IOSR Journal of Business and Management (IOSR-JBM)
e-ISSN: 2278-487X, p-ISSN: 2319-7668. Volume 18, Issue 11. Ver. II (November. 2016), PP 84-89
www.iosrjournals.org

The Role of Recent Versus Established Seller Reputation Ratings in Predicting Price Dispersion

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Abstract: *When evaluating sellers in an online marketplace, consumers often have information concerning the seller's quality broken down for them by the marketplace in the form of buyer created reputation scores, which indicate levels of customer satisfaction with the seller. Consumers can view any seller's reputation over their lifetime, in the past year, as well as recent as the past 30 days. Previous research has found that long-term, yearly scores are effective in predicting price dispersion, which is the variation in the prices that sellers charge for products. However, few studies have analyzed recent seller reputation scores such as those in past month. The goal of this research is to determine if recent seller reputation scores are indeed effective in predicting prices that sellers charge and to compare the effect that recent online seller reputation scores have on predicting price dispersion as compared to longer-term reputation scores.*

Keywords: *Internet Marketing, Internet Pricing, Online Reviews, Price Dispersion*

I. Introduction

The Internet has dramatically lowered the costs of organizing markets. This has led to a tremendous growth in online markets, however the Internet also brings with it anonymity and extensive potential for abuse. Now buyers are placed in situations where they are engaging in transactions with sellers with whom they have little or no previous interaction with. This simple fact introduces risk to traders. Consumers who purchase goods may be faced with situations where sellers may not deliver the item, deliver the incorrect item, or not ship their purchase within the specified time period [1].

One of the most common means for both auction sites such as EBay and retail commerce sites such as Amazon mitigate these risks is to maintain feedback mechanisms. Feedback mechanisms are very similar conceptually to word of mouth networks and are used as a measure of the reputation of the seller to buyers. This reputation is created through feedback by consumers who simply offer their advice to others based on their previous experiences with sellers. However, there are some fundamental differences between feedback mechanisms and traditional word of mouth networks, the most prominent being that online feedback mechanisms boast unprecedented scale due to the prevalence of the Internet [2].

Previous research concerning online price dispersion has thoroughly examined the role of seller reputation ratings [3][4][5][6][7][8][9][10][11][12][13]. These studies have often analyzed seller aggregate ratings over either a lifetime or over a year. This approach yields numerous advantages. Critically, there is the advantage of high sample size, which comes with it greater statistical reliability and a more holistic overview of a seller's performance. However, this information is not all that is available to consumers and may not be all that impact their decision to purchase the product or the price that sellers are willing to pay.

On the current dominant retail and auction websites (Amazon.com and Ebay.com, respectively), there is information concerning not just the "overall" or "yearly" performance of sellers, but also the recent (past 30 days) performance of a seller [14]. Analyzing the last 30 days only of a seller's performance has the disadvantage of low sample size relative to yearly reputation, however it also offers insight into their recent performance to indicate the latest trends into their behavior. Considering the fact that there are sellers with high lifetime and yearly ratings, yet relatively poor recent ratings and vice versa, there remains a question as to which is more relevant in the mind of the consumer and if those prices are reflective of any recent changes made by the seller that could explain the prices that they charge. This research seeks to identify if seller prices are correlated with their recent (30 day) reputation.

II. Hypothesis Development

It has been found that well known retailers have higher prices on average than lesser known retailers. However, at times, these well-known retailers have lower prices for selected products. Such varied pricing by these large retailers results in price dispersion [15]. Other researchers have presented studies which seek to explain how consumers make sense of such a large quantity of information when consumers make a purchase

[16]. Cohen identified the distortion of information function which states that, when making purchasing decisions, consumers will analyze the increasing number of choices that they are presented with and make a choice which will maximize their individual utility, but only up to a certain threshold. When given a number of choices beyond this threshold, consumers will then begin to use heuristics such as service quality or brand name to make a selection. This is similar conceptually to recent work concerning price dispersion which shows that the high number of sellers on the web overloads consumers with information, which makes their purchasing decision more difficult [17]. The apparent lack of well-established brand names, high number of sellers, and the focus on retailer quality metrics such as the reputation system is something that makes the Amazon.com marketplace such an interesting market to analyze and will likely result in a strong relationship between seller reputation and price.

