ESSAYS ON ONLINE REVIEWS: THE RELATIONSHIPS BETWEEN REVIEWERS, REVIEWS, AND PRODUCT SALES, AND THE TEMPORAL PATTERNS OF ONLINE REVIEWS

by

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1. INTRODUCTION

Interpersonal conversation, or word-of-mouth (WOM), is one of the important factors in affecting product sales (e.g. Herr et al. 1991, Laczniak et al. 2001). Potential buyers can gather information on the quality of the product through other consumers' WOM. WOM can not only increase product awareness among potential buyers but can also affect their buying decisions. With the development of online review systems, consumers can express personal opinions on a particular product freely online without being limited to face-to-face interactions. This new form of WOM, such as online reviews, has generated great interest to companies and researchers since more and more consumers are engaging in the online review systems. For example, a best seller book, such as one in the Harry Potter series, or a popular movie, such as one in the Star Wars series, can generate hundreds even thousands of online reviews. Studies have shown that those online reviews are significantly associated with consequent product sales (e.g. Chevalier and Mayzlin 2006, Liu 2006). In this proposal, we outline two studies to first investigate the relationships between reviewers and their reviews and between reviews and product sales and second examine the temporal patterns of review ratings and content.

Study 1 empirically examines the relationships between reviewer characteristics, such as their identity and reputation, and their reviews and between different review dimensions in terms of the volume, valence, quality, and position of reviews and the product sales of different product types. We use data from Amazon.com regarding information on books, reviews, and reviewers. To better capture the impact of reviews on product sales, we collect data from the release date of each book in our sample. Since studies have found that reviews at early stage tend to be more powerful on product sales than reviews at later stage (e.g. Liu 2006), our data enables us to observe such influence from the very first review. This study first analyzes how various reviewers provide reviews differently. Specifically, it focuses on contrasting reviews from anonymous or identified reviewers and high or low ranking reviewers. Second, it studies the impact of different review dimensions on the sales of popular or obscure products.

This study has at least two unique contributions. First, it considers the impact of the information source on the impact of reviews. It studies the influence of reviewers' characteristics on their reviews which have not been considered in the previous studies. Second, it differentiates the review impact on product sales based on product popularity. Although the majority of the previous studies try to understand the impact of online reviews on product sales, they tend to ignore the product level heterogeneity and assume the impact of reviews is the same across different product types. However, findings in the marketing literature point out that consumers do discount WOM impact for different products (e.g. Herr et al. 1991, Laczniak et al. 2001). Therefore, it is important to separately measure the impact of online reviews on product sales.

Study 2 investigates the temporal pattern of online reviews in terms of the ratings and the content. It also measures whether consumers can correct early review bias due to consumer heterogeneous tastes by using the helpfulness vote. Specifically, we address the following research questions: (1) What is the temporal pattern of online reviews? (2) What are the characteristics of the textual of online reviews in different time periods?

This study contributes to the growing literature on examining the pattern of online reviews in the following ways. First, it is among the few studies which investigate the content of online reviews rather than just the numerical ratings. It helps researchers and companies to better understand the unique characteristics of reviews at different time stage. Second, our results can infer reviewers' motivations on writing reviews and their actions at different time periods. Third, we propose a way to directly measure the existence of early review bias as discussed in Li and Hitt (2008) by using the helpfulness vote. In addition, we also measure whether consumers can self correct for the early review bias so that consumer surplus should not be affected by the misleading early reviews.

The rest of the proposal is organized as follows. Chapter 2 proposes a study to examine the relationship between reviewers, reviews and the product sales. Chapter 3 presents the second study to investigate the temporal pattern of online reviews including the ratings and the content. Chapter 4 concludes the proposal.

CHAPTER 2: EXAMINING THE RELATIONSHIP BETWEEN ONLINE REVIEWS, REVIEWERS, AND PRODUCT SALES

1.1 Introduction

Online reviews play an important role in consumers' purchasing decisions (e.g. Chevalier and Mayzlin 2006, Liu 2006). Not only do online reviews increase product awareness among potential consumers, but they can also provide information on product quality which assists consumers' decision making processes. Studies have confirmed that the greater the number of online reviews, the higher the product sales will be (e.g. Liu 2006). Therefore, it is often considered an important driver of product sales.

Prior literature has mainly focused on the consequence of online reviews, which is the impact on product sales (Chevalier and Mayzlin 2006, Dellarocas et al. 2005, Duan et al. 2008, Reinstein and Snyder 2005, Liu 2006). For example, Liu (2006) and Duan et al. (2005) found that the volume of online reviews has a positive impact on product sales but the valence, the positive or negative nature of the reviews, does not. While these studies tried to identify the link between the volume and valence of online reviews and product sales, little work considers other interesting aspects of online reviews. In this study, we investigate the relationships and the impact of these important aspects other than the volume and the valence of online reviews.

First, in terms of the impact of reviews on product sales, prior literature mainly mentions two dimensions of online reviews: the volume and the valence. However, when potential buyers are facing thousands of reviews regarding one product, they typically fail to process the information in a systematic manner. In fact, consumers will process the information heuristically and selectively (Forman et al. 2008). In other words, using the total number of reviews (the volume) or the average ratings (the valence) assumes all reviews to be equally valuable to the consumers. However, due to limited resources such as time and effort, consumers will most likely not pay equal attention to every review. Therefore, we need to consider other dimensions such as the quality and position of online reviews, and study the impact of these dimensions on product sales in addition to just volume and valence.

Second, few studies consider the impact of reviewer information such as their identity and their online reputation on the reviews they write. To the best of our knowledge, Forman et al. (2008) is the only study tried to understand the effect of reviewer identity disclosure. While their study initiated the first step towards understanding reviewer behavior and the impact on online reviews, they did not study the impact from another important reviewer characteristic, reviewer reputation, on subsequent reviewer behavior and on product sales. Studies in other similar context, such as open source software development, have found that reputation is one of the important motivations for individuals to contribute voluntarily (e.g. Lerner and Tirole 2002). However, no prior study considers this important effect of reviewer reputation on driving reviewer's behavior.

Third, in terms of differentiating product types, to date, we are not aware of any prior studies evaluating the influence of online reviews on product sales of different product types. As found in the marketing literature, consumer WOM has different impact on products with high brand impressions and low brand impressions (e.g. Herr et al. 1991, Laczniak et al. 2001). For example, according to attribution theory, consumers tend to discount the negative WOM on a favorable brand product since they perceive positive prior impression on the product which is typically very difficult to alter (Laczniak et al. 2001). This theory is applicable in the context of online reviews. Since consumers may hold a stronger prior impression for a popular product than for an obscure product, the impact of online reviews may be different between these two product types. Therefore, ignoring product level heterogeneity in terms of the popularity may overlook some interesting interactions between online reviews and product sales.

This paper aims to examine the relationships (1) between reviewer characteristics and their reviews and (2) between different review dimensions in terms of the volume, valence, quality, and position of reviews and the product sales of different product types. More specifically, we try to answer the following research questions. Do reviewers choose products to review purposely? Do powerful top ranking reviewers review products systematically differently from low ranking reviewers? Do identified reviewers review products systematically differently from anonymous reviewers? Do reviews affect product sales differently across different product types? How do different dimensions of reviews impact product sales across various product types?

Our study has several important contributions. First, it is critical to examine the effect of reviewer characteristics such as identity disclosure and reputation on reviewer behavior. Essentially, reviewers are the information providers whose behavior determines the volume, valence, and quality of online reviews which in turn affect product sales. Therefore, understanding how reviewers provide reviews is important for both practitioners and researchers. In this study, we investigate how reviewers write reviews in terms of the volume, the valence, the quality, the timing, and the product categories of their reviews. Our results can help researchers and practitioners to better understand and predict reviewer behavior and the subsequent review impact.

Moreover, we contribute to the growing body of literature by addressing the relationship between online reviews and product sales in a more comprehensive way. In addition to just the volume and valence of online reviews, we further examine the impact of the quality and the position of online reviews on sales. Since consumers' recourses are limited in terms of their time and efforts, they are unlikely to systematically process hundreds of online reviews available for a particular product. As a result, consumers may process the information heuristically (Forman et al. 2008). For example, consumers may only be able to read the top listed reviews or reviews with high quality indicators. In such case, using the total number of reviews (volume) or the average ratings (valence) may not capture the essence of review effects precisely. In this study, we propose two additional dimensions of online reviews (the quality and the position) to understand the dynamic impact of reviews more precisely. Our analysis may resolve the argument of the mixed findings in the early studies on the impact of review valence on product sales.

Most importantly, this is the first study which differentiates the impact of reviews by different product types. We control for the product types in terms of the popularity of the product and separately examine the impact of online reviews on products sales for different types. Our analysis indicates that companies selling obscure products may be able to expand their market by attracting more powerful high ranking reviewers to review their products. From the reviewer perspective, high ranking reviewers also have the incentive to review obscure products rather than popular products so as to lower the risk of getting negative votes and avoid severe competition for attention. These findings yield interesting managerial implications. For example, some companies frequently visit online review sites to identify influential reviewers. They then send free samples to them and hope to obtain positive WOM (Thompson 2003). Our results can guide their marketing strategies by targeting the right reviewers more precisely.

The rest of this paper is organized as follows. In section 1.2, we review the relevant theories in the IS, marketing, and social psychology literature to build up the conceptual model of this study. Then, based on the theories we present our hypotheses in section 1.3. We outline an empirical study to test the hypotheses in section 1.4 which includes a detailed discussion on the data we will use and the empirical models. Section 1.5 reports some preliminary results from a pilot sample we collected in September 2008. We then conclude in the last section.

1.2 Theoretical Background

In this section, we discuss the theoretical background of this study from three perspectives. First, we review the literature in social psychology and IS regarding the influence of individuals' identity and reputation on their behavior. Second, we summarize the prior studies which examine the impact of online reviews on product sales. We discuss the needs for measuring the impact from other aspects of online reviews such as review quality and position. Third, we draw from the marketing literature on how WOM can affect consumers' brand choices and propose to study the impact of online reviews on different product types in terms of product popularity.

