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RETURNS ON REPUTATION IN RETAIL E-COMMERCE

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ABSTRACT

This paper examines the effect of a seller's reputation on pricing in retail e-markets. Our data comprises price quotations from over 6000 markets of homogeneous consumer products listed in Pricegrabber. We model seller reputations as a combination of the aggregate rating scores and ratings histories which are provided by consumers in Pricegrabber's feedback mechanism. We analyze this data with standardized variables regression. The results indicate that there are some positive returns on reputation for different seller types which could also explain price dispersion in e-markets.

Keywords: retailing, e-markets, asymmetric information, standardized variables regression

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1. INTRODUCTION

The Internet gives consumers unprecedented power in purchase decisions. As the cost of search is minimal on the Internet, buyers can easily compare prices at several vendors before the purchase decision. While price information becomes more accessible, consumers may face other information-related risks in e-commerce. In e-commerce transactions, buyers disclose sensitive information, such as credit card details, to sellers. Usually it is not possible to verify the quality of merchandise or the identity of the seller. Moreover, the delivery of merchandise takes place after the seller has received the payment. Facing these problems of asymmetric information, buyers may need some assurance that sellers do not cheat them. For this reason, a good reputation or widely recognized brand may be a valuable asset in e-commerce.

New online information services have reduced asymmetric in retail e-commerce. To make price comparisons more convenient, several companies have started to offer comparison shopping services. These websites enable comparison shopping on the Internet by providing up-to-date price quotes for various products. Very often these sites are equipped with reputation systems which collect and distribute information about the past activities of sellers. As a consequence, a comparison shopping website creates highly competitive markets for homogeneous goods, where buyers are able to compare prices and risks associated with any particular seller. Comparison shopping websites appear to be popular. Measured by website traffic, many of them are among the 1000 most visited websites on the Internet[1]. Since large consumer flows can translate into higher revenues, firms have a solid financial incentive to participate in comparison shopping markets. In addition, comparison shopping websites offer firms market information services on the customer base and a low cost method to monitor rivals.

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[1] Examples of comparison shopping websites include shopping services of portals and search engines such as AOL (21), CNET (127), Google (2), MSN (5) and Yahoo (1) and specialized comparison shopping websites such as Become.com (2786), Dealtime.com (465), PriceGrabber.com (870) and NexTag (546). Global webtraffic rank in parentheses (retrieved July 1st 2008) as reported by Alexa (www.alexa.com) which is a company that tracks webtraffic.

Comparison shopping markets present a great opportunity to gain insights on market structures of e-markets. The determinants of market structure are market concentration, product differentiation, conditions of entry and exit and information (Jacobson and O'Callaghan-Andréosso, 1996). In comparison shopping markets, products are identical and the barriers to entry and exit are low. Therefore, market concentration and information will determine market structure. Since market structure determines pricing and profits, the market data from comparison shopping markets might help us understand how market concentration and information influence competition in e-markets.

The asymmetric information between buyer and seller has inspired numerous researchers to inspect the relationship between a seller's reputation and prices in online auctions. Overall, these studies conclude that a good reputation entails some pricing power to a seller[2]. However, burgeoning online retail markets have been largely unnoticed by researchers. Baylis and Perloff (2002) study two homogeneous goods e-markets, where they find that the firms that provide good service also set lower prices. They also use consumers' quality rankings from an outside source, but it is deemed "largely random information, in which case the ratings are worthless."

This study differs from the previous research because we examine the effect of reputation on seller's pricing in retail e-markets. We use a random sample cross-sectional data from over 6000 homogeneous goods markets in a comparison shopping website Pricegrabber[3]. The product categories in the sample include appliances, auto parts, children's products, cameras, computers, electronics, furniture, health and beauty products, indoor living products, musical instruments, outdoor living products, software, sporting goods, toys, TVs and video games. In addition to price data from these products, our study includes data from Pricegrabber's reputation system which is integrated to the comparison shopping service. Buyers elicit feedback on sellers which is reported by the reputation system as an aggregated rating score, a ratings history and verbal comments. We use quantitative measures to model a seller's reputation as a combination of its rating score

[2] See Sun (2008) for a concise review of results.
[3] www.pricegrabber.com .

and ratings history. We examine how a seller's reputation impacts its pricing in homogeneous goods markets. More precisely, we ask "Is there returns on reputation in retail e-markets?" We also consider the influence of auxiliary variables such as different seller types and market concentration on sellers' pricing.

The rest of this paper is organized as follows. Section 2 provides theoretical background and a brief literature review. In Section 3, we present data descriptions and conduct statistical tests and regression analysis. Section 4 discusses the results and Section 5 concludes the paper.

2. TRUST AND REPUTATION IN ONLINE TRANSACTIONS

Asymmetric information between trading agents is pervasive in most markets. Even if information is available for free, gathering and processing information is costly. Another source of asymmetry stems from contracts that determine the terms of trade. Agents cannot be certain that the counterparty fully obliges to the contract. To level informational asymmetry, an agent's reputation becomes an important signal of her trustworthiness. Cabral (2005) defines reputation as a situation, when "the agents expect a particular agent to *be* something", whereas trust is defined as a situation, when "the agents expect a particular agent to *do* something."

The emergence of trust between trading partners can be formulated with game theory. The amount of trust the buyer places on the seller depends on the seller's reputation (Resnick et al., 2000). In other words, the buyer's beliefs on risks involved in a transaction with the seller are based on the assessment of reputation. This can be based on a transaction history or learning from other agents. The incentive structure of the game is influenced by the threat of retaliation or reciprocity. For example, if the seller cheats the buyer (or vice versa), the seller may lose all future transactions with the buyer, or there will be legal consequences from a faulty action.

Although lower information costs of e-markets could make market incumbents better informed about the market in many respects, concerns about the trustworthiness of a trading partner become prominent in e-commerce transactions. E-commerce as a means of transaction is a fundamental reason for this. In e-commerce, buyers and sellers conduct business through a website or other electronic channel. Lack of direct contact between buyers and sellers in online transactions leads to uncertainty about the identity of the trading partner and product quality (Ba and Pavlou, 2002). More precisely, two main concerns are loss of money and privacy (Resnick et al., 2000). Apart from information goods, the buyer cannot examine the good before purchase. Moreover, the seller's online store may not give any information about the quality of the seller. Thus, it is harder to verify the quality of the good or the seller in e-markets than it is in conventional markets. More concerns surface in payment of the purchase. A large bulk of (retail) e-commerce transactions are conducted by credit card. Therefore, disclosing sensitive information, such as a credit card number, to the seller involves risks of misconduct on behalf of the seller. The ease of switching one's identity on the Internet accentuates these problems. The shipping of goods is again problematic because the buyer can only trust that the seller obeys the contract they have entered into. This does not mean, however, that the buyer is concerned only about the seller's trustworthiness. Third parties, such as criminals or marketing companies, may gain access to sensitive information by stealing the information from the seller, by capturing information during the transaction or by the seller's consent. The delivery agency may also lose the ordered purchase which also places burden on the buyer-seller relationship.

Trust in transactions is built on reputation. In conventional retail markets, locality of transactions is important contributor in reputation building (Resnick and Zeckhauser, 2002). Since transactions take place in the same physical environment, buyers have frequent contacts with the seller. Thus, the seller's identity is known, and buyers are able to inspect the merchandise before purchasing it. They are also able to learn from each other's experiences with the seller, so the word-of-mouth also contributes to the seller's reputation. Moreover, the risks of privacy and shipping are negligible because buyers monitor the payment and organize the transportation of the purchased items by themselves. Sellers can also signal reputation by acquiring retail space in an upscale location. In addition to location, sellers in conventional markets can borrow reputations (certifications), buy reputations (acquisition of an existing brand) or leverage existing reputations to new markets.

