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Spreading the Online Word-of-Mouth

A Study on the Impact of Feedback in the Online Hotel Reservation Industry

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Abstract

In this paper we empirically analyse if feedback systems at online hotel booking websites affect the behaviour of partner hotels by providing them with an incentive to invest in better quality to please their customers. This is done by creating a model to forecast the expected behaviour of partner hotels and thereafter performing a number of statistical tests on review data from the online hotel reservation agency Booking.com to assess if the predicted behaviour can be observed in reality. What we expect to find is a significant difference between new and old partner hotels with respect to their level as well as variance of reputation.

Our results cannot verify the stated hypothesis at a significance level of five percent. However, the coefficients derived exhibit the expected signs and, most likely, the failure stems from inadequate validity of data and biased feedback. The assumption of feedback provision after every transaction is relatively doubtful and moreover, we find that location, price, and the number of stars affect hotel reputation, suggesting irrational rating behaviour. To achieve the results proposed by economic theory the feedback system has to be redesigned to guarantee unbiased feedback provided by all customers. To achieve a win-win situation for hotels and consumers there is moreover a crucial need for further interdisciplinary research in the area, conducted jointly by economists, data scientists, and behavioural psychologists.

Key words: online feedback, reputation, hotels, feedback mechanism, behaviour

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1. Introduction

Imagine that you want to take a trip to an unknown destination and that you want to book accommodation for your stay in advance. Your most likely behaviour in this situation will probably be to browse the Internet for information on suitable hotels within the appropriate price and quality range. However, this is a rather new approach. Only ten years ago a person in a similar situation would most probably have based her decision on advertisement, advice from a professional travel agency, or a recommendation from a friend or neighbour.

Although the access to information has improved enormously over the years there are still many displeased customers. Statistics reveal that during the first nine months of 2008 ARN, the Swedish National Board for Consumer Complaints, registered 1,165 complaints regarding hotels and travelling matters, corresponding to an increase by approximately 7% compared to the same period 2007 (Swedish National Board for Consumer Complaints, 2008). This pattern is probably not exclusive to Sweden and there is hence a need for better mechanisms forcing hotels to provide their stated quality, or greater transparency in transaction procedures providing prospective customers with the correct information about hotels' behaviour. Today, the Internet and the existence of online feedback mechanisms provide easily accessible, low cost hubs where people can share their experiences with service providers, making it easier for future customers to assess the quality of the good or service provided. Except for the public access to persistent traces of electronic word-of-mouth[1], online feedback moreover facilitates the measurability of reputation, as the fraction of positive and negative reviews of a product or service carries important information about its quality.

By influencing the costs, scale, and performance of reputation mechanisms, information technology and websites such as www.booking.com allow the planning traveller to collect a vast amount of information about other people's prior experiences just by browsing the

[1] We define electronic word-of-mouth 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.

Internet. The ability to access feedback information from previous customers before proceeding with a booking hence renders feedback mechanisms like these an attractive capability of reducing the problem of asymmetric information existing in transactions of this type and, when they work, they may facilitate cooperation without requiring any supplementary enforcement mechanisms. That is, in the perfect world, you should not have to be worried that the hotel accommodation you book won't come up to your expectations as hotels always would have the incentive to provide the promised level of comfort and service. Moreover, an increased likelihood that a feedback report for a specific transaction, e.g. a night at a certain hotel, will influence a large fraction of future transactions strengthens the impact of reputation effects, making the area of online feedback mechanisms an even more important and interesting field to study.

1.1 Statement of Purpose and Limitations

When investigating earlier research in the area of online feedback (mainly focusing on the design of feedback mechanisms and their implications for the behaviour of buyers and sellers) no single report considering the *realised* effects could be found. Although theoretical models may generate strong implications, these are less valuable if they do not correspond to reality. Therefore, this paper takes a hypothetical-deductive approach, *analysing the impact of online feedback mechanisms* by formulating hypotheses based on economic theory which thereafter are tested to combine theory with empirical observations in, hopefully, a fruitful way. *The particular object examined is the online hotel booking industry,* where potential customers can read reviews written by previous customers prior to making their reservation, and the specific question we will try to answer is *whether the existence of online feedback mechanisms affect the behaviour of participating partner hotels by providing them with an incentive to cooperate and invest in better quality to please their customers.*

The procedure will be the following: After reviewing earlier research conducted in the area of online reputation mechanisms a hypothesis about the expected behaviour of partner hotels of online hotel reservation agencies providing a feedback mechanism to their customers will be developed. This hypothesis will be tested by performing an empirical case study using review data from the company Booking.com to see whether the expected behaviour also can be observed in reality. If it can, what are the implications on economic efficiency and welfare? If it cannot, why is that?

Due to the limited time and the dynamics of the area of research a few limitations concerning the depth of the study have been necessary. Caused by the different characteristics of online hotel reservation websites and the resulting difficulty in comparing review data across them, Booking.com has been chosen as the only agency in the case study. However, the company is the European market leader with the most extensive data material and the most reliable feedback system where feedback only can be provided by those who have stayed at a certain hotel booked through Booking.com. Moreover, due to the restricted dimensions of this paper and the time consuming activity of data collection, a limitation of the data material to two cities with approximately 60 hotels each has been necessary. This will most probably not distort our results since the trend in expected behaviour is assumed to be the same everywhere. Moreover, a sample of hotels large enough and the fact that feedback is globally collected from all guests, irrespective of origin, provides us with a broad and representative data set that should provide for a significant outcome. However, we have to be aware that these circumstances might limit the reliability of the results. Other restricting circumstances concern the data period as well as biased reviews. Firstly, the earliest data available is from September 2007, i.e. the data set (collected in November 2008) consists of 14 months. However, clear signs of strategic action by hotels should also be visible over such a short period. Secondly, data used to consider the actions taken by hotels is generated by previous guests, making our results dependent on consumer honesty and rating behaviour rationality. Thus, we cannot be completely confident that a certain feedback corresponds to a certain investment decision taken by the hotel. To circumvent this disadvantage we assume that customers are completely honest when providing feedback and that feedback is provided after every transaction. However, when interpreting the results this is the most crucial delimitation to keep in mind.

Since the occurrence of online feedback mechanisms is rather new there is a limited amount of literature and previous research in the area. This implies that the greater part of the studies reviewed in this paper stems from a small number of authors. This must be kept in mind together with the fact that, due to the interdisciplinary nature of most of the research, most results derived from these studies are not based on pure economic theories but involve computer science as well as behavioural psychology. Since this paper does not allow for a more extensive examination of this very dynamic area we will try to focus on the economic part and more extensive evaluations might instead be the focus of future research.

1.2 Outline of the Study

The rest of the paper is structured as follows. Section 2 provides a brief overview over the potentials and challenges of the new era of information technology and the role of online reputation mechanisms in this setting. Thereafter, Booking.com, its review system, and feedback mechanism is explicitly explained to provide the reader with the necessary framework for the rest of the paper. In section 3, the most relevant research in the area of reputation building and online feedback systems is presented, first its characteristics and implications and thereafter, important considerations regarding online word-of-mouth. After setting up the theoretical framework we turn to the construction of a formal model of reputation building in section 4. The section starts by creating a model of a feedback system adjusted to fit the characteristics and prerequisites of the online hotel reservation industry. Next, its implications for the coming case study are discussed and before turning to the empirical part, a hypothesis to be tested is developed. In order to assess whether the economic theories of section 3 and the customized model of section 4 bear any relevance to reality the results of the empirical case Booking.com are presented in section 5, ending with a discussion of the implications of the test results as well as a small subsection with some further exploration of the collected data. The last section summarises the paper and conclusions are made regarding the findings of this study.

2. Background

In this section the evolution of information technology over the past decade and its implications for the potentials of online feedback mechanisms is elucidated to provide the reader with the framework necessary to understand the purpose and scope of this paper. Thereafter, the concept of online feedback mechanisms is described and the company Booking.com, its website, and its feedback mechanism are all explained in more detail. This is to show explicitly how a feedback mechanism in reality can be constructed.

2.1 The Potentials and Challenges of the New Era of Information Technology

Word-of-mouth concerning hotel accommodation as well as other services, products, and companies has always been a very important driver of consumer behaviour, but has until recently exhibited a “perishable” nature since only taken place within relatively small and disjoint groups of neighbours, friends, co-workers etc. As already touched upon in the introduction to this paper the rapid progress in information technology during the past ten years has changed this and facilitated a number of improvements limiting the information asymmetries in transactions. The increased amount of information available has reduced the transaction costs of making the best decision when purchasing a good or a service and persistent traces of electronic word-of-mouth provide a measurement of quality that ambivalent consumers can take into consideration before making a purchase.

However, despite the vast amount of information available to anyone familiar with the Internet, we still observe some information asymmetries and many customers with bad experiences from online shopping. Recent statistics from Brå, the Swedish National Council for Crime Prevention, show that over the first 11 months of 2008, 6,910 cases of Internet fraud were reported to the Swedish police. This corresponds to an increase by 30% compared to the same period the previous year (Swedish Board of Crime Prevention, 2008), indicating that the Internet is a growing crime scene with the creation of open communities requiring new architectures, capable of coping with unreliable network infrastructures, limited trust between agents, and the possibility of systemic failures. There is a need for electronic social institutions that can help guarantee stability and efficiency in markets characterised by search frictions and asymmetric information between buyers and sellers. In these trading environments, where it is relatively easy for sellers to mislead buyers and difficult for buyers to assess the quality of the products before the purchase, online feedback mechanisms have emerged over the past ten years as a means to guide consumers in their search.

2.2 The Role of Online Feedback Mechanisms

Feedback mechanisms are in one sense nothing else than new versions of the old concept of word-of-mouth. However, although online versions of this concept have a lot in common with their offline counterparts, the Internet has added two important new dimensions to this old concept: Firstly, it enables the opinions of one single individual to reach millions of consumers instantly. Secondly, it makes traces of word-of-mouth persistent and measurable, which in turn facilitates the assessment of this measure of quality instantly after the opinions have been posted (Dellarocas et al., 2007, p.24).

In this way Internet based feedback mechanisms become powerful institutions in situations where traditional word-of-mouth is considered ineffective, but simultaneously a demand for appropriate systems able to collect, aggregate, and distribute all available information in a suitable way to fully reap the benefits of the global connectivity and ensure cooperation and efficiency in a world of strangers is created.

Another way to describe a feedback mechanism is to say that it generally is a third party, collecting and publishing information about past seller behaviour. Such mechanisms existed also before the era of the Internet, e.g. guide books or expert movie reviews, but due to the lower cost of collecting, analysing, and publishing reputational information electronically the Internet has facilitated the emergence of *online* feedback mechanisms. These mechanisms, in the shape of websites where people can pool their experiences with service providers, are today emerging as an alternative to more traditional trust building devices and when they work, they might facilitate cooperation among service providers and their customers without the need for any additional enforcement mechanisms. This statement provides feedback mechanisms with the *potential of providing more economically efficient solutions in a wide range of settings where information asymmetries until today have given rise to situations of adverse selection and moral hazard* (Kennes & Schiff, 2007, p.71). However, the concept of online feedback mechanisms is rather broad and the exact mechanism design can differ from one website to another. Since the empirical case study focuses on the online hotel reservation agency Booking.com we will in the next two subsections try to give a more profound understanding of the online feedback mechanism in this particular case.

2.3 Booking.com

The company Booking.com, established in 1996, is Europe's leading online hotel reservations agency by room nights sold (26 million room nights booked between June 2007 and June 2008). Each month, the website (available in 18 languages and offering over 52,000 hotels in 69 countries) has over 20 million unique visitors from worldwide leisure and business markets. The company has 22 offices in Europe, Africa, Asia, the Middle East, and the U.S. and the headquarters is located in Amsterdam. To remain competitive in the increasingly crowded market of online hotel reservation websites, Booking.com offers reservation service free of charge without any booking, administration, or cancellation fees.

Partner hotels are offered a distribution network consisting of over 4,500 websites. The model allows any kind of accommodation (budget or first class, independent hotels or chains) to use the Internet to increase exposure, occupancy, and revenue by giving each hotel a webpage with photos, a description, and a map, all translated into 18 languages. Each hotel has also access to an Extranet where online room availability, room rates, pictures, and text can be updated. In addition, hotels can access information on the number of visitors, conversion rates[2], and commission to be paid to Booking.com (Booking.com, 2008).

2.4 The Review System and Feedback Mechanism

After staying at a hotel booked through Booking.com the person who made the reservation receives a feedback form by email. There are four sections with questions to be answered

[2] The conversion rate is the ratio of website visitors who actually book a room at a certain hotel through Booking.com.

voluntarily: The first concerns the website and its usefulness, hotel prices, selection of hotels, and information about hotels and rooms; the second concerns the hotel of choice with five parameters to be valued: staff, service, cleanliness, comfort, and value for money. The respondent can assign each parameter a value judgement stated as “bad”, “fair”, “good”, or “excellent”. The third section concerns what was especially good or bad at the hotel, if the respondent would recommend the hotel to someone else, and whether he thinks that other reviews of the hotel correspond to his own experience. The last section is of more general character, asking the respondent about the primary reason for his choice of hotel, the purpose of his trip, and whether he was travelling alone, with a partner, with a group, or in any other constellation of people, e.g. a family with small children. This is due to the assumption that the preferences of different constellations of people and people with differing travelling purpose (such as business or leisure) differ regarding the importance of the various features of accommodation. The outcome of the second section is published at the hotel’s Booking.com website and in addition to this there is an average rating of the five parameters and an aggregated rating of the hotel available to create a good overview for prospective customers. At the website, the value judgements are assigned numerical values ranging from zero to ten, where zero is the value assigned if the respondent avoids ranking the hotel and ten is the value for “excellent”, transforming the qualitative judgements into quantitative data. Reviews are sorted chronologically and according to origin of the respondent. People visiting the website can choose whether to read all reviews or only a particular selection, e.g. reviews by young couples or families with young children.