1.2.1 Reviewer

Deindividuation theory in social psychology suggests that in the anonymous environment, individuals are not "seen or paid attention to as individuals" (Festinger et al. 1952, p.382). Being unidentified reduces inner constraints and causes a minimization of self-observation, self-evaluation, and concerns of social evaluation (Zimbardo 1969). As a result, individuals may engage in behavior in which they would not when identified (e.g. Diener et al. 1976, Zimbardo 1969). This theory has been used to explain the abnormal behavior observed in violent crowds, mindless hooligans, and lynch mobs (Postmes and Spears 1998). For example, in an experiment, Zimbardo (1969) demonstrated that anonymous subjects who were wearing identical coats delivered electrical shocks to others for twice as long as identified subjects who were wearing large name tags. Diener et al. (1976) found that children remained anonymous were twice as likely to steal Halloween candy as children who were asked for their names and home addresses.

In addition, deindividuation theory has also been applied to account for individual's different behavior in computer-mediated communication (Kiesler and Sproull 1992) and group decision support systems (Connolly et al. 1990, Jessup et al. 1990). For instance, Jessup et al. (1990) showed that subjects in an anonymous group participated more actively than an identified group when performing an idea-generating task. Anonymous groups also were more likely to criticize others' opinions and generated more critical ideas than the groups with identified contributions. Similarly, Connolly et al. (1990) also found that groups working anonymously produced more unique solutions and comments than the identified groups when using a group decision support system to accomplish an idea-generation task.

In the context of an online review system, reviewers are able to choose to reveal their real name or remain anonymous. (Appendix A shows two examples from Amazon, one with real name reviewer[1] and the other with anonymous reviewer.) Based on the above-mentioned theory, anonymous reviewers should exhibit different behaviors in terms of writing reviews from identified reviewers whose true identities can be verified. In other words, such choice of revealing one's real world identity should affect reviewers' reviewing behaviors in terms of the effort they put in writing reviews, the amount of their contributions, the content and the quality of their reviews, and the time when they write reviews. For example, since anonymity enables reviewers to be isolated from their reviews, anonymous reviewers may be less self-regulated than identified reviewers. As a result, anonymous reviewers could be more likely to brag or moan online than identified reviewers. In this study, we apply the theory in social psychology to contrast reviewers' reviews between anonymous and identified reviewers.

In addition to identity disclosure, reputation is another important characteristic which differentiates online reviewers. In the studies of member contributions in online communities, reputation has been shown as an important driver for community members to contribute voluntarily (e.g. Lerner and Tirole 2002). For example, in the open source software literature, Lerner and Tirole

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[1] Amazon uses reviewer's name on the credit card to verify whether it is a real name identity. If the reviewer chooses to reveal the real name, then Amazon will attach a "real name" badge below the reviewer's name.

(2002) found that reputation and peer recognition can motivate providers to contribute to the community without monetary rewards. They argued that the main driver of providers' efforts is the "reputation capital" they gained by contributing to the community. Providers' reputation signals their competence which drives them to participate online. In the context of firm-hosted user communities, firm recognition of user contributions is also reported as valuable to the users (Jeppesen and Frederiksen 2006). Positive reputation and peer recognition can motivate participants to keep contributing voluntarily (Pavlou and Gefen 2004, Resnick et al. 2000).

In an online review system, reviewers have to devote substantial amount of time and efforts to write reviews. However, they typically do not get any monetary rewards for their contributions. This type of community is similar to the open source software development community as mentioned above. Based on the findings in the open source software literature, we argue that reviewers' reputation in terms of their rankings would be viewed as an important reward to the reviewers. Motivated by reviewers' reputation, they are willing to keep contributing voluntarily. In this study, we try to compare the reviews provided by reviewers with different level of reputation (high or low) so as to capture the role of reputation in driving reviewers' behaviors.

Table 2.1. **Online Reviewer Characteristics**	
Identity Disclosure	Theory on Anonymity: Diener et al. (1976), Jessup et al. (1990), Zimbardo (1969), etc.
Reputation	Reputation and peer recognition as an important motivation in contributing to online community: Lerner and Tirole (2002), Jeppesen and Frederiksen (2006), etc.

1.2.2 Online Review

Although there is a growing body of literature addressing the effect of online reviews on product sales (e.g. Basuroy et al. 2003, Dellarocas et al. 2004, Li and Hitt 2008, Zhang et al. 2004), the dynamic impact of such effect has not been fully explored. Prior literature mainly focused on measuring the impact from two dimensions of online reviews on product sales, (1) the *volume* and (2) the *valence* (e.g. Liu 2006, Zhang et al. 2004).

Volume measures the number of online reviews, and has been used to see the impact of more online reviews on product sales (e.g. Chevalier and Mayzlin 2006). A high volume of online WOM can increase the awareness of a product among potential buyers and therefore can increase product sales (Liu 2006).

Valence measures the positive or negative nature of online reviews. Unlike volume, the impact from the valence of online reviews is mixed. For example, using user reviews on Yahoo! Movies, Liu (2006) and Duan et al. (2005) found that the valence of previous movie reviews does not have significant impact on later weekly box office revenues. However, Zhang and Dellarocas (2006) found a significant relationship between the valence of online WOM and box office revenues. They reported that a 1-point increase in the rating of user reviews on Yahoo! Movies is associated with an increase in box office revenues in the range of 4-10%. A common way to assess the impact of valence is to use the average review rating as the measurement. This method assumes that all reviews would have equal impact on product sales which ignores the impact of other characteristics associated with each individual reviews. For example, the credibility of the information source has been shown to have great influence on consumers' purchase decisions (Guadagno and Cialdini 2003). Therefore, we need to consider other dimensions of the online reviews in addition to volume and valence.

Recently, some researchers noticed other important dimensions of online reviews which could potentially affect consumers' purchase decisions, such as the *quality* and the *position* of online reviews. The quality of the reviews indicates the usefulness and the credibility of the information. It can be based on either the reputation of the information source or the perceived helpfulness or usefulness of the information content (Chen et al. 2006). Forman et al. (2008) and Chen et al. (2006) used the online helpfulness vote as an indicator of the review quality and found that consumers do pay attention to the quality of the reviews in addition to just the volume or the valence. Moreover, Forman et al. (2008) showed that reviews with identified reviewers are perceived to be more credible than reviews with anonymous reviewers and thus have stronger impact on product sales. In terms of the position, only Chen et al. (2006) has compared the featured reviews which are posted on the top of the first page with other reviews. They concluded that featured reviews do have marginal positive impact on product sales while other reviews do not.

Table 2.2. **Online Review Dimensions**	
Volume	High volume positively associates with product sales: Liu (2006), Zhang et al. (2004), etc.
Valence	Valence associates with product sales: Zhang and Dellarocas (2006), etc. Valence does not associate with product sales: Liu (2006), Forman et al. (2008), etc.
Quality	Information quality increases the persuisiveness of information: Chen et al. (2006)
Position	Featured reviews have stronger impact on product sales than rest reviews: Chen et al. (2006)

1.2.3 Product Sales

While the above studies have examined the impact of online reviews on product sales, they either treated all the reviews equal by using the average review ratings or did not consider the product level characteristics. Prior research has suggested that consumers' WOM is likely to have different impact on different product types depending on the level of prior impressions or expectations (Herr et al. 1991, Laczniak et al. 2001). Since consumers' prior impressions on a particular product are shown to be persistent and resistant to change (Hoch and Deighton 1989), information that is inconsistent with their prior impressions is likely to be discounted or even ignored (Herr et al. 1991). This notion is consistent with the attribution theory which indicates that if information receivers have favorable association with an object, it is unlikely they attribute the negativity at the object since the negative information is inconsistent with their positive impression (Harvey and Weary 1984). Therefore, as found in Laczniak et al. (2001), consumers tend to discount the effect of negative WOM on a more favorable brand name and attribute the negativity to the communicator rather than the brand name. Negative WOM communications have reduced impact on product selections when consumers hold positive prior impressions (Herr et al. 1991).

In our context, the influence of online reviews shares the similarity with offline WOM on consumers' choices. Online reviews should have different effects on products with different level of prior knowledge, which can be measured as the level of popularity among consumers. For popular and well accepted products, online reviews provide less helpful information for judgment and choice. However, for obscure products, reviews will have stronger influence on consumers' judgment since they are lack of prior knowledge of the product quality.

Table 2.3. **Product Sales**	
Product Type	The attribution theory on the impact of prior impresssions on the effect of WOM: Laczniak et al. (2001), etc.

Figure 2.1 presents the general conceptual framework of this study. Our objectives are to investigate the effects of reviewers' characteristics on their reviews, and the dynamic impact of reviews on product sales for different product types in terms of product popularity.

