survey underlines the emphasis of online reviews as an important communication channel that creates value to the consumer by reducing uncertainty towards experimental products, such as hotels. However, the user-generated business model, of many large online consumer reviews platforms, seems to underscore the quality of these reviews and its potential for value creation. Even though it encourages users to share their opinions, it also incentivizes behaviors with the intent of manipulation since there are large potential benefits to gain with little to no costs. Therefore, for this thesis, the online review platform TripAdvisor is examined, since as one of the major review platforms, it also pursues user-generated business model providing an interesting setting to investigate review fraud.
Presently, TripAdvisor claims to be the largest travel website in the world as it holds more than 385 million reviews and 350 million average monthly unique visitors. It is also a dominant review website for the hospitality sector with more than 1 million registered businesses, mostly hotels (TripAdvisor, 2016b). Its growth in the last years has been exponential as visualized in the collected reviews from the sample of hotels (figure 1).

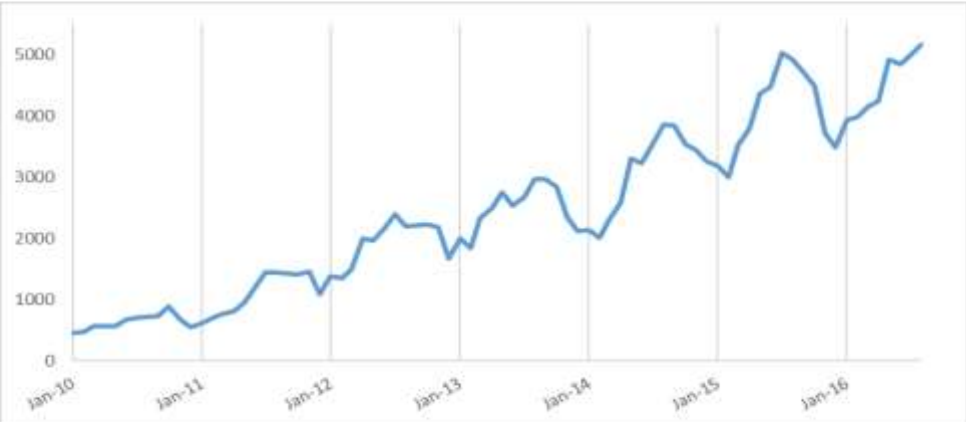

Figure 1: Number of reviews in the sample, per day (from Jan/2010 to Aug/2016)

In this online platform, besides writing a textual review, users have to provide a bubble rating assessment of the service (any natural number from 1 to 5), which will be used by TripAdvisor in order to perform an aggregated average bubble rating. Businesses with a higher average will be displayed preeminently on the front page, which grants them more visibility to potential customers and can earn them a Traveler's Choice distinction. Although these benefits are offered by TripAdvisor as a feature of review "helpfulness", since it eases customer's decision making, it may also encourage review manipulation by hotels who wish to reap some of the advantages provided by the increase in visibility.

3.2. Sample Extraction

The raw sample data consists of a number of hotels from the cities of Brussels and Amsterdam registered in the online review platform TripAdvisor. These two cities were selected based on the different competition scenarios, with Brussels having a more dispersed and lower hotel density than the more touristic city of Amsterdam.

As the goal of this thesis is to evaluate review manipulation, the tenuous job of obtaining the submitted user reviews from this sample of hotels was necessary. Therefore, a python based "scrapper" with beautifulsoup4 software package was developed which automatically collected certain aspects of the review, including: user attributed bubble rating, review date, textual review, previous user contributions, username, hotel name and hotel address. This programming tool, however, had some limitations: it could not extract more than 300 characters from textual reviews, it could only collect English reviews (TripAdvisor offers multiple language options) and faced some difficulties extracting reviews from certain hotels. Overall, the "scrapper" was able to extract 211.451 English reviews from 450 hotels, a full list of the extracted hotels is available at the appendix in table 11.

3.3. Measures

For the purpose of assessing the proposed hypotheses, both cross-sectional and panel data models were developed, hence, this section will be segmented based on this constraint. Starting first with an in-depth explanation of the measures employed in the cross-sectional and panel study and finishing with a table that describes the interpretation to follow on each employed measure.

3.3.1. Cross-Sectional Study

Dependent Variables:

One-time contributor user reviews: As fake reviews try to mimic unbiased ones, and hence are difficult to detect, it is hard to find a perfect measure for this unit of analysis. Auspiciously, for this thesis, this is not as an important criterion as the aim is to understand the different economic incentives that drive review manipulation. Thus, an alternative unit of analysis is established, which consists of reviews made by contributors with one review in their profile reviewing history (designated one-time contributors, hereafter). The reasoning for this harsh assumption has four underlining supporting arguments. First, the most cost efficient way to engage in review fraud is to create a fake account on TripAdvisor, which only requires an email address, and submit a fake review. Second, Luca and Zervas (2016) found that suspected fake reviews, filtered by Yelp's built-in algorithm, are mostly associated with characteristics of a novelty accounts, such as, a lack of profile image, friends and contributions. Third, according to review "helpfulness" theory, reviewer reputation is an important source of credibility by consumers using this communication channel (Chua and Banerjee, 2015). Lastly, it is possible to infer from figures 2 and 3 that one-time contributor user reviews are particularly more extreme in their ratings than the average of the sample, which arouses further suspicions.

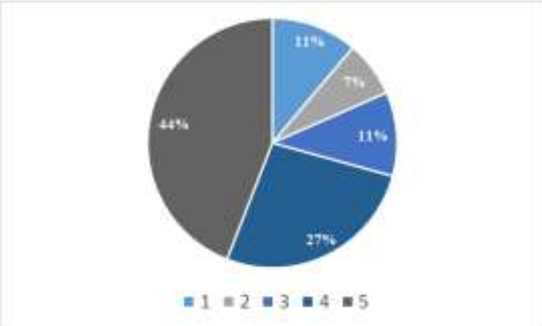

Figure 2: Rating distribution of one contributor reviews

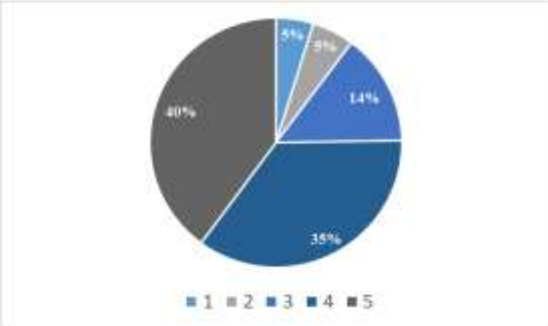

Figure 3: Rating distribution of the sample

Based on this alternative unit of analysis, three dependent variables were developed that aim to capture the different conditions under which review manipulation may be instigated. The first dependent variable relates with the volume of suspected fake reviews and is represented by the share of one-time contributor user reviews in the sample, as follows:

$$1)\quad \frac{onecontrib_i}{Totalsample_i}$$

Additionally, two further dependent variables with the intent of measuring the incidence of a specific bubble rating assessment on one-time contributor user reviews were constructed. This was achieved by performing the difference between the share of a specific rating on one-time contributor user reviews and that of the sample. Hence, to study the incidence of 5 bubble rating reviews on one-time contributor user reviews, compared with that of the sample (known as the positive difference of shares, hereafter), the following equation is proposed:

$$2)\quad \frac{onecontrib5bubblr_i}{onecontrib_i} - \frac{Total5bubblr_i}{Totalsample_i}$$

Likewise, to assess the incidence of negative one-time contributor user reviews, a similar equation is constructed by elaborating the difference of shares of user reviews with 1 and 2 bubble ratings (known as the negative difference of shares, hereafter), hence:

$$3)\quad \frac{onecontrib12bubblr_i}{onecontrib_i} - \frac{Total12bubblr_i}{Totalsample_i}$$

These difference of shares, selected as dependent variables (equation 2 and 3), are based on the proposed hypotheses that seek to test an increase in negative and positive review manipulation activity, while the share of one-time contributor user reviews (equation 1) aims to evaluate overall review manipulation activity. It is important to highlight that equation 2 pursues the study of positive review manipulation activity. Although positive reviews encompass reviews with a 5 and 4 bubble rating assessment, figure 2 demonstrates that there is a particularly higher incidence of one-time contributor user reviews with a 5 bubble rating assessment, which might create more insightful patterns.