All this information collected has an enormous potential of reducing the search frictions in this kind of online transactions through reduced information asymmetries and smaller incentives of moral hazard (see section 3.2 for a discussion of these implications). Thanks to this, online feedback mechanisms are today gaining increased attention from economists as well other academics, but even though the phenomenon of the Internet (and hence online feedback) is rather new, most economic theories in this area rely on old, fundamental findings in the field of game theory and reputation building. To give an overview of the related work and research carried out so far in the area of reputation building and the behaviour of buyers and sellers in environments characterised by asymmetric information the next section presents the most relevant findings of earlier research.

3. Theoretical Framework

Although the implications of online feedback mechanisms in the context of goods and service transactions not until recently have been investigated carefully they mostly rely on fundamental theories of reputation developed already in the late 70's and early 80's. However, with the emergence of the Internet and a new information based society the framework has changed and consequently, new models based on old theories have been developed to fit the new conditions. This section provides a summary of the most relevant research, from the earliest game theoretic principles of reputation effects to the most recent research in the area of online reputation building. The section ends by addressing a few considerations important to have in mind when studying online environments and the voluntary nature of the provision of feedback.

3.1 Reputation in Game Theory and Economics

The theory of reputation mechanisms goes back to research conducted by Kreps, Milgrom, Wilson, and Roberts in the early 80's. In three papers[3] published in the Journal of Economic Theory they introduce the *reputation effect*[4], describing agents' preferences to build a reputation for a certain "type". The authors stress that reputation building often is costly and therefore has to be compensated by a larger payoff in the future when the reputation becomes credible, which in the game theoretic framework implies that certain criteria have to be fulfilled for reputation effects to emerge in the first place. The framework used in this early research is mostly that of a monopolist with the choice to fight or to permit a potential entrant where the presence of asymmetric information plays a crucial role, providing the rationale for the entrants to base their expectations about the monopolist's future behaviour on its past actions.

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[3] D.M. Kreps, P. Milgrom, J. Roberts and R. Wilson (1982), "Rational Cooperation in the Finitely Repeated Prisoner's Dilemma", *Journal of Economic Theory*, 27:245-252; D.M. Kreps and R. Wilson (1982), "Reputation and Imperfect Information", *Journal of Economic Theory* 27:253-279; P. Milgrom and J. Roberts (1982), "Predation, Reputation and Entry Deterrence", *Journal of Economic Theory*, 27:280-312

[4] A player's reputation is in this context defined as the beliefs that other players hold about his unknown characteristics and on the basis of which they predict his behavior. These beliefs depend on their initial beliefs and on their observations of the player's past behavior.

The model developed is distinguished from earlier versions in that the fighting strategy of a monopolist does not involve threats irrational to carry out, as the gains from building a reputation (reduced threat of further entry) are greater than the immediate loss from fighting the entry of a new firm when the number of entrants is large enough. What moreover makes a distinction between this model and earlier research, such as the Chain Store Paradox[5] by Selten, is the presence of information asymmetries. Selten assumed that firms are fully informed about the game structure, the payoffs to all players, as well as the other players' past actions, but Milgrom and Roberts find an incentive to invest in a reputation emerging as soon as the complete information assumption is relaxed and the logics of backward induction no longer work (Milgrom & Roberts, 1982, p.282).

The main finding is that there are two factors necessary and sufficient for reputation building to occur: *informational asymmetries* and *repeated actions with the possibility of observing past behaviour to forecast future actions*. Moreover, the authors derive that strategies depend on history *only* through reputations and they show that the value of a reputation (and the cost a player would incur to achieve it) increases with the frequency with which it may be used. Hence, if a player can to use the reputation more often at a given rate or with less delay between uses, his incentive to invest in and maintain a reputation increases (Milgrom & Roberts, 1982, p.300).

The choice variables in these early reputation building studies are for the most part price or output quantity. However, the economic theories can be applied to other settings as well, such as problems involving the choice of product quality, which is the focus of this paper. The wide applicability of these theories in today's electronic world could most likely not be forecasted by Kreps and his colleagues in the early 80's, but the revolution of the Internet and its impact on the sharing of private information has created an entirely new area of study where the conclusions of their research can be applied in a completely new context.

[5] The chain store game theory predicts that, given a finite horizon, a monopolist will choose to permit all entrants in the last period of the game and by the logics of backward induction this behaviour will also be supported for all previous periods up to that date. The paradox is that this behaviour is unprofitable to the monopolist, compared to a strategy of deterrence (Selten,1978).

3.2 The Characteristics and Implications of Online Feedback Mechanisms

The role of *online* feedback mechanisms has only been studied since the beginning of the 21st century with most research conducted in the context of *binary* reputation mechanisms for quality signalling and quality control. The typical object of empirical studies has been eBay's[6] feedback mechanism, giving sellers incentives to declare the true quality of their goods.

However, before turning to the question of optimal reputation building strategies we briefly review the most recent research concerning the welfare effects of online reputation building. In an article in the Scandinavian Journal of Economics from 2007, Kennes and Schiff examine the welfare implications of online feedback mechanisms where buyers publish information about sellers, but not the other way around (as in our hotel review case). They present a model with good and bad sellers, selling goods of high or low quality. Good sellers have a higher expected product quality than bad sellers, implying that their gain from having a good reputation always is greater compared to the bad sellers. All sellers choose whether to advertise their products truthfully or not in period one, and in period two buyers share the information about the true product quality with each other. Honest sellers always advertise their true product quality in period one and, for obvious reasons, a seller of high quality goods is always honest and will always get a good reputation. Therefore, only bad sellers and good sellers with a low quality realisation in period one have to take make the decision whether to advertise truthfully or not. The authors find that the more information shared among buyers online, the higher the level of welfare in equilibrium. The reason is reduced search frictions stemming from more precisely directed buyer search (Kennes & Schiff, 2007, p.74).

Although welfare implications of feedback mechanisms are important as well as interesting the focus of most research has instead been the determination of optimal online reputation building behaviour. One person devoting large parts of his research to online word-of-mouth phenomena and their impact on marketing, product development, and public opinion formation is Chrysanthos Dellarocas, professor at the University of Maryland, USA. He studies the use of online feedback mechanisms as a trust building mechanism in electronic markets and has published a number of articles of great interest and importance for this paper.

[6] The auction site eBay was launched in 1995 and is an electronic community where buyers and seller can rank each other to build trust and reduce information asymmetries in transactions.

In a paper from 2005 Dellarocas discusses some important dimensions in which Internet-based reputation mechanisms differ from traditional word-of-mouth networks and addresses the most important issues related to their design, evaluation, and use. He moreover discusses how the theoretical body of research in section 3.1 is extended and combined with insights from computer science, marketing, and psychology in order to take into consideration the special properties of the online environments existing today. The paper defines two roles of online reputation mechanisms; *signalling* and *sanctioning*, coping with problems of adverse selection and moral hazard. In this way, reputation mechanisms enable efficient transactions where cooperation is hindered by post-contractual opportunism or information asymmetries.

In the framework of an online hotel reservation website, consumers cannot be certain about the quality provided before they have actually stayed at the hotel[7], and at the same time there are no incentives for hotels to advertise any of their weak points. Dellarocas refers to the lemons problem, originating from Akerlof in the 70's (Akerlof, 1970), and stresses that eventually this may lead to a situation where all hotels offering higher quality are driven out of the market since the consumers won't be willing to pay more than the price for the average level of quality. In this setting, a reputation mechanism may serve as a signalling device, helping the customers to learn the true quality of each hotel to better match buyers and sellers in a more efficient market. However, the hotel reservation website also suffers from a moral hazard problem in the sense that attributes such as cleanliness of facilities, service, and staff professionalism are results of the hotel's level of "effort", rather than its "type" (location, size of rooms etc.). If these attributes can be varied strategically on a daily basis the reputation mechanism also serves the purpose of sanctioning hotels providing an inadequate level of service compared to their advertisement (Dellarocas, C., 2005, p.5).

In the context of this paper, this has potentially strong implications for the behaviour of partner hotels of Booking.com. There is no doubt that the interaction between hotels and their potential customers is characterised by information asymmetries and by reading reviews people looking for a hotel can use other guests' past experiences to forecast the likely level of service provided. If strategies only depend on history through reputations and the value of reputation increases with the frequency it can be used (i.e. with the number of people taking feedback into account), partner hotels would have substantial incentives to invest in and maintain a reputation

[7] This is the characteristic of goods often referred to as *experience goods*.

by providing a high level of quality pleasing their customers. In settings where reputation phenomena arise, equilibrium strategies often emerge over time as information about the players' types accumulates and although the derivation of explicit solutions in repeated games like these often is complicated, a small number of specific cases have been studied. The common finding is that performance incentives based on reputation are very dynamic and that agents tend to behave differently at different stages of the game.

Dellarocas stresses that in the initial phase of the game, (when reputation effects begin to work and can be very strong as players have to work hard to establish a reputation), some players might realise low or negative profits while customers learn their type. Such situations might lead to a state where only players with a present value of gains from a better reputation in later parts of the game large enough will attempt to build a reputation (Dellarocas C., 2005, p.11).

In our model, this implies that a new partner hotel initially receiving bad reviews is facing the decision whether to invest in a good reputation by providing a higher level of quality, to lower its price to increase the value for money perceived by the customers, or to end the website membership to avoid a bad reputation. If Dellarocas is right in his findings, there would be a critical value of the present value of gains from reputation building below which hotels would refrain from quality investments undertaken to improve reputation in subsequent periods. In this paper we will assume that there are two types of hotels with differing costs of quality investments. We then interpret Dellarocas' findings as an incentive for hotels with a favourable cost structure to invest in quality whereas hotels with higher costs do not find it worthwhile to incur the cost of investing in a better reputation and instead choose to end the partnership.

However, Dellarocas points to a crucial requirement of observable outcomes of individual sub games to all players for a steady state to emerge. Since a single negative rating is a signal of non-cooperative behaviour, customers will consequently lower their willingness to pay for this product or service infinitely. This outcome is not attractive to the seller and in this way reputation considerations induce him to *cooperate forever*. If we, on the other hand, have a noisy environment where all sub games cannot be perfectly monitored (a more realistic scenario) reputation cannot be sustained indefinitely (Dellarocas C., 2005, p.12). This implies that if not all customers provide honest feedback after staying at a certain hotel, the hotel's cost of cheating is not as large as it could be, but the more people providing the community with ratings, the higher the loss from cheating and the better the expected hotel behaviour.

This raises two new considerations. Firstly, feedback mechanisms have to ensure that sufficient feedback actually is provided, and secondly, they have to induce truthful reporting. According to economic theory, voluntary feedback should be underprovided as exhibiting the characteristics of a public good. Nevertheless we observe a vast amount of information (positive and negative feedback) being provided without any monetary compensation. This behaviour might seem irrational from an economic point of view, but might be explained by incorporating theories of other disciplines into the analysis. In the next subsection we will briefly touch upon some relevant considerations important to have in mind when analysing feedback mechanisms from a pure economic perspective.

3.3 Other Considerations Regarding Online Word-of-Mouth

As stated earlier, most empirical research on reputation mechanisms has focused on eBay. This is the case also regarding the motivation for voluntary participation in feedback provision. The binary relationship characterising the reputation system at eBay is, however, not applicable in our case of a hotel reservation agency and in this concern, product and service review forums have so far received less attention. Yet, there is some research conducted. In 2004 Henning-Thurau et al. performed an empirical study, finding that there mainly are four motives driving the voluntary participation in electronic word-of-mouth communication. The first is *social benefits* (people enjoy participating in online discussions). The second is *economic incentives* in terms of rewards given to those who post reviews (this is, however, not the case for Booking.com as no compensation is given to respondents). A third motive is the *altruistic concern for other consumers* (a desire to help others with their buying decision or to save them from negative experiences). *Extraversion or self-enhancement* (a positive feeling from sharing one's success with others or an improvement of one's self image by projecting oneself as an intelligent customer) constitutes the last motive. Reasons like a *motivation to help the company*, driven by a desire to give the company something in return for a good experience, or people's *needs to express positive emotions or to vent negative feelings* to restore the inner balance and reduce psychological tensions after a consumption experience, were found not to have a significant impact on the participation in online word-of-mouth communication. The authors further stress that electronic word-of-mouth can be used as an instrument of power. Given the great number of potential recipients of online word-of-mouth communication, its persistent nature, and accessibility by companies, an individual consumer's complaints can contribute to a collective exertion of buyer power over companies. Since consumers know that negative criticism has the potential to affect the perception of a company and its image they might use electronic word-of-mouth as an instrument to shift power from companies to consumers (Henning-Thurau et al., 2004, p.42).

A further factor, potentially contributing to the provision of online feedback, is *reciprocity or "warm glow" feelings of contribution* where customers respond to friendly actions by conducting similar actions even though no material gain is expected. Such behaviour can be thoretically supported by the concept of "psychological game theory", developed by Geanakopolos, Pearce and Stacchetti in 1989. According to their model, players' utilities do not solely depend on end node payoffs, but on their beliefs about other players' intentions. That is, the utility from some particular action is greater to a player if he believes that the other player's intentions towards him have been kind (Geanakopolos, J., Pearce, D. and Stacchetti, E. 1989, p.61). This phenomenon can easily be applied in the eBay setting where byers and sellers provide mutual feedback but in the framework of the hotel rewiev mechanism the reasoning is less straight forward. However, reciprocity may still be a valid reason for feedback provision if customers profiting from earlier feedback when booking a room get a "warm glow" feeling from giving something similar in return, creating a continous chain of feedback provision.