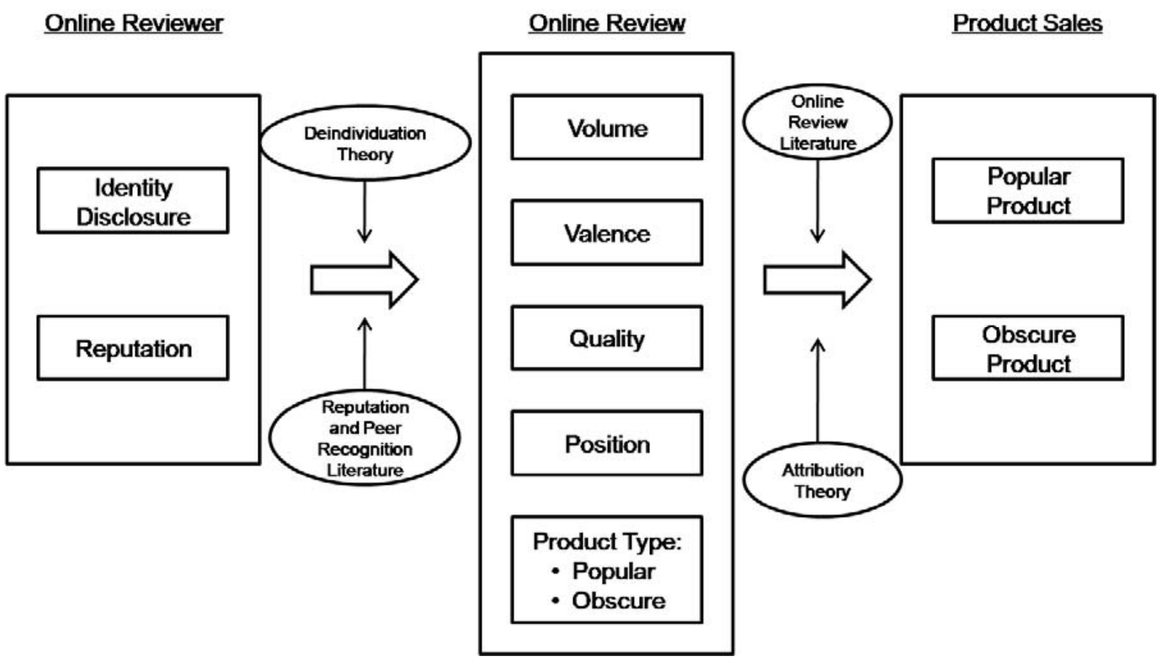

Figure 2.1. Conceptual Framework

1.3 Hypotheses

1.3.1 Online Reviewer and Online Review

1.3.1.1 Identity Disclosure and Online Review

As indicated in the social psychology literature, anonymity can reduce the risk of being singled out or interacted which reduces participant's anxiety (e.g. Diehl and Stoebe 1987). As a result, an anonymous environment can increase the level of participation. Even shy people can participate equally in an anonymous environment. For example, both Connolly et al. (1990) and Jessup et al. (1990) found that using group decision system to solve an idea-generating task, anonymous groups always generated more comments than identified groups.

Similarly, in the context of an online review system, the anonymous nature gives consumers more freedom to leave any type of feedback online with very little responsibility than in an identified system. Anonymity means the reviews cannot be traced or attributed to any individual. Since it greatly reduces the social constraints and the risk of interaction (e.g. Diener 1980, Zimbardo 1969), consumers who would not participate elsewhere would be willing to participate anonymously. As a result, we hypothesize that there will be more anonymous online reviews than identified reviews.

H1a: ***Volume****. There are more anonymous reviews than identified reviews.*

Since anonymity can lead to a reduction of inner constraints and self-regulation (Diener 1980), it poses a lack of accountability problem to online systems (Gavish and Gerdes 1998). As predicted by deindiviuation theory, online anonymous users are more likely to engage in uninhibited behaviors such as flaming or critical comments, use of strong language, or highly degrading replies to messages (Jessup et al. 1990, Gavish and Gerdes 1998). For example, Jessup et al. (1990) demonstrated that anonymous subjects were more likely to criticize other's ideas and leave more critical comments than the identified subjects in the experiment.

In tune with the above studies, the anonymous nature of an online review system also inherits the lack of accountability problem. Anonymous reviewers are less self-regulated than identified reviewers, and thus tend to post more critical ratings or over-state ratings online. The later effect has been observed in Hu et al. (2007) where they reported that the majority of online ratings were either extremely positive or negative which led to a J-shaped pattern of online reviews. We try to attribute this effect to the anonymity nature of online review systems and hypothesize that reviewers are more likely to brag or moan when review is anonymous than when it is identified.

*H1b: **Valence**. Anonymous reviews are more extreme than identified reviews.*

As reviewed above, the influence of the persuasiveness or the credibility of the information relies on either the reputation of the information source or the quality of the information (Chen et al. 2006). Identified reviews provide information on the source of the message and therefore are perceived to be more useful and reliable (Forman et al. 2008). Moreover, identified reviews conform to the norms of the community which meets members' expectation and reinforce community norms. As a result, members will evaluate such reviews more positively than anonymous reviews (Forman et al. 2008).

*H1c: **Quality**. Identified reviews will be rated as more helpful than anonymous reviews.*

In addition, various studies have shown that peer recognition is one important motivation for people to contribute voluntarily (e.g. Jeppesen and Frederiksen 2006, Lerner and Tirole 2002). Since anonymous reviewers are less motivated than identified reviewers, anonymous reviewers usually devote limited effort writing reviews (Forman et al. 2008). Although posting reviews early can not only capture more attention from the peers but also impact more potential buyers, it requires much more effort and motivation than posting reviews later on. Therefore, leaving a review at the early stage of a product's life cycle is not as attractive to anonymous reviewers as to identified reviewers who desire high peer recognition.

*H1d: **Position**. Identified reviews will be posted earlier than anonymous reviews.*

1.3.1.2 Reviewer Reputation and Online Review

Reputation has been found as a driver of voluntary contributions in community settings such as open source software development (Lerner and Tirole 2002). It is an alternative reward that goes beyond monetary incentives for participants to contribute in the community (Pfeffer 1990). For example, Lerner and Tirole (2002) found that reputation is viewed as one type of virtual capital which ultimately helps providers to enhance their job market positions. In this respect, online reviewers' contribution seems similar to that of the open source software developers'. The reviewer ranking can be viewed as virtual capital to the reviewers in the online community which motivates reviewers to contribute to the community and rewards their efforts. In this regard, reviewers with high ranks are perceived to have high reputation among community members, which is valuable to the reviewers. Therefore, high ranking reviewers will devote more effort and are more active than low ranking reviewers to protect and reinforce their reputation.

H2a: ***Volume****. High ranking reviewers keep posting more reviews than low ranking reviewers.*

As identified in Feldman and Lynch's (1988) accessibility-diagnosticity model, information is not perceived as useful or diagnostic if it does not help the consumer to select one product (only one) against other alternatives. In other words, ambiguous information which can be interpreted in multiple ways is not perceived to be helpful and used as an input in consumer's judgment.

In the context of online reviews, extreme reviews which either strongly recommend or prohibit are viewed as more informative and helpful information to the potential consumers. Since top reviewers value their reputations more than low ranking reviewers, they are more anxious to maintain their reputations. As a result, top reviewers' reviews will be less ambiguous than low ranking reviewers'. In other words, top reviewers will tend to provide more extreme reviews than low ranking reviewers.

H2b: ***Valence****. High ranking reviewers post more extreme reviews than low ranking reviewers.*

With the same argument as above, high ranking reviewers will put more effort in writing high quality reviews to maintain their established reputations. In addition, from readers' perspective, high ranking reviewers signal higher credibility than low ranking reviewers. Therefore, readers will tend to evaluate high ranking reviewers' reviews as more helpful than low ranking reviewers'.

H2c: ***Quality****. High ranking reviewers post higher quality reviews than low ranking reviewers.*

Posting reviews early can have stronger influence on potential buyers' choices since there are fewer reviews available and less competition for attentions. For example, Liu (2006) found that only the early weeks' movie reviews are correlated with box office revenues. Late weeks' movie reviews are merely indicators but not influencers. As an experienced reviewer with high reputation, he/she will less likely waste time and effort to contribute to the community if that review cannot generate adequate attention and enhance his/her reputation. However, for reviewers with lower reputations, they do not have enough incentives to devote sufficient time and effort to contribute early. As a result, they will not purposely write reviews at the early stage. In other words, they will participate across the product's life cycle.

H2d: ***Position****. High ranking reviewers prefer to post reviews at the early stage of a product's life cycle. Low ranking reviewers do not exhibit this preference.*

1.3.2 Online Review and Product Sales

1.3.2.1 Volume

The theory of "the strength of weak ties" suggests that people can obtain more useful information from relative strangers than close tied friends or family members (Granovetter 1973). This is because strong-tied people are typically people with similar interests or thoughts which reduce the diversity of information sharing. When information is unavailable from strong-tied members, people will gather it from weak-tie relationships such as online reviews. One argument proposed by weak-tie theorists is that when information is additive, numerous weak ties increase the probability that people find useful information (Friedkin 1982). Along with this argument, product reviews is also additive information, that is, each review may evaluate one aspect of the product. Therefore, more reviews will increase the usefulness of the information than fewer reviews, which could increase the overall usefulness of the contributions (Constant et al. 1996). In other words, when reviews are very few, such information does not add value to consumer's judgment which in turn fails to impact on product sales. However, when the volume of reviews is high, it then becomes an important information source for consumer's to evaluate among products.

H3: Reviews have stronger impact on product sales when the volume is high as compared with when the volume is low.

1.3.2.2 Valence

For popular products, consumers may have a strong prior belief of the products. For example, there are numerous TV commercials, promotions, or critic reviews for a popular star's movies such as the Star Wars series. Consumers can easily obtain information of a popular product from other sources and form their own impressions of the product before reading the reviews. Therefore, as discussed above, since consumers' prior impressions are often hard to change, we expect that review impact on popular products would be small. However, for obscure products, since information is often limited, consumers may not hold strong prior impressions on the product as compared to popular products. Therefore, reviews can have greater impact on obscure products than popular products.

In particular, prior research shows that the impact of negative WOM on brand evaluations are likely to be reduced when prior positive brand impressions exist in consumers' memories (Herr et al. 1991). Therefore, a more popular or favorable product is expected to reduce the persuasiveness of negative WOM because impression-inconsistent information is typically deflected away from the product and discounted (Harvey and Weary 1984, Laczniak et al. 2001). In this regard, we expect that negative reviews will influence obscure products more than popular products.

H4: Review valence has a stronger impact on obscure product sales than popular products sales. In particular, negative reviews have stronger impact on obscure product sales than popular product sales, while positive reviews do not impact on the product sales of these two types differently.

1.3.2.3 Quality

Consumers' resources are limited in terms of their time and effort for selecting among products. Given their limited resources, consumers will not process all the reviews systematically but selectively or heuristically (Forman et al. 2008). This implies that not all reviews will have equal impact on consumers' decisions. Since reviews with high peer recognition (i.e. high helpfulness vote) signal high quality and reliability of the information, consumers may allocate more weight when they process the review information. Therefore, we expect that reviews with higher quality in terms of the helpfulness votes will receive more attention and affect more significantly on product sales than low quality reviews.