Due to the lack of physical retail space, the advantages of location in building reputation cannot be as large in e-commerce as in conventional retail. Nevertheless, there are some parallels in e-markets. Several websites attract large consumer flows daily. First, comparison shopping websites such as Bizrate or Pricegrabber provide marketplace platforms for e-retailers. Second, on-line auction sites, most notably eBay, are global centers of consumer-to-consumer e-commerce as well as a sales channel for small-scale e-retailers. Third, web portals such as MSN, Yahoo or CNET offer a wide range of services to their customers, and are therefore potential locations to set-up an online store. Moreover, some websites that provide services for specific interest groups also support platforms for e-commerce. For example, Discogs, an electronic database for discographies, offer a marketplace for its members. Finally, well-known e-commerce vendors, such as Amazon.com or Play.com, have set-up marketplaces where sellers can benefit from the brand and customer base of the marketplace provider.

Due to the risks involved in an e-commerce transaction, consumers require some assurance that they can trust the seller. Providing fast shipping and traceability of the purchased good, generous guarantees and return policies can also foster trust. Alternative ways to pay for the product could also signal trust, because credit cards and some e-payment solutions such as PayPal provide consumers protection in purchases[4]. Receiving approval ratings from an impartial third party is another way to signal trust. As in financial markets, where credit ratings from companies such as Standard & Poor's serve this purpose, e-commerce merchants use certifications from the Internet security providers, such as McAfee or VeriSign, to signal that appropriate measures have been taken to protect consumers in e-commerce transactions. Other ways to signal trust are not as easily verifiable. Easy navigation and a "professional look" of the merchant's website

[4]The seller is also protected because the creditor bears the risks of consumer insolvency.

could be crucial factors in purchase decisions[5]. Customer service, ease of contacting the seller, effectiveness of communication and consumer empowerment can also be important in the reputation building process. Selling items at low prices, at least initially, can be used to build a reputation of an inexpensive seller, as frequent transactions are instrumental in reputation building among consumers.

Since building a reputation is a dynamic, costly and time-consuming effort, there are alternative shortcuts to establish the goal. Established businesses in conventional markets often leverage their offline reputations in on-line markets. In this case, the existing business model is expanded to e-markets. Another strategy is to buy a reputation by an acquisition of an established business or its brand or a franchising agreement. Smaller merchants may find it profitable to sell their merchandise under the umbrellas of strong, established on-line brands that offer some protection to buyers in their marketplace purchases.

To address the problems of asymmetric information, e-commerce marketplaces have devised reputation systems that provide information about market incumbents past actions. One can think of this as digital word-of-mouth. Resnick (et al. 2000) define a reputation system as a system that "collects, distributes and aggregates feedback about participants past behavior". To be effective, a reputation system should be long-lived and efficient in distribution of information about reputations. Such a system could alleviate asymmetric information between trading partners and encourage behavior that increases trust. Participation to a reputation system in itself could signal that an agent is a trustworthy trading partner. On the other hand, building a reputation in one marketplace creates switching costs for the established sellers because reputations are not transferable between competing marketplaces (Melnik and Alm, 2002). For this reason, the marketplace operator has an incentive to encourage participation to the marketplace's reputation system because it creates a lock-in for sellers (and buyers, if buyers also act as sellers and vice versa). Another way to level the information asymmetry is to collect and

[5] This may not help because websites that have a "professional look" are easy to forge (Kumaraguru et al. 2006).

distribute performance histories. Performance histories are user accounts on interactions between buyers and the seller. These are integral part of a feedback mechanism. They provide quantitative (e.g. the length of history) and qualitative (e.g. a description about the seller/buyer performance) information about a transaction. According to Resnick (et al. 2000), performance histories are a tool that enables assessment of the potential risks involved in a transaction.

Despite the benefits for the participants of a feedback mechanism, they are not foolproof solutions to the problems of asymmetric information. While feedback mechanisms usually are based on some quantitative measurements, awarding feedback is subjective. As a result, a homogeneous product can receive very different assessments because agents are heterogeneous in their preferences. By the law of large numbers, feedback converges to some value, but with small amounts of feedback the problem exists. Another problem emerges from voluntary participation, because eliciting feedback imposes an incremental cost to the trade. This compares to contributing to a public good: avoiding the cost of giving feedback creates an incentive to free-ride on the information that other agents provide. It is also possible that feedback becomes biased because only the extraordinarily bad or good performances are reported. Moreover, the fear of retaliation could deter eliciting negative feedback. As reputation systems do not distinguish between the monetary values of sold items, it is plausible that a seller amasses a good reputation by selling inexpensive items and eventually cheats in a sale of a valuable item (Livingston, 2005).

More damaging to the reputation systems could be proliferation of markets for feedback. Brown and Morgan (2006) describe situations where feedback mechanisms are manipulated by selling merchandise that is essentially worthless in exchange for positive feedback. The accumulated positive feedback can then be used to signal good reputation in fraudulent listings of valuable items. Another way to go around reputation systems is *shilling* which is forbidden in online marketplaces. For example, a seller could act as a buyer and purchase a product from its own online store and then return positive feedback for itself. This could undermine the value of reputation systems for buyers because the inability to manipulate one's reputation is partly responsible for the value of reputation (Standifird, 2001). Distinguishing manipulation from normal business practices may be difficult though. For example, a seller offering a used CD for a nominal fee of 1 cent may be clearing the inventory, or investing in reputation by offering the merchandise at low prices.

A major handicap for reputation building on the Internet is that changing one's identity is relatively costless. For example, creating a new seller identity in online auctions requires only registration. In the online retail industry, comparison shopping services such as Pricegrabber or Yahoo! offer packages that enable a quick set-up of an online store at low costs. While these features guarantee low entry-costs to the market, incomplete and asymmetric information between buyers and sellers deters frequent switches of identity. If a seller switches its identity, it must start building its reputation again from the beginning because the seller ratings and ratings histories are not transferable. For this reason, investment costs from reputation building serve as effective entry costs to another market. Similarly, online marketplaces create switching costs for the market incumbents by not allowing a transfer of reputations between marketplaces (Brown and Morgan, 2006). Therefore, the marketplace operators have an incentive to encourage sellers into positive reputation building, because they gain more sales fees from the locked-in sellers.

The issues of trust and reputation can lead to problems of adverse selection and moral hazard in e-markets. A strong positive reputation can be seen as an insurance against opportunistic behavior (Standifird, 2001). The cost of adverse selection can be that sellers receive lower prices for their goods, or even unraveling of the markets in the extreme cases (Akerlof, 1970; Dewan and Hsu, 2004). As the full price of a product is a combination of a purchase price, search costs and costs of a disappointing purchase, a good reputation can mitigate the costs of a disappointing purchase (Kim and Xu, 2007). Thus, a reputable seller could enjoy a price premium over its less trustworthy rivals. Melnik and Alm (2002) suggest that reputation can raise barriers to entry in an e-market because new entrants may find it impossible to compete with the established reputable sellers. Indeed, a study of eBay auctions by Lin (et al. 2006) suggests that the population of sellers with high reputation scores has higher growth rate than the sellers with lower reputation scores. Interestingly, Professional eBay Sellers Alliance, a trade association of high-ranking eBay sellers, complains that exactly the opposite is taking place in eBay, because the marketplace does not provide enough incentives for sellers to invest in the measures that could provide better reputation[6].