It is crucial for retailers without well-known brand names to establish a reputation. Some authors believe that reputation is even more important online than in traditional retail stores [18]. Reputation itself has numerous dimensions, but one of the most prominent on the Amazon.com Marketplace as well as numerous sites across the web are customer generated seller feedback scores also known as reputation systems. Before the impact of mass communications, communities relied on word of mouth as the primary enabler of economic and social activity, and many aspects of social and economic life still do so today [19]. The Amazon.com reputation mechanism which allows customers to rate sellers is defined as a reputation system. Reputation systems collect information on the past behavior of a seller, and make that information available for other consumers to view. Primarily, these systems inform buyers about whether or not a seller is trustworthy [20]. Reputation systems are a form of word of mouth at a dramatically increased scale. They allow for the collection of comments for users of a commerce website. These comments are collected to form a user's feedback profile which essentially creates a public record of a user's performance in prior transactions. These systems can be in place for both buyers and sellers, as is common for EBay, or they could be strictly for sellers only, as is the case for Amazon and most online retail sites [1].

The past reputation of the seller can act as a mechanism by which information about the current behavior of the seller can be transmitted to buyers. In such a setting a seller's reputation may well reduce information asymmetries and allow the market to function efficiently. Theoretical models have typically generated a positive effect between the reputation of the seller and the price, in large part because the seller's reputation is a proxy for quality characteristics that are unobserved prior to the transaction [21]. These feedback mechanisms become a means from which an unknown seller can differentiate themselves from others by consistently delivering on promises and establishing a record of honest transactions. In addition, if sellers could indeed charge a higher prices by having higher feedback ratings, then they are given an incentive to deliver solid performance [1].

Due to the fact that reputation scores are well established in previous research as being strong predictors of price and the reputation mechanism is so prevalent on Amazon.com, it is expected that reputation scores will be able to predict price dispersion whether they are recent or established. However, due to the higher stability of the established scores, it is expected that they will have a greater predictive effect on prices. Hence, the following hypotheses:

Hypothesis 1: *Established reputation scores will be able to explain variation in prices*
Hypothesis 2: *Recent reputation scores will be able to explain variation in prices*
Hypothesis 3: *Established reputation scores will explain more variation in prices than recent reputation scores*

III. Methodology

It has been established that both service quality and reputation are very important to online retailers. Amazon.com's marketplace boasts numerous dimensions of reputation. Buyers may view star ratings as well as the percent of negative reviews, positive reviews and neutral reviews in the past 30 days, 90 days, year, or over the sellers' lifetime. An example of the ratings system employed in the Amazon.com marketplace is offered below in fig. 1:

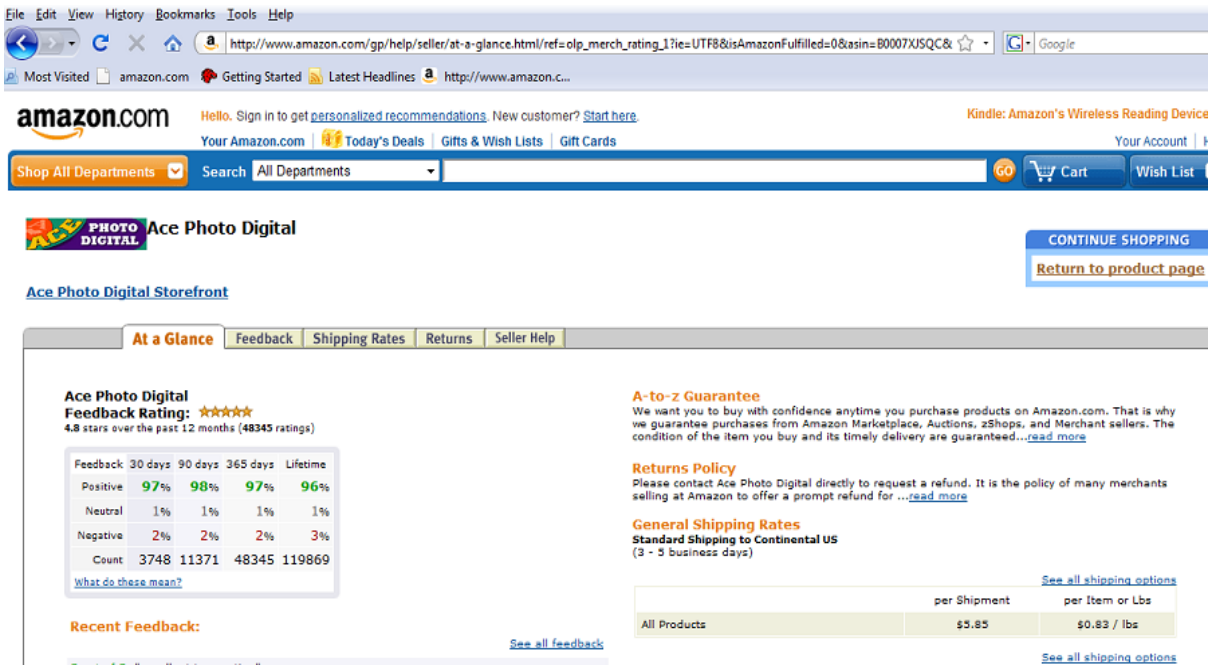

Figure 1 – Amazon.com Marketplace Reputation System (Source: Amazon.com 2015)

As can be seen in fig. 1, there are numerous dimensions of reputation in the Amazon Marketplace. Scores are offered for a seller's lifetime, as well as the past 365, 90 days and 30 days. However, for the purposes of this study the year (365 day) scores and 30 day scores will remain the focus. A scoring mechanism was used to determine overall reputation score. This is necessary due to the percentage format of reputation. For example, a seller with a positive score of 80 could have a negative score of 20 while another seller with a positive score of 80 could boast a neutral score of zero. By placing neutral, positive, and negative scores as separate independent variables in a regression, they are all treated the same even though there are stark differences among the sellers. Hence a simple scoring mechanism was employed to create a single variable for each seller that takes into account positive, neutral and negative scores. For each percent positive the score increases by one, and for each percent positive, the score decreases by one, and are counted as zero.This creates a range of overall reputation scores from -100 to 100, which allows for a scoring mechanism that encapsulates all aspects of the year reputation score. Sometimes due to the rounding mechanism of Amazon.com, scores are not exactly 100 (the minimum is 97 and maximum is 103). In order to ensure that this did not affect the data, all total percentages and their components were normalized to 100.

There are a wide variety of products sold on the amazon market place making the choice of products to test difficult. However, as noted by researchers of price dispersion, electronic products are commonly studied due to the fact that they have been established in previous research[11][17][22]. Since this is a study focused on an online market which has not yet been researched thoroughly, and is based on previous price dispersion studies, it would be best to use products that have been already well established. Hence, this paper focuses on consumer electronics of varying types.

There are differing methods of researching price dispersion. Some authors have opted to analyze numerous types of heterogeneous offerings of a product using hedonic regression to control for differences in the product or service [22]. However, if not all differences are accounted for, then inaccurate results can be obtained [13]. These studies generally obtain price quotes concerning numerous products from a relatively small, randomly selected group of sellers. Another approach used in price dispersion studies is the selection of a single product in a category and obtaining a relatively large sample of sellers of that product. Baylis and Perloff analyzed two distinct products, an Olympus C-2000Z digital camera and a Hewlett-Packard 6300 flatbed scanner and used traditional regression to determine the effect of service factors on dispersion [6]. This approach is also acceptable since it has been noted that by drawing the data from an online source, price comparisons of identical products instead of similar but somewhat differentiated products. This is something that increases the validity of price dispersion research [22].This study will employ the method of selecting single products in each category. By employing this method, information can be obtained from every seller in the marketplace that is offering that specific product. Table 1 below identifies the products that were selected for analysis:

Table 1. Products and Product Categories Analyzed

Product Category	Specific Product
CD Player	COBY MP-CD521 Personal MP3/CD Player with 120 Second Anti-Skip Protection
Memory Stick	Sony MSMT4G 4GB Memory Stick PRO Duo
GPS	Garmin nüvi 255 3.5-Inch Portable GPS Navigator
Portable DVD Player	Audiovox VE927 9-Inch LCD Drop-Down TV with Built-In DVD Player and Clock Radio
Router	D-Link Ethernet Broadband Router EBR-2310
Digital Camera	Canon Digital Rebel XSi 12.2 MP Digital SLR Camera with EF-S 18-55mm f/3.5-5.6 IS Lens (Black)
Printer	Canon MP480 All-in-One Photo Printer
Mouse	Logitech 931690-0403 VX Revolution Cordless Laser Mouse for Notebooks (Black)
Universal Remote	DirecTV RC64 Universal Remote Control
Headphones	Sennheiser HD201 Headphones

Specific products were chosen for analysis by following this process: going to amazon.com, searching for a product in a product category, analyzing the search results to see the number of sellers offering the product in new condition, dismissing the product if there are less than 50 sellers offering that product in new condition, removing the offering from amazon.com, and removing sellers with no reputation scores. Offerings from Amazon.com had to be removed from analysis due to the fact Amazon is not comparable to other sellers for the following reasons: it is the site which moderates the marketplace in addition to being a seller on it, free shipping options are given if consumer basket size price is greater than 35 dollars, and Amazon.com has no ratings system for itself. Additionally, sellers with no customer ratings were removed since those without ratings lack any reputation scores, and it is expected that reputation scores will be a significant predictor of price dispersion.

After data was collected, seller profiles were examined to collect the specific information required for analysis. A description of the variables tested in analysis is offered in table 2 below:

Table 2. Variables Tested

Independent Variable	Description
Reputation Score	Raw Reputation score using determined mechanism
Reputation85to100	Dummy variable - indicates if reputation score was between 85 and 100
Reputation85to100int	Interaction between above two variables
Reputation Score Square	Reputation score squared

Both 30 day and year reputation scores were analyzed. It was determined that a vast number of sellers had scores between 85 and 100. On a scale that ranges from -100 to 100, this concentrated variation required more than just a direct linear representation of the variable. In order to fully understand the effect of reputation on price dispersion a dummy variable was created to test for the effect of having such a high score and as an interaction effect with the actual reputation score. Finally, the actual scores were squared since curvilinear tests in preliminary analysis indicated the presence of a non-linear relationship between reputation score and price dispersion.

Percentage of variation from average price is the dependent variable used in analysis. This has been used in previous research in price dispersion since it has been established in previous research that prices can be adjusted by deflating them according to the mean price to create a relative measure [22].Analyzing percentage of variation from average price is the best approach for this study for two reasons. First, when analyzing individual product regressions, percentage variation from average price offers the same exact results as using raw price. Second, when data from multiple products are aggregated, analysis of percentage of variation from average price adequate captures dispersion while at the same time offers more accurate regression results due to the fact that raw price variation is significant between products. It has been determined that shipping prices do have a very strong impact on consumer behavior in shop-bot websites [23]. Also some firms may be charging higher shipping fees to offset lower prices [24]. In this study shipping costs are indeed included.Table 3 below offers the measures of price dispersion found in the Online Marketplace:

Table 3. Dispersion in the Online Marketplace

Product	N	Range	Minimum	Maximum	Mean	Std. Deviation	Variance
CD Player	53	35.23	21.20	56.43	30.2053	5.89252	34.722
Digital Camera	46	671.51	633.48	1304.99	765.6259	115.06660	13240.323
Memory Stick	49	35.33	20.75	56.08	33.3951	12.06938	145.670
Printer	62	80.49	67.99	148.48	108.2223	19.27363	371.473
GPS	46	156.37	154.48	310.85	198.8154	31.50664	992.668
Mouse	46	55.59	41.99	97.58	66.6470	12.93876	167.411
DVD Player	48	121.51	230.48	351.99	268.9350	28.56573	816.001
Remote	51	101.02	7.95	108.97	27.0510	17.97140	322.971
Router	49	27.64	32.49	60.13	48.0516	5.45910	29.802
Headphones	48	27.85	20.94	48.79	31.4438	5.92760	35.136

Out of 498 sellers 430 had a reputation score between 85 and 100.In order to determine the impact of the tested variables, ordinary least squares regression was employed. Regressions were run for each product individually to check for consistencies and model robustness. The data was also aggregated using all products in order to create a comprehensive model of consumer electronics.

IV. Results

First, year scores are analyzed to see if they are effective predictors of price dispersion. A summary of the findings is offered below in Table 4.

Table 4. Effect of Year Reputation Scores on Price Dispersion

IV	B	T	sig
(Constant)	-.028	-.470	.639
Year Score	-.011	-8.999	.000
Yearscore85to100	2.780	7.792	.000
Yearscore85to100int	-.033	-8.047	.000
Yearscoresq	.000	9.882	.000
Modelstatistics			
R-Square	.202		
Adjusted R-Square	.196		
Model significance	.000		

The overall model is statistically significant ($p<.001$), as well as all measures of seller reputation ($p<.001$). The adjusted R-squared is .196 indicating that about 19.6% of the variation in price is explained by yearly reputation scores. These findings offer support for hypothesis 1, as they indicate that year reputation scores can effectively predict variation in prices.

Next, 30-day reputation scores are analyzed, the results are highlighted below in Table 5.

Table 5. Effect of 30 Day Reputation Scores on Price Dispersion

IV	B	t	sig
(Constant)	-.061	-1.468	.143
30 Day Score	.001	.409	.683
30dayscore85to100	1.052	2.688	.007
30dayscore85to100int	-.012	-2.658	.008
30dayscoresq	.000	.691	.490
Modelstatistics			
R-Square	.025		
Adjusted R-Square	.017		
Model significance	.015		

Of the four measures of reputation tested, two are statistically significant, the dummy variable 30-day score 85 to 100 ($p<.05$) and the interaction between 30-day score and 85 to 100 score dummy variable ($p<.05$). The base 30-day score and the 30 day scores are not statistically significant ($p>.05$). The overall model is statistically significant ($p<.05$), indicating that 30-day scores can predict variation in prices, which offers support for hypothesis 2. The adjusted R-squared of the model is .017, showing that 1.7% of price variation is explained by the model. This 1.7% is less than the 19.6% which is explained by year scores, indicating that year scores are more effective at predicting price variation, which offers support for hypothesis 3.

V. Conclusions

A summary of the findings of this research are offered below in Table 6:

Table 6. Summary of Findings

Hypothesis	Result
Hypothesis 1: *Established reputation scores will be able to explain variation in prices*	**Supported**
Hypothesis 2: *Recent reputation scores will be able to explain variation in prices*	**Supported**
Hypothesis 3: *Established reputation scores will explain more variation in prices than recent reputation scores*	**Supported**

The results of this study indicate that both recent and established reputation scores do explain variation in seller prices. It was also shown that established reputation scores were much more effective in predicting variation in prices that sellers in the Amazon Marketplace charge. This does not mean that year scores are necessary more important to consumers than 30-day scores. Without sales data it cannot be stated whether established or recent reputation scores matter more to consumers when choosing which retailer to purchase

from. Future research should focus on the role of the consumer to determine their preference when analyzing sellers.

This research shows that recent seller reputations can predict price variation, albeit in a much more limited manner when compared to established seller reputation. However, this research employed data from a single marketplace and a single product category in consumer electronics. Future research should examine other product categories and other marketplaces to determine if recent seller reputation ratings can explain price dispersion among them as well.

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