Independent Variables:

Chain-hotels dummy: A distinction is made whether the hotel is chain-affiliated or an independent hotel, since ownership structure provides different incentives to engage in review fraud (Mayzlin et al., 2014; Luca and Zervas, 2016). To be considered chain-affiliated a hotel has to be part of a brand with two or more hotels. Through their name, some hotels provide this information upfront (e.g. Holiday Inn Express Amsterdam, part of the Holiday Inn Group), others are more discrete (e.g. Bank's Hotel, part of the Carlton Group). In order to make this distinction, each hotel website was investigated since their chain-affiliation is acknowledged there. Unlike Mayzlin et al. (2014), in this thesis, franchised hotels are considered chain-affiliated hotels due to lack of data to make such segmentation.

Neighbor dummy: Spatial competition increases the benefits from engaging in review fraud (Mayzlin et al., 2014). As in Mayzlin et al. (2014), the threshold of less than 0,5 km is used in order to determine if a hotel has a nearby competitor. To perform this distinction each hotel address, extracted from the "scrapper", was converted into a geographical coordinate and introduced into Google Maps Distance Matrix API, which calculated the distance between the different coordinates.

Chain-affiliated and Independent neighbor dummies: Similarly, like the previous dummy, the same method and threshold is used in order to determine whether a hotel has a chain-affiliated or an independent neighbor since different ownership structures offer different review manipulation equilibriums which may be interesting to study in a competitive scenario (Mayzlin et al 2014).

Control Variables:

City dummy: As previously mentioned, both the city of Amsterdam and Brussels display unique characteristics in terms of concentration and hotel density, providing the necessity of this dummy for the sake of capturing these differences.

Share of short reviews: Since reviewers with the intent of manipulation are mostly concerned with the bubble rating assessment, they are likely to give little care to its textual component and provide few details about the quality of the product or service. Therefore, it is assumed that the existence of short reviews goes hand in hand with review manipulation activity. For this thesis, reviews with less than 300 characters were considered short reviews, as this is the limit by which TripAdvisor displays the full review[3].

Average bubble rating: The average bubble rating is provided of a great predictive power in terms of sales performance (Luca, 2011). Henceforth, this variable is of great importance since it captures the impact that different review ratings may have over the benefits to engage in review manipulation. Unlike user attributed bubble ratings, a hotel average bubble rating can take middle values of any natural number between 1 and 5 (e.g. 4.5).

3.3.2. Panel Study

Dependent Variables:

One-time contributor user reviews: As previously mentioned one-time contributor user reviews is the employed unit analysis since it is hard to identify and gauge fake reviews. Based on this reasoning, two dependent variables are developed for the purpose of assessing the stated hypotheses, these are: the share of one-time contributor user reviews and the positive difference of shares. The underlining description and calculation of these variables is similar to the ones, with the same name, mentioned in the cross-sectional study, however, in this case, within a panel study setting.

Independent Variables:

Bubble rating lagged variables: In order to identify how the user rating of a submitted review alters the incentives to engage in review manipulation, all possible user attributed bubble ratings (5,4,3,2,1) are employed as independent variables. However, it is assumed that this effect will not be instant as the agents with the intent to engage in review fraud will not take an immediate response in order to decrease the possibilities of getting caught, hence the necessity of the lagged measures $(t-1)$.

Logarithm of the total number of reviews: The purpose of this control variable is to capture the effects of the growth of the number of cumulative reviews and its potential impact over the benefits to gain from engaging in review manipulation. As hotels usually

3- Long reviews (>300 characters) are not fully displayed and the consumer must manually expand the review.

exhibit an exponential growth of reviews, through time, a logarithm transformation is used which converts this growth pattern into a linear one.

3.3.3. Table of Measures

Table 2: Measures description and code

Variable	Code	Description
Dependent variable	$\frac{onecontrib_i}{Totalsample_i}$	Share of the number of one-time contributor user reviews for each hotel in the sample.
Dependent variable	$\frac{onecontrib5bubblr_i}{onecontrib_i} - \frac{Total5bubblr_i}{Totalsample_i}$	Difference of shares of 5 bubble rating reviews between one-time contributors and the total sample, for each hotel in the sample.
Dependent variable	$\frac{onecontrib12bubblr_i}{onecontrib_i} - \frac{Total12bubblr_i}{Totalsample_i}$	Difference of shares of 1 and 2 bubble rating reviews between one-time contributors and the total sample for each hotel in the sample.
Dependent variable	$\frac{onecontrib_{it}}{Totalsample_{it}}$	Share of the number of one-time contributor user reviews, per hotel in the sample and per month.
Dependent variable	$\frac{onecontrib5bubblr_{it}}{onecontrib_{it}} - \frac{Total5bubblr_{it}}{Totalsample_{it}}$	Difference of shares of 5 bubble rating reviews between one-time contributors and the total sample, per hotel in the sample and per month.
Independent variable	$Chain_i$	Dummy variable: a binary value of 1 for chain-affiliated hotels and 0 for independent hotels, for each hotel in the sample.
Independent variable	$Neigh_i$	Dummy variable: a binary value of 1 for the existence of nearby competitors and 0 for the lack of it, for each hotel in the sample.
Independent variable	$NeighChain_i$	Dummy variable: a binary value of 1 for the existence of nearby chain-affiliated competitors and 0 for the lack of it, for each hotel in the sample.
Independent variable	$NeighInd_i$	Dummy variable: a binary value of 1 for the existence of nearby independent competitors and 0 for the lack of it, for each hotel in the sample.
Independent variable	$five_{it-1}, four_{it-1}, three_{it-1}$ two_{it-1}, one_{it-1}	One month lagged variables of the amount of reviews with a specific attributed bubble rating (five, four, three, two and one bubbles) per hotel in the sample and per month.
Independent variable	$\text{Log}(count)_{it}$	The logarithm of the cumulative number of reviews, per hotel in the sample and per month.
Control variable	$Bubble_i$	Aggregated average bubble rating (any natural number from 1 to 5) for each hotel in the sample.
Control variable	$Brsls_i$	Dummy variable: a binary value of 1 for each hotel located in Brussels and 0 for each hotel located in Amsterdam.
Control variable	$Shareshort_i$	The percentage of textual short reviews (reviews with less than 300 characters) for each hotel in the sample.

3.4. Analysis

The constructed models used to enable the development of the findings are described here, as well as the expected conclusions to achieve from the variables in order to support the stated hypotheses. Similarly, to the previous section, the models are segmented based on the type of study pursued.

3.4.1. Cross-Sectional Study

Cross-sectional studies rely on data, of a sample of observations, taken at a specific point in time. A stressing feature of this type of study, however, is that not all observations correspond precisely to the same time period. Hence, it differs from time series analysis where the natural temporal ordering of observations is an important component of the analysis (Wooldridge, 2000). For the purpose of assessing hypotheses H1a, H1b, H2a and H2b three cross-sectional models were constructed using a combination of the previously mentioned measures. Additionally, it is worthy of mentioning that the employed sample, in these models, consists of 450 hotels comprising all 211.451 reviews extracted from TripAdvisor.