Flourishing online auctions have become a popular data source for researchers because reputation systems are commonplace in most auction sites. Standifird (2001) finds only limited evidence of price premiums for a seller with a good reputation, but a highly negative reputation forces a seller to sell items at discount, Furthermore, he finds evidence that a negative reputation has more impact on buyers' purchase decision than a positive reputation. This finding is supported by Ba and Pavlou (2002). They find little evidence of a positive correlation between rating scores and price premiums, but a statistically significant impact of a negative rating on a seller's price when the auctioned items are expensive. In contrast to these findings, Melnik and Alm (2002) show that a seller's reputation has a small positive impact on the prices in the auctions for gold coins. They argue that the price premium from reputation is likely to grow along the value of an auctioned object. Dewan and Hsu (2004) also report similar findings on a seller's reputation in the collectible stamps auctions. They also estimate that quality uncertainty lowers the prices of auctioned stamps by 10-15%. They interpret this as evidence of effective dealing with the "lemons problem". Livingston (2005) finds decreasingly increasing returns on seller's positive reputation in eBay auctions. Using quantile regression, Sun and Hsu (2007) detect nonlinear responses to a seller's reputation: buyers place more emphasis on a seller's reputation when bid values are high.

The impact of e-commerce reputation in the online retail markets has not garnered as much attention as the online auctions. In a pioneering study, Baylis and Perloff (2002) observe price developments in two homogeneous consumer electronics products. Their findings are startling. They observe that "good firms" charge lower prices while "bad

[6] See Professional eBay Sellers Association (2007): "Unhealthy Marketplace Dynamics – Seller Perspective".

firms" charge higher prices. Moreover, the relative price positions among firms do not change over time, which implies that periodic sales do not take place. Using a survey data from customers of an online bookstore, Kim and Xu (2007) find that a seller's reputation can reduce a buyer's price sensitivity. Another survey by Fuller et al. (2007) suggests that the seller ratings, which are provided by a reputation system, do not have a lasting impact on a buyer's decision making. In fact, buyers place more emphasis on direct personal experience either from the previous transactions with the seller or the information she receives on the seller's website.

3. DATA DESCRIPTION AND ANALYSIS

3.1 PRELIMINARY ANALYSIS

The data in this study is a cross-sectional random sample from various product categories. These include appliances, auto parts, children's products, cameras, computers, electronics, furniture, health and beauty products, indoor living products, musical instruments, outdoor living products, software, sporting goods, toys, TVs and video games. The data was collected from Pricegrabber in May 2008.

Altogether, the sample consists of 6885 different markets for homogeneous goods. Descriptive statistics together with variable descriptions are shown in Table 1. The data contains information on prices, the number of sellers, seller types, the seller rating scores and ratings histories for each market. We use price as the dependent variable in regression analysis. The price data consists of 18044 price quotes from homogeneous products. All prices are in the United States dollars (USD). The price quotes range from 0.01 USD to 41049.84 USD with the mean at 394.65 USD and the median at 99.99 USD which makes the data positively skewed.

Market thickness measures the number of sellers in a single market. Market thickness varies from 1 to 49 with the mean at 2.6, the median at 1 and the standard deviation of 3.9. Over a half of the markets (3834) were dominated by a single seller at the time of the study. Excluding the single-seller markets increases the mean and the median to 4.7 sellers in competitive markets with the standard deviation of 5.1. These figures are considerably less than the average of 17.5 sellers in a market which Leiter and Warin (2007) report. A likely reason for the discrepancy is the sampling method because their sample consists of the most popular products in Pricegrabber.

Table 1. Descriptive Statistics.

Variable	*Description*	*Mean*	*Median*	*STD*	*Min.*	*Max.*
THICK	The number of sellers in a market.	2.62	1	3.85	1	49
THICK*	*THICK* excluding single-seller markets.	4.66	4.66	5.09	2	49
PRICE	The list price of an item in USD.	394.65	99.99	1049.46	0.01	41049.83
ARATE	Seller's average all-time rating.	3.99	4.37	0.95	1.00	5.00
3RATE	Seller's average rating during past three months.	4.00	4.47	1.01	1.00	5.00
HIST**	The number of ratings.	824.22	121.50	2619.88	10	35972
RDIF	The difference between *3RATE* and *ARATE*.	-0.19	0.08	0.97	-3.58	3.74

*Markets with two or more incumbent firms. ** Histories below 10 are not reported.

A seller's rating score is the measure for a seller's reputation. A rating score is a decimal value that ranges from 1 to 5. These are provided by consumers who asses the seller's overall performance in a transaction in 1 (the lowest) to 5 (the highest) scale. As a result, the rating score is an aggregate value of the overall consumer opinion on the seller. The data set contains rating scores from the past three months (*3RATE*) and all-time rating scores (*ARATE*). Measured with the standard deviation, *3RATE* displays more variation than *ARATE*. Since the mean and median are larger in the three-month scores, this may indicate that sellers on average have attempted to improve service. This can be measured by *RDIF* which is calculated by subtracting *ARATE* from *3RATE*. The slightly positive median of *RDIF* verifies that customers feel that service has improved in time. The high averages of the rating scores point to a fairly high level of consumer satisfaction, however.

Although the rating scores provide an easily quantifiable measure for seller reputations, they are not without limitations. First, each buyer's assessment on the seller's performance is subjective. Due to buyer heterogeneity, the same level of service may lead to different ratings. Second, the rating scores are often accompanied by verbal comments. These may contain very important information about the seller's conduct which is not captured by the numerical score. For example, a verbal comment on charging the credit card without shipping the purchase or a significant delay in delivery could accompany a similar rating, but send a starkly different signal to other buyers. Third, leaving feedback is optional, which may lead to biased feedback. This could be a result if only exceptionally good or really bad performances become reported. Finally, it may be possible for sellers to manipulate their rating scores (Brown and Morgan, 2006). However, this may not be as likely in retail as in online auctions because online retailing is characterized by large volumes and new merchandise, whereas the items sold in auctions are often used and sales volumes are low.

Another way to estimate a seller's trustworthiness is to include ratings histories in the examination. A ratings history provides an indicator of how long the seller has been active in the market under the same identity. The longer the ratings history, the more reliable the seller is. Descriptive statistics indicate that ratings histories are heavily skewed to the left. They range from zero to nearly 36 000 entries with the mean at 1365.90 and the median at 119. These figures suggest that most sellers are relatively new to the market, their sales through the comparison shopping website are low, or their sales volumes in the comparison shopping market are low.

Firms of all sizes compete in comparison shopping markets. Pricegrabber has two fundamentally different seller types which results from a choice over a sales channel. We define "merchants" as the firms that run their own websites. Merchants register to a comparison shopping website to lure in customers but process commercial transactions through their own e-commerce systems. We define "storefronts" as the firms that do not run their own websites. Instead, the comparison shopping website processes commercial transactions between consumers and storefronts. Pricegrabber sets its fees in a way that merchants pay a fee for each click-through whether or not this leads to a purchase, but storefronts pay fees only for the purchases. The click-through fee for merchants is significantly lower than the purchase fee for storefronts[7]. As a result, large-volume sellers benefit from being merchants, whereas low-volume sellers are induced to opt for the storefront package. We devise dummy variables to distinguish between different seller types. The dummy variable *SF* takes the value 1 if a seller is a storefront and the value 0 if a seller is a merchant. Furthermore, dividing the number of storefronts in a market by market thickness of the respective market, we obtain a variable for storefront ratio (*SFR*). Further distinctions are based on the level of sales. We use the most recent (2007) annual list of *The Internet Retailer* to separate the large volume sellers from the rest of the seller population[8]. The dummy variable *TOP500* takes value 1 if a seller is among the 500 hundred largest retail e-commerce sellers measured by the value of their annual sales in the United States. Thus, the control groups are at the opposite sides of the seller spectrum: storefronts are small players in the market, whereas Top500-sellers are household names with wide brand recognition among consumers.