The next issue concerns honesty. In the previous section it was stressed that truthful feedback increases efficiency and in economic modelling feedback is mostly assumed to be completely honest. This has given rise to several studies addressing the problem of inducing people to provide honest feedback and the creation of mechanisms to solve the problem of dishonesty. In an article from 2002 Dellarocas deals with the issue of honest feedback by levying a periodic membership fee from buyers and then offering them periodic rebates contingent on their rating behaviour. This solution is not applicable to our setting, and moreover, the author stresses that developing such a mechanism is not of largest concern. More important is the creation of a mechanism that induces "lazy" customers to submit any feedback at all to avoid the reviews published on the website to be biased such that only extremely satisfied or dissatisfied customers provide feedback (Dellarocas C., 2002, p.249).

The question of reporting bias is further illuminated in a recent article from March 2008 where Dellarocas and Woods stress that the value of feedback only can be as good as the quality of reported information. The characteristic of transaction outcomes as privately observed, together with voluntarily reporting, introduces a scope for reporting bias where some outcomes are reported more than other, distorting the distribution of feedback relative to the distribution of outcomes and potentially inducing people to make non-optimal decisions. Reasons why we might observe biased feedback are e.g. the widely accepted proposition that people are more willing to disclose extreme than average experiences as well as the suggestion that people are reluctant to transmit bad news. Moreover, overwhelmingly positive feedback in many online systems is interpreted as empirical evidence of reporting bias. The authors believe that this is due to the fact that many displeased buyers prefer to remain silent as they are scared getting negative feedback in return from the seller involved in the transaction. This phenomenon is contingent on the reciprocal nature of eBay-like feedback and is not applicable in our case. If the electronic market is of large scale where buyers and sellers are supposed to interact at most once, game theory predicts that the person posting feedback is indifferent between truthful and untruthful reporting. This statement motivates the later assumption of honest feedback provision in our empirical case study.

The authors further assume an altruistic motivation for feedback provision. New sellers need positive feedback more than experienced ones, and simultaneously the rest of the community benefits more if bad sellers are exposed as soon as possible, implying that the altruistic motivation to post feedback will be stronger after interaction with new sellers than with more experienced ones. In their regression, the authors derive a particularly large corresponding coefficient in the case of bad outcomes, suggesting that displeased buyers are more willing to post negative feedback for sellers who already have received bad feedback in the past (Dellarocas & Woods, 2008, p.465).

With this said, we have illuminated some of the difficulties in the research area of online feedback mechanisms. In the next section a formal model of a feedback mechanism is developed followed by an explanation of its implications for the empirical case study of Booking.com. As always in the case of economic modelling, one has to keep in mind that this involves applying a rather abstract model to a dynamic framework where human decisions are affected by more than pure economic rationality. Thus, it is important not to forget the discussion in this section when evaluating the results following.

4. A Formal Model of a Reputation System and a Hypothesis about its Implications

As suggested in previous sections the existence of empirical research in the area of online feedback is rather limited with most studies concerning binary reputation mechanisms in an eBay-like setting. This section presents a formal model of a feedback system applicable to the online hotel reservation industry where customers post reviews on sellers but not the other way around. After building the model, its implications are discussed and an explicit hypothesis about the presumed behaviour of partner hotels in the case Booking.com is developed to prepare the reader for the empirical case study performed in section 5.

4.1 A Formal Model of a Reputation System

In this section a formal model of a reputation system is developed to explicitly show that feedback mechanisms under certain circumstances should induce cooperative behaviour among hotels participating in online reservation networks. The model does to some extent build on and is in several ways inspired by previous work by Zhou, Dresner, and Windle (2008) as well as Jurca and Faltings (2004) and to create a reliable hypothesis for the behaviour of hotels of different types, we integrate previous research in the context of signalling by Spence (1973). However, to comply with the special conditions of online hotel reservation agencies the model is in many aspects developed by the author of this paper. Specifically, it is distinguished from earlier work by combining the direct effect of reputation on hotel occupancy with a system taking *all* historic feedback into account and further, an exit hypothesis is developed resting on the additional assumption that a reputation bad enough affects hotel occupancy negatively.

4.1.1 The Reputation Mechanism and the Exit Hypothesis

To develop a model and construct the framework for later analysis a set of initial assumptions is needed. First of all, we assume that the number of hotels and potential customers is large, implying that buyers and sellers are price takers. The object of each hotel is to maximise profit, whereas each potential customer wants to maximise his or her utility. In the model, we only consider hotels that already are partners of the hotel reservation company. Hence, we do not take into consideration how the reputation mechanism should be constructed to attract as many new partner hotels as possible. By mediating the experiences of prior customers to potential guests the reputation mechanism is the main reason to become a partner. If hotels manage to get many positive reviews, reputation and occupancy rate increases, leading to increased revenues (ceteris paribus).

We further assume that the single choice variable for hotels is the level of quality investment, i.e. each hotel (partner as well as non-partner) decides whether to invest in better quality to please its customers (behaviour denoted as cooperative) or to refrain from investment (denoted cheating). The level of investment determines the probability that a customer will get "high quality", i.e. that he will get satisfied, and is in this way incorporated in the value of the subsequently aggregated feedback. The level of investment is normalised to be denoted by the resulting probabilities of obtaining a high quality experience, $x \in [0,1]$.

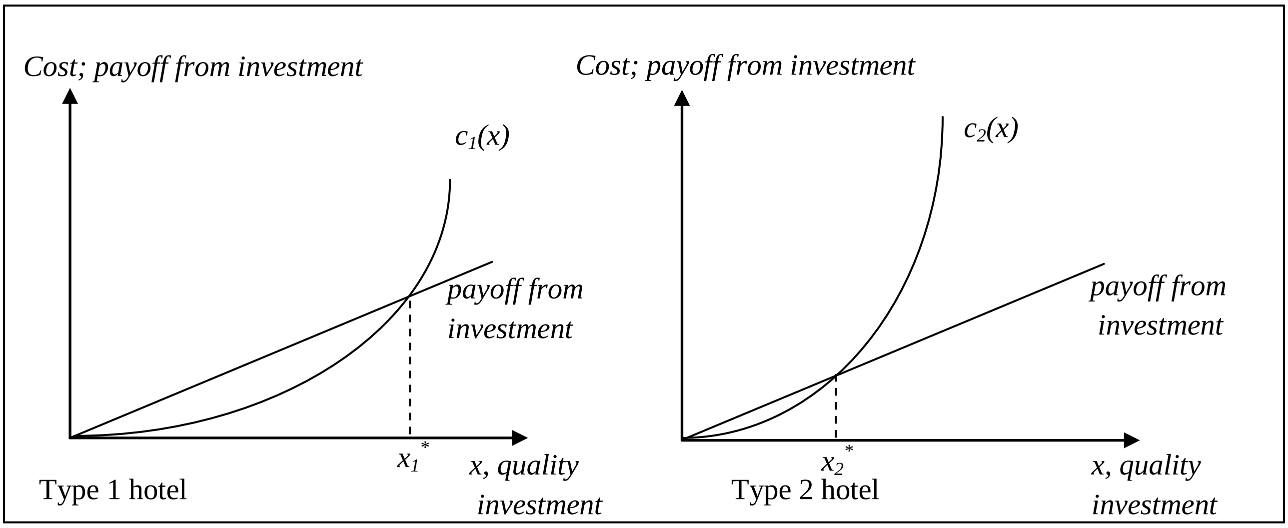
Since quality investment is assumed to be costly and customers cannot assess the hotel's level of investment before consuming the service, there is a problem of adverse selection and moral hazard (described in section 3.1). Settings like these were analysed already in the 70's by e.g. Michael Spence, whose work is used here to support the developed model and hypothesis.

In his article "Job Market Signaling" from 1973, Michael Spence introduced the theory of education as a means for workers to signal high productivity in an environment with employers unable to observe anything but visible characteristics and attributes of the job applicants. If employers were able to determine the marginal productivity of a potential employee prior to hiring him or her, the employee would receive a wage corresponding to his or her marginal productivity. If, however, productivity is a hidden characteristic and there are workers with differing productivities, employers are only willing to pay a wage corresponding to the average productivity, attracting only low productive workers. Spence argues that, in this kind of setting, signalling becomes an important means for high productive workers to reveal their true productivity, feasible through the opportunity to invest in education. The underlying assumption here is that investment in education is more expensive for low-productivity workers than for high-productivity ones (since low-productivity workers may have to devote more time to studying and may have to pay for tutors, study guides and special classes – costs referred to as signalling costs). Consequently, an individual will invest in education if the return is large enough, i.e. if the wage for a high-productivity worker is high enough compared to that of a low-productivity worker (Spence, 1973, p.358). These arguments can be used in the context of reputation building as well and will here contribute to the development of a hypothesis concerning the expected effects of online reputation mechanisms in the hotel reservation case.

Our model starts out assuming quality investment a costly action, with each hotel having a cost function, $c(x)$, satisfying the following properties: $c(0)=0$, $c'(x)>0$, as well as $c''(x)>0$. Moreover, hotels are assumed to be of two types, differing only with respect to their cost functions where quality investment is assumed always to be costlier for a hotel of type 2 than for one of type 1, generally and at the margin (i.e. $c_1(x)<c_2(x)$ and $c_1'(x)<c_2'(x)$ for all $x>0$). Except for quality investment costs, we assume no further costs, neither fixed nor variable.

As investments in higher quality bring about pleased customers posting positive reviews that encourage future customers to choose that particular hotel (increasing hotel revenues) there is a positive effect accruing to a hotel undertaking quality investments (denoted payoff from investment in the figure below). This is similar to the wage premium of a high-productivity worker in Spence's labour market case. However, since investment is costlier for type 2 hotels, these will not find it worthwhile to undertake as much investment as type 1 hotels, thus creating a separating equilibrium with a critical level of quality investment, x*, signalling the true type of a hotel. If customer satisfaction, and hence the reputation a hotel receives, is a function of the level of quality investment the separating equilibrium can be modelled as in figure 4.1.

Figure 4.1: Optimal level of quality investment for low- and high cost hotels respectively



Source: Own figures

As figure 4.1 reveals, the optimal level of investment is higher for type 1 hotels than for type 2 hotels. If hotels invest optimally according to their cost structures, type 1 hotels should converge to a higher value of reputation than type 2 hotels, as the value of reputation is assumed to correspond to the level of quality investment.

For the purpose of the model we further assume that at some low value of reputation, customers will find a hotel unattractive and avoid booking a room there. This assumption can be motivated by intuition, since most prospective customers would refrain from booking a room at a hotel with a very bad reputation signalling non-satisfaction by previous customers. This implies that reputation can generate positive as well as negative effects on revenues since it may affect occupancy in either way. If this statement holds, and assuming that quality investments are costly, high cost hotels not finding it profitable to invest in better quality will instead chose to leave the website to avoid the negative consequences of a bad reputation. This will occur as the hotels reach some critical value of reputation where continuing as partner of Booking.com is economically more hurtful than exiting the partnership and instead advertise through other channels. We will denote this assumed pattern of behaviour our *exit hypothesis.*

The exit hypothesis can be justified by the following empirical observation. Assume that hotels cannot leave the booking website once they have entered it. Since hotels differ in their costs of providing high quality services we would expect to observe a significant number of hotels with a long history combined with a low reputation (i.e. old partner hotels with a bad reputation). However, in reality there are not many hotels with low reputation values (the average value of reviews is 7.1 in Copenhagen and 7.5 in Bucharest and solely one out of 113 hotels displays a value below 5). Hence, it is reasonable to assume that rational hotels with a value of reputation below some critical level have exited the website. A third option available to hotels with a bad reputation is the lowering of prices to increase the value for money perceived by the guests. However, to avoid making the analysis more complicated this option is ruled out. Instead it is assumed that increases in reputation solely stem from higher investment levels.

The next step in building the model is to explicitly explain the reputation mechanism. As already mentioned, customers cannot observe the effort exerted by the hotel until they have actually consumed the service. Each customer *k* thereafter reports the outcome of the transaction by providing the booking agency with a review, assigning the hotel a value of quality (reputation), $r^k_t(x_t) \in [0,1]$, where *t* denotes the time period and *x* is the level of quality experienced by the customer. We assume that the reputation a customer assigns a certain hotel directly corresponds to the level of investment undertaken by the hotel in the same period, i.e. $r_t^k = x_t$. In the empirical case of Booking.com, $r^k_t(x_t)$ $\epsilon[0,10]$, but this does not change anything regarding the applicability of this model. The explicit value of reputation for month *t* (disregarding all previous time), r_t, is obtained by summarising all individual reviews during that month and thereafter dividing this figure with the number of reviews provided. The reputation mechanism thereafter aggregates all past ratings and publishes a summary of each hotel's ratings at the website. The visible reputation at time T, r_T, is the summary of all reviews up to that point, divided by the total number of reviews, K:

$$r_T = \frac{\sum_{t=1}^{T} r_t}{K}$$

That is, the reputation visible to prospective customers on the website is an aggregated average of all reviews up to that date. For the purpose of the model we assume that all customers provide honest feedback.