H5: Reviews with high helpfulness votes have a stronger impact on product sales than reviews with low or no helpfulness votes.

1.3.2.4 Position

Prior research has shown that the order of information displayed has a profound impact on consumers' behavior (Chen et al. 2006, Smith and Brynjolfsson 2001). Due to the degree of efforts required to systematically process hundreds of reviews and consumers' limited resources, they will give more attention to the reviews appear on the first page than the rest. Therefore, we hypothesize that reviews on the first page will have a stronger impact on product sales than the others.

H6: Reviews on the first page has a stronger impact on product sales than reviews on the other pages.

1.3.3 Reviewer, Product Type, and Product Sales

1.3.3.1 Reviewer Reputation

When reviewer chooses a product to write a review, there are several facts they will consider. First, since popular products usually attract more reviews, the competition for readers' attention is more intense than that of obscure products. As a result, it is relatively more difficult to get high peer recognition (i.e. helpful votes) for popular products' reviews than obscure products'. Second, because of the high volume of reviews in popular products, the marginal value or impact of each review is smaller than that for obscure products. Third, since potential buyers for popular products are more diversified than obscure product buyers, it increases the possibility of getting a negative vote which could discourage high ranking reviewers to contribute. Therefore, high ranking reviewers will most likely not put much effort in contributing to popular products' reviews and will prefer to review less popular products where they can have much stronger influence on readers' decisions.

H7a: High ranking reviewers will review more obscure books than popular products as compared to low ranking reviewers.

Reviewers with high reputations are perceived as a more credible information source than low reputation reviewers. As a result, consumers will give more weight to high ranking reviewers' reviews as compared to low ranking reviewers'. Hence, the impact of high ranking reviewers' reviews on product sales should be stronger than that of low ranking reviewers'.

H7b: High ranking reviewers' reviews have stronger impact on product sales than low ranking reviewers.

1.3.3.2 Reviewer Identity Disclosure

Since theory in social psychology and marketing suggests that the source of information has a direct impact on product evaluation, identified reviewers' reviews will be more persuasive than anonymous reviewers' reviews (Forman et al. 2008). We expect that identified reviewers should be more powerful than anonymous reviewers in affecting product sales.

H8: Identified reviewers will have stronger impact on product sales than anonymous reviewers.

Figure 2.2 summarizes the research framework of this study.

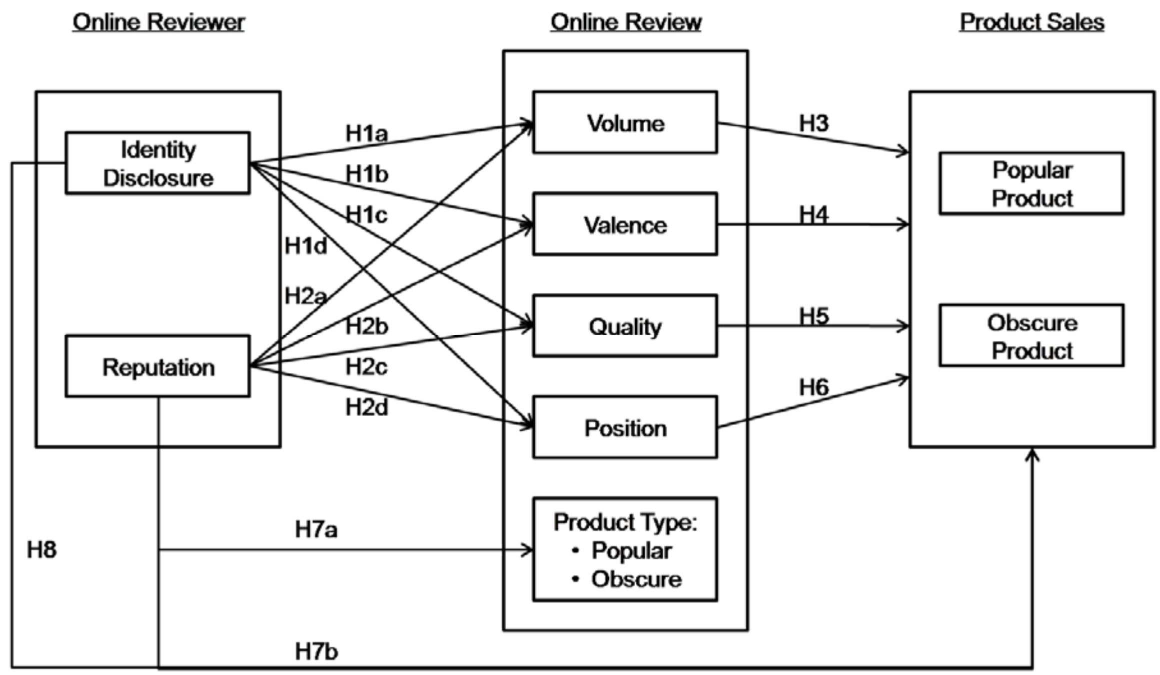

Figure 2.2. Research Framework

1.4 Empirical Study

1.4.1 Data

This study uses book reviews on Amazon.com. We select Amazon as it is the leading electronic retailer for books which represents 70% of the whole market transactions. It has also been chosen to study research questions in this context by other previous research (e.g. Chen et al. 2006, Forman et al. 2008, Li and Hitt 2008). Our sample will include all fictions released between October 1 and November 31 2008 which will contain about 1400 books. We choose fictions as it is one of the top book categories on Amazon which usually attract adequate reviews for our analysis. In addition, fiction is also among the categories which have a relatively large amount of new releases every month.

The data in our sample includes daily information on books, reviews, and reviewers. For books, we collect the book's daily price and sales rank which will be used as a proxy of its actual sales volume. For reviews, we collect the date when the review is posted, the reviewer's user name which could be a real name or a pen name, the review rating, and the helpfulness vote (this indicates how many readers find this review helpful). The helpfulness vote is collected daily. Based on the reviews, we then obtain the information from each reviewer's online profile on Amazon. This includes the reviewers' user name, the total number of reviews they have posted in history, and their reviewer rank on Amazon (Amazon ranks reviewers according to the number of views and the helpfulness vote of their reviews). Again, we track the daily changes of reviewer's profiles such as their ranks, the total number of reviews they have posted, and the total helpfulness votes they receive. Table 2.4 summarizes the data in our sample. One unique feature of our sample is that we collect all the information from the release date of the books. Therefore, we are able to observe the dynamic market reactions to the reviews. We plan to collect a two-month period for each book in the sample.

Table 2.4. **Data Summary**	
Subject	**Variable**
Book	Price
	Sales rank
	ISBN
	Format
	Publisher
	Pages
Review	Date posted
	Reviewer name
	Helpfulness vote
	Rating
Reviewer	Number of reviews posted in history
	Reviewer rank
	Total helpfulness vote

The detailed steps of data collection are presented in Figure 2.3. First, we download the upcoming book list from the advanced search function on Amazon to obtain the entire list of the upcoming books in October and November 2008. Then, we collect the corresponding book information from Amazon daily. Note that since Amazon allows consumers to preorder an upcoming book, we start collecting the book's sales rank and price one week prior to its releasing date. This information can help us to control for the initial awareness or popularity of the book and examine how reviews affect the follow-up sales. In addition, Amazon does not allow users to post reviews prior to the release date. Therefore, reviews can only impact on the sales after the book is released.

Meanwhile, we also collect the reviewers' information from each reviewer's personal page. Since reviewer rank, total number of reviews posted and number of helpful vote change periodically, we also capture daily information for reviewers.

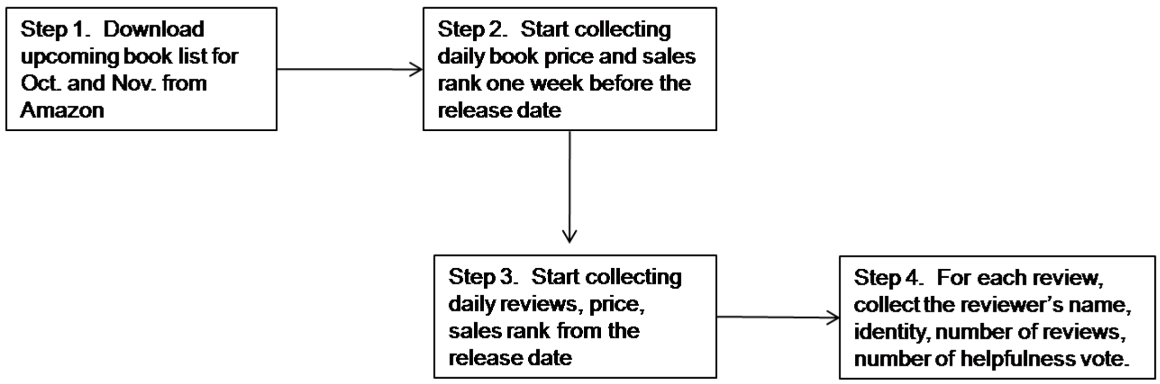

Figure 2.3. Data Collection Procedures

1.4.2 Methodology

1.4.2.1 Online Reviewer and Online Review

Hypothesis 1 suggests that online reviewer's identity disclosure decision would affect the reviews they write. To test each sub-hypothesis in terms of the four dimensions of online reviews, we use each review dimension as the dependent variable. *Volume* is measured as the number of reviews a reviewer *i* has posted. *Valence* is measured as the extreme nature of the rating of each review *j* of book *k*. The definition of valence here is similar to the variable

Equivocal in Forman et al. (2008). It takes value 1 to indicate an extreme rating which is either 5-, 4-, 2- or 1-star and 0 for a moderate rating which is 3-star rating. In addition, we also operationalize the valence by subtracting 3 from the normal review ratings. This sets the moderate rating 3 to be zero and the perceived negative ratings 1 and 2 to be -2 and -1. *Quality* is operationalized as the ratio of the helpful votes over the total votes[2] for each review *j* of book *k*. *Position* is measured as the time when the review *j* of book *k* is posted which is operationalized as the number of days elapse from the releasing date.