1) $$\frac{onecontrib_i}{Totalsample_i} = \alpha_i + \beta_1 Chain_i + \beta_2 Neigh_i + \beta_3 Bubble_i + \beta_4 Brsls_i + \beta_5 Shareshort_i + \varepsilon_i \qquad i = 1 \dots n$$

2) $$\frac{onecontrib5bubblr_i}{onecontrib_i} - \frac{Total5bubblr_i}{Totalsample_i} = \alpha_i + \beta_1 Chain_i + \beta_2 NeighInd_i + \beta_3 NeighChain_i + \beta_4 Bubble_i + \beta_5 Brsls_i + \beta_6 Shareshort_i + \varepsilon_i \qquad i = 1, \dots N$$

3) $$\frac{onecontrib12bubblr_i}{onecontrib_i} - \frac{Total12bubblr_i}{Totalsample_i} = \alpha_i + \beta_1 Chain_i + \beta_2 NeighInd_i + \beta_3 NeighChain_i + \beta_4 Bubble_i + \beta_5 Brsls_i + \beta_6 Shareshort_i + \varepsilon_i \qquad i = 1, \dots N$$

With the exception of model 1, each regression model is associated with a different hypothesis, therefore, allowing for a clearer distinction of its purpose. First, model 1 identifies the impact of organizational structure on the share of one-time contributor user reviews with the purpose of assessing hypothesis H1a. Therefore, it is expected that the coefficient of the variable $Chain_i$, will result in a negative value as chain-affiliated hotels are predicted to have a smaller share of one-time contributor user reviews due to a lower review manipulation activity. Concerning the independent variable $Neigh_i$, it is noteworthy to mention that it is not segmented based on ownership structure, as in the other models, so as to appraise hypothesis H2b. Since competition is expected to increase review manipulation activity, the coefficient of this variable is predicted to have a positive effect over the share of one-time contributor user reviews.

On the other hand, model 2 and 3 apply the positive and negative difference of shares, in order to evaluate hypothesis H1b and H2a, respectively. First, from model 2, the coefficient of the variable $Chain_i$ is expected to be negative, as chain-affiliated hotels are predicted to have a smaller share of positive one-time contributor reviews than the share of the sample, due to lower incentives to engage in self-inflicted positive review manipulation. Moreover, in model 3, the independent variable $NeighInd_i$ is foreseen to be positive. Since independent competitors are stated to have more incentives to engage in review fraud they are more likely to downwardly manipulate the average bubble rating of nearby hotels, in order to increase their own attractiveness, boosting the share of negative one-time contributor user reviews of these competitors in the process.

3.4.2. Panel Study

Lastly two additional models were employed in order to reproduce the proposed panel study. A panel study relies on panel data which basically consists of a time series for each cross-sectional observation in the data set. The major advantage of this study, over the cross-sectional one, is the ability to track the behavior of an observation through time (Wooldridge, 2000). Henceforth, for the purpose of testing the proposed hypotheses, a panel dataset was constructed which consists of 450 panels (representing every hotel in the sample) and each measure organized on a monthly basis (t = 1 month) within the timeframe of Jan/2010 to Aug/2016 (Dec/2009 to July/2016 for the lagged measures), consisting of 158.062 submitted reviews overall. Since most of the hotels were not registered on TripAdvisor, throughout this timeframe, the resulting panel data set is unbalanced, giving a total number of observations of N = 24544. The following are the proposed panel study models established to assess hypothesis H3 and H4:

$$4)\quad \frac{onecontrib_{it}}{Totalsample_{it}} = \alpha_{it} + \beta_1 five_{it-1} + \beta_2 four_{it-1} + \beta_3 three_{it-1} + \beta_4 two_{it-1} + \beta_5 one_{it-1} + \beta_6 \text{Log}(count)_{it} + \varepsilon_t \qquad t = 1,2,\dots N \qquad i = 1,2,\dots N$$

$$5) \quad \frac{onecontrib5bubblr_{it}}{onecontrib_{it}} - \frac{Total5bubblr_{it}}{Totalsample_{it}} = \alpha_{it} + \beta_1 five_{it-1} + \beta_2 four_{it-1} + \beta_3 three_{it-1} + \beta_4 two_{it-1} + \beta_5 one_{it-1} + \beta_6 \mathrm{Log}(count)_{it} + \varepsilon_{it} \qquad t = 1,2, \dots N \quad i = 1,2, .. N$$

Alike the cross-sectional models, each panel study model corresponds to a unique underlining hypothesis with model 4 and 5 associated with hypothesis H3 and H4, respectively. First, in model 4 it is expected that the variable $\mathrm{Log}(count)$, will have a negative coefficient on the monthly share of one-time contributor user reviews since an increase in the number of reviews is foreseen to decrease the incentives to engage in review manipulation, due to the diminishing impact it has over the average bubble rating of a hotel. Second, model 5 investigates the effects of the lagged variables of user attributed bubble ratings on the positive difference of shares, on a monthly basis. In this model it is expected that the positive user attributed ratings ($five_{it-1}$ and $four_{it-1}$) will have a negative coefficient and the negative user attributed ratings (two_{it-1} and one_{it-1}) will have a positive coefficient. The reasoning behind these projected results comes from the understanding that a positive rating provides no benefits to engage in positive review manipulation, as the average bubble rating will not be adversely impacted. However, if the user attributed rating is negative, these benefits increase as agents with the intent of manipulation will be incentivized to submit a fake review in order to prevent the possible adverse effects of a faltering average bubble rating.

4. Results

In the following section the applied estimation techniques and its underlining assumptions are elaborated. Furthermore, the interpretation of descriptive statistics as well as the results obtained from the regression models, in order to test the proposed hypotheses, are scrutinized and detailed.

4.1. Statistical Assumptions

4.1.1. Cross-Sectional Study

For the models used in the cross-sectional study, the estimation technique ordinary least squares (OLS) is employed. This estimation method is applied since it determines the unknown parameters in a linear regression model with the intent of minimizing the sum of the squares residuals. Moreover, the OLS estimators are one of the few estimators which, under certain conditions, can be deemed BLUE (Best Linear Unbiased Estimator) (Wooldridge, 2000).

Some underlining assumptions, however, have to be respected in order to conduct inference of the estimators and to consider the results from the OLS the best linear unbiased estimators (Wooldridge, 2000). These assumptions include: normality; no multicollinearity; and homoscedasticity of the error terms. All of these assumptions were tested using the econometric tools available on Stata.

Firstly, the normality assumption needs to be assessed. Although normality plays no significant role in demonstrating that the OLS estimator is the best linear unbiased estimator, it is necessary to conduct exact statistical inference. Hence, for each model, a histogram (figure 9,10 and 11 at the appendix) is constructed, in order to visualize the distribution of residuals and the existence of skewness and kurtosis. Furthermore, the Shapiro-Wilk test is conducted (figure 4), to address the null hypothesis of existence of normality. The results from the histograms are inconclusive, however the Shapiro-Wilk test clearly rejects ($p<0.05$) the hypothesis of existence of normality of the residuals in every developed OLS model.

Shapiro-Wilk W test for normal data
Ho: Normal distribution of the residuals

Model 1:
Prob > z = 0.0009

Model 2:
Prob > z = 0.0000

Model 3:
Prob > z = 0.0000

Figure 4: Shapiro-Wilk test for normal data

Since, for this thesis, the goal is to use parametric tests (since they possess more statistical power), it is assumed that the central limit theorem applies. This theorem states that non-normal data has an approximate normal distribution, no matter what the distribution of the original data looks like, as long as the sample size is large enough. Therefore, as the sample size in this study is somehow large (N = 450), asymptotic normality is accepted, although the power of the model is greatly diminished (Wooldridge, 2000).

An additional important assumption of the OLS estimators is that the independent variables do not display multicollinearity. Violation of this assumption can lead to bias of the coefficients of the independent variables meaning that the OLS estimators are no longer BLUE. In order to test this assumption, the variance inflation factor (VIF) as well as a correlation matrix are developed. Table 3 demonstrates the inexistence of any substantial correlation between variables from the same model, a conclusion further supported by the VIF, where all measures were found below the threshold of 10.