Reputation affects the future payoff of the hotels by directly affecting their occupancy rate. That is, negative feedback from customers in period one affects the occupancy in period two negatively, the feedback in period two affects occupancy in period three and so on. The way in which reputation affects occupancy is described by:

$$O_T = (1 - a)(r_{T-1} - r^*) + a \qquad (i)$$

s.t.

$$a \geq \frac{r^* - (r_{T-1})}{1 + r^* - (r_{T-1})} \qquad (ii)$$

where O_T is hotel occupancy rate at time *T*, a $\epsilon[0,1]$ is the fraction of rooms occupied independently of the reputation of the hotel, (r_{T-1}) $\epsilon[0,1]$ is the aggregated reputation, and r^* is a critical value of reputation. That is, a reputation above r^* will affect occupancy positively and a reputation below will affect occupancy negatively, as discussed earlier in the context of the exit hypothesis. All feedback is assumed to be weighted equally, with the overall reputation effect as the net impact of positive and negative reviews.

To illustrate the direct effect of feedback on hotel occupancy a numerical example is provided using *(i)* to calculate the occupancy rate for different values of a and r^*. Assume a hotel in period *T* with an aggregate value of reputation stemming from the previous period, $r_{T-1} = 0.7$, and the critical value $r^*=0.5$. This corresponds to an aggregate review status of 7.0 in the empirical case of Booking.com and may seem like a high value of reputation. However, we will show that the higher the fraction of a hotel's occupancy affected by reputation (i.e. the lower the value of a), the more impact reputation will have on occupancy and hence on hotel revenues. If a=0.5 the resulting occupancy rate of the hotel in period T will be 60%, whereas if a=0.1 the occupancy rate will reduce to 19%. If the value of a is held fixed at 0.5 and we instead let r^* fluctuate, we can show that the lower the critical value of reputation where people start finding the hotel unattractive, the smaller the effect on hotel occupancy. The occupancy rate would for instance increase from 60% to 70% if r^* decreased from 0.5 to 0.3. However, the effect from changes in r^* on hotel occupancy rate is smaller than the effect from changes in a, further illuminating the potential effects of online reputation mechanisms in settings where the proportion of transactions affected by the feedback provided is large and growing.

4.1.2 The Situation without a Reputation Mechanism

In the reference case without a reputation mechanism the differing levels of quality investment across hotels are completely invisible to prospective customers. Consequently, some customers will have a low-quality experience while others will be very satisfied. In this type of setting (analysed by Spence in the context of workers and their incentives to signalise productivity by undertaking different levels of education, discussed in subsection 4.1.1) the only Nash equilibrium is one where hotels always exert zero effort since the fraction of occupied rooms is the same irrespective of effort and a high level of effort always is more expensive than a lower level. As a result, buyers know that they will get disappointed and no trade will take place.

4.1.3 Introducing a Reputation Mechanism

The introduction of a reputation mechanism, affecting hotel occupancy and hence hotel revenues, provides the hotels with an incentive to cooperate and invest in quality to satisfy their customers. Hotels attempting to undertake quality investments might initially suffer a loss before they have established a reputation. However, if this loss is outweighed by a larger payoff from higher occupancy in the future, the incentives to undertake the necessary investments might still be strong. This will now be shown by means of some algebra.

We assume that the first transaction takes place at time $t=1$. Since there is no established reputation at this point, hotel occupancy rate will be $O_1=a$ for all hotels, regardless of type and behaviour. The analysis of the effects of reputation on hotel incentives will be conducted in the framework of a two-period model. However, the general results are also valid in a model of infinite horizon. The period discount factor is $\frac{1}{(1+i)}$ (where i is the discount rate). For a hotel with a high level of investment, the present value of payoffs will be the following:

Table 4.1: Present value of payoffs for a cooperating hotel

Period	Revenue	Cost	Profit
1	aP	$c(x_h)$	$aP - c(x_h)$
2	$\frac{P[(1-a)\times(r_{2h}-r^*)+a]}{(1+i)}$	$\frac{c(x_h)}{(1+i)}$	$\frac{P[(1-a)\times(r_{2h}-r^*)+a]-c(x_h)}{(1+i)}$
Σ	$\frac{aP(2+i)}{(1+i)}+\frac{(r_{2h}-r^*)(1-a)P}{1+i}$	$\frac{c(x_h)(2+i)}{(1+i)}$	$\frac{\big(aP-c(x_h)\big)(2+i)+(r_{2h}-r^*)(1-a)P}{(1+i)}$

Source: Own calculations

Where P is the price per night for a hotel room and x_h is the notation for a high level of quality investment. For a hotel with this strategy to break even or earn economic profit the following must hold:

$$\frac{\big(aP-c(x_h)\big)(2+i)+(r_{2h}-r^*)(1-a)P}{(1+i)} \geq 0$$

Which simplified and rewritten gives us the following condition:

$$P(1-a)(r_{2h}-r^*) \geq (2+i)(c(x_h)-aP) \qquad \textit{(iii)}$$

It can easily be seen that r_{2h}-r^* can be interpreted as a premium of reputation and that the strategy choice of the hotel is dependent on the present value of future rents. The better the reputation, the smaller the discount rate, or the larger the fraction of potential guests taking the feedback into account (ceteris paribus), the greater profit is earned by a cooperating hotel. The choice to invest in quality is moreover motivated by the willingness to maintain a continuous stream of income that is threatened to diminish if the hotel does not invest much and thus has to accept lower occupancy. A hotel undertaking very low or no quality investment has a payoff structure depicted in table 4.2

Table 4.2: Present value of payoffs for a cheating hotel

Period	Revenue	Cost	Profit
1	aP	$c(x_l)$	$aP - c(x_l)$
2	$\frac{P[(1-a) \times (r_{2l} - r^*) + a]}{(1+i)}$	$\frac{c(x_l)}{(1+i)}$	$\frac{P[(1-a) \times (r_{2l} - r^*) + a] - c(x_l)}{(1+i)}$
$\sum$	$\frac{aP(2+i)}{(1+i)} + \frac{(r_{2l} - r^*)(1-a)P}{1+i}$	$\frac{c(x_l)(2+i)}{(1+i)}$	$\frac{\left(aP - c(x_l)\right)(2+i) + (r_{2l} - r^*)(1-a)P}{(1+i)}$

Source: Own calculations

The sum of discounted payoffs for a hotel with a low investment level can be interpreted as the opportunity cost for a hotel with a high investment level. Therefore, for a hotel to strategically choose a high level of quality investment, there are two necessary conditions that must hold: On the one hand a requirement of positive revenues from the cooperative strategy, *(iii)*, and on the other hand a requirement that the cooperative strategy must be more profitable than the cheating strategy *(iv)*. Algebraically, it is represented by the following condition:

$$\frac{aP(2+i)}{(1+i)} + \frac{(r_{2h} - r^*)(1-a)P}{1+i} - \frac{c(x_h)(2+i)}{(1+i)} - \frac{\left(aP - c(x_l)\right)(2+i) + (r_{2l} - r^*)(1-a)P}{(1+i)} \geq 0$$

$$\rightarrow$$

$$\frac{(2+i)(c(x_l) - c(x_h))}{(1+i)} + \frac{(r_{2h} + r_{2l} - 2r^*)(1-a)P}{(1+i)} \geq 0$$

$$\rightarrow$$

$$(r_{2h} + r_{2l} - 2r^*)(1-a)P \geq (2+i)(c(x_h) - c(x_l)) \qquad \textit{(iv)}$$

From the left hand side of *(iv)* we find that the *better the reputation (i.e. the sum of reputation from high and low levels of quality investment), the smaller the critical value of reputation, the larger the fraction of transactions affected by reputation, and the higher the price,* the more likely it is that a hotel will choose to exert a high level of effort. When looking at the right hand side, we observe that the likelihood of cooperative behaviour moreover increases with a *small discount rate,* i, or a *smaller difference in costs between high and low investment*. Since the right hand side always will be greater than zero, the left hand side has to be greater than zero as well for *(iv)* to be satisfied. This is only true if $(r_{2h} + r_{2l} - 2r^*)$ is positive. Hence, we have to impose one further constraint if hotels are to choose the high investment (cooperative) strategy:

$$(r_{2h} + r_{2l} - 2r^*) > 0 \qquad \textit{(v)}$$

Above requirement stipulates that the average reputation of the high and the low investment level has to exceed the critical reputation level for a hotel to find it profitable to cooperate. Hence, if the value of reputation directly corresponds to the level of investment such that $r=x \in [0,1]$, and we assume that hotels choose between $x=1$ and $x=0$, a cooperative strategy will only be profitable if $r^{*}<0.5$. If people e.g. avoid booking a hotel already at a reputation of 0.55, a cooperative behaviour cannot be supported and hotels will avoid investing in better quality.

If we assume that *(v)* holds, the characteristics of online feedback mechanisms will influence *a* in a way such that the likelihood of cooperation among partner hotels (in contrast to non-partners) increases as the outcome of every transaction immediately is made known to all prospective customers, increasing the fraction of transactions affected by reputation, $(1-a)$.

Until now we have not distinguished between hotels with different cost structures. However, if quality is costlier to certain hotels (e.g. due to poor management or staff less willing to undergo training), those hotels will find it less profitable to undertake quality investment and will thus have a higher propensity to cheat on their guests. Consequently, some hotels with an undesirable cost structure invest less, leading to negative feedback and lower occupancy. Eventually, these hotels reach a point where the negative reputation effect on occupancy makes costs exceed revenues, thereby making it more profitable to exit the market. If the fraction of rooms affected by reputation is large, these hotels might choose to exit the online market at an early stage to avoid the consequences of a bad reputation and instead advertise through channels without feedback mechanisms and reputation effects, such as newspaper ads or travel agencies.

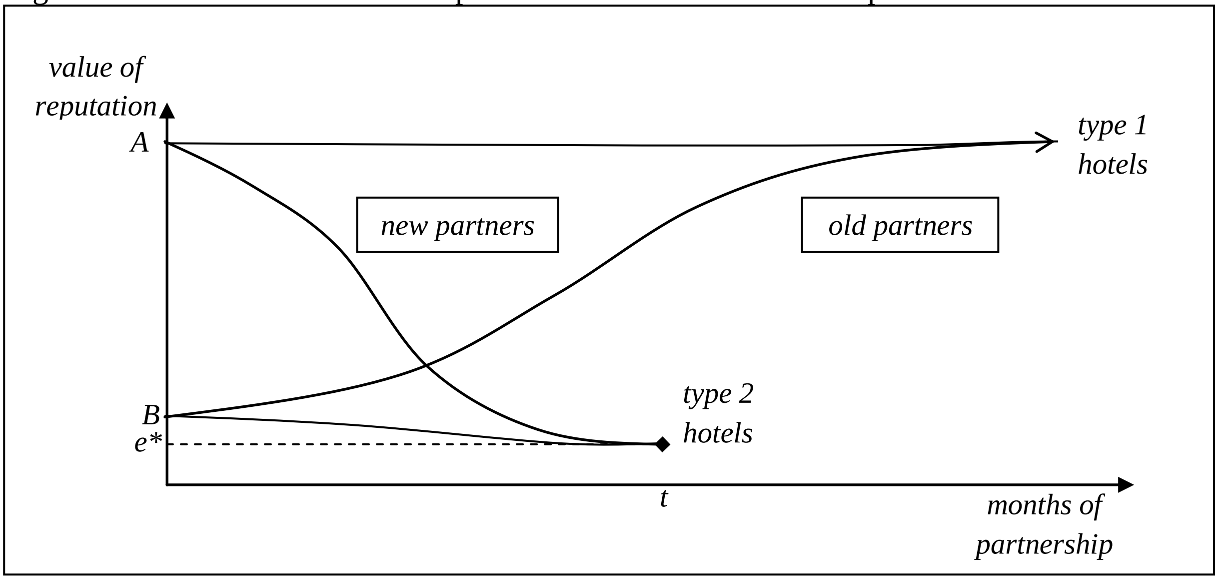
4.2 Conclusion and Implications for the Case Booking.com

As now should be clear, the role of feedback mechanisms in the online hotel reservation context is to ensure that hotels will have an incentive to behave cooperatively, i.e. to undertake a quality investment level high enough to please the customers. From previous sections we conclude that this can be done by assuring that misbehaviour in one period will attract a penalty in future revenues due to a bad reputation. If the future penalty outweighs the short-term gain from cheating, *a rational hotel will never cheat on its customers*. This bold statement relies on the crucial assumption that people voluntarily post honest feedback and that hotels believe that potential customers take previous guests' feedback into consideration when deciding which hotel to choose for their stay. The more people visiting the website the greater the impact of the reputation mechanism on the behaviour of partner hotels and the greater the reduction of search frictions and efficiency improvement.

Since Booking.com charges neither registration fees nor fixed costs, the only cost incurring to partners with a zero investment level is that of a bad reputation. However, this cost can be substantial if reviews posted by earlier guests deter potential customers from staying at that particular hotel. Consequently, these hotels might find it profitable to undertake some low level of quality investment. According to previous research in the field of online reputation mechanisms (see chapter 3.1.1) a good reputation is most crucial for new partner hotels, as the initial reputation constitutes the base for future revenues. It has also been stressed that people are more prone to post negative ratings on new hotels and on hotels with a history of bad reputation, indicating that hotels should be interested in initially creating a good reputation as well as maintaining a high reputation over time. To keep this study as close to reality as possible we must take into consideration that negative reviews not always are induced by cheating. Of course, the negative critique can result from a low level of effort, but it can also be due to bad luck in providing the usual level of service, or dishonest feedback by previous guests. However, this likelihood is equal for old and new partners and for the purpose of this study, the propositions of bad luck and dishonest feedback are ruled out, leaving us with two strategies: large quality investments to signal the hotel's true type and small or no quality investment if the costs exceed the benefits at a high investment level. However, as stressed earlier, hotels always have the additional choice to exit the market, avoiding a bad reputation stemming from negative reviews but at the same time forgoing the benefits of a good reputation (see the earlier discussion of the exit hypothesis).