A fundamental distinction between markets is the level of their competitiveness. Single-seller markets were monopolistic, whereas there were two or more sellers in competitive markets at the time the observations were made. Descriptive statistics and statistical tests on seller reputations based on the market settings are represented in Table 2 and Table 3. There is no statistically significant difference between reputations in the seller types that operate in the same market setting. In contrast, a statistically significant difference exists between the similar seller types that operate in different market settings. On average, competitive storefronts have lower reputations than single-seller storefronts. However, the mean of single-seller merchants' reputations is lower than competitive merchants' reputations, but the median is slightly higher. It is obvious that some extremely low rated firms cause this. These overall results might constitute evidence that a good reputation could deter entry to the markets where the intensity of competition is low. With this data, however, the evidence is only suggestive and more research is needed to verify the result.

[7] See http://www.pricegrabber.com/sell_here.php .
[8] See http://www.internetretailer.com/Top500/list.asp .

Table 2. Seller All-time Rating Score Statistics.

Category	*Obs.*	*Mean*	*Median*	*STD*	*Min.*	*Max.*
Competitve Merchants	11391	4.01	4.44	0.91	1.00	5.00
Competitve Storefronts	1897	4.02	4.06	0.62	1.00	5.00
Single-seller Merchants	2759	3.86	4.45	1.25	1.00	5.00
Single-seller Storefronts	108	4.25	4.33	0.42	3.00	5.00

Table 3. T-Test/Mann-Whitney Test for All-time Rating Score Statistics of Seller Types

Hypothesis: equal mean/median	*T-Test*	*Mann-Whitney*	*Conclusion*
Single-Seller Merchants Single-Seller Storefronts	3.185102**	0.315621	Rejected / Accepted
Competitve Merchants Competitve Storefronts	0.571521	10.97523***	Accepted / Rejected
Single-Seller Storefronts Competitive Storefronts	3.773743***	4.254029***	Rejected / Rejected
Single-Seller Merchants Competitive Merchants	7.009682***	2.730485***	Rejected / Rejected

*** indicates a p-value<0.01; ** indicates a p-value<0.05; * indicates a p-value<0.1.

To facilitate a direct comparability between different markets, we use standardized variables. In general, a standardized variable $z_{i,j}$ is obtained by

$$z_{i,j} = \frac{x_{i,j} - \bar{x}_j}{STD(x_{i,j})}, \tag{1}$$

in which $x_{i,j}$ is an observation of the variable x_i in the market j, $\bar{x}_j$ is the mean of x in the market j and $STD(x_{i,j})$ is the standard deviation of x in the market j. Standardization concentrates observations around zero. We denote the standardized variables with the letter z in front of the variable. The standardized variables include price (*zPRICE*), the all-time rating score (*zARATE*), the ratings history (*zHIST*), the difference between the rating scores (*zRDIF*), market thickness (*zTHICK*) and the storefront ratio (*zSFR*). As an example of standardization, Figure 1 illustrates the distribution of standardized prices. The distribution is positively with the median at -0.165 and the mean at 0.000. The right tail is longer than the left tail, because the maximum is 5.327 and the minimum is -2.888.

3.2 OLS REGRESSION

To test the effects that the rating scores, the ratings history and the standardized market variables (*zSFR*, *zTHICK*) have on sellers' prices, we devise three regression models. The theory suggests that if a good reputation enables a price premium for a seller, estimated coefficients for the rating score as a measure of reputation should be positive. In contrast, the estimates for the market variables should be negative because increasing competition is likely to depress prices. The dummy variables *SF* and *TOP500* separate the effects on these specific seller types from the general effects. Moreover, only competitive markets, which means that $THICK > 1$, are considered. We test also if market thickness influences results. For this reason, we run five OLS regressions that constrain data-sets to *THICK*>1 (A), *THICK*>5 (B), *THICK*>10 (C), *THICK*>20 (D) and 1<*THICK*<6 (E). We will refer to them as A, B, C and D in the text and tabulations. Using the terminology from the industrial organization literature, these data-sets can be characterized as "all competitive markets" (A), "medium to low concentration" (B), "low concentration" (C), "very low concentration" (D) and "high concentration" (E).

Since each regression has problems with heteroscedasticity, we augment the estimates with the White's heteroscedasticity consistent estimates (HSCE). Furthermore, we run auxiliary regressions on each variable to detect multicollinearity (the results from these are omitted from this paper), which is often problematic in the regression models that utilize standardized variables. The variance inflation factors (VIF), which are obtained from the auxiliary regressions, suggest that there is no problematic multicollinearity in the estimates. The VIFs range from 1.000 to 2.225 with the average values for each regression ranging from 1.005 to 1.517. We report only the average VIFs for each regression.

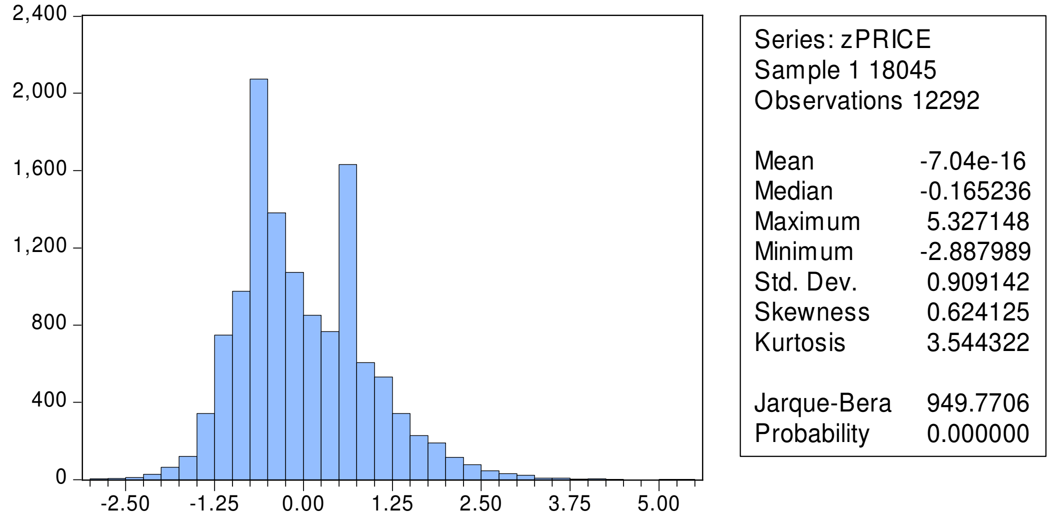

Figure 1. Distribution of Standardized Prices (*zPRICE*).

In Model 1, we regress the standardized reputation variables (*zARATE*, *zHIST*) and their interaction on the standardized price (*zPRICE*). As a consequence of standardization, the expected value of the dependent variable equals zero and so, the intercept is omitted from the regression equation. However, the unstandardized dummy intercepts are included to preserve their meaning. Model 1 becomes

$$\begin{aligned} zPRICE = {} & \alpha_1 SF + \alpha_2 TOP + \beta_1 zARATE + \beta_2 SF \cdot zARATE + \beta_3 TOP \cdot zARATE \\ & + \eta_1 zHIST + \eta_2 SF \cdot zHIST + \eta_3 TOP \cdot zHIST + \gamma_1 zARATE \cdot zHIST \\ & + \gamma_2 SF \cdot zARATE \cdot zHIST + \gamma_3 TOP \cdot zARATE \cdot zHIST + \varepsilon \end{aligned} \tag{2}$$

The effect of a change in the all-time rating score on the expected standardized price is given by Equations (3) to (5)

$$\frac{\partial E[zPRICE \mid SF = 0, TOP = 0]}{\partial zARATE} = \beta_1 + \gamma_1 zHIST \tag{3}$$

$$\frac{\partial E[zPRICE \mid SF = 1, TOP = 0]}{\partial zARATE} = \beta_1 + \beta_2 + (\gamma_1 + \gamma_2) zHIST \tag{4}$$

$$\frac{\partial E[zPRICE \mid SF = 0, TOP = 1]}{\partial zARATE} = \beta_1 + \beta_3 + (\gamma_1 + \gamma_3) zHIST\ . \tag{5}$$

Since an interaction term is a product of two or more covariates, the effect of a change in the value of one covariate depends on the level of the other covariates that compose the interaction term. Very often interactions are a product of a dummy variable and a continuous variable which gives a straightforward "on/off" interpretation. Such a simple interpretation is not possible in our model because the interaction terms include a dummy variable and two continuous variables.