Variable	1	2	3	4	5	6	7	8	9	10	VIF
1) onecontrib	1										-
2) PositiveDiff	-0.178	1									-
3) NegativeDiff	-0.2451	-0.3568	1								-
4) Chain	-0.2793	0.0574	0.0432	1							1.14 (1.18)
5) Neigh	0.1096	-0.0656	-0.0721	-0.1716	1						1.13
6) NeighInd	0.0883	-0.0414	-0.0371	-0.2346	0.6497	1					1.11
7) NeighChain	0.0620	-0.0946	-0.0263	-0.1509	0.5526	0.2746	1				1.11
8) Bubble	-0.4752	0.2156	-0.1870	0.3059	-0.0712	-0.0701	-0.0754	1			1.03
9) Brsls	-0.3514	0.0901	0.1799	0.0314	-0.0258	-0.0168	-0.1111	0.0194	1		1.00 (1.01)
10) Shareshort	0.4768	-0.1147	-0.1702	0.0598	0.0467	0.0189	-0.0382	-0.0723	0.0333	1	1.02

Table 3: Correlation Matrix and VIF results (cross-sectional)

Note: onecontrib: Share of one-time contributor user reviews; PositiveDiff: Positive difference of shares; NegativeDiff: Negative difference of shares. Number in brackets represents VIF for models 2 and 3, all other VIF values are equal in all models.

Lastly, a Breusch-Pagan test is employed in order to assess the existence of homoscedasticity in the proposed OLS regression models. This assumption states that the variance of the unobservable residuals conditional on the independent variables, is constant. From figure 5, it is possible to infer that all models reject the null hypothesis of existence of homoscedasticity in favor of the alternative hypothesis of existence of heteroscedasticity. Since heteroscedasticity causes the standard errors to be biased and the OLS estimators no longer BLUE, heteroscedasticity-robust standard errors are used as they relax the assumption that error terms are independent and identically distributed, and provide a reliable t statistic if the sample size is significantly large (Wooldridge 2000).

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
Ho: Constant variance
Model 1:
chi2(1) = 39.53
Prob > chi2 = 0.0000

Model 2:
chi2(1) = 38.80
Prob > chi2 = 0.0000

Model 3:
chi2(1) = 36.54
Prob > chi2 = 0.0000

Figure 5: Breusch-Pagan test for heteroscedasticity

4.1.2. Panel Study

Given the panel study nature of the last two regression models, estimating regression analyses in panel data structures requires special econometric modelling. This thesis estimated the empirical model employing the panel estimation procedures in Stata, which offers a broad range of tools for the analysis of panel data. (Stata Manual, 2005)

There are several possible estimation techniques to select from when adopting a panel data approach. In order to do so, one has to consider certain problems in panel data structures, that might affect the efficiency and explanatory power of the coefficients and standard errors, such as, serial correlation, heteroscedasticity and multicollinearity.

Initially a Hausman test is performed (figure 6) to find whether the random-effects model or the fixed-effects model is the most appropriate method to conduct the panel regression analysis. As it is possible to visualize in figure 6, the null hypothesis of random effects model is rejected ($p<0.05$) in favor of a fixed-effects model.

Hausman Test:
Test: Ho: difference in coefficients not systematic
Model 4:
chi2(6) = 19.67
Prob>chi2 = 0.0032

Model 5:
chi2(6) = 167.50
Prob > chi2 = 0.0000

Figure 6: Hausman test

Furthermore, as in the cross-sectional study, the assumption of existence of homoscedasticity was evaluated. In order to perform this assessment, a modified Wald test was employed which tested the null hypothesis of existence of homoscedasticity. As it is possible to infer below (figure 7), the null hypothesis is rejected ($p<0.05$) in favor of the alternative hypothesis of existence of heteroscedasticity in both regression models.

Modified Wald test for groupwise heteroscedasticity:
Model 4:
chi2 (450) = 6.5e+05
Prob>chi2 = 0.0000

Model 5:
chi2 (450) = 1.5e+08
Prob>chi2 = 0.0000

Figure 7: Modified Wald test for groupwise heteroscedasticity

A further problem that often occurs when carrying out panel regressions is the presence of serial correlation (also known as autocorrelation). Serial correlation in linear panel data models causes the estimates of the regression coefficients to be consistent but less efficient, and may create an underestimation of the standard errors rendering hypothesis testing no longer valid. (Wooldridge, 2000). Hence, the Wooldridge test for autocorrelation in panel data was implemented in order to detect the presence of this phenomenon. As it is possible to conclude from figure 8, the null hypothesis ($p<0.05$) of no serial correlation is rejected in favor of the alternative hypothesis of its existence

Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
Model 4:
Prob>F = 0.0000

Model 5:
Prob>F = 0.0000

Figure 8: Wooldridge test for autocorrelation in panel data

Faced with the presence of both serial correlation and heteroscedasticity a fixed-effects model is no longer statistically reliable and a Feasible Generalized Least Squares (FGLS) model will be pursued in this thesis. The downside of the FGLS estimator is that it may not be consistent in small or medium samples. Nevertheless, it is asymptotically more efficient than the OLS estimator when the AR(1)[4] model of serial correlation holds and the sample is large. Additionally, the FGLS disregards the necessity of homoscedasticity in the model (Wooldridge 2000).

Lastly, table 4 demonstrates the correlation matrix of the variables used in the panel study. Although there is some significant correlation between the measures five and four lagged bubble ratings, the VIF column discards the existence of any possible multicollinearity since the achieved results are below the threshold of 10.

Variable	1	2	3	4	5	6	7	8	VIF
1) onecontrib	1								-
2) PositiveDiff	-0.6160	1							-
3) five lagged	-0.0622	-0.0772	1						2.22
4) four lagged	-0.0683	-0.0475	0.6558	1					3.34
5) three lagged	-0.0582	0.0009	0.3235	0.5384	1				1.11
6) two lagged	-0.0307	0.0123	0.1499	0.2780	0.3461	1			1.11
7) one lagged	-0.0023	0.0266	0.0732	0.1493	0.2314	0.2102	1		1.03
8) Log(count)	-0.5583	0.2968	0.4213	0.4590	0.3416	0.2035	0.1260	1	1.02

Table 4: Correlation Matrix and VIF results (panel study)

Note: onecontrib: Share of one-time contributor user reviews; PositiveDiff: Positive difference of shares.

4- Autoregressive model of first order: current value is based on an immediate preceding value.

4.2. Descriptive Statistics

Descriptive statistics for the cross-sectional models are reported in Table 5 and include average, standard deviation and value ranges from a sample of 450 hotels. From this table it is possible to infer that, on average, 14.29% of the reviews from each hotel are from users with a single contribution in their profile history. The value ranges are, however, large (58.25% maximum and 0.84% minimum).

Regarding the positive and negative difference of shares, it is concluded that there is a very high standard deviation, in the sample, concerning both dependent variables (10.95% and 10.77% respectively), compared with the average (7.54% and 8.1% respectively). This is also reflected on the wide discrepancy demonstrated on the maximum and minimum value ranges.