The independent variable, *Disclosure*, is a dummy variable indicating whether the reviewer *i disclosed* his or her real name. It takes value 1 for an identified reviewer and 0 for an anonymous reviewer. For H1b, we control for the sales effect for that book *k* as high sales usually associate with more positive rating of the reviews. For H1c, we control for the *Valence* of a review *j* as it may affect the perceived helpfulness of the review (Forman et al. 2008) and for the *ln(volume)* as more online reviews for one particular book *k* may reduce the number of votes on each individual review. Therefore, we test the following models:

$$H1a: \quad Volume_i = \alpha + \beta Disclosure_i + \varepsilon_i$$

$$H1b: \quad Valence_{jk} = \alpha + \beta Disclosure_i + \gamma ln(SalesRank_k) + \varepsilon_{jk}$$

$$H1c: \quad Quality_{jk} = \alpha + \beta Disclosure_i + \gamma_1 Valence_{jk} + \gamma_2 ln(Volume_k) + \varepsilon_{jk}$$

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[2] This operationalization has also been adopted in Forman et al. (2008) and Chen et al. (2006).

H1d: $Position_{jk} = \alpha + \beta Disclosure_i + \varepsilon_{jk}$

The parameter of interest is *β* which is expected to be significant and positive for the model of H1c and negative for all the other three models.

Models for testing hypothesis 2 take a similar form. We use the same measurements for the dependent variables as for H1 except for *Volume*. Since we measure the reviewers behavior after they achieved a certain level of reputation, we measure the *Volume* as the change in number of reviews from the day we started collecting the data rather than the total number of reviews reviewer *i* has ever posted. So *Volume* can also be interpreted as *ΔVolume*. The independent variable, *ln(ReviewerRank)*, is the natural log of the rank of each reviewer *i* on the day he or she posted the review. For similar reasons, we control for the sales effect for H2b, and the *Valence* and *ln(Volume)* for H2c.

H2a: $Volume_i = \alpha + \beta ln(ReviewerRank_i) + \varepsilon_i$

H2b: $Valence_{jk} = \alpha + \beta ln(ReviewerRank_i) + \gamma ln(SalesRank_k) + \varepsilon_{jk}$

H2c: $Quality_{jk} = \alpha + \beta ln(ReviewerRank_i) + \gamma_1 Valence_{jk} + \gamma_2 ln(Volume_k) + \varepsilon_{jk}$

H2d: $Position_{jk} = \alpha + \beta ln(ReviewerRank_i) + \varepsilon_{jk}$

Again, the parameter of interest is *β* which is expected to be significant and negative for all four models.

1.4.2.2 Online Review and Product Sales

Since H3 to H6 try to test the impact of online reviews on product sales, the dependent variable is the product's *ln(SalesRank)*. Using *ln(SalesRank*) as a linear proxy of actual sales has been adopted in various prior studies on measuring the relationship between online reviews and product sales (e.g. Chevalier and Mayzlin 2006, Forman et al. 2008).

For H3, we first split the sample into two subsets of the products, one with numerous reviews and the other with relatively few reviews. Then we define two independent variables to measure the impact of review ratings for different review volume on product sales, *RatingVolumeHigh* and *RatingVolumeLow*. These two variables measure the daily average of the ratings for books in two subsets. The objective is to compare the coefficient of these two variables and we expect the coefficient of *RatingVolumeHigh* to be significant and negative whereas the coefficient of *RatingVolumeLow* to be insignificant. We control for the *Price* of each book *k* and the days elapsed in day *t* from the releasing date, *DateElapsed*. The model for H3 is as follows.

$$\text{H3:}\quad ln(SalesRank_{kt}) = \alpha + \beta RatingVolumeHigh_{kt}\ (\text{or } RatingVolumeLow_{kt}) + \gamma_1 Price_{kt} + \gamma_2 ln(DateElapsed_{kt}) + \varepsilon_{kt}$$

Similarly, for H4, we split the sample into two subsets, one with high sales rank (obscure products) and the other with low sales rank (popular products). The independent variables are the daily average ratings for books in the two sets, *AvgRatingPop* and *AvgRatingObs*. To measure the impact of negative reviews on product sales, we include the number of 1-star reviews[3], *NegReview*. The control variables are *Price* and *DateElapsed.*

$$H4: \quad ln(SalesRank_{kt}) = \alpha + \beta_1 AvgRatingPop_{kt} \ (or \ AvgRatingObs_{kt}) + \beta_2 NegReview_{kt} + \gamma_1 Price_{kt} + \gamma_2 ln(DateElapsed_{kt}) + \varepsilon_{kt}$$

We compare the coefficient β_1 and β_2 for two subsets. β_1 of the popular product set is expected to be less significant and less negative than that of the obscure product set. β_2 is expected to be more significant and more positive for the obscure product set than for the popular product set.

The independent variable to test H5 is the average daily review rating of high quality reviews, *HighQualityRating*, where high quality review is defined as the review with high helpful vote ratio[4]. Another independent variable *TopPositionRating*, which is defined as the average rating of the top 10 reviews as shown in the first page, is used to test H6. The model for testing H5 and H6 is therefore:

$$H5 \ \& \ H6: \quad ln(SalesRank_{kt}) = \alpha + \beta_1 HighQualityRating_{kt} + \beta_2 TopPositionRating_{kt} + \gamma_1 Price_{kt} + \gamma_2 ln(DateElapsed_{kt}) + \varepsilon_{kt}$$

We expect the coefficient β_1 to be significant and negative and β_2 to be significant and positive.

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[3] We will also test the model with both 1- and 2-star reviews as negative reviews and compare the results with these different operationalizations.

[4] We will test different thresholds to determine the sensitivity of defining high quality reviews.

1.4.2.3 Reviewer, Product Type, and Product Sales

We define the percentage of high ranking reviewers for product *k*, *PercentTopReviewer*, as the measurement to capture the power and the preference of top reviewers. To test H7a, we use *ln(SalesRank)* as the dependent variable and *PercentTopReviewer* as the independent variable. Again, we control for the *Price* and the *DateElapsed*. Since H7a does not predict the impact of reviews on sales changes, we just need to test the model using data from the last day *T* which includes the most reviews for each product. Different from the previous models, the dependent variable, *ln(SalesRank)*, indicates the popularity of the product rather than a proxy of product sales. β is expected to be positive.

$$H7a: \ln(SalesRank_{kT}) = \alpha + \beta PercentTopReviewer_{kT} + \gamma_1 Price_{kT} + \gamma_2 \ln(DateElapsed_{kT}) + \varepsilon_{kT}$$

For H7b, the dependent variable is also *ln(SalesRank)*. However, it represents the transformation of product sales since we use all data in our sample. The independent variables are the average review ratings from high ranking reviewers, *AvgTopReviewer*, and average review ratings from low ranking reviewers, *AvgLowReviewer*. β_1 is expected to be significant and more negative than β_2 which indicates that the top reviewer has stronger impact on product sales. We test the following model for H7b.

$$H7b: \ln(SalesRank_{kt}) = \alpha + \beta_1 AvgTopReviewer_{kt} + \beta_2 AvgLowReviewer_{kt} + \gamma_1 Price_{kt} + \gamma_2 \ln(DateElapsed_{kt}) + \varepsilon_{kt}$$

The dependent variable for the model of H8 is also *ln(SalesRank)*. Different from the above model, we are interested in the association between independent variable *PercentIdentity*, which is defined as the percentage of identified reviews, and the *ln(SalesRank)*. To test H8, we estimate the following regression:

$$H8: \quad ln(SalesRank_{kt}) = \alpha + \beta PercentIdentity_{kt} + \gamma_1 Price_{kt} + \gamma_2 ln(DateElapsed_{kt}) + \gamma_3 AvgRating_{kt} + \varepsilon$$

The parameter of interest is β and should be significant and negative.

1.5 Preliminary Results

The collection of the complete data set for this study is still in progress. In this session, we report some preliminary findings using a much smaller sample we collected in September 2008 to show some initial results. This pilot sample contains the same variables as in the complete sample. However, it has much fewer books (128 books) and only covers one month. We obtain the book list for this pilot sample from the upcoming book list on Buy.com. Then we match the ISBNs of the books with that on Amazon to collect the information from Amazon. Other procedures of the data collection are the same as the steps described in the Data section. Due to the small size of the pilot sample, there are only 45 books which have reviews. Table 2.5 reports the descriptive statistics for the data in this pilot sample.

Table 2.5. **Descriptive Statistics for the Sample Data (N = 45 books)**					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Number of Reviews: The daily number of reviews per book	2315	8.00	11.13	0	44
ln(SalesRank): The daily natural log of sales rank per book	2211	8.74	3.29	2.56	15.26
Helpfulness Ratio: The number of helpful vote over total vote per review per day	1459	0.70	0.30	0	1
ln(Reviewer Rank): The natural log of the daily reviewer rank	1529	12.03	2.23	6.22	15.09
Identity Disclosure: 1 = Real name reviewer; 0 = Anonymous reviewer	2315	0.45	0.50	0	1

Because of the small number of reviews for each book (on average there are only 8 reviews for each book), we are not able to run the regression within each book. Therefore, we are not able to test hypotheses H3 to H8 which require between book comparisons. However, we can still get some preliminary results on the aggregate level for the first three hypotheses.

Table 2.6 shows the results by using the *Valence* as the dependent variable. We operationalized *Valence* in two ways. First, in the models of column (a), (b), and (c), we define *Valence* as either 1 or 0, *Valence(1/0)*, where 1 for a rating at 1, 2, 4, and 5, and 0 for a rating at 3. Thus, these models measure the effect of reviewer's identity disclosure information and reviewer rank on the extreme natural of the ratings. We find support for our H1b that anonymous reviewers tend to give more extreme ratings than identified reviewers as they are usually less self-regulated. However, high ranking reviewers are actually providing less extreme ratings than low ranking reviewers, i.e. the coefficient is positive and significant (β = 0.02). This implies that the opposite of our H2b is true.