If the assumption that some hotels opt to exit the website is valid, what we observe in our dataset is a self-selected sample consisting of two groups of hotels. Firstly, there are hotels that have been partners of Booking.com for a long time. These are most probably of low cost type finding reputation an important source of revenue (and will thus try to keep a high reputation over time to reap large profits in the future). Secondly, there are newer partners (of both cost types), which have not discovered their true type yet. These hotels will initially undertake an arbitrary level of quality investment and thereafter discover which feedback that level of investment renders. If reviews are positive, the hotel is likely to be of type 1, and will hence increase investment in quality until the optimal level is reached. If reviews are negative, the hotel is likely to be of type 2. As stated earlier in this section, we predict that those hotels at some point will reach a critical reputation level where the most profitable action is to leave Booking.com. However, the online environment is noisy and therefore, reviews do not always signal the underlying behaviour clearly. Despite of this, there eventually comes a day when a type 2 hotel cannot survive anymore just as a result of luck and therefore will choose to exit the market. This behaviour is illustrated in figure 4.2 where some hotels of both types start out with a high (*A*) and a low (*B*) value of reputation respectively.

Figure 4.2: Illustration of the anticipated behaviour of new and old partner hotels



Source: Own figure

At a critical value of reputation, denoted *e** in the figure, hotels no longer find it profitable to stay in the market but choose to leave the website. In figure 4.2 this occurs at time *t* for type 2 hotels. Hence, after time *t*, only hotels of type 1 are left in the market and consequently, all old partner hotels should be of this type. This pattern moreover suggests that the variance in reputation should be greater for new partners during the time when their true types are revealed compared to older partners, whose true types already are known by them and by the potential customers (and hotels finding the partnership unprofitable have exited the market already).

4.3 Hypothesis

Based on the model developed, what we would expect our data to reveal is *a reputation that is more stable and on a higher level for older partner hotels compared to more recent partners.* In terms of a null hypothesis and an alternative hypothesis the statements are the following:

H_0: Booking.com (and other online reputation mechanisms with the same characteristics) is only a medium of information and transaction, having no influence on the behaviour of hotels.

H_1: The existence of a feedback mechanism at online hotel reservation websites such as Booking.com induces strategic behaviour from partner hotels. New partners observe a value of reputation based on their initial level of quality investment and thereafter act corresponding to their revealed cost structure. This induces high cost hotels to leave the website as they realise that the costs of quality investment exceed the gains from a better reputation and low cost hotels to maintain a high level of quality investment as the resulting revenues outweigh the costs.

To assess whether the null hypothesis can be rejected or not a number of tests will be performed on a data sample of approximately 60 hotels in Copenhagen and Bucharest respectively. The objectives of the tests are primarily to assess whether there is a difference in the level of reputation between old and new partner hotels and to test whether old and new partner hotels differ in their variance/stability of reputation. Moreover, we will analyse if there are further parameters affecting a hotel's reputation, indicating that reputation does not truly mirror the investment level undertaken by the hotel.

The specific tests to be undertaken are explained and motivated in the next section, where also the results are presented and their implications evaluated. However, even though the statistical tests are chosen to provide us with the most reliable results, it is important to keep in mind the limitations discussed in sections 1.1 and 3.3 when interpreting the results following in the next section.

5. Empirical results

In this section, the statistical tests applied to evaluate the hypothesis of this paper are demonstrated and motivated and the obtained results are presented followed by a short discussion of their implications. The section ends with a further short exploration of the collected data to assess whether there are other interesting angles of approach to this subject.

5.1 Data set

The tests in this section of the paper are applied on selected samples of a data set from Booking.com, covering 59 hotels in Copenhagen and 54 hotels in Bucharest with 12,908 and 3,090 reviews respectively. The review data is collected from the website in November 2008, covering the period September 2007 to October 2008 on a monthly basis. Worth noticing is that 26 out of the 54 hotels in Bucharest are new partners of Booking.com (referred to as group 2 hotels[8]) whereas only 8 out of the 59 hotels in Copenhagen belong to this group and that the majority of group 2 hotels did not become partners of Booking.com until April or May 2008. The composition of the data set is visible in table 5.1. A complete overview of the most relevant parts of the data material used in the tests is provided in Appendix I.

Table 5.1: Composition of the data set

	Group 1		Group 2		Total	
	Hotels	**Reviews**	**Hotels**	**Reviews**	**Hotels**	**Reviews**
Copenhagen	51	12,427	8	481	59	12,908
Bucharest	28	2,386	26	704	54	3,090
Total	79	14,813	34	1,185	113	15,998

Source: www.booking.com

[8] Group 2 hotels are defined as new partners, joining Booking.com during 2008, whereas group 1 hotels have been partners since 2007.

The choice of Copenhagen and Bucharest as the two cities for the empirical study is based on their rather equal number of hotels, their common status as European capital cities, as well as their disparity in the level of economic development. By taking the location of hotels into consideration when applying all tests, similarities and differences worth noticing are easily detected and we can infer whether the results can be generalised or not. However, we have to be very careful when interpreting and generalising any of the obtained results as the temporal coverage of the data material is rather limited.

5.2 The Mann-Whitney U-test

Our first test examines whether the level of reputation differs significantly between the two hotel groups (new versus old partners). According to the hypothesis in section 4.3 we expect older partner hotels to converge to some higher level of reputation compared to newer partners due to their greater fraction of type 1 hotels. The test applied is the Mann-Whitney U-test, a non-parametric test calculating whether two samples are significantly different or not. Normally, a parametric t-test applied to the means of two samples can be used to examine this type of problem. However, the t-test rests on a number of critical assumptions, such as normally distributed populations with equal variances and further, a scale of at least interval nature is required. When these prerequisites are unrealistic or one simply wants to avoid making these assumptions, the Mann-Whitney U-test is the most useful alternative. Two favourable features of this test are its rather simple data constraints and its wide applicability, mainly due to its non-parametric nature, not resting on any critical assumptions concerning the underlying distribution. The only requirement is that observations must be on at least an ordinal scale but the samples do not need to have the same number of observations. There is, however, some critique that the Mann-Whitney test is less powerful than the t-test as it first converts the observed values into ranks and thereby loses some information in the process. Yet, for large samples (as in this case), this is not a problem. The main reason for applying the U-test here, however, is the t-test's sensitivity to differences in variances between the two samples, especially when samples are of different size (Siegel, S., 1956, p.116). We apply the U-test on the two last months in our data set, September and October 2008, to assess whether older partners at this point in time had converged to a higher level of reputation compared to newer partners. The hypotheses of the test are the following:

H_0: Old and new partner hotels do not differ significantly in their mean level of reputation.

H_1: Old partner hotels have a higher mean level of reputation than new partner hotels.

The result obtained from the U-test is displayed in table 5.2 where N1 and N2 are the number of hotels in group 1 and 2 respectively and U is the U-statistic calculated from the test.

Table 5.2: Results from the Mann-Whitney U-test

City	Month	N1	N2	U	P (one-tailed)
Bucharest	September 2008	27	22	354.5	0.125
Bucharest	October 2008	28	26	439	0.1
Copenhagen	September 2008	50	7	194	0.33
Copenhagen	October 2008	45	8	208	0.251

Source: Own calculations using the online U-test available at http://elegans.swmed.edu/~leon/stats/utest.html and review data from www.booking.com.

Since p-values are larger than the significance level of 5% we cannot reject the null hypothesis, i.e. the level of reputation for old partner hotels can *not* be proven to be significantly higher than the level of new partners at this level of significance (the p-value is the smallest significance level at which we can reject the null hypothesis, i.e. conclude that old partners have a significantly higher reputation). Hence, our first test does not support our hypothesis since new and old partners cannot be separated due to the level of reputation. To confirm this result we will as our next test introduce two dummy variables in a linear regression model.

5.3 White's Heteroskedasticity-consistent Covariance Matrix Estimation; Dummy Variable test

After the U-test we perform two tests based on a linear regression with reputation as the dependent variable. By first including a dummy variable for group affiliation we analyse whether the group as such has a significant impact on the level of reputation. We moreover include a dummy variable representing hotel location to assess whether there is any significant difference in reputation across cities. The test is applied on the same data as the previous U-test. Hotels with review data missing for one or both months are excluded from the sample, leaving us with 52 hotels in the Copenhagen sample and 49 in the Bucharest sample. The software used here and in subsequent tests is Eviews. Complete test results are attached in Appendix II. To estimate our regression equations we use White's heteroskedasticity-consistent covariance matrix estimator. After first estimating the equations using the ordinary least squares estimator (OLS) and thereafter applying White's test for heteroskedasticity we discovered a problem of non-identical variance for the error terms (heteroskedasticity) in our observations. By re-estimating the equation using White's heteroskedasticity-consistent covariance matrix we avoid this problem and can nevertheless perform correct inference on our data. The advantage of White's estimator compared to the OLS estimator is a variance-covariance matrix robust against all types of heteroskedasticity. Hence, we do not need to know the exact type of heteroskedasticity in our data. The only necessary condition is a sample of observations large enough. Moreover, if data turn out to be homoskedastic, White's estimator equals the OLS estimator with the only difference that the error term is unknown. This is, however, not a problem as our data sample is large enough and we therefore can replace the error term with the OLS residuals without distorting the results (Westerlund, J., 2005, p.180).

By estimating the equation: *Reputation = C(1) + C(2)*Group affiliation +C(3)*City* and thereafter applying a Wald test with the null hypothesis that the coefficients of the dummy variables equal zero, the following results are generated:

Table 5.3: White's regression estimates with dummies for group affiliation and location

Independent variable: Coefficient [p-value]	**Sep 2008**	**Oct 2008**
Constant	7.094	7.435
	[0.000]	[0.000]
Group affiliation	0.317	0.432
= 1 if hotel old partner, and 0 else	[0.267]	[0.215]
City	-0.406	-0.751
= 1 if hotel in Copenhagen, and 0 else	[0.061]	[0.007]
Adjusted R^2	0.02	0.069

Source: Own calculations using Eviews and review data from www.booking.com.

At a first glance the test results suggest that being an old partner hotel has a small but positive impact on reputation, increasing the average reputation for a new hotel by 4.5-5.9%. This is perfectly consistent with our hypothesis. However, the result of the Wald test represented by the p-values in the table above indicates that we are unable to reject the null hypothesis at a 5% significance level. Hence, again we cannot conclude that older partners have a significantly higher level of reputation compared to new partners at a certain point in time. To be able to robustly reject the null hypothesis regarding group affiliation we must increase the significance level to 27%. The impact of a hotel's location on reputation seems to be more significant. At a significance level of 6.1% we derive a negative impact on reputation for hotels in Copenhagen compared to hotels in Bucharest. The magnitude of this impact is larger than the proposed impact of group affiliation and amounts to 5.6-9.9%. That is, an average hotel in Bucharest would lower its reputation by 5.6-9.9% if it was located in Copenhagen instead. This is an interesting finding since hotels in Bucharest do not claim to be of any higher quality than those in Copenhagen. The result does thus imply that customers tend to rank hotels according to other attributes than pure quality experience, something analysed further in the next subsection with more variables included. Evaluating the adjusted R^2-values in table 5.1 we find that the total variation in reputation explained by the estimated regression is very small in relation to the total variance in reputation. Simply put, the two independent variables do not explain the dependent variable very well (approximately 7% of the variation in reputation can be explained), indicating that there probably are other variables affecting the value of reputation. With this statement the next step is to undertake a similar test, including a number of other variables that may influence the value of reputation customers assign a certain hotel.

5.4 Regression with Further Variables Included

Our economic model suggests that the value of reputation solely depends on the level of quality investment undertaken by a certain hotel and according to our hypothesis older partner hotels should have a higher probability of being of low cost type and hence have incentives to undertake a higher level of investment compared to newer partners. However, previous tests reveal that group affiliation does not have a significant impact on reputation and therefore, we will now conduct a test involving further variables to assess whether there are other features than quality investment systematically influencing reputation. This would be the case if for instance customers tend to assign expensive hotels higher values of reputation compared to cheaper hotels only because they have paid much for the room, or if four or five star hotels systematically are ranked higher than one or two star hotels. The test models the value of reputation as dependent on group affiliation, location, price, and the number of stars. To avoid multicollinearity we estimate two separate regressions to test for the impact of price and the number of stars respectively. This is due to the likely correlation of the two variables, as hotels with many stars often are expensive as well. To avoid distorted results due to the difference in price level between Denmark and Romania, we use the logarithm of the standard price of a double room (instead of the absolute price) as the continuous price variable in our regression.

The estimated regression equations are the following and the results are displayed in tables 5.4 and 5.5.

1) *Reputation = C(1) + C(2)*Group affiliation +C(3)*City +C(4)*LogPrice*
2) *Reputation = C(1) + C(2)*Group affiliation +C(3)*City + C(4)*Stars*

Table 5.4: White's regression estimates with a price variable included

Independent variable: Coefficient [p-value]	Sep 2008	Oct 2008
Constant	4.432 [0.001]	2.808 [0.039]
Group affiliation **= 1 if hotel old partner, and 0 else**	0.299 [0.297]	0.385 [0.198]
City **= 1 if hotel in Copenhagen, and 0 else**	-0.647 [0.005]	-1.171 [0.000]
Log price	1.298 [0.049]	2.256 [0.001]
Adjusted R^2	0.068	0.302

Source: Own calculations using Eviews and review data from www.booking.com.