As Equations (3) to (5) display, the effect decomposes to the sum of β_i coefficients (the main effect) and the sum of γ_i coefficients multiplied by *zHIST* (the interaction effect) where $i = 1, 2, 3$ in both. If the interaction is statistically significant, the effect of *zARATE* on *zPRICE* is dependent on the level of *zHIST*. In addition, the main effect should not be interpreted in isolation of the interaction effect[9]. Standardization of the variables makes the interpretation somewhat easier. The effect at the average length of the ratings history reduces equal to the main effect because the mean of each standardized covariate is zero. Rearranging equations (3) to (5) provides results that are easy to interpret. Let B and Γ denote the sums of β_i and γ_i where $i = 1, 2, 3,$ respectively, in each equation. Setting equations (3) to (5) equal to zero and solving any of them for *zHIST* yields a threshold value

$$zHIST^* = \frac{\mathrm{B}}{\Gamma}\ . \tag{6}$$

[9] For this reason, we refrain from giving any interpretations for $\frac{\partial E[zPRICE]}{\partial zHIST}$ because it is difficult to interpret the interaction effects.

The values greater than the threshold indicate that $\frac{\partial E[zPRICE]}{\partial zARATE} > 0$. Thus the sellers whose ratings histories exceed $zHIST^*$ reap positive returns on reputation. This also implies that the effect is increasing in the length of history.

The results of OLS on Model 1 are reported in Table 4. The dummy variables suggest that in the absence of other effects, storefronts set higher prices in A, B and C, whereas Top500-sellers set higher prices in A and E but lower in D. The threshold values and main effects for Model 1 are shown in Table 5. They indicate that only storefronts and Top500-sellers benefit from increases in their rating scores. The threshold values for storefronts range from 1.240 (C) to 2.145 (E) which correspond to roughly 1 to 2 STDs. This suggests that longer ratings histories are needed in the more concentrated markets for the positive effect on price. The effect is opposite for Top500-sellers, for which the range is from 0.028 (D) to 8.167 (B). These correspond to 1/3 to 8 standard deviations. The latter value is outside the boundaries of the observed ratings histories distribution which is displayed in Figure 2. If these theoretical values are removed, Top500-sellers have positive returns on reputation only in the more competitive markets in C and D.

Next we examine how improvement in the rating score affects a seller's pricing. For this reason, we regress *zRDIF*, *zHIST* and their interaction on *zPRICE*. Model 2 is

$$\begin{aligned} zPRICE = {} & \alpha_1 SF + \alpha_2 TOP + \beta_1 zRDIF + \beta_2 SF \cdot zRDIF + \beta_3 TOP \cdot zRDIF \\ & + \eta_1 zHIST + \eta_2 SF \cdot zHIST + \eta_3 TOP \cdot zHIST + \gamma_1 zARATE \cdot zRDIF \\ & + \gamma_2 SF \cdot zRDIF \cdot zHIST + \gamma_3 TOP \cdot zRDIF \cdot zHIST + \varepsilon \end{aligned} \tag{7}$$

and the partial derivatives $\frac{\partial E[zPRICE]}{\partial zRDIF}$ are similar to those in Equations (3) to (5).

Table 4. OLS Estimates for Model 1.

Variable	*A*	*B*	*C*	*D*	*E*
SF	**0.258*****	**0.300*****	**0.252*****	-0.098	0.051
	(0.027)	**(0.035)**	**(0.076)**	(0.145)	(0.043)
TOP	**0.067*****	0.026	-0.032	**-0.152****	**0.177*****
	(0.023)	(0.029)	(0.039)	**(0.072)**	**(0.041)**
zARATE	**-0.125*****	**-0.148*****	**-0.219*****	**-0.297*****	**-0.125*****
	(0.017)	**(0.021)**	**(0.029)**	**(0.043)**	**(0.030)**
SF*zARATE	**-0.279*****	**-0.280*****	**-0.246***	**-0.550***	**-0.126****
	(0.042)	**(0.063)**	**(0.133)**	**(0.321)**	**(0.064)**
TOP*zARATE	0.006	0.001	0.084	**0.306*****	**0.117****
	(0.029)	(0.036)	(0.052)	**(0.108)**	**(0.057)**
zHIST	**-0.028***	0.016	**0.100*****	**0.200*****	**-0.103*****
	(0.015)	(0.020)	**(0.026)**	**(0.045)**	**(0.029)**
SF*zHIST	**-0.192*****	**-0.320*****	**-0.658*****	**-1.680*****	0.105
	(0.042)	**(0.059)**	**(0.158)**	**(0.334)**	(0.065)
TOP*zHIST	-0.037	-0.052	**-0.160****	**-0.430*****	-0.057
	(0.032)	(0.041)	**(0.063)**	**(0.145)**	(0.060)
zARATE*zHIST	**-0.187*****	**-0.258*****	**-0.361*****	**-0.499*****	**-0.066***
	(0.022)	**(0.029)**	**(0.040)**	**(0.068)**	**(0.039)**
SF*zARATE	**0.413*****	**0.513*****	**0.736*****	0.384	**0.183****
****zHIST***	**(0.061)**	**(0.095)**	**(0.225)**	(0.607)	**(0.088)**
TOP*zARATE	**0.203*****	**0.276*****	**0.434*****	**0.826*****	0.007
****zHIST***	**(0.039)**	**(0.052)**	**(0.082)**	**(0.191)**	(0.071)
Adjusted R^2	0.105	0.134	0.173	0.227	0.039
Observations	8916	6668	4201	1826	2248

***** p-value<0.01; ** p-value<0.05; * p-value<0.1;Standard errors in parentheses.**

Table 5. Threshold and Main Effect values for OLS Estimates in Model 1.

Model 1	*Seller Type*	β_1	β_2	β_3	γ_1	γ_2	γ_3	*Threshold*	*Main Effect*
	All	-0.125			-0.187			<-0.668	-0.125
A	***Storefront***	-0.125	-0.279		-0.187	0.413		**>1.788**	-0.404
	Top500	-0.125			-0.187		0.203	***>7.813***	-0.125
	All	-0.148			-0.258			<-0.574	-0.148
B	***Storefront***	-0.148	-0.280		-0.258	0.513		**>1.678**	-0.428
	Top500	-0.148		0.001	-0.258		0.276	***>8.167***	-0.147
	All	-0.219			-0.361			<-0.607	-0.219
C	***Storefront***	-0.219	-0.246		-0.361	0.736		**>1.240**	-0.465
	Top500	-0.219			-0.361		0.434	**>3.301**	-0.219
	All	-0.297			-0.499			<-0.595	-0.297
D	***Storefront***	-0.297	-0.550		-0.499			*<-1.697*	-0.847
	Top500	-0.297		0.306	-0.499		0.826	**>0.028**	**0.009**
	All	-0.125			-0.666			<-0.188	-0.125
E	***Storefront***	-0.125	-0.126		-0.666	0.183		**>2.145**	-0.251
	Top500	-0.125		0.117	-0.666			<-0.121	-0.008

Values outside the observed distribution in italics.