Next, for models in the column (a'), (b'), and (c'), we define *Valence* as subtracting 3 from the normal 5-star ratings, *Valence(-3)*. Therefore, these models capture the impact of positive or negative nature of the ratings. The results show that anonymous reviewers are not only offering more extreme ratings than identified reviewers, but more positive ratings as well (β = -0.34 and -0.42). In other words, identified reviewers tend to be more critical than anonymous reviewers. Similarly, although top ranking reviewers provide less extreme ratings than low rank reviewers, top reviewers rate products more critically. They tend to give more negative ratings than low rank reviewers (β = -0.11).

Table 2.6.	**The Valence and The Reviewer Identity & Rank**					
Independent Variable	(a)	(a’)	(b)	(b’)	(c)	(c’)
Disclosure	-0.03** (0.011)	-0.34** (0.059)			-0.04** (0.014)	-0.42** (0.067)
ln(ReviewerRank)			0.02** (0.003)	-0.11** (0.016)	0.02** (0.003)	-0.11** (0.015)
ln(SalesRank)	0.01** (0.002)	0.10** (0.009)	0.002 (0.0021)	0.13** (0.011)	0.002 (0.0021)	0.12** (0.010)
Observations	1830	1830	1452	1452	1452	1452
R-squared	0.02	0.09	0.04	0.10	0.04	0.12
F	18.04**	95.15**	28.56**	81.18**	22.31**	68.65**
** and * denote significance at 1% and 5%						

Table 2.7 summarizes the results for testing H1c and H2c. The dependent variable is the percentage of helpful vote among the total vote. Interestingly, we find that identified reviews are actually rated as less helpful than anonymous reviews, which is opposite to our H1c. This result also contradicts the finding reported in Forman et al. (2008) where they found that reviews with identity disclosure information are more positively recognized by peers because of the credibility and community norm. We will be cautious of this finding when we analyze the complete sample. For reviewer’s ranking effect, our H2c is supported as the coefficient has the expected negative sign (β = -0.01 and -0.02). This means that top reviewers’ reviews are rated as more helpful than low ranking reviewers’.

The coefficients for the control variables also have the expected signs. We control for the extreme rating effect by using the dummy variable *Valence(1/0)* which is defined the same as above. As expected, extreme ratings will be rated as more helpful than moderate ratings since they are less ambiguous. We also control for the volume effect with *ln(Volume)*. The negative sign implies that with a large number of reviews for one product, the competition for readers' attention is also high. As a result, for product with a relatively large number of reviews, the helpful vote will be low for each individual reviews. All the results are significant at 1% level.

Table 2.7. **The Quality and The Reviewer Identity & Rank**

Independent Variable	(a)	(b)	(c)
Disclosure	-0.09** (0.015)		-0.11** (0.015)
ln(ReviewerRank)		-0.01** (0.003)	-0.02** (0.003)
Valence(1/0)	0.11** (0.028)	0.16** (0.029)	0.14** (0.028)
ln(Volume)	-0.11** (0.009)	-0.11** (0.009)	-0.12** (0.009)
Observations	1458	1326	1326
R-squared	0.14	0.14	0.17
F	78.50**	70.00**	67.04**

** and * denote significance at 1% and 5%

For hypotheses H1d and H2d, since the average number of reviews is only 8 (only 3 books have more than 10 reviews), testing these two hypotheses by using the early reviews are equivalence to using all reviews. Thus, we are unable to observe the difference between early reviews and late reviews. We will need a much larger sample to test these hypotheses.

1.6 Conclusion

In this study, we propose a framework to identify the relationships between reviewers' characteristics (identity disclosure and reputation) and their reviews and between four review dimensions and product sales of two types. We add to the literature on online review consequence by expanding the dimensions of online reviews. Specifically, we introduce two additional dimensions, namely the quality and the position.

Moreover, as the primary focus of the literature is on the consequence of reviews, there is a lack of understanding of the antecedence of reviews, the reviewer behaviors. We fill in this gap by associating the reviewer characteristics with the reviews they write. Our findings can help companies to better structure their marketing strategies so as to target the right reviewer easily.

Finally, this is the first study considers product type effects when examining the review influence. By separately measuring the impact of reviews on different product type, we are able to capture the role of online reviews in consumers' decision process more precisely.

Like other empirically studies, this study is not without limitations. First, we use data from one online review system. Those reviewers' behaviors may not be representative for the whole market. However, as Amazon is the leading online book sellers which occupies over 70% of the market share, our data should be nevertheless informative. Second, there may be seasonality effect in the book market which is not considered in this study. Since we use daily data within two months, we expect that the seasonality effect should be minimized in our analysis. Third, although our primary goal is to capture how reviewers provide reviews and how consumers use reviews to make purchasing decisions, our data does not directly observe such reviewer and consumer behaviors. For example, we are unable to observe what reviews a consumer reads before he or she purchase a product and how a reviewer decides which product to review. Future research is required to further explore these individual level interactions which are usually unobservable through online data.

CHAPTER 3: THE TEMPORAL PATTERN OF ONLINE REVIEWS

2.1 Introduction

Word-of-mouth (WOM) has been widely considered as an important driver of product sales. Consumers' WOM is one important source for collecting information on the quality of the product before purchasing. With the advent of online review systems, online WOM, such as online reviews, starts play an important role in affecting consumers' buying decisions (Chevalier and Mayzlin 2006). Thus, the majority of the studies in online review literature focused on identifying the impact of online WOM on consumer purchases and on product sales (e.g. Chevalier and Mayzlin 2006, Dellarocas 2003b, Dellarocas and Narayan 2005, Liu 2006, Reinstein and Snyder 2005, Zhang et al. 2004, Zhang and Dellarocas 2006).

There are two major measurements that have been used to assess the effectiveness of online WOM, (1) the *volume* and (2) the *valence*. Volume measures the number of online reviews, and has been used to see the impact of the amount of online reviews on product sales (e.g. Liu 2006). A high volume of online WOM can increase the awareness of a product among potential buyers and therefore increase product sales (Liu 2006). Valence measures the positive or negative nature of online review ratings. Unlike volume, the impact from the valence of online reviews is mixed. For example, using user reviews on Yahoo! Movies, Liu (2006) found that the valence of previous movie reviews does not have significant impact on later weekly box office revenues. However, Zhang and Dellarocas (2006) found a significant relationship between the valence of online reviews and box office revenues.

While the previous research tries to establish an association between online reviews and product sales, few studies investigate the temporal pattern of online reviews. There are at least three reasons why understanding the temporal pattern of online reviews is important. First, since reviews have been shown to have significant impact on product sales, firms need to understand how reviews evolve over time so as to adjust their strategies accordingly. For example, if the follow-up reviews are merely restating the early reviews, the usefulness of the follow-up reviews would be marginal as compared to the early reviews. Therefore, the magnitude of the impact from the reviews in different time periods should be different. If the follow-up reviews do have different attributes from the early reviews, firms have to treat reviews differently and construct different strategies depending on the time stage of their products' life cycle.

Second, reviews reflect customers' evaluation of the product. If using online reviews can help potential buyers to make better decisions, the late reviews should be on average more positive than the early reviews. Studying the temporal pattern of the reviews can help researchers and companies to assess the effectiveness of the review systems. If reviews merely increase the awareness of the product rather than convincing consumers to try the product (e.g. Duan et al. 2008, Liu 2006), investing in improving review systems would not be necessary. However, if consumers do benefit from the reviews, then developing appropriate schemes to improve review quality could be a profitable investment.

Third, as a reviewer, writing reviews requires time and effort. However, since usually the number of reviews for some popular product is large, readers most likely do not read each review systematically due to their limited time and attention. To facilitate potential consumers getting useful information, review sites usually offer helpful votes for each review and sort reviews by helpful votes when displaying reviews[5]. As a result, reviewers would compete for helpful votes in order to be displayed in the top place. This behavior would be observed if reputation, peer recognition and attention are the main incentives for them to contribute voluntarily as found in other similar context (e.g. Jeppesen and Frederiksen 2006, Lerner and Tirole 2002). Otherwise, if writing reviews is just a hobby and is to enjoy the process itself, the current helpful vote and reviewer ranking scheme would fail to motivate reviewers to offer high quality reviews. This incentive is similar to the “warm-glow” theory in public goods literature, which identifies one of the incentives of contributing to a public good is feeling good about the action and is independent from the amount of money the other

[5] For example, the default display on Amazon is by helpful votes (i.e. the most helpful review first).

parties benefit (Andreoni 1990). Therefore, it is interesting to investigate reviewers' different actions of writing reviews at different time periods. Their actions can directly affect the quality of their reviews and thus the impact of the reviews on sales. Although we do not directly test various reviewers' incentives, our results can indirectly infer their motivations of writing reviews. As to our knowledge, no previous studies have examined the reviewers' actions and how they contribute to the review systems.

In this study, we try to empirically address the following research questions. (1) What is the temporal pattern of online reviews? We try to identify the trend of online reviews in terms of the review ratings and compare the quality of reviews at different time periods so as to understand the effect of consumer heterogeneity on the reviews and whether reviews can help improve consumers' decisions. (2) What are the characteristics of the textual of online reviews in different time periods? We then apply text mining technique to investigate the content of reviews at different time periods. Specifically, we try to understand whether late reviews provide different perspectives of the product from early reviews or just restate the early reviews and how reviews compete for readers' attention and obtain helpfulness votes during different time periods. Studying the second question allows us to infer reviewers' incentives of writing reviews and their actions at various time stages.

We begin by reviewing the related study in the literature on the impact of online reviews. Next, we present our research hypotheses. Then, we discuss the data and methodology we will use to test the hypotheses. Finally, we conclude with the expected contributions.

2.2 Literature Review

As mentioned earlier, the majority of previous studies have focused on measuring the effectiveness of online WOM in promoting product sales (e.g. Chevalier and Mayzlin 2006, Liu 2006, Zhang and Dellarocas 2006, Zhang et al. 2004). However, few studies consider the overall pattern of online reviews. In the online review literature, there are two major measurements of the effectiveness of online reviews: the *volume* and the *valence*.