Table 5.5: White's regression estimates with a number-of-stars-variable included

Independent variable: Coefficient [p-value]	Sep 2008	Oct 2008
Constant	5.998 [0.000]	5.841 [0.000]
Group affiliation **= 1 if hotel old partner, and 0 else**	0.219 [0.418]	0.291 [0.306]
City **= 1 if hotel in Copenhagen, and 0 else**	-0.259 [0.234]	-0.538 [0.022]
Number of stars	0.324 [0.005]	0.471 [0.006]
Adjusted R^2	0.082	0.165

Source: Own calculations using Eviews and review data from www.booking.com.

Before analysing the obtained results there is one thing worth noticing regarding the expected effect of price on reputation. Due to the fact that the hotel price most likely affects more than one of the parameters in the hotel review posted by previous customers its effect on reputation is not clear-cut. One the one hand are expensive hotels often high quality hotels and we would hence expect a higher price to render higher values of reputation. On the other hand is price also implicitly included in the parameter "value for money" and a high price should in this way decrease the overall reputation. As displayed in table 5.4 we find a strongly positive and significant correlation between price and reputation. A price increase from €100 to €200 for an average new partner hotel in Bucharest corresponds to a reputation increase by 17.5-30.3% and in Copenhagen the corresponding increase amounts to 17.3-33.9%, indicating that customers tend to associate high price with high quality also after experiencing the *true* level of quality. This implies that the first of the two price effects seems to outweigh the second and that customers put more weight on the price effect on quality perception than the value for money. Regarding the dummy variables of group affiliation and location, our results are almost identical to the previous test. Being an old member would now increase the reputation of an average new partner hotel by 3.1-5.3% and an average hotel in Copenhagen would increase its reputation by 3.6-15.3% if located in Bucharest instead. We moreover find the coefficient for location significant for both months at a significance level as low as 1%. On the contrary, group affiliation can still not be proven to have a significant impact on the value of reputation.

From the second regression, examining the impact of the number of stars on reputation, we derive a positive relationship between reputation and stars. The difference in reputation between a one and a two star hotel is approximately between 0.32 and 0.47, corresponding to an increase in reputation of approximately 5.5-9.6% for an average one star hotel obtaining one more star. The coefficients are significant at a 1% significance level for both months.

Summarising the findings of the two tests leads to the conclusion that price and stars both seem to have a large and significant impact when previous customers evaluate hotels. Predetermined characteristics as a high price or many stars are found to result in a better reputation (ceteris paribus), regardless of hotel quality investment. Moreover, hotels located in Bucharest are generally assigned higher review values than hotels in Copenhagen, perhaps due to the fact that people expect hotels in Bucharest to be of worse standard than hotels in Copenhagen and therefore rank them higher after an experience comparable to what they expect from a Danish hotel. The results thus indicate a lack of rationality in feedback provision (biased feedback). Instead of evaluating pure quality, customers rank hotels according to predetermined attributes. This conclusion is not very encouraging, suggesting that the reputation does not mirror the quality investment level properly (one of our core assumptions in the model in section 4). However, the adjusted R^2-values in the tables above indicate that only a small fraction of reputation (7-30%) can be explained by the variables included in the regressions and hence, we should not give up the thought of investment level as a further, important driver of reputation.

After this conclusion, one final test remains to assess whether there is a significant difference between old and new partner hotels. The focus this time is the variance in reputation. As stressed earlier, a new partner hotel is assumed not to know its type. This assumption together with the exit hypothesis leads us to expect that the variance in reputation should differ between new and old partner hotels.

5.5 Test for Equality of Variances between Groups

By testing if the variance in reputation is significantly different across the two hotel groups we will try to assess whether older partners converge to some level of reputation while new partners' reputations fluctuate more, indicating that older partners have learned their true type and most probably are of the same type (hotels with a favourable cost structure).

The motivation of the variance test rests on the assumption that partner hotels have no experience regarding the explicit relation between investment and reputation when first joining Booking.com. They will hence invest some arbitrary amount in quality, which they believe will satisfy customers and result in a good reputation. Since the hotel does not know its type, the resulting value of reputation cannot be a clear signal of its type either, but eventually hotels discover their true types and start acting accordingly. That is, high cost hotels with an initial high reputation cannot sustain this infinitely but will invest their optimal level in quality with a decreasing reputation as a result and low cost hotels hit by bad luck in the initial period will eventually increase their reputation, signalling a favourable cost structure (this presumed behaviour was illustrated in figure 4.2).

At a critical value of reputation hotels no longer find it profitable to stay in the market but choose to leave the website and hence, all old partners should be of type 1. This suggests that the variance in reputation should be greater for new partners during the time when their true types are revealed compared to older partners, whose true types already are known by them as well as by the potential customers (and hotels finding the partnership unprofitable have exited the market already). This proposition is tested in an F-test with the following hypotheses:

H_0: The variance in reputation does not differ significantly between group 1 and group 2 partner hotels.

H_1: The variance is greater for group 2 hotels compared to group 1 hotels.

The results are found in table 5.6.

Table 5.6: Results from the F-test for significant differences in variance between groups

	Variance Group 1	Variance Group 2	F-statistic	P-value
Total September 2008	0.764	1.823	2.385	0.006
Total October 2008	1.094	2.275	2.354	0.007
Bucharest September 2008	1.028	1.978	1.925	0.065
Bucharest October 2008	1.380	1.946	1.410	0.212
Copenhagen September 2008	0.537	1.572	2.926	0.089
Copenhagen October 2008	0.785	3.378	4.941	0.026

Source: Own calculations using Eviews and review data from www.booking.com

From table 5.6 it can easily be seen that, for the aggregate sample, the variance is greater for new hotels, just as predicted. The null hypothesis can be rejected at a significance level of 1%, thus giving us a reliable result. However, a closer look at the individual cities does change this result and although we observe larger variance in reputation for group 2 hotels for all time periods and both cities, we cannot robustly reject the null hypothesis at a 5% significance level. The largest difference in variance between partner groups can be observed in Copenhagen due to the fact that the number of new partners relative to old partners is small, giving outliers in the new-partner group relatively more weight. However, a higher variance for group 2 partners compared to group 1 partners is also found in the more balanced Bucharest sample, indicating robustness.

Moreover interesting is the observation of a generally larger variance for all hotels in Bucharest compared to Copenhagen, indicating either a greater propensity of Romanian hotels to milk their reputation, a longer period before hotels learn their true type, or inconsistent feedback behaviour. This is probably the reason behind our aggregate sample result as Copenhagen hosts relatively many old partner hotels in comparison to Bucharest. Again location is shown to matter, indicating that the feedback mechanism not is rendering the desired results.

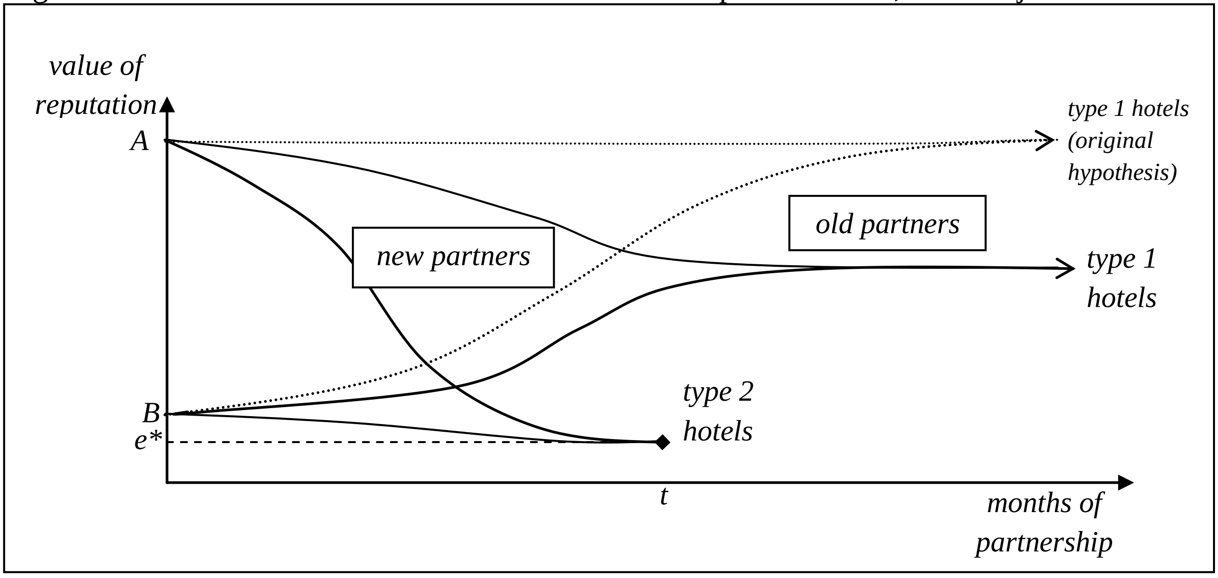
5.5 Implications

After examining the data in our empirical case we cannot reject the null hypothesis of this paper that feedback mechanisms in the online hotel reservation industry do not affect the behaviour of participating hotels. However, our obtained results *do* point in the right direction and by examining the reasons for the failure we can suggest ways to capture the impact of information flows in new, extended models.

In our variance test we found an *indication* of higher variance in reputation among new partners compared to older ones, supporting the exit hypothesis based on the assumption that hotels are of different types. What we observe in the initial phase are reputations of very diverse magnitude, indicating that hotels initially undertake arbitrary levels of investment in quality. As time passes by, however, we assume that hotels learn their true type and start investing accordingly. Hotels with a bad cost structure exit the market at some point when costs of quality investment exceed the benefits in terms of higher occupancy. This is supported by test results showing a lower variance but a similar or slightly higher absolute level of reputation for older partner hotels compared to newer ones. If hotels with a bad cost structure had been included in our sample of old partner hotels we would most probably have revealed a lower level of reputation, at least for a greater proportion of the hotels, than we actually do. Given that hotels undertake optimal quality investments according to their cost structure the value of reputation converges to some normal level over time and we observe less variance in the data. The hypothesis outlined in section 4.3 assumed that this course of events would imply a higher value of reputation for older partners compared to newer ones. However, this is not supported by our data. What we observe is no significant difference in the value of reputation between new and old partner hotels, although the derived coefficients exhibit the expected signs. The explanation for this is not clear-cut, but two conjectures will now be provided which might justify the obtained results.

The first conjecture concerns the initial amount of quality investment by new partners. If some hotels tend to overinvest in quality (i.e. invest more than the optimal amount for a type 1 hotel) the average value of reputation might not differ drastically between the two groups. This is illustrated in figure 5.1, where new partners exhibit a larger variance but not a lower average value of reputation than older partners do.

Figure 5.1: Illustration of the behaviour of new and old partner hotels, new conjecture



Note: The pattern of behaviour assumed in the original hypothesis, different from the new conjecture, is represented by dotted lines to illuminate the difference.

At a first glance, overinvesting in quality might seem irrational. However, in reality decision makers do not always behave rationally. It can e.g. either be the case that some new partner hotels just have no idea what their optimal level of investment is, or they just might want to be sure of receiving a very high initial reputation, attracting many guests in future periods.

The second conjecture concerns feedback behaviour by previous customers. The hypothesis of this paper relies on the very strict and crucial assumption that *all* previous customers provide *honest* feedback but, as stated already in the theory section, a reputation mechanism is always just as good as the quality of its information. If people tend to provide biased feedback this will distort the results and it will be difficult to find any evidence supporting our initial hypothesis. This kind of distorting behaviour is difficult to handle in a pure economic model like this one since it is a matter of incorporating theories of behavioural psychology. However, today an interdisciplinary area of research is emerging as psychologists as well as economists are gaining increased understanding of each other’s expertise and it will probably not be long before problems like these are examined jointly by academics of the two professions.

To get a hint whether customers’ feedback behaviour can be considered rational or not we now explore the collected data in yet another way. However, this does not contribute to the test of the hypothesis of this paper, but is a pure extension and also an example of the potential of additional research on the subject.

5.6 Exploring the Data Further

As presented earlier, our data set consists of value judgements of five parameters, posted by prior hotel guests and collected for each hotel on a monthly basis. Additionally, data is extended with the number of stars and the standard price for a double room for all hotels. Out of the five parameters judged by previous customers: staff, service, cleanliness, comfort, and value for money, the first four should be independent of price whereas the fifth is a ratio of the first four and the hotel price. Using this statement, we will create our own "value for money"-parameter, calculate its corresponding values, and study whether this measure differs from the fifth parameter, the "value of money" assigned intuitively on a scale from "bad" to "excellent". That is, we will try to assess whether the value of the fifth parameter makes sense when considering the first four parameters in relation to the hotel price and thereby get an indication whether previous customers act rationally or not when posting reviews.

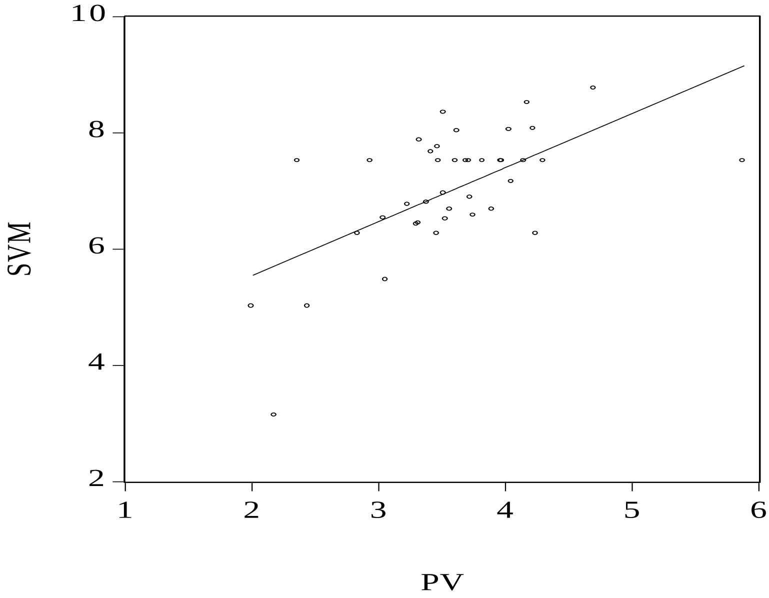
To distinguish our two measures of value for money from each other we denote our new variable PV (standing for price value) whereas the original variable is denoted SVM (stated value for money). The PV is calculated as follows:

$$PV_i = \frac{\sum_1^4 q_i}{\log p_i}$$

Where $\sum q_i$ is the arithmetic mean of the remaining four parameters (staff, service, cleanliness, and comfort) and p_i is the standard price (one night in double room). To minimise the distortions stemming from large price differences between Bucharest and Copenhagen we use the natural logarithm of the price. This variable can now be compared to the SVM parameter.