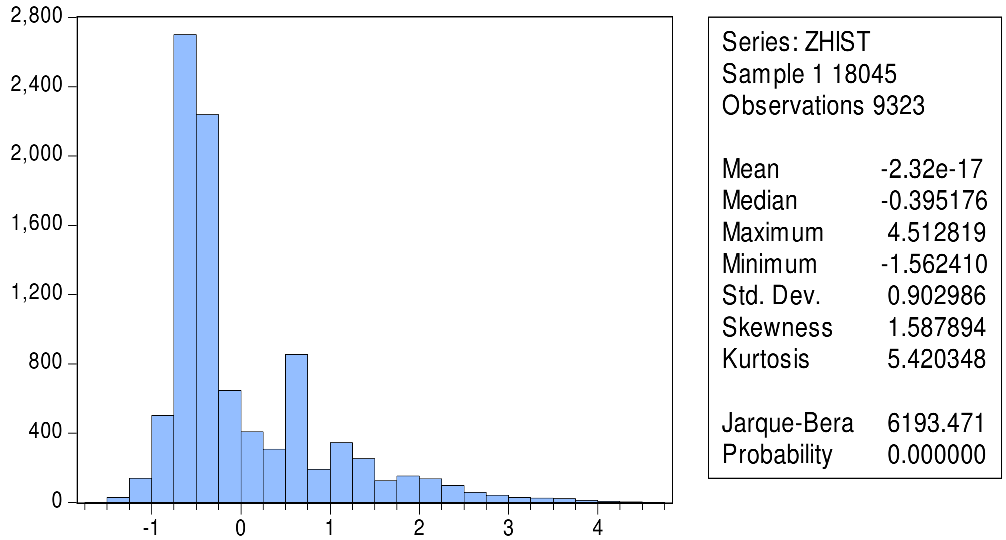

Figure 2. Distribution of Standardized Ratings Histories (*zHIST*).

The OLS estimates for Model 2 are reported in Table 6. The magnitude of the dummy variables is greater than in Model 1. They suggest again that storefronts and Top500-sellers set higher prices than the general seller population. The threshold values and main effects can be found in Table 7. First, we notice that the interactions are statistically significant only for Top500-sellers. The estimates are negative, which indicates that improvement in the ratings score does not offer positive returns. Second, the estimates for the rating scores are also negative for the control groups. Only the group that contains all sellers displays positive estimates for coefficients on *zARATE* in A, B, C and E. The magnitudes of the coefficients range from 0.031 (C) to 0.142 (E). These magnitudes imply that improvement in the rating score provides a price premium of approximately 15% of STD in the high concentration markets.

Model 3 is built on Model 1 and Model 2. We base the model on *zARATE*, *zHIST* and their interaction. Since the product of *zRDIF* and *zHIST* was statistically significant only for Top500-sellers, we omit the interaction term and include only *zRDIF* into Model 3. To provide a more comprehensive view on competition, we include the market variables *zTHICK* and *zSFR* into the regression equation. Model 3 is

Table 6. OLS Estimates for Model 2.

Variable	***A***	***B***	***C***	***D***	***E***
SF	**0.337*****	**0.384*****	**0.346*****	-0.080	0.083
	(0.029)	**(0.035)**	**(0.058)**	(0.158)	(0.051)
TOP	**0.115*****	**0.097*****	**0.071****	0.035	**0.163*****
	(0.020)	**(0.024)**	**(0.032)**	(0.046)	**(0.037)**
zRDIF	**0.066*****	**0.049*****	**0.031****	0.023	**0.142*****
	(0.012)	**(0.013)**	**(0.015)**	(0.021)	**(0.027)**
SF*zRDIF	**-0.264*****	**-0.356*****	**-0.335***	**-1.892****	**-0.202****
	(0.070)	**(0.103)**	**(0.178)**	**(0.754)**	**(0.094)**
TOP*zRDIF	**-0.124*****	**-0.112*****	**-0.079****	**-0.108****	**-0.200*****
	(0.023)	**(0.025)**	**(0.031)**	**(0.044)**	**(0.051)**
zHIST	**-0.109*****	**-0.107*****	**-0.088*****	**-0.069*****	**-0.133*****
	(0.011)	**(0.013)**	**(0.015)**	**(0.019)**	**(0.028)**
SF*zHIST	**-0.189*****	**-0.246*****	**-0.521*****	**-1.620*****	0.061
	(0.044)	**(0.055)**	**(0.108)**	**(0.380)**	(0.077)
TOP*zHIST	**-0.047****	**-0.044***	**-0.055***	-0.054	-0.042
	(0.023)	**(0.025)**	**(0.031)**	(0.044)	(0.055)
zRDIF*zHIST	-0.002	-0.009	0.005	-0.004	0.023
	(0.013)	(0.014)	(0.014)	(0.030)	(0.036)
SF*zRDIF	0.099	0.127	0.301	-1.708	0.047
****zHIST***	(0.099)	(0.146)	(0.291)	(1.497)	(0.131)
TOP*zRDIF	**-0.100*****	**-0.100*****	**-0.104*****	**-0.147****	-0.100
****zHIST***	**(0.027)**	**(0.030)**	**(0.037)**	**(0.060)**	(0.063)
Adjusted R^2	0.070	0.088	0.107	0.148	0.035
Observations	8788	6650	4201	1826	2138

*** p-value<0.01; ** p-value<0.05; * p-value<0.1;Standard errors in parentheses.

Table 7. Threshold values and Main Effects for OLS Estimates in Model 2.

Model 2	***Seller Type***	β_1	β_2	β_3	η_1	η_2	η_3	***Threshold***	***Main Effect***
A	***All***	0.066							**0.066**
	Storefront	0.066	-0.264						-0.198
	Top500	0.066		-0.124			-0.100	<-0.580	-0.058
B	***All***	0.049							**0.049**
	Storefront	0.049	-0.356						-0.307
	Top500	0.049		-0.112			-0.100	<-0.630	-0.063
C	***All***	0.031							**0.031**
	Storefront	0.031	-0.335						-0.304
	Top500	0.031		-0.079			-0.104	<-0.462	-0,048
D	***All***								
	Storefront		-1.892						-1.892
	Top500			-0.108			-0.147	<-0.735	-0.108
E	***All***	0.142							**0.142**
	Storefront	0.142	-0.202						-0.060
	Top500	0.142		-0.200					-0.058

Values outside the observed distribution in italics.

$$
\begin{aligned}
zPRICE = {} & \alpha_2 SF + \alpha_3 TOP + \beta_1 zARATE + \beta_2 SF \cdot zARATE + \beta_3 TOP \cdot zARATE \\
& + \eta_1 zHIST + \eta_2 SF \cdot zHIST + \eta_3 TOP \cdot zHIST + \gamma_1 zARATE \cdot zHIST \\
& + \gamma_2 SF \cdot zARATE \cdot zHIST + \gamma_3 TOP \cdot zARATE \cdot zHIST + \varpi_1 zTHICK \\
& + \varpi_2 SF \cdot zTHICK + \varpi_3 TOP \cdot zTHICK + \theta_1 zSFR + \theta_2 SF \cdot zSFR \\
& + \theta_3 TOP \cdot zSFR + \varepsilon
\end{aligned} \tag{4}
$$

The partial derivatives describing the interaction effects are the same as in Equations (3) to (5).

The OLS estimates for Model 3 are presented in Table 8, and the threshold values and main effects are presented in Table 9. The estimated coefficients for the intercept dummy variables do not differ much from those in Model 1 and Model 2. As in Model 1, the interaction effects show that only storefronts and Top500-sellers enjoy positive returns on reputation. The magnitudes of the thresholds range from 1.129 (C) to 3.641 (A) for storefronts. This means that a lower threshold level of *zHIST* is required for positive returns in the high concentration markets. The pattern is not as straightforward for Top500-sellers. The range for them spans from 0.358 (D) to 3.292 in A if we omit 6.125 (B) which is out of the bounds. This means that only Top500-sellers have returns on reputation in the highly competitive markets. Moreover, a length of history that is modestly above the average is needed for a price premium. In contrast, the main effects are negative for all sellers indicating that more favorable rating scores do not provide pricing power at the average level of ratings history.