From the variable that measure competition (Neigh), it is deduced that most hotels in the sample have a nearby competitor (92.44%). If we dwell into the organizational structure of these competitors (NeighInd and NeighChain), it is reported that, on average, there is a higher presence of nearby independent competitors (83.78%) when compared with chain-affiliated competitors (78.89%). This might be a consequence of the smaller share of chain-affiliated hotels in the sample (38.44%, as displayed by Chain) as opposed to independent hotels (61.56%)

Variable	N	Average	Standard deviation	Max	Min
onecontrib	450	0.1429	0.0942	0.5825	0.0084
PositiveDiff	450	0.0754	0.1095	0.5854	-0.5336
NegativeDiff	450	0.0810	0.1077	0.5867	-0.1690
Chain	450	0.3844	0.4870	1	0
Neigh	450	0.9244	0.2646	1	0
NeighInd	450	0.8378	0.3691	1	0
NeighChain	450	0.7889	0.4086	1	0
Brsls	450	0.3111	0.4635	1	0
Bubble	450	3.7267	0.6837	5	1.5
Shareshort	450	0.2031	0.0634	0.5208	0.06

Table 5: Descriptive statistics for the cross-sectional *study*

Note: onecontrib: Share of one-time contributor user reviews; PositiveDiff: Positive difference of shares; NegativeDiff: Negative difference of shares.

Table 6 displays the descriptive statistics for the variables used in the panel study and, similarly to the previous table, it includes average, standard deviation and value ranges from 24.544 observations within the timeframe mentioned in the previous section. Concerning the submitted reviews per month, it is noteworthy to mention that reviewers, on average and within the determined timeframe, tend to submit more positive reviews (2.4789 and 2.2539, 4 and 5 bubbles rating reviews, respectively) than negative reviews (0.2802 and 0.1983, 2 and 1 bubbles rating reviews, respectively). This is also highlighted in table 5, where the average bubble rating assessment of the sample was 3.7267, meaning that most of the user assessments are concentrated within 5 and 4 bubbles (also similar to the results obtained in figure 3).

Moreover, both dependent variables, share of one-time contributor user reviews and the positive difference of shares, exhibit a wide incongruity in the descriptive results with a high standard deviation (170,25% and 574,46%, respectively) compared with their average values (74.64% and -101.2%). It is also important to mention that the value of the positive difference of shares is negative on the descriptive results, meaning that the share of 5 bubble rating user reviews made by one-time contributors is, on a monthly average, smaller than the total share of 5 bubble rating user reviews, for each hotel in the sample.

Lastly, the variable of the logarithm of the number of cumulative reviews has an average of 1.6503 and a small standard deviation (0.7736) compared with the average. Nevertheless, the value ranges present a large discrepancy, with a maximum of 3.5615 and a minimum of 0.

Variable	N	Average	Standard deviation	Max	Min
onecontrib	24544	0.7464	1.7025	3.40	0.005
PositiveDiff	24544	-1.0120	5.7446	6.60	-2.49
five lagged	24544	2.4789	5.1356	68	0
four lagged	24544	2.2539	3.3850	43	0
three lagged	24544	0.8943	1.4093	14	0
two lagged	24544	0.2802	0.6384	8	0
one lagged	24544	0.1983	0.5242	6	0
Log(count)	24544	1.6503	0.7736	3.5615	0

Table 6: Descriptive statistics for the panel study

Note: onecontrib: Share of one-time contributor user reviews; PositiveDiff: positive difference of shares.

4.3. Regression Results

4.3.1. Cross-Sectional Study

Table 7 shows the results of the OLS regressions of the performed cross-sectional study by displaying the effects of the chosen independent and control variables on the dependent variables. As previously mentioned, the following dependent variables are used: share of one-time contributor user reviews; positive difference of shares; and negative difference of shares on models 1,2 and 3, respectively. Additionally, these models aim to test hypothesis H1a, H1b, H2a and H2b.

Independent variables	Model 1	Model 2	Model 3
$Chain_i$	-0.0343*** (0.0060)	-0.0039 (0.0110)	0.0266** (0.0089)
$Neigh_i$	0.0080 (0.0087)		
$NeighInd_i$		-0.0025 (0.0145)	-0.0046 (0.0157)
$NeighChain_i$		-0.0200 (0.0128)	-0.0024 (0.0126)
$Bubble_i$	-0.0521*** (0.0051)	0.0333*** (0.0064)	-0.0384*** (0.0071)
$Brsls_i$	-0.0722*** (0.0061)	0.0189 (0.0121)	0.0437*** (0.0123)
$Shareshort_i$	0.6998*** (0.0633)	-0.1764** (0.0696)	-0.3419*** (0.7359)
Observations	450	450	450
R-squared	0.58	0.07	0.12

Notes: ***p<0.01, **p<0.05, *p<0.10
Values in brackets are robust standard errors

Table 7: Results of the cross-sectional regression models

Model 1 demonstrates a significant and negative impact (β = -0.0343, p<0.01) of the share of one-time contributor user reviews on the variable $Chain_i$, at a 99% significance level. This lends support for hypothesis H1a which predicted a negative effect between a chain-affiliated organizational structure and the incentives to engage in review fraud. As it is demonstrated, the results of this model specification imply that hotels that are chain-affiliated have, on average, a smaller share of one-time contributor user reviews compared with independent hotels. Nevertheless, the same model rejects hypothesis H2b, which predicted a positive effect between the presence of a nearby competitor and the incentives to submit fake reviews. Although the coefficient of $Neigh_i$ is positive (β = 0.0080), which suggests that hotels with a nearby competitor have, on average, a higher share of one contributor reviews, it is not statistically significant (p>0.10).

In **model 2** it is inferred that the independent variable $Chain_i$ has a negative effect (β = -0.0039) on the positive difference of shares. This goes hand in hand with the conjectured hypothesis H2b, where it was argued that independent hotels have a stronger positive review manipulation activity than chain-affiliated hotels. However, these results are not statistically significant (p>0.10), hence hypothesis H2b is not supported.

Moreover, **model 3** assesses hypothesis H2a, which stated that hotels with a nearby independent neighbor have a larger influx of negative fake reviews. Henceforth, it was predicted that the independent variable $NeighInd_i$ had a negative effect on the negative difference of shares. However, this is not the case as the coefficient is neither positive (β = -0.0046) nor statistically significant (p>0.10), therefore, hypothesis H2a is not supported. Interestingly, although not within the scope of this study, the independent variable $Chain_i$ was found to have a negative and significant effect on the negative difference of shares (β = 0.0266, p<0.05). This indicates that chain-affiliated hotels have, on average, a disproportionally large share of negative one-time contributor user reviews.

Lastly, it is also important to highlight the small value of the R-squared of model 2 and 3. The R-squared is a goodness of fit estimator that can be interpreted as the fraction of the dependent variable that is explained by the independent and control variables (Wooldridge, 2000). As it is possible to conclude, model 2 and 3 have a R-squared of only 7% and 12%. This value is not unfamiliar since Mayzlin et al. (2014) achieved similar results in their research. Therefore, it seems that the complex nature of the dependent variables, as it represents a difference of shares, largely explains the low values achieved in both models.

4.3.2. Panel Study

Concerning the panel study, table 8 displays the results of these two analyzes. As previously mentioned, the following dependent variables are used: share of one-time contributor user reviews and the positive difference of shares in models 4 and 5, respectively, in a monthly basis. Additionally, these models aim to test hypothesis H3 and H4, respectively.

Independent variables	Model 4	Model 5
$five_{t-1}$	0.0407*** (0.0023)	-0.1944*** (0.0089)
$four_{t-1}$	0.0653*** (0.0039)	-0.1980*** (0.0152)
$three_{t-1}$	0.0614*** (0.0076)	-0.1101*** (0.0299)
two_{t-1}	0.0830*** (0.0147)	-0.0927 (0.0576)
one_{t-1}	0.1267*** (0.0171)	0.1156* (0.0671)
$\text{Log}(count)_t$	-1.5366*** (0.0129)	3.2201*** (0.0507)
Observations	24544	24544
Type of Model	FGLS	FGLS

Notes: ***p<0.01, **p<0.05, *p<0.10
The time unit is t = 1 month

Table 8: Results of the panel study regression models

The results of **model 4** show a negative and significant impact of the independent variable, $\text{Log}(count)_{it}$, on the share of one-time contributor user reviews (β = -1.5366, p<0.01). This lends support for hypothesis H3 which stated that review manipulation activity decreases as the cumulative number of reviews increases, since it progressively makes it harder for fake reviews to have a significant impact on the average bubble rating of a hotel. Furthermore, from this model, it is possible to infer that the bubble rating assessment of the previous month has a significant and positive impact on the share of one-time contributor user reviews in the next month. This effect is larger on reviews with a negative bubble rating assessment of one and two (β = 0.0830 and β = 0.1267, for two and one bubble rating assessments, respectively).