With a high volume of online reviews, the product awareness can be enhanced. In other words, the probability of a potential buyer being aware of the product is higher with a greater number of online reviews. Therefore, the high volume of online reviews enlarges the pool of potential buyers and thus can generate high product sales (Liu 2006).

However, the valence of online reviews, which is typically measured as the average ratings of online reviews, might only convey the attitudes of previous purchasers on average, which may or may not be sufficient to convince future buyers to purchase the product. As a result, studies concluded differently regarding the impact of the valence on product sales. For example, using user reviews on Yahoo! Movies, Liu (2006) and Duan et al. (2008) found that the valence of previous movie reviews does not have significant impact on later box office revenues. However, Zhang and Dellarocas (2006) found a significant relationship between online review valence and sales where they reported a 1-point increase in the review ratings on Yahoo! Movies user reviews is associated with an increase in box office revenues in the range of 4-10%.

Recently, some researchers noticed other important attributes of online reviews which could potentially affect consumers' purchase decisions and product sales, the quality and the source of online reviews. The quality of the reviews is often measured as the ratio of the helpful votes to total votes for each review. This ratio indicates the usefulness and the credibility of the information as perceived by the readers (e.g. Chen et al. 2006). A high ratio of helpfulness indicates higher quality of the review which is perceived as more useful information. Reviews with a high ratio of helpfulness are more persuasive than other reviews to entice potential buyers to try the product. Therefore, reviews with high helpfulness votes are positively associated with the subsequent product sales (Chen et al. 2006). Forman et al. (2008) and Chen et al. (2006) used the online helpfulness votes as an indicator of the review quality and found that consumers do pay attention to the quality of the reviews in addition to just the volume or the valence.

Studies also showed that the source of online reviews includes reviewers' identity information also has an impact on potential buyers' decisions (Forman et al. 2008). For example, Forman et al. (2008) showed that reviews with reviewers' identity information are perceived to be more helpful than reviews provided by anonymous reviewers and thus have stronger impact on product sales. These findings are consistent with the theory in social psychology literature that the source characteristics of the information can affect individuals' judgment (Chaiken 1980, Chaiken 1987).

Different from the above studies which looked at the impact from the different attributes of online reviews, some researchers began to consider the pattern of the reviews. For example, Hu et al. (2007) examined the aggregate pattern of online reviews and found that online reviews ratings reveal either a U- or J-shaped pattern. They showed that most online reviews are either extremely positive (e.g. 5 stars in a 5-star review system) or extremely negative (e.g. 1 star). Few reviews have moderate ratings (e.g. 3 stars). However, they aggregated review patterns based on the total number of ratings rather than the time when the review is posted. Since only the current reviews can affect consumers' and late reviewers' choices on which product to buy and how to provide reviews, ignoring the time dimension will lose the interesting interactions between consumers, reviews, and reviewers. In this study, we try to capture such interactions in the time dimension.

Li and Hitt (2008) also mentioned review patterns. They compared the early reviews with late reviews and tried to identify the difference in ratings between reviews at different time window. They argued that due to consumer heterogeneity and self-selection bias, early reviews could be systematically different from late reviews which may deliver biased opinions on the product. They reported evidence showing that for some books early review ratings could be systematically higher or lower than the late reviews. Thus, they concluded that early review bias exists and could potentially reduce future consumer surplus.

However, their findings can only infer the existence of early review bias rather than directly capture the impact of such reviews bias. We use the review quality indicator, the helpfulness votes, to directly capture the consumer heterogeneity effect on review ratings. In addition, we argue that consumers can correct for the early review bias through the helpfulness votes, which is not considered in their study. Moreover, different from our study, their focus is still on the rating *per se*, not the content. We examine both ratings and content of online reviews so as to obtain a complete picture of how online reviews evolve over time.

In this study, we first try to investigate the change in review ratings over time and identify the timeline trend of the review ratings. Next, we consider the content of each review and try to find the characteristics of the review content so as to discover the actions taken by the reviewers during different time periods. Finally, we cluster the reviews based on the keywords and identify the powerful pattern of reviews which influence product sales stronger than other patterns. When capturing the temporal pattern of online reviews, we aim to test the hypotheses presented in the following section.

2.3 Research Hypotheses

2.3.1 Temporal Pattern of Review Ratings

One of the major objectives of allowing consumers to post online reviews is to reduce the uncertainty of the quality of a particular product and improve future buyers' satisfaction. If potential buyers use the reviews to guide their purchase and benefit from the review information, future buyers would be more satisfied than early buyers as the uncertainty is lower with relatively more complete information in the late stage. However, Li and Hitt (2008) pointed out that the early buyers can be a unique group of consumers whose tastes or opinions may be systematically different from the late majority's. Therefore, early buyers' reviews can mislead future buyers and reduce their surplus. Consistent with their argument, they found that for certain products, review ratings experience an undershooting period after the early stage, which they used as an evidence of the existence of early review bias. After that period, the ratings then go back to the normal average level. Thus, they concluded that early review bias exists and consumers can not correct for such bias and suffer from those biased reviews.

However, with the advent of IT, consumers have the opportunity to rate the helpfulness of the reviews. This function offers information on the quality and the credibility of each review. If early reviews are biased reviews, they should be rated as less helpful than the late reviews. However, if there is no self-selection bias, the early reviews should not be less helpful than the late reviews.

H1a: (Self-Selection Bias) Early reviews are rated as less helpful than late reviews.

H1b: (No Self-Selection Bias) Early reviews are not rated as less helpful than late reviews.

In addition, if consumers do pay attention to the helpful vote or the helpful vote can reflect the quality of the reviews, the effect from early review bias can be greatly reduced or even removed. In other words, consumers should be able to self-correct for early review bias by utilizing the helpful vote and make a better decision. Therefore, late consumers should be more satisfied than early consumers. The review ratings should not experience an undershooting period, but gradually improving over time.

H2: If consumers can correct for early review bias, reviews should gradually increasing with no undershooting period.

2.3.2 Temporal Pattern of Review Content

Since the distribution of review ratings is typically bimodal (Hu et al. 2006), the average ratings may not convey useful information regarding the quality of the product. In such case, consumers have to read a certain amount of the review content so as to figure out which positive or negative part of the product is of their interest. For companies, they can use the content of reviews to identify which feature of the product drives or diminishes the sales. However, only a few studies have discussed the impact of review content in addition to the numerical aspects of reviews such as the volume and the valence (e.g. Ghose and Ipeirotis 2007, Ghose and Ipeirotis 2008). Ghose and Ipeirotis (2008) investigated the informativeness, subjectivity and readability of online reviews and try to associate these aspects with the perceived helpfulness and the subsequent impact on product sales. While their goal is to identify the economic impact of review content, we try to identify the temporal pattern of the content so as to understand how reviewers compete for attentions in different time periods.

Reviewers usually devote substantial time and effort to write reviews without any monetary return. In a similar context of open source software development, studies have shown that peer recognition and reputation are the major incentives for the developer to contribute voluntarily (e.g. Lerner and Tirole 2002). If online reviewers are motivated by peer recognition or online reputation, they should be careful about the reviews they provide in order to maintain or enhance their reputation and gain more positive peer recognition (Forman et al. 2008). In other words, reviewers would not write a review randomly. They would form some strategies to attract more attention to their reviews and gain more helpful votes.

However, readers may only be able to read the top several reviews such as reviews on the first page due to their resource constraint. Reviews at the bottom will be less likely to influence or help consumers to make decisions than top reviews (Chen et al. 2007). In other words, reviews at the bottom will fail to attract enough attention and gain helpful votes. Consequently, for early reviews, since there is little competition among reviews, reviewers do not need to offer distinct reviews and can attract attention easily. However, for late reviews, since the competition for attention is more severe than the early period, reviewers have to provide unique perspectives of the product from the previous reviews rather than merely restate the facts so as to be perceived as helpful. These unique perspectives may include evaluations on additional features of the product and using different keywords.

H3a: Late reviews contain more distinct perspectives of the product than early reviews do.

In addition, since there is more information available at the late stage than the early stage, late reviews should be able to provide more complete information than the early reviews. In other words, late reviews will have more features than early reviews.

H3b: Late reviews contain more complete features of the product than early reviews do.

In addition, since more extreme or subjective reviews usually provide direct recommendations of the product than moderate reviews, extreme and subjective reviews are more informativeness and thus are voted as more helpful (Chen et al. 2007, Ghose and Ipeirotis 2008). In order to provide more information and attract more helpful votes, late reviewers will tend to offer more subjective reviews than the early reviewers. We define a review as a subjective review if it evaluates the features of a product which are different from those in the official product descriptions.

H4: Late reviews are more subjective than early reviews.

2.4 Data and Methodology

We will use book reviews from Amazon.com to test our hypotheses. Our data includes all the online reviews for the books in our sample from their release date to the end of our data collection period (a two month period). Table 3.1 shows the details of the data we will collect. For the books, we collect the price, the daily sales rank, the unique ISBN, the format, the publisher, and the pages. For each review, we collect the date the review posted, the reviewer ID and whether it is a real name ID, the daily helpful votes, the numerical rating, and the content of the review. Further, for each review, we collect the information of the corresponding reviewer. This includes the reviewer daily rank, the total number of reviews he or she has posted in history, and the overall helpful vote the reviewer receives.

Table 3.1. Data Summary	
Subject	**Variable**
Book	Price
	Sales rank
	ISBN
	Format
	Publisher
	Pages
Review	Date posted
	Reviewer name
	Helpful vote
	Rating
	Review content
Reviewer	Reviewer rank
	Total number of reviews
	Overall helpful vote

To test the temporal pattern of the review content, we will use text mining technique. First, we will obtain two training sets, one set with the objective feature of the product from the product descriptions and the other set with the subjective descriptions from randomly selected reviews. Next, we will calculate the subjectivity score for each review using the similar method as introduced in Ghose and Ipeirotis (2008). To determine whether late reviews mention a unique perspective, we will compare the keywords from the late reviews with the early reviews. We can also determine the similarity between early reviews and late reviews by clustering reviews with similar patterns and calculate the distance score.