Using review data from November 2008 for a sample of 20 hotels from each city (10 from each group of partner hotels) we conduct a simple test. First, we calculate the average correlation coefficient between the two variables for both cities and hotels in both groups. Its value is 0.608, indicating a rather strong correlation. Taking location into consideration, we derive a correlation of 0.768 in Copenhagen and 0.435 in Bucharest, and calculations for the individual groups result in correlations of 0.671 for older partners and 0.515 for newer ones, indicating robustness in the obtained result. Thereafter, we plot the SVM and PV-values for the aggregated sample in a scatter diagram, adding a regression line. This provides us with a clear picture of what the correlation visually looks like, see figure 5.2.

Figure 5.2: Correlation between SVM and PV, November 2008



Source: Own calculations using Eviews and review data from www.booking.com

As stated above, the figure reveals a positive correlation between the two variables, indicating a certain (however not perfect) rationality of customers. A further method to analyse the relationship between SVM and PV is by estimating an equation with SVM as the dependent variable and PV, group affiliation, and location as independent variables. The result supports the previous findings and reveals a positive correlation between SVM and PV, see table 5.7.

Table 5.7: SVM as dependent on group, location, and PV

Independent variable: Coefficient [p-value]	**Nov 2008**
Constant	4.116 [0.002]
Group affiliation **= 1 if hotel old partner, and 0 else**	-0.132 [0.650]
City **= 1 if hotel in Copenhagen, and 0 else**	-0.293 [0.285]
PV	0.885 [0.015]
Adjusted R^2	0.323

Source: Own calculations using Eviews and review data from www.booking.com.

By complete rationality (individuals basing the SVM on the first four parameters in relation to the price like a "homo oeconomicus" [9]), we would obtain a significantly positive coefficient of

[9] *Homo oeconomicus* is an agent with given preferences, acting in self-interest to do the best he can given his opportunities, a behaviour often defined as economic rationality in economic literature, see e.g. Vriend, N. (1996).

PV, explaining all variation in SVM. However, even though we do find a positive and significant coefficient of PV it cannot explain more than approximately 30% of the variation in SVM. This implies that people to some extent are rational when evaluating the parameters, but their economic rationality is not complete. This finding is not very surprising since economic models mostly do not correspond completely to reality. This is also illuminated by our results obtained in section 5.3 where we found a tendency of biased feedback, based on hotel price or the number of stars instead of the pure quality investment level undertaken by the hotel.

Returning to table 5.7, we moreover derive insignificant coefficients for group affiliation as well as location. Just as in earlier tests the coefficient for location is negative, indicating that hotels in Bucharest in general are assigned higher SVM values compared to hotels in Copenhagen. However, regarding group affiliation, we now derive a small but negative coefficient for this variable, indicating that old partner hotels generally are assigned lower SVM values than newer partners. This coefficient can, however, only be considered significant at a significance level of 65%, rendering this a very unreliable result.

The main finding in this additional data exploration is thus that previous hotel guests assign hotels a “value for money” based only approximately 30% on the other value parameters in relation to hotel price. The remaining 70% cannot be explained by the model and are probably due to randomness in human behaviour. This renders us some interesting implications and raises some further questions. If only 30% of the SVM parameter is determined by rationality, is the same true for the other parameters such as cleanliness, service, staff, and comfort? And if this is true, is the review system with its feedback mechanism really a reliable source of information for subsequent customers?

The data material available on websites like www.booking.com is very extensive and the scope for future research is almost unlimited. However, one must always keep in mind that informational data based on value judgement of human beings always is only as reliable as the quality of the data – hence as the degree of human rationality. By including the discipline of behavioural psychology when analysing this type of data in the future, the risk of distortions can be diminished and feedback mechanisms can probably be designed in a better way to increase the reliability of the information provided.

6. Final Conclusions and the Scope for Future Research

This paper has analysed the impact of feedback mechanisms in the context of the online hotel booking industry, where potential customers can read reviews written by previous guests prior to making their reservation. The aim was to examine whether such mechanisms affect the behaviour of participating partner hotels by providing them with an incentive to cooperate and invest in better quality to please their customers. In this section, our findings and their implications are discussed to answer this fundamental question. Moreover, the potentials and challenges of analyses in the field of online reputation mechanisms are discussed to pave the way for future research.

The results obtained in this study do not confirm our initial hypothesis and consequently we cannot conclude that the existence of a feedback system in the online hotel reservation industry promotes cooperative behaviour by partner hotels. However, even though the anticipated behaviour cannot be supported at a significance level of 5% we still find the coefficients of group affiliation exhibiting the expected signs in our estimated regression and a tendency of higher variance for new partner hotels, indicating that there is some substance in our stated hypothesis. As pointed out already in the introduction the data material exhibits a number of limitations, such as e.g. a limited temporal coverage. If the same tests were to be applied on a larger data sample collected over a longer time, significant results might be found. However, additional improvements are most likely needed to achieve the wanted results.

Our model builds on the critical assumptions that all customers provide honest feedback after every transaction and that the value of feedback directly corresponds to the level of quality investment undertaken by the hotel. However, this is not a very realistic scenario since customers often are more willing to report extreme experiences rather than average ones. Moreover, our test results show tendencies of biased feedback, with generally higher reputation accruing to hotels with many stars or a high price. Also location tends to affect reputation, perhaps due to the fact that customers expect hotels in countries with a lower level of economic development to be of lower quality than they actually are.

The inferior quality of the underlying data suggests that we have to be very careful when interpreting and generalising the obtained results. There is extensive scope for improvements of the reputation mechanism data collection, where the optimal solution would be a guarantee of unbiased feedback provided after every transaction, creating more reliable test results. Moreover, to understand the test results better, an inclusion of other sciences such as behavioural psychology and data science in the analysis would be preferred as rating behaviour in the online environment can be difficult to understand from a pure economic perspective. People are not always rational in their behaviour and a market place with rather anonymous agents, and goods or services impossible to value in advance, constitutes a very special setting with potential problems of adverse selection and moral hazard. However, this is exactly the reason why online feedback mechanisms and their implications are very interesting to study.

The rather ambiguous conclusion is thus that even though our empirical case cannot prove an explicit impact of a feedback system on the behaviour of participating hotels, we cannot jump to the conclusion that the mechanism has no effect at all and that hotels behave exactly in the same way as they would without the mechanism present. In the absence of a review system there is a risk that the incentives for type 1 hotels to undertake high levels of quality investment are too small, hence leading to an inferior situation compared with the case including a feedback system. One way of examining this is to conduct a difference in differences analysis with a test group consisting of partner hotels and a reference group consisting of hotels outside the online booking system, analysing the investment behaviour over time in both groups respectively. However, this paper does not provide for such an extensive analysis, and therefore we leave this to be the focus of future research.

In the extension analysing customer feedback rationality we found that approximately 30% of the "value of money"-value that customers assign a hotel is consistent with their rating of the other four parameters in relation to the hotel price. If this indication of irrational rating behaviour is valid for all review parameters one can ask whether the feedback mechanism really is a reliable source of information for subsequent customers or if the reputation simply is a random value, based on occasional reviews posted by some extremely satisfied or dissatisfied customers. This is a very important finding, illuminating the need for improvement of the reputation mechanism for it to work efficiently and generate the expected results.

The potential for future research is, as pointed out already, extensive but for a meaningful conduction of groundbreaking investigations to be possible the following suggested improvements are crucial:

- The design of the feedback system must be improved to induce all customers to provide feedback.
- Feedback must mirror the actual experience and not be biased by predetermined characteristics such as hotel price or the number of stars.
- To achieve this and to better understand the effects of online feedback mechanisms, economics, behavioural psychology, and data science must be merged in the analysis and interpretation of research results.

There is no doubt that if online feedback systems are designed in a proper way, mirroring the actual behaviour of hotels and customers, they could reduce search frictions more than they presently do, increasing the amount of happy customers and cooperating hotels and improving the overall welfare and economic efficiency.

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Appendix I

Data material from www.booking.com used in the empirical tests

Table 1: Reputation, stars, and price, Copenhagen group 1 hotels

Hotel	September 2008	October 2008	Stars	Price (€)
71 Nyhavn Hotel	6,60	7,50	4	267,26
Absalon Annex	6,83	7,07	1	81,92
Absalon Hotel	7,58	7,15	3	157,8
Adina Apartment Hotel Copenhagen	8,50	8,00	4	181,31
Ascot Apartments	7,32	N.A.	4	147,6
Ascot Hotel	6,18	7,04	4	147,6
Axel Hotel Guldsmeden	7,80	8,54	4	267,93
Bertrams Hotel Guldsmeden	7,79	7,20	4	241,07
Best Western Hotel City	6,60	7,02	3	181,31
CABINN City Hotel	6,51	6,94	2	116,17
Calton Hotel Guldsmeden	8,11	8,06	3	214,21
City Hotel Nebo	7,59	6,76	2	114,16
Clarion Collection Hotel Mayfair	8,60	8,12	3	241,07
Clarion Collection Hotel Neptun	6,82	7,02	4	227,64
Clarion Collection Hotel Twentyseven	7,34	7,75	4	184,86
Clarion Hotel Copenhagen	7,42	N.A.	4	147,06
Comfort Hotel Esplanaden	6,22	7,20	3	200,78
Comfort Hotel Europa	6,80	7,28	3	281,36
Comfort Hotel Excelsior	5,50	N.A.	3	147,06
Comfort Hotel Österport	6,03	6,81	3	147,06
Copenhagen Admiral Hotel	7,43	8,07	4	230,32
Copenhagen Crown	6,24	6,20	3	184,66
Copenhagen Island	7,87	7,10	4	231,67
Copenhagen Plaza	6,39	8,71	4	289,27
Copenhagen Strand	6,40	8,17	3	132,29
DGI-Byen Hotel	6,93	6,93	3	208,16
First Hotel Skt, Petri	7,50	8,54	5	268,42
First Hotel Vesterbro	6,34	N.A.	4	227,64
Grand Hotel	5,78	5,52	4	160,49
Hotel Alexandra	7,94	7,20	3	218,24
Hotel Amager	7,18	8,06	2	120,2
Hotel Ansgar	7,11	7,04	3	154,44
Hotel Astoria	6,05	6,64	3	171,23
Hotel Centrum	6,60	6,36	3	187,35
Hotel Christian IV	7,46	7,50	3	147,06
Hotel Danmark	5,89	4,67	3	186,68
Hotel du Nord	7,50	N.A.	3	200,78
Hotel Fox	8,50	N.A.	N.A.	204,14
Hotel Kong Arthur	8,08	8,18	4	247,11
Hotel Maritime	6,67	5,33	3	188,02
Hotel Opera	6,97	7,50	3	130,51
Ibsens Hotel	6,29	6,61	3	198,76

Imperial Hotel	7,00	6,67	4	165,49
Le Meredien Palace Hotel	7,10	8,44	4	294,79
Norlandia Mercur Hotel	6,24	5,50	3	209,89
Norlandia Richmond Hotel	5,79	6,25	3	209,89
Norlandia Star Hotel	6,21	6,15	3	174,24
Phoenix Copenhagen	7,68	8,24	4	312,25
Saga Hotel	7,15	7,03	2	73,86
Selandia Hotel	7,02	7,46	2	106,77
The Square	6,80	7,22	4	265,24

Source: Own calculations based on data from www.booking.com

Table 2: Reputation, stars, and price, Copenhagen group 2 hotels

Hotel	September 2008	October 2008	Stars	Price (€)
Hotel Euroglobe	5,59	2,67	1	73,86
Copenhagen Marriot Hotel	9,16	8,16	5	242,05
Danhostel Copenhagen City	5,58	5,42	N.A.	57
Hilton Copenhagen Airport	N.A.	7,78	5	126,47
Hotel Sct. Thomas	6,74	7,26	3	147,06
Savoy Hotel	6,62	6,04	3	160,49
Scandic Copenhagen	6,90	6,22	4	294,12
Scandic Webers	7,78	8,50	4	265,91