Model 5 evaluates hypothesis H4, which predicted an increase of positive review manipulation activity after a submitted user review with a negative rating in the previous month. This hypothesis is partially supported as the results show that a submitted review with a bubble rating of one, has on average, a positive and significant impact on the positive difference of shares (β = 0.1156, $p<0.10$), in the next month. However, the independent lagged variable that measures the impact of a 2 bubbles rating user review over the positive difference of shares, lacks supporting evidence for the stated hypothesis as its coefficient is neither positive nor significant (β = -0.0927, $p<0.10$).

Additionally, the developed model demonstrates that positive user submitted reviews have a negative and statistically significant ($p<0.01$) effect on the positive difference of shares (β = -0.1944 and β = -0.1980, for five and four bubble rating respectively). This relationship shows that positive user reviews disincentivizes positive review manipulation, in line with what was stated in the conjectured hypothesis.

Hypothesis	Expected result	Result	Significance	Supported
H1a	-	-	Y	Yes
H1b	-	-	N	No
H2a	+	+	N	No
H2b	+	-	N	No
H3	-	-	Y	Yes
H4	+/+/-/-	+/+/+/-	Y/Y/N/Y	Partially

Table 9: Hypotheses testing results

5. Discussion

In the subsequent section, the implications of the empirical findings are discussed. Henceforth each factor that was conjectured has having a contributing effect on review manipulation activity is segmented and further analyzed based on the developed hypothesis and the conclusions of the results section.

5.1. Organizational Structure

The findings regarding organizational structure are partially in accordance with previous literature on the subject (Mayzlin et al., 2014). First, the results achieved, in model 1, demonstrate that the costs to engage in review manipulation is higher for chain-affiliated hotels since they face possible spillover effects over the entire brand if caught. Moreover, it provides supporting evidence that chain-affiliated hotels yield less benefits from engaging in review fraud as it would only subsidize one hotel in the entire chain. Nevertheless, the results from model 2, seem to display a lack of prolific five bubble rating review manipulation abuse by independent hotels, since the estimate coefficient of the variable $Chain_i$ lacks statistical significance, removing some credibility to the underlining argument.

However, looking into table 10 at the appendix, it is evident that if the dependent variable is altered to the difference of shares of 4 bubble rating reviews, the independent variable of interest ($Chain_i$) is both negative and statistically significant (β = -0.0215, $p<0.05$). The manifested finding demonstrates that positive review manipulation activity, of independent hotels, is mainly concentrated within self-inflicted 4 bubble rating assessments. The reasoning for the deployment of such behavior might be the need of agents with the intent of manipulation to remain undetected since extreme positive reviews may look more suspicious than the more moderate 4 bubble rating assessments.

5.2. Competition

As it is possible to infer from the constructed cross-sectional models, there is no statistical significance in all of the variables used to analyze the effects of spatial competition on review manipulation activity. A possible explanation for the lack of suitable findings is the different methodology used to analyze the inherent competition factors that may incentivize review manipulation. Mayzlin et al. (2014), neglected cities with a large hotel density as to avoid difficulties in interpreting spatial competition patterns. Nevertheless, in this thesis this criterion was not employed, and two cities, with a somehow large number of hotels, are studied which may have created difficulties in finding support for the proposed hypotheses.

However, there is some supportive evidence of the existence of an ampler concept of competition not captured by the proposed measures. As seen in model 3, the variable $Chain_i$ is both positive and statistically significant. This finding demonstrates that chain-affiliated hotels are disproportionally more frequently targeted by negative fake reviews. Since they have, on average, a larger average bubble rating assessment (3.9913 for chain-affiliated hotels and 3.5614 for independent hotels) it seems straightforward that this type of organizational structure offers a good target for competitors who wish to increase their own attractiveness. Hence, although not within the measures used to analyze competition, it might provide a reliant alternative for the existence of competition effects on a wider scale that were not captured by the proposed measures as these were meant to obtain spatial competition effects.

5.3. Number of Reviews

Model 4 demonstrates that, on average, as the number of reviews grows the share of one-time contributor user reviews decreases as shown by the negative and statistically significant coefficient of the variable $\text{Log}(count)_{it}$. This supports previous literature (Luca and Zervas, 2016), since it establishes that reviewers with the intent to engage in review manipulation will find less incentives when there is a larger number of reviews, because the effectiveness of review fraud in such scenario will yield minimal change to the average bubble rating of a hotel. However, if the hotel has yet a small number of reviews, the impact of a potential fake review bubble rating assessment will be more severe on the average bubble rating and therefore providing more benefits to engage in review manipulation.

Additionally, in the same model, it is possible to conclude that as the lagged bubble rating increases, the coefficient of the lagged variables on the share of one-time contributor user reviews generally decreases. This is a largely expected result as a negative review incentivizes further review manipulation in order to keep the average bubble rating constant or towards an increasing trend. On the other hand, positive reviews decrease these incentives as there is a lack of economic factors that justify the need to alter the average. The following sub-section looks into this phenomenon into more detail.

5.4. Review Rating

Model 5 shows a positive and statistically significant effect of reviews with a bubble rating of one on the positive difference of shares. This reveals that submitting a negative review with a bubble rating assessment of one encourages five bubble rating review manipulation, in the next month, as agents with the intent of fraud will attempt to counterbalance the potential adverse consequences that this rating may impose. However, this is not verified on all negative bubble rating assessments since the effects of the lagged variable of submitting a review with a bubble rating of two is neither positive nor statistically significant on the positive difference of shares. A conceivable explanation for this phenomenon is present at model 4 where the coefficient of the lagged variable of reviews with a bubble rating of two (β = 0.0830) is much lower than the coefficient of the lagged variable that measures the effects of a review with a bubble rating of one (β = 0.1267). Therefore, demonstrating that the motivation to publish fake reviews is substantially larger after a review with a bubble rating of one than in the case of a review with a bubble rating of two.

Providing some additional supporting evidence to the existence of a relationship between review rating and incentives to engage in review manipulation, it is possible to look into the effects of the lagged variables of the five and four bubble rating reviews in model 5. Both of these measures have a negative coefficient, meaning that a positive rating, in the previous month, disincentives the submission of fake reviews with a five bubble rating assessment in the next month. This reasoning is in line with what was expected as agents with the intent of manipulation will have less motivations to positively influence the average bubble rating of a hotel after a positive review.

Interestingly the variable Log$(count)_t$, shows a positive relationship with the positive difference of shares. This denotes that as the number of reviews grows, a disproportionate share of one-time contributor user reviews possesses a bubble rating assessment of five. This finding is difficult to interpret, however, it is assumed that the majority of review manipulation is self-inflicted by hotels in order to increase their own average bubble rating or to counterbalance negative reviews. Therefore, as the number of reviews increases a larger share of fake reviews will be concentrated within this rating assessment.

6. Implications

6.1. Theoretical

The main conclusions of this thesis support that review manipulation is sufficiently economically important. Therefore, it is regarded that the hypothesized manipulation equilibrium is not far from reality since agents with different economic incentives will indulge in review fraud in a dissimilar extent. This greatly expands current literature on review manipulation that has been too focused on the inputs that aim to detect fake reviews, neglecting the understanding of what drives review manipulation activity. Henceforth, this thesis broadens this field of research towards a newer and alternative method that can be easily replicated due to the sheer amount of data displayed in current online review platforms. This data can also be employed on the construction of a panel data set which can be useful to further investigate the drivers of review manipulation activity through the spectrum of time.