The total effects on other variables are reported in Table 10. The general seller population seems to benefit only from improvement in rating scores. The positive coefficients range from 0.036 to 0.140 in B to E indicating a more powerful effect in the high concentration markets. Since the estimates for Top500-sellers are statistically insignificant, they share the estimated coefficients of the general population in C and D. The coefficients for storefronts are negative everywhere.

Table 8. OLS Estimates for Model 3.

Variable	***A***	***B***	***C***	***D***	***E***
SF	**0.460*****	**0.539*****	**0.577*****	0.215	0.193
	(0.057)	**(0.069)**	**(0.122)**	(0.316)	(0.232)
TOP	**0.091*****	**0.075****	0.048	0.136	0.504
	(0.025)	**(0.036)**	(0.062)	(0.147)	(0.168)
zARATE	**-0.079*****	**-0.079*****	**-0.097*****	**-0.095****	**-0.082*****
	(0.017)	**(0.022)**	**(0.031)**	**(0.045)**	**(0.031)**
SF*zARATE	**-0.347*****	**-0.356*****	**-0.332*****	**-0.860*****	**-0.206*****
	(0.046)	**(0.065)**	**(0.127)**	**(0.304)**	**(0.073)**
TOP*zARATE	-0.041	**-0.068***	-0.057	0.048	0.075
	(0.029)	**(0.037)**	(0.054)	(0.098)	(0.057)
zHIST	**-0.043*****	-0.021	0.010	0.033	-0.107***
	(0.015)	(0.020)	(0.026)	(0.041)	(0.029)
SF*zHIST	**-0.109****	**-0.177*****	**-0.374*****	**-1.007*****	0.065
	(0.046)	**(0.062)**	**(0.145)**	**(0.338)**	(0.074)
TOP*zHIST	-0.008	-0.004	-0.044	**-0.206***	-0.039
	(0.032)	(0.042)	(0.063)	**(0.122)**	(0.059)
zRATE*zHIST	**-0.143*****	**-0.171*****	**-0.184*****	**-0.180****	-0.063
	(0.023)	**(0.030)**	**(0.042)**	**(0.070)**	(0.039)
SF*zRATE*zHIST	**0.260*****	**0.335*****	**0.564*****	-0.198	0.120
	(0.068)	**(0.099)**	**(0.212)**	(0.589)	(0.105)
TOP*zRATE*zHIST	**0.169*****	**0.195*****	**0.260*****	**0.445*****	-0.005
	(0.040)	**(0.053)**	**(0.082)**	**(0.165)**	(0.070)
zRDIF	**-0.068*****	**0.059*****	**0.036****	**0.033***	**0.140*****
	(0.012)	**(0.013)**	**(0.014)**	**(0.020)**	**(0.029)**
SF*zRDIF	**-0.217*****	**-0.221*****	**-0.249***	**-0.757****	**-0.193****
	(0.062)	**(0.085)**	**(0.139)**	**(0.335)**	**(0.094)**
TOP*zRDIF	**-0.086*****	**-0.062****	0.009	0.018	**-0.192*****
	(0.023)	**(0.025)**	(0.031)	(0.049)	**(0.053)**
zTHICK	**-0.086*****	**-0.089*****	**-0.088*****	**-0.069*****	**0.099****
	(0.011)	**(0.011)**	**(0.013)**	**(0.016)**	**(0.044)**
SF*zTHICK	**0.191*****	**0.146*****	**0.109****	0.073	0.208
	(0.029)	**(0.034)**	**(0.045)**	(0.082)	(0.388)
TOP*zTHICK	**0.058*****	**0.063*****	**0.074****	0.018	**0.538***
	(0.020)	**(0.024)**	**(0.032)**	(0.053)	**(0.305)**
zSFR	**-0.061*****	**-0.078*****	**-0.077*****	**-0.146*****	**-0.052***
	(0.016)	**(0.021)**	**(0.029)**	**(0.055)**	**(0.028)**
SF*zSFR	**-0.133*****	**-0.158*****	**-0.257*****	-0.127	0.056
	(0.035)	**(0.042)**	**(0.064)**	(0.188)	(0.066)
TOP*zSFR	**-0.065****	-0.056	**-0.153*****	**-0.275****	-0.058
	(0.031)	(0.039)	**(0.058)**	**(0.111)**	(0.050)
Adjusted R^2	0.134	0.160	0.204	0.257	0.054
Observations	8784	6650	4201	1826	2134

***** p-value<0.01; ** p-value<0.05; * p-value<0.1; Standard errors in parentheses.**

The market variables display mixed results. The standardized measure for market thickness, *zTHICK*, is statistically significant and negative in A to D but positive in E. The negative estimates indicate that an increase in market thickness by one standard deviation decreases prices approximately 0.07 (D) to 0.09 (B) standard deviations. The positive coefficient implies that price increases by 0.1 standard deviations in the low concentration markets. The control groups show a different pattern. The estimates for storefronts are statistically significant and positive in A to C, where the total effect ranges from 0.105 to 0.109. The estimates for Top500-sellers are also statistically significant in A to C and E. Except for 0.637 in E, the magnitudes are lower ranging from -0.028 (A) to 0.063 (B). This evidence suggests that neither storefronts nor Top500-sellers resort to price cuts when the number of market incumbents increases.

Table 9. Threshold values and Main Effects for OLS Estimates in Model 3 (OLS).

Model 3	***Seller Type***	β_1	β_2	β_3	γ_1	γ_2	γ_3	***Threshold***	***Main Effect***
	All	-0.079			-0.143			<-0.552	-0.079
A	***Storefront***	-0.079	-0.347		-0.143	0.260		**>3.641**	-0.426
	Top500	-0.079			-0.143		0.167	**>3.292**	-0.079
	All	-0.079			-0.171			<-0.462	-0.079
B	***Storefront***	-0.079	-0.356		-0.171	0.335		**>2.652**	-0.435
	Top500	-0.079		-0.068	-0.171		0.195	***>6.125***	-0.079
	All	-0.097			-0.184			<-0.527	-0.097
C	***Storefront***	-0.097	-0.332		-0.184	0.564		**>1.129**	-0.429
	Top500	-0.097			-0.184		0.564	**>1.276**	-0.097
	All	-0.095			-0.180			<-0.528	-0.095
D	***Storefront***	-0.095	-0.860		-0.180			*<-5.306*	-0.955
	Top500	-0.095			-0.180			**>0.358**	-0.095
	All	-0.082							-0.082
E	***Storefront***	-0.082	-0.206						-0.288
	Top500	-0.082							-0.082

Values outside the observed distribution in italics.

The storefront ratio, z*SFR*, provides more theoretically sound results than market thickness. The estimates for all sellers range from -0.052 (E) to -0.146 (D) which suggests that the number of storefronts in the market is a more significant driver for price cuts. The estimates for storefronts and Top500-sellers show starker results. The total effect for storefronts ranges from -0.052 (E) to -0.334 (D). The effect on Top500-sellers ranges from -0.052 (E) to -0.421 (D). These magnitudes suggest that an increase in the storefront ratio erodes prices more effectively than an increase in market thickness especially in more competitive markets.

Table 10. Total Effects in Model 3 (OLS).