Source: Own calculations based on data from www.booking.com

Table 3: Reputation, stars, and price, Bucharest group 1 hotels

Hotel	September 2008	October 2008	Stars	Price (€)
4Seasons Hotel	8,07	8,40	4	80
Agentia H Accommodation	8,00	8,00	3	75
Antheus	7,75	7,50	3	69
Best Western Parc Hotel	7,38	7,57	4	178
Calea Victoriei Residence	8,75	8,20	3	50
Carol Parc Hotel	N.A.	9,50	5	263,12
Crowne Plaza Bucharest	6,50	3,50	5	168,95
Elizeu Hotel	6,08	6,17	3	81
Golden Tulip Times Hotel	8,00	7,63	4	136
Hotel Armonia	7,50	8,50	4	130
Hotel Charter	6,36	7,75	3	55
Hotel Diplomat	7,00	7,50	4	145
Hotel Est	5,50	8,67	3	70
Hotel Opera	7,50	8,00	3	129
Hotel Residence Oliviers	8,17	7,86	4	130
Hotel Suter Inn	9,20	9,20	3	95
Hotel Unique	7,25	7,89	4	119
Howard Johnson Grad Plaza Hotel	9,00	6,50	5	240
K+K Hotel Elisabeta	8,00	9,50	4	246
Le Boutique Hotel Moxa	8,08	7,77	4	210
NH Bucharest	7,83	8,27	4	196
Prince Residence	7,21	7,56	4	100
Ramada Majestic Bucharest Hotel	7,71	7,28	4	185

Residence Villa Marchisa	6,00	8,50	4	69
Siqua Hotel	6,18	6,18	3	90
Tania Hotel	5,80	8,38	3	114
Tulip Inn Bucharest City Hotel	7,83	8,88	4	195
Villa Edera Residence	9,00	8,75	3	60

Source: Own calculations based on data from www.booking.com

Table 4: Reputation, stars, and price, Bucharest group 2 hotels

Hotel	September 2008	October 2008	Stars	Price (€)
Caro Golf	6,50	6,50	4	132
Duke Hotel	9,00	9,25	3	180
Hotel Funnytime	6,30	6,25	3	49
Hotel Michelangelo	10,00	8,80	3	140
Hotel Sofitel Bucharest	7,00	8,73	4	87,2
Hotel Venezia	6,75	8,50	4	129
Marshal Hotel	8,17	9,75	4	155
Novotel Bucharest City Centre	4,00	9,33	4	294,3
Rainbow Accommodation	7,17	7,39	3	65
Ramada Plaza Bucharest	8,27	8,21	4	200
Rin Grand Hotel	6,60	6,89	4	120
Coco's Cerna Hotel	5,29	5,00	1	65
Colentina Motel	N.A.	7,50	2	70
Dalin Hotel	5,00	5,50	3	107
Hotel Lev Or	6,75	8,07	3	139
Hotel Nelisse	6,72	6,71	2	60
Hotel Nelisse One	N.A.	5,25	2	60
Hotel Residence Cerisiers	8,50	7,50	4	150
Hotel Trianon	8,00	6,85	3	110
JW Marriott Bucharest Grand Hotel	6,50	9,00	5	333
Monte Carlo Palace Apart Hotel	7,06	7,17	4	119
Omega Suites	N.A.	7,63	4	120
Phoenica Grand Hotel	N.A.	6,75	4	134
Royal Bucharest	8,75	9,00	4	160
Stil Suites Accommodation Apartments	6,50	5,69	3	53
Yourhotels Kogalniceanu	5,70	6,00	3	75

Source: Own calculations based on data from www.booking.com

Table 5: PV, SVM, and Log Price for Copenhagen hotels, November 2008

Hotel	SVM	PV	Log Price	Group
Selandia Hotel	6,7	3,57	2,03	1
Adina Apartment Hotel Copenhagen	6,5	3,54	2,26	1
Absalon Annex	7,1	4,06	1,91	1
Saga Hotel	7,5	3,98	1,87	1
71 Nyhavn Hotel	3,1	2,19	2,43	1
Hotel Amager	7,5	3,49	2,08	1
Absalon Hotel	6,4	3,31	2,20	1
Clarion Collection Hotel Mayfair	7,7	3,48	2,38	1
Axel Hotel Guldsmeden	8,0	3,63	2,43	1

Calton Hotel Guldsmeden	7,7	3,43	2,33	1
Copenhagen Marriot	6,9	3,52	2,38	2
Hotel G	6,3	3,47	2,07	2
Scandic Webers	8,3	3,52	2,42	2
Hilton Copenhagen Airport	7,5	4,31	2,10	2
Danhostel Copenhagen City	6,6	3,76	1,76	2
Hotel Euroglobe	5	2,01	1,87	2
Savoy hotel	5,5	3,07	2,21	2
Hotel Sct Tomas	6,5	3,05	2,17	2
Scandic Copenhagen	6,3	2,85	2,47	2
Danhostel Copenhagen Downtown	6,8	3,39	1,84	2

Source: Own calculations based on data from www.booking.com

Table 6: PV, SVM, and Log Price for Bucharest hotels, November 2008

Hotel	SVM	PV	Log Price	Group
Hotel Charter	7,5	3,83	1,74	1
Crowne Plaza Bucharest	6,4	3,33	2,23	1
Calea Victoriei Residence	7,5	5,89	1,70	1
4Seasons Hotel	8,1	4,23	1,90	1
Hotel Est	7,5	3,73	1,85	1
Golden Tulip Times Hotel	6,7	3,91	2,13	1
Howard Johnsson Grand Plaza Hotel	5,0	2,45	2,38	1
Best Western Parc Hotel	7,9	3,33	2,25	1
Hotel Unique	7,5	3,98	2,08	1
Tania Hotel	9	4,71	2,06	1
Hotel Sofitel Bucharest	8,5	4,19	1,94	2
Hotel Venezia	7,5	3,70	2,11	2
Coco's Cerna Hotel	6,8	3,24	1,81	2
Hotel Caro Golf	7,5	2,95	2,12	2
Hotel Nelisse	6,9	3,73	1,78	2
Hotel Nelisse One	8,0	4,04	1,78	2
Rainbow Accommodation	7,5	3,62	1,81	2
Hotel Funnytime	6,3	4,25	1,69	2
Duke Hotel	7,5	4,16	2,26	2
Colentina Motel	7,5	2,37	1,85	2

Source: Own calculations based on data from www.booking.com

Appendix II

Complete test results from Ewievs

1. Test with dummy variables for group affiliation and location

Dependent Variable: Reputation September 2008
Method: Least Squares
Included observations: 101
White Heteroskedasticity-Consistent Standard Errors & Covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	7.093784	0.260216	27.26117	0.0000
GROUP	0.316770	0.283609	1.116927	0.2668
CITY	-0.405502	0.213743	-1.897143	0.0608
R-squared	0.039548			
Adjusted R-squared	0.019947			

Dependent Variable: Reputation October 2008
Method: Least Squares
Included observations: 101
White Heteroskedasticity-Consistent Standard Errors & Covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	7.434876	0.279056	26.64291	0.0000
GROUP	0.432174	0.346592	1.246925	0.2154
CITY	-0.751165	0.272448	-2.757090	0.0070
R-squared	0.086209			
Adjusted R-squared	0.067560			

2. Regression with further variables included

Dependent Variable: Reputation September 2008
Method: Least Squares
Included observations: 101
White Heteroskedasticity-Consistent Standard Errors & Covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	4.431635	1.233255	3.593445	0.0005
GROUP	0.289893	0.276215	1.049517	0.2965
CITY	-0.646925	0.222863	-2.902792	0.0046
LOG_PRICE	1.298162	0.650042	1.997043	0.0486
R-squared	0.095826			
Adjusted R-squared	0.067862			

Dependent Variable: Reputation October 2008
Method: Least Squares
Included observations: 101
White Heteroskedasticity-Consistent Standard Errors & Covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2.808035	1.339569	2.096222	0.0387
GROUP	0.385460	0.297128	1.297289	0.1976
CITY	-1.170760	0.319342	-3.666160	0.0004
LOG_PRICE	2.256218	0.631240	3.574262	0.0005
R-squared	0.206004			
Adjusted R-squared	0.181448			

Dependent Variable: Reputation September 2008 Method: Least Squares Included observations: 101 White Heteroskedasticity-Consistent Standard Errors & Covariance				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	5.997661	0.427757	14.02118	0.0000
GROUP	0.219373	0.269484	0.814051	0.4176
CITY	-0.258736	0.216169	-1.196915	0.2343
STARS	0.323792	0.111203	2.911718	0.0045
R-squared	0.109444			
Adjusted R-squared	0.081901			

Dependent Variable: Reputation October 2008 Method: Least Squares Included observations: 101 White Heteroskedasticity-Consistent Standard Errors & Covariance				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	5.840925	0.629524	9.278315	0.0000
GROUP	0.290542	0.282335	1.029069	0.3060
CITY	-0.537741	0.230486	-2.333075	0.0217
STARS	0.470849	0.166759	2.823522	0.0058
R-squared	0.190363			
Adjusted R-squared	0.165322			

3. Variance test

All hotels September 2008
Test for Equality of Variances Between Series
Included observations: 72

Method	df	Value	Probability	(two-tailed)
F-test	(71, 28)	2.384966	0.0123	
Siegel-Tukey		1.403840	0.1604	
Bartlett	1	8.275924	0.0040	
Levene	(1, 99)	5.030632	0.0271	
Brown-Forsythe	(1, 99)	3.651123	0.0589	

Category Statistics

Variable	Count	Std. Dev.	Mean Abs. Mean Diff.	Mean Abs. Median Diff.	Mean Tukey-Siegel Rank
GR1	72	0.874187	0.727234	0.726935	53.60417
GR2	29	1.350035	1.027221	0.995168	44.53448
All	101	1.028729	0.813369	0.803952	51.00000

Bartlett weighted standard deviation: 1.031284

All hotels October 2008
Test for Equality of Variances Between Series
Included observations: 72

Method	df	Value	Probability	(two-tailed)
F-test	(71, 28)	2.354591	0.0135	
Siegel-Tukey		3.083121	0.0020	
Bartlett	1	8.025128	0.0046	
Levene	(1, 99)	8.790808	0.0038	
Brown-Forsythe	(1, 99)	8.798093	0.0038	

Category Statistics

Variable	Count	Std. Dev.	Mean Abs. Mean Diff.	Mean Abs. Median Diff.	Mean Tukey-Siegel Rank
GR1	72	1.045774	0.794502	0.787035	56.71065
GR2	29	1.604707	1.286331	1.286109	36.82184
All	101	1.225479	0.935721	0.930334	51.00000

Bartlett weighted standard deviation: 1.229893

Bucharest September 2008
Test for Equality of Variances Between Series
Included observations: 44

Method	df	Value	Probability	(two-tailed)
F-test	(26, 21)	1.924672	0.1296	
Siegel-Tukey		1.153297	0.2488	
Bartlett	1	2.450834	0.1175	
Levene	(1, 47)	1.456749	0.2335	
Brown-Forsythe	(1, 47)	1.096015	0.3005	

Category Statistics

Variable	Count	Std. Dev.	Mean Abs. Mean Diff.	Mean Abs. Median Diff.	Mean Tukey-Siegel Rank
GR1	27	1.013680	0.806609	0.793000	27.14198
GR2	22	1.406304	1.063450	1.036528	22.37121
All	49	1.213204	0.921925	0.902339	25.00000

Bartlett weighted standard deviation: 1.205023

Bucharest October 2008
Test for Equality of Variances Between Series
Included observations: 44

Method	df	Value	Probability	(two-tailed)
F-test	(26, 21)	1.410165	0.4249	
Siegel-Tukey		2.734470	0.0062	
Bartlett	1	0.676599	0.4108	
Levene	(1, 47)	3.538181	0.0662	
Brown-Forsythe	(1, 47)	3.486908	0.0681	

Category Statistics

Variable	Count	Std. Dev.	Mean Abs. Mean Diff.	Mean Abs. Median Diff.	Mean Tukey-Siegel Rank
GR1	27	1.174627	0.769018	0.758576	30.05556
GR2	22	1.394875	1.195674	1.191184	18.79545
All	49	1.269374	0.960578	0.952808	25.00000

Bartlett weighted standard deviation: 1.277736

Copenhagen September 2008				
Test for Equality of Variances Between Series				
Included observations: 44				

Method	df	Value	Probability	(two-tailed)
F-test	(43, 6)	2.929948	0.1779	
Siegel-Tukey		0.588521	0.5562	
Bartlett	1	3.733935	0.0533	
Levene	(1, 49)	2.262643	0.1389	
Brown-Forsythe	(1, 49)	1.737598	0.1936	

Category Statistics

Variable	Count	Std. Dev.	Mean Abs. Mean Diff.	Mean Abs. Median Diff.	Mean Tukey-Siegel Rank
GR1	44	0.732555	0.598886	0.597529	26.50000
GR2	7	1.253921	0.891122	0.863750	22.85714
All	51	0.806513	0.638997	0.634069	26.00000

Copenhagen October 2008				
Test for Equality of Variances Between Series				
Included observations: 44				

Method	df	Value	Probability	(two-tailed)
F-test	(43, 6)	4.940898	0.0516	
Siegel-Tukey		2.176602	0.0295	
Bartlett	1	9.190141	0.0024	
Levene	(1, 49)	7.055458	0.0106	
Brown-Forsythe	(1, 49)	6.675868	0.0128	

Category Statistics

Variable	Count	Std. Dev.	Mean Abs. Mean Diff.	Mean Abs. Median Diff.	Mean Tukey-Siegel Rank
GR1	44	0.885909	0.656723	0.656723	27.81818
GR2	7	1.969211	1.413878	1.399048	14.57143
All	51	1.104947	0.760646	0.758610	26.00000
Bartlett weighted standard deviation: 1.078686					

4. Relationship between SVM and PV

Dependent Variable: SVM				
Method: Least Squares				
Included observations: 40				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	4.116124	1.213267	3.392597	0.0017
CITY	-0.292722	0.269604	-1.085746	0.2850
GROUP	-0.132459	0.289398	-0.457706	0.6500
PV	0.884595	0.344650	2.566644	0.0147
STARS	-0.018773	0.090723	-0.206925	0.8373
R-squared	0.392520			
Adjusted R-squared	0.323094			