6.2. Practical

Previous research has found that consumer welfare is greatly impacted by review fraud as this deceiving behavior makes consumers take suboptimal purchase decisions. Furthermore, it incites mistrust of this communication channel in later purchases (Dellarocas, 2006; Chevalier and Mayzlin, 2006). Therefore, online review platforms have the obligation of minimizing review manipulation by removing reviews deemed suspicious from the aggregated average rating, in order to avert its possible consequences. Currently, most of the major online review platforms use built-in detection algorithms who perform this task automatically. By including the findings of this thesis, as additional inputs to complement these algorithms, there are three main outcomes that may provide some benefits to improve their detection ability. First, fraud detection would be quicker to respond in situations that are commonly associated with an increase in review manipulation activity (e.g. after a surge of negative ratings). Additionally, the conclusions of this thesis can add to algorithm validation. For example, if the algorithm is not identifying fake reviews in situations where businesses are more likely to leave a fake review then this should raise concerns about its quality. Lastly, adding these inputs into the algorithms would likely make it costlier for actors with the intent of engaging in review manipulation to remain undetected. For instance, it is relatively inexpensive and easy to circumvent algorithms that detect review manipulation based on the review characteristics (e.g. textual cues). However, the organizational structures of a hotel, for example, is more difficult and expensive to alter making in such case harder to remain undetected.

7. Limitations and further research

A distinct limitation of this study is the chosen unit of analysis: reviews made by users with one contribution in their profile history. This unit of analysis serves as an alternative measure of review manipulation which, as previously mentioned, is difficult to gauge. However, it is likely that most of these reviewers have legitimate intentions and are not attempting to cheat the system. Moreover, there are alternative ways to engage in review fraud, such as, by buying fake reviews or providing incentives for users to post positive reviews. Both of these methods may involve users who already have a substantial number of submitted reviews and hence not within the scope of the proposed measure of review manipulation. Therefore, it would be interesting, in future research, the development of alternative unit of analyses that capture these different methods and that may stance themselves as a more suitable measure of review fraud.

A further limitation encompasses the focus offered to the bubble rating assessment of reviews in detriment to its textual characteristics. As users need to provide, besides the bubble rating evaluation, a complementary written review, it is possible to make a particularly strong claims in the text of a fake review that may increase its impact. Future research may also combine both of these characteristics of reviews and study its effects on the incentives to engage in review manipulation.

Another limitation is the lack of understanding that it provides about the impact of review manipulation on consumer purchase decisions. Future work can complement this research by combining consumers' purchase decisions with the different economic incentives to engage in review manipulation. Such decision may involve whether the consumer discounts the possibility of an increase in review manipulation activity or simply makes more suboptimal choices when facing an increase of this behavior.

Additionally, future research can broaden the perspective by adding more elements or characteristics that may alter the review manipulation equilibrium besides the ones mentioned in this thesis. This can also include further research in other products or services or even different online review platforms that provide a suitable setting to investigate review manipulation.

8. Conclusion

In essence, this thesis addresses the question of which economic factors drive review manipulation. Hence, it is hypothesized that every hotel has a perfect equilibrium between the costs and benefits of review fraud that translates into the amount of review manipulation activity. Overall, the findings of both the cross-sectional and panel study reveal three major factors that may alter this equilibrium. First, the type of organizational structure diminishes the benefits and increase the costs of review manipulation. Second, as the number of reviews of a hotel increases the benefits from review fraud diminish. Third, the bubble rating of a submitted review has an impact on review manipulation activity and acts as a good predictor of this phenomenon. This is especially true for reviews with an extreme negative rating and those with a positive rating. Moreover, although spatial competition was not found to be a significant driver of review manipulation, based on the employed measures, it may be an essential factor when used in a broader approach.

Clearly this thesis advances the field of research on review manipulation. Although not able to detect directly the characteristics that define a fake review, it provides an alternative and unique approach that identifies the scenarios where review manipulation activity increases. This might have practical implication that facilitate and improve review fraud detection with the aim of preventing consumer deception. Furthermore, it can be easily replicated due to its usage of review "helpfulness" characteristics, widely available on current online review platforms, that eases future research on review manipulation

9. Bibliography

Addady, M. (2016). This Controversial Business Practice May Soon Be Outlawed. Retrieved January 07, 2017, from http://fortune.com/2016/09/13/consumer-review-fairness-act/

Arndt, J. (1967). Role of product-related conversations in the diffusion of a new product. Journal of marketing Research, 291-295.

Babić Rosario, A., Sotgiu, F., De Valck, K., & Bijmolt, T. H. (2016). The effect of electronic word of mouth on sales: A meta-analytic review of platform, product, and metric factors. Journal of Marketing Research, 53(3), 297-318.

Bickart B., Schindler R.M. (2001). Internet forums as influential sources of consumer information, Journal of Interactive Marketing 15 (3) 31–40.

Bishop, T. (2016). Amazon puts new limit on customer reviews: No more than 5 a week except for verified purchases. GeekWire. Retrieved from: http://www.geekwire.com/2016/amazon-puts-new-limit-customer-reviews-no-5-week-except-verified-purchases/

Chen, Y., Wang, Q., & Xie, J. (2011). Online social interactions: A natural experiment on word of mouth versus observational learning. Journal of marketing research, 48(2), 238-254.

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

Chintagunta, P. K., Gopinath, S., & 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.

Chua, A. Y., & Banerjee, S. (2015). Understanding review helpfulness as a function of reviewer reputation, review rating, and review depth. Journal of the Association for Information Science and Technology, 66(2), 354-362.

Connors, L., Mudambi, S. M., & Schuff, D. (2011, January). Is it the review or the reviewer? A multi-method approach to determine the antecedents of online review helpfulness. In System Sciences (HICSS), 2011 44th Hawaii International Conference on (pp. 1-10). IEEE.

Connors, L., Mudambi, S. M., & Schuff, D. (2011, January). Is it the review or the reviewer? A multi-method approach to determine the antecedents of online review helpfulness. In System Sciences (HICSS), 2011 44th Hawaii International Conference on (pp. 1-10). IEEE.

Dellarocas, C. (2006). Strategic manipulation of internet opinion forums: Implications for consumers and firms. Management science, 52(10), 1577-1593.

Dellarocas, C., Zhang, X. M., & Awad, N. F. (2007). Exploring the value of online product reviews in forecasting sales: The case of motion pictures. Journal of Interactive marketing, 21(4), 23-45.

Dhar, R., & Wertenbroch, K. (2000). Consumer choice between hedonic and utilitarian goods. Journal of marketing research, 37(1), 60-71.

eMarketeer (2015) By 2016, Most Digital Travel Bookers Will Use Mobile Devices - Retrieved January 07, 2017, from: https://www.emarketer.com/Article/By-2016-Most-Digital-Travel-Bookers-Will-Use-Mobile-Devices/1013248#sthash.xe9QIu0x.dpuf

Forman, C., Ghose, A., & Wiesenfeld, B. (2008). Examining the relationship between reviews and sales: The role of reviewer identity disclosure in electronic markets. Information Systems Research, 19(3), 291-313.

FTC (2009). "Guides Concerning the Use of Endorsements and Testimonials in Advertising." Retrieved January 07, 2017, from http://ftc. gov/os/2009/10/091005revisedendorsementguides.pdf

Fuller, C. M., Biros, D. P., & Delen, D. (2011). An investigation of data and text mining methods for real world deception detection. Expert Systems with Applications, 38(7), 8392-8398.

Fuller, C. M., Biros, D. P., Burgoon, J., & Nunamaker, J. (2013). An examination and validation of linguistic constructs for studying high-stakes deception. Group Decision and Negotiation, 22(1), 117-134.