2.5 Conclusion

This study examines the temporal pattern of online reviews so as to infer reviewers' actions at different time periods. It is among the few studies in the literature which focus on the pattern of online reviews. Our results can help researchers to obtain a complete picture of how online reviews evolve over time. More importantly, we consider not only the numerical ratings but also the content of reviews at the same time. It is important to consider the content of reviews as it represents the major part of reviewers' contributions. However, only a few studies start considering this important part. These findings can complement previous findings on the impact of review ratings. Moreover, we will try to discover the best time and pattern of reviews to attract the most attention among potential buyers. This result can guide reviewers' actions and help companies to predict the impact of the reviews early on.

CHAPTER 4. CONCLUSION

Based on the theories of anonymity, online reputation, information processing, and consumers' decision making, we propose two studies to empirically examine the relationships between online reviewers, reviews, and product sales, and the temporal pattern of online reviews. Specifically, for study 1, we try to capture the reviewer's actions on how to provide reviews and the dynamic impact of reviews on product sales for popular products and obscure products. In study 2, we offer a measurement to directly measure the existence of early review bias and whether consumers correct for such bias when making a decision. Furthermore, we contrast the characteristics of the early reviews with late reviews in terms of the features mentioned and the keywords used in the review content. Therefore, this dissertation proposal illustrates the strategic implications on how reviewers compete for potential buyers' attentions and how reviews influence product sales across product types.

Our findings can yield several interesting managerial implications. First, we show reviewers' actions to gain reputation and attentions in an online community which can be applied to other emerging Web 2.0 applications such as Facebook, or Myspace. Our results can be used to guide system developers to improve the current review systems so as to produce more useful reviews and better motivate reviewers. Second, since online reviews significantly affect consumers' purchasing decisions, understanding how reviews form and change over time can help managers to better predict the impact of reviews and utilize such impact to boost their product sales. Third, the review content analysis helps practitioners and researchers to understand how consumers process review information so that companies can focus on reviews with certain patterns.

Future research in this domain may want to use lab experiments to directly observe reviewers' strategic actions and consumers' decisions so as to verify the findings of these studies.

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Appendix A Reviewer Identity Examples

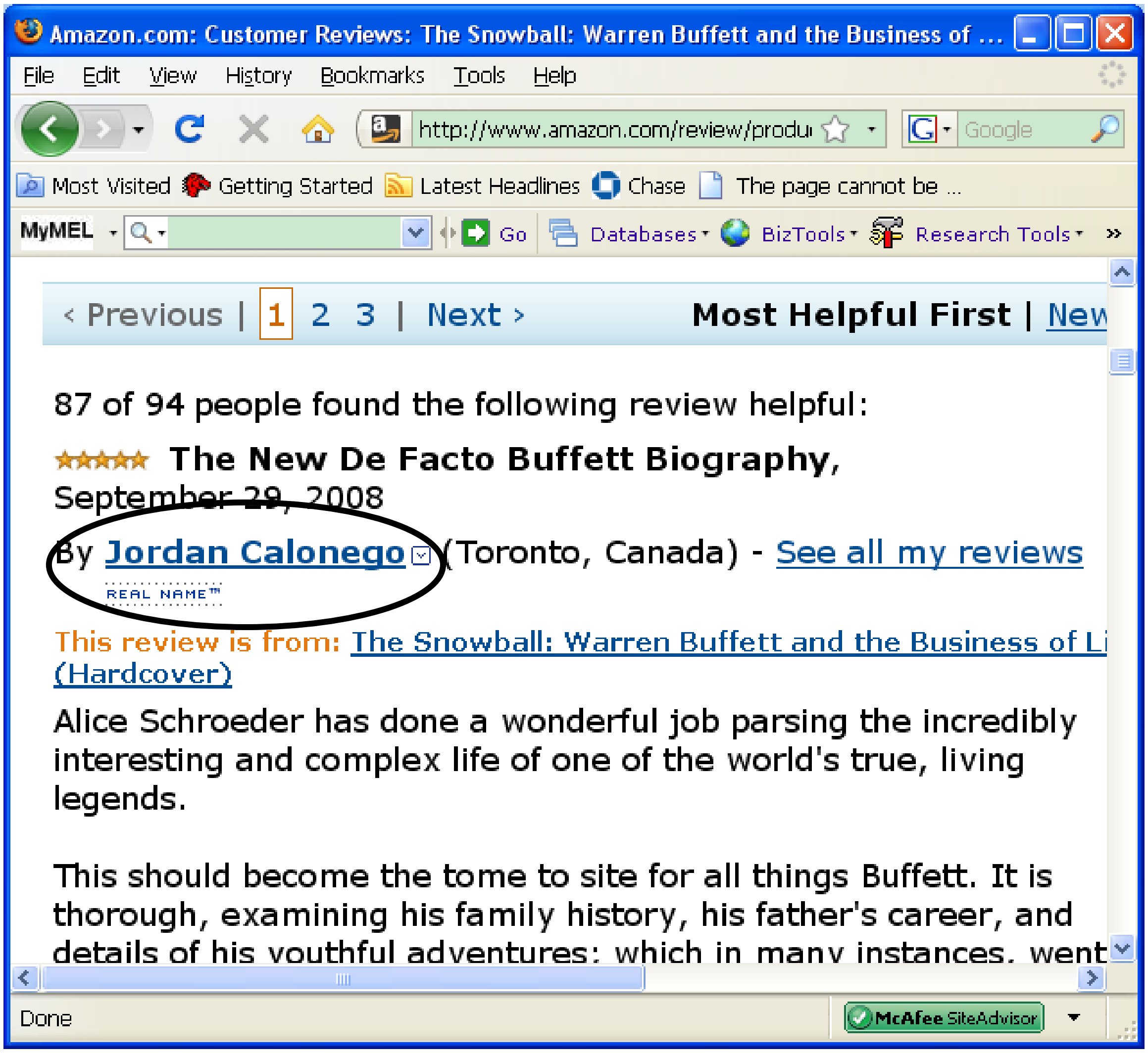

Figure A.1. Reviewer with Real Name Identity

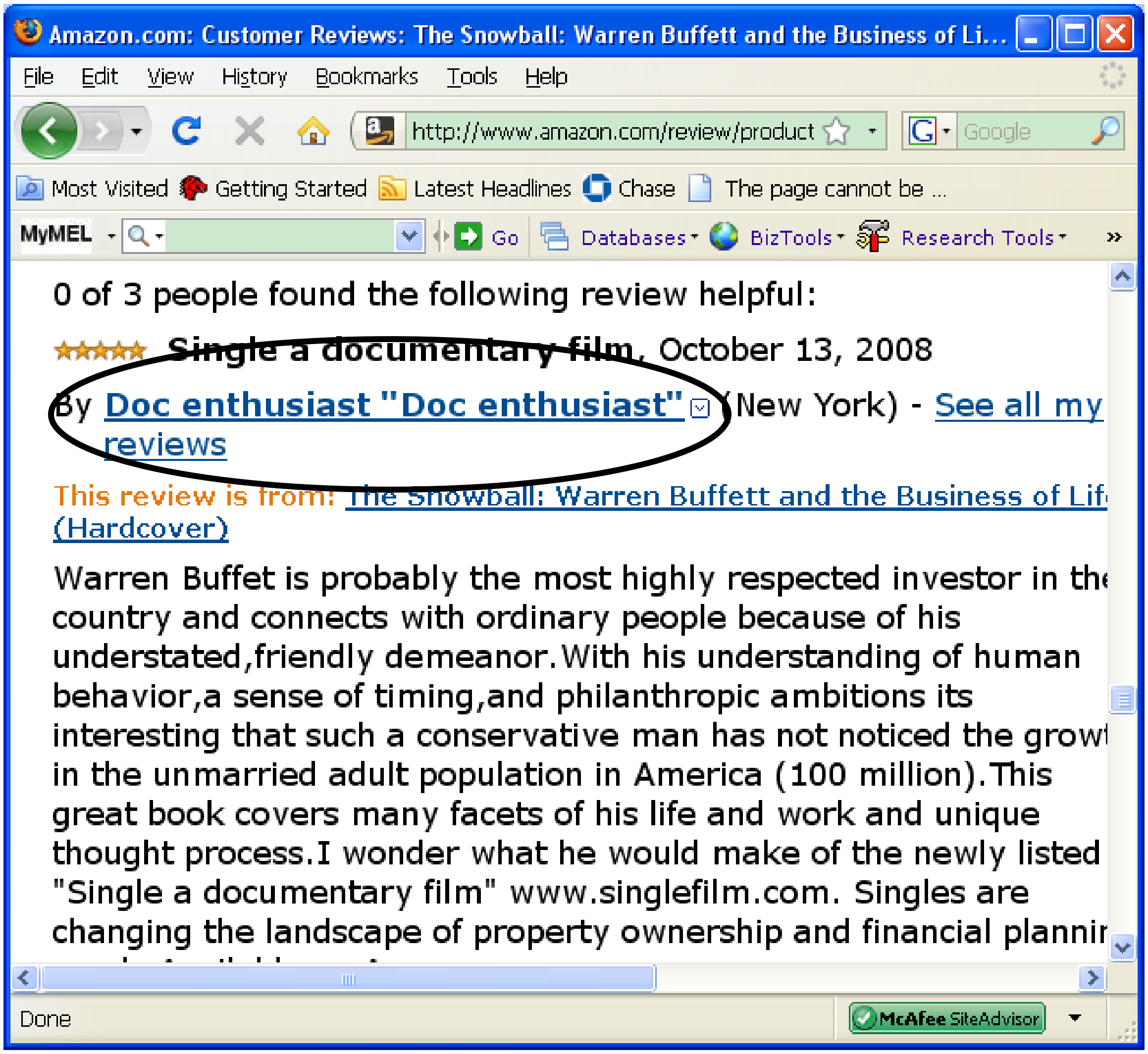

Figure A.2. Reviewer with Anonymous Name

Appendix B A sample review page on Amazon.com

Figure B.1. Helpfulness Vote on Amazon.com