Ghose, A., & Ipeirotis, P. G. (2011). Estimating the helpfulness and economic impact of product reviews: Mining text and reviewer characteristics. IEEE Transactions on Knowledge and Data Engineering, 23(10), 1498-1512.

Goldsmith, R. E., & Horowitz, D. (2006). Measuring motivations for online opinion seeking. Journal of interactive advertising, 6(2), 2-14.

Gu, B., Park, J., & Konana, P. (2012). Research note-the impact of external word-of-mouth sources on retailer sales of high-involvement products. Information Systems Research, 23(1), 182-196.

Hennig-Thurau, T., Gwinner, K. P., Walsh, G., & Gremler, D. D. (2004). Electronic word-of-mouth via consumer-opinion platforms: What motivates consumers to articulate themselves on the Internet?. Journal of interactive marketing, 18(1), 38-52.

Herr, P. M., Kardes, F. R., & Kim, J. (1991). Effects of word-of-mouth and product-attribute information on persuasion: An accessibility-diagnosticity perspective. Journal of consumer research, 17(4), 454-462.

Ho-Dac, N. N., Carson, S. J., & Moore, W. L. (2013). The effects of positive and negative online customer reviews: do brand strength and category maturity matter?. Journal of Marketing, 77(6), 37-53.

Hu, M., & Liu, B. (2004). Mining and summarizing customer reviews. In Proceedings of the tenth ACM SIGKDD international conference on Knowledge discovery and data mining (pp. 168-177). ACM.

Jin, G. Z., & Leslie, P. (2009). Reputational incentives for restaurant hygiene. American Economic Journal: Microeconomics, 1(1), 237-267.

Jindal, N., Liu, B., & Lim, E. P. (2010, October). Finding unusual review patterns using unexpected rules. In Proceedings of the 19th ACM international conference on Information and knowledge management (pp. 1549-1552). ACM.

King, C. W., & Summers, J. O. (1970). Overlap of opinion leadership across consumer product categories. Journal of Marketing Research, 43-50.

Lappas, T. (2012). Fake reviews: The malicious perspective. In International Conference on Application of Natural Language to Information Systems (pp. 23-34). Springer Berlin Heidelberg.

Lim, E. P., Nguyen, V. A., Jindal, N., Liu, B., & Lauw, H. W. (2010, October). Detecting product review spammers using rating behaviors. In Proceedings of the 19th ACM international conference on Information and knowledge management (pp. 939-948). ACM.

Litvin, S. W., Goldsmith, R. E., & Pan, B. (2008). Electronic word-of-mouth in hospitality and tourism management. Tourism management, 29(3), 458-468.

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

Luca, M., & Zervas, G. (2016). Fake it till you make it: Reputation, competition, and Yelp review fraud. Management Science.

Luca, Michael. "Reviews, reputation, and revenue: The case of Yelp. com." Com (September 16, 2011). Harvard Business School NOM Unit Working Paper 12-016 (2011).

Mayzlin, D. (2006). Promotional chat on the Internet. Marketing Science, 25(2), 155-163.

Mayzlin, D., Dover, Y., & Chevalier, J. (2014). Promotional reviews: An empirical investigation of online review manipulation. The American Economic Review, 104(8), 2421-2455.

McDonagh, P. (2012). Hotel told staff to fake reviews on TripAdvisor. Retrieved January 06, 2017, from http://www.independent.ie/irish-news/hotel-told-staff-to-fake-reviews-on-tripadvisor-26694325.html

Metzger, M. J. (2007). Making sense of credibility on the Web: Models for evaluating online information and recommendations for future research. Journal of the American Society for Information Science and Technology, 58(13), 2078-2091.

Mirror (2012,). Cornwall hotel bribes guests to write good reviews on TripAdvisor.com. Retrieved January 07, 2017, from http://www.mirror.co.uk/news/uk-news/cornwall-hotel-bribes-guests-to-write-140593

Moe, W. W., & Trusov, M. (2011). The value of social dynamics in online product ratings forums. Journal of Marketing Research, 48(3), 444-456.

Mudambi, S. M., & Schuff, D. (2010). What makes a helpful review? A study of customer reviews on Amazon. com. MIS quarterly, 34(1), 185-200.

Mukherjee, A., Venkataraman, V., Liu, B., & Glance, N. S. (2013b). What yelp fake review filter might be doing?. In ICWSM.

Mukherjee.a, A., Kumar, A., Liu, B., Wang, J., Hsu, M., Castellanos, M., & Ghosh, R. (2013a). Spotting opinion spammers using behavioral footprints. In Proceedings of the 19th ACM SIGKDD international conference on Knowledge discovery and data mining (pp. 632-640). ACM.

Ott, M., Choi, Y., Cardie, C., & Hancock, J. T. (2011). Finding deceptive opinion spam by any stretch of the imagination. In Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies-Volume 1 (pp. 309-319). Association for Computational Linguistics.

Otterbacher, J. (2009). 'Helpfulness' in online communities: a measure of message quality. In Proceedings of the SIGCHI conference on human factors in computing systems (pp. 955-964). ACM.

Pan, Y., & Zhang, J. Q. (2011). Born unequal: a study of the helpfulness of user-generated product reviews. Journal of Retailing, 87(4), 598-612.

Pavlou, P. A., & Dimoka, A. (2006). The nature and role of feedback text comments in online marketplaces: Implications for trust building, price premiums, and seller differentiation. Information Systems Research, 17(4), 392-414.

Perez, S. (2016). Amazon bans incentivized reviews tied to free or discounted products. Retrieved January 07, 2017, from https://techcrunch.com/2016/10/03/amazon-bans-incentivized-reviews-tied-to-free-or-discounted-products/

Pierce, L., & Snyder, J. (2008). Ethical spillovers in firms: Evidence from vehicle emissions testing. Management Science, 54(11), 1891-1903.

Schindler, R. M., & Bickart, B. (2005). Published word of mouth: Referable, consumer-generated information on the Internet. Online consumer psychology: Understanding and influencing consumer behavior in the virtual world, 32.

Stata Manual (2005). STATA Longitudinal/Panel Data Reference Manual, Release 9. College Station, TX: STATA Press.

TripAdvisor (2016a). TripBarometer. Retrieved January 07, 2017, from https://www.tripadvisor.com/TripAdvisorInsights/n2750/four-booking-behaviors-driving-travelers.

TripAdvisor (2016b). Fact Sheet. Retrieved January 07, 2017, from https://www.tripadvisor.com/PressCenter-c4-Fact_Sheet.html

Wooldridge, J. M. (2000). Introductory econometrics : A modern approach. Cincinnati, OH: South-Western College.

Wu, G., Greene, D., Smyth, B., & Cunningham, P. (2010). Distortion as a validation criterion in the identification of suspicious reviews. In Proceedings of the First Workshop on Social Media Analytics (pp. 10-13). ACM.

Wu, P. F., Van der Heijden, H., & Korfiatis, N. (2011). The influences of negativity and review quality on the helpfulness of online reviews. In International conference on information systems.

Xiong, G., & Bharadwaj, S. (2014). Prerelease buzz evolution patterns and new product performance. Marketing Science, 33(3), 401-421.

Xu, C., Zhang, J., Chang, K., & Long, C. (2013). Uncovering collusive spammers in Chinese review websites. In Proceedings of the 22nd ACM international conference on Conference on information & knowledge management (pp. 979-988). ACM.

Z, S. M., & Schuff, D. (2010). What makes a helpful review? A study of customer reviews on Amazon. com. MIS quarterly, 34(1), 185-200.

Zhou, L., & Zhang, D. (2008). Following linguistic footprints: Automatic deception detection in online communication. Communications of the ACM, 51(9), 119-122.

Zhu, F., & 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.