Model 3	*Seller Type*	*zRdif*	*zTHICK*	*zSFR*
	All	-0.068	-0.086	-0.061
0.1	***Storefront***	-0.285	0.105	-0.194
	Top500	-0.154	-0.028	-0.126
	All	0.059	-0.089	-0.078
0.25	***Storefront***	-0.162	0.146	-0.236
	Top500	-0.003	0.063	-0.078
	All	0.036	-0.088	-0.077
0.5	***Storefront***	-0.213	0.109	-0.334
	Top500	0.036	-0.014	-0.230
	All	0.033	-0.069	-0.146
0.75	***Storefront***	-0.724	-0.069	-0.146
	Top500	0.033	-0.069	-0.421
	All	0.140	0.099	-0.052
0.9	***Storefront***	-0.053	0.099	-0.052
	Top500	-0.052	0.637	-0.052

3.3 QUANTILE REGRESSION

Quantile Regression (QR) is a semiparametric estimation method. The strength of QR is that it is robust to outliers in data (Koenker & Hallock 2001). A special case of QR is median regression, which is a semiparametric counterpart to OLS. As the name suggests, median regression reveals only a fraction of the information that QR can provide. With QR, it is possible to get estimates for coefficients across the conditional distribution of the dependent variable.

As an application of QR, we estimate Model 3 with QR. We use the data set A because it is the broadest market setting. The estimates are for the 0.1, 0.25, 0.5, 0.75 and 0.9 quantiles[10]. These figures are also used in making references to specific quantiles. The estimated coefficients are reported in Table 11.

[10] We refer to the 0.1 quantile as the lower tail and the 0.9 quantile as the upper tail. The other quantiles are referred to as the first quartile (0.25), the median (0.5) and the third quartile (0.75).

The interaction effect of *zARATE*zHIST* and the main effect of *zARATE* are reported in Table 12. The QR estimates reveal that the interaction effect shows great variation in different points of the price distribution. Only storefronts that have a long ratings history (>3.920 and >2.361, respectively) have positive returns on reputation in the lower tail and the first quartile. The threshold value is positive for Top500-sellers at the median but the magnitude is out of bounds. So, no firm realizes benefits from a good reputation around the middle of the price distribution. In the third quartile and the upper tail, all firms realize positive returns on reputation. For the general seller population these values are below the mean because the thresholds are -0.924 (0.75) and -0.690 (0.9). Storefronts and Top500-sellers have realistic threshold values only in the third quartile. The magnitude is very high (4.217) for storefronts but less so (1.511) for Top500-sellers. In the upper tail, their threshold values are out of bounds.

The effects of other variables are reported in Table 13. The QR estimates for *zRDIF* reveal that the effect is not uniform across the distribution. For all sellers, the effect is statistically significant and positive at and above the median. The values range from 0.058 (0.5) to 0.165 (0.9) which corresponds to 6% to 17% increase in price when *zRDIF* increases by one standard deviation. The effect on storefronts is negative in the 0.5 and 0.75 quantiles. The total effect on Top500-sellers is mildly negative (-0.025) at the median, whereas at and above the third quartile the effect is slightly positive. This evidence suggests that the positive impact of an improved reputation is more effective above the median.

The QR estimates reveal interesting qualities about the market variables. The OLS estimates suggested that market thickness is negative only for the general seller population. The QR estimates alter this view because also Top500-sellers are negative and statistically significant above the median. This implies that an increase in the number of market incumbents erodes pricing power among the higher priced sellers. The storefront ratio shows a constant negative pattern among all sellers. As with market thickness, an increase in *zSFR* is felt more heavily in the upper tail of the price distribution.

Table 11. QR Estimates for Model 3 (A).

Variable	***0.1***	***0.25***	***0.5***	***0.75***	***0.9***
SF	**-0.910***** **(0.058)**	**-0.461***** **(0.075)**	**0.463***** **(0.089)**	**1.308***** **(0.080)**	**1.955***** **(0.097)**
TOP	**-0.827***** **(0.030)**	**-0.509***** **(0.029)**	**0.137***** **(0.039)**	**0.636***** **(0.031)**	**1.044***** **(0.035)**
zRATE	**-0.492***** **(0.021)**	**-0.325***** **(0.021)**	**-0.135***** **(0.026)**	**0.085***** **(0.028)**	**0.238***** **(0l021)**
SF*zRATE	**0.100**** **(0.047)**	**-0.100*** **(0.055)**	**-0.446***** **(0.063)**	**-0.473***** **(0.069)**	**-0.452***** **(0.078)**
TOP*zRATE	**0.400***** **(0.034)**	**0.246***** **(0.032)**	0.027 (0.044)	**-0.224***** **(0.041)**	**-0.441***** **(0.037)**
zHIST	**0.197***** **(0.020)**	**0.117***** **(0.020)**	0.021 (0.025)	**-0.154***** **(0.022)**	**-0.263***** **(0.015)**
SF*zHIST	**-0.338***** **(0.043)**	**-0.319***** **(0.067)**	**-0.142**** **(0.059)**	0.043 (0.093)	0.150 (0.105)
TOP*zHIST	**-0.173***** **(0.035)**	**-0.160***** **(0.036)**	**-0.093*** **(0.048)**	**0.083*** **(0.044)**	**0.213***** **(0.032)**
zRATE*zHIST	**-0.777***** **(0.034)**	**-0.513***** **(0.032)**	**-0.199***** **(0.038)**	**0.092**** **(0.038)**	**0.345***** **(0.030)**
SF*zRATE*zHIST	**0.877***** **(0.061)**	**0.693***** **(0.097)**	**0.194**** **(0.082)**	0.039 (0.109)	**-0.319**** **(0.125)**
TOP*zRATE*zHIST	**0.653***** **(0.046)**	**0.452***** **(0.048)**	**0.211***** **(0.062)**	0.009 (0.060)	**-0.243***** **(0.052)**
zRDIF	-0.002 (0.011)	0.014 (0.013)	**0.058***** **(0.016)**	**0.109***** **(0.014)**	**0.165***** **(0.012)**
SF*zRDIF	-0.004 (0.064)	0.014 (0.102)	**-0.321***** **(0.071)**	**-0.223**** **(0.094)**	-0.230 (0.173)
TOP*zRDIF	**-0.062*** **(0.034)**	**-0.089***** **(0.024)**	**-0.083***** **(0.027)**	**-0.093***** **(0.031)**	**-0.137***** **(0.032)**
zTHICK	**-0.363***** **(0.011)**	**-0.262***** **(0.010)**	**-0.150***** **(0.010)**	0.000 (0.015)	**0.155***** **(0.014)**
SF*zTHICK	**0.444***** **(0.039)**	**0.384***** **(0.041)**	**0.225***** **(0.039)**	0.050 (0.035)	0.063 (0.114)
TOP*zTHICK	**0.394***** **(0.023)**	**0.290***** **(0.019)**	**0.068***** **(0.023)**	**-0.116***** **(0.029)**	**-0.242***** **(0.035)**
zSFR	-0.014 (0.016)	**-0.040*** **(0.020)**	**-0.096***** **(0.025)**	**-0.156***** **(0.050)**	**-0.148***** **(0.017)**
SF*zSFR	-0.064 (0.040)	-0.049 (0.043)	**-0.113**** **(0.051)**	**-0.156***** **(0.050)**	**-0.143***** **(0.052)**
TOP*zSFR	-0.056 (0.040)	-0.010 (0.032)	**0.146****** **(0.042)**	-0.023 (0.056)	**0.082*** **(0.044)**

*** p-value<0.01; ** p-value<0.05; * p-value<0.1;Standard errors in parentheses.

Table 12. Threshold values and Main Effects for QR Estimates in Model 3.

Model 3QR	***Seller Type***	β_1	β_2	β_3	γ_1	γ_2	γ_3	***Threshold***	***Main Effect***
	All	-0.492			-0.777			<-0.633	-0.492
0.1	***Storefront***	-0.492	0.100		-0.777	0.877		**>3.920**	-0.392
	Top500	-0.492		0.400	-0.777		0.653	<-0.742	-0.092
	All	-0.325			-0.513			<-0.634	-0.325
0.25	***Storefront***	-0.325	-0.100		-0.513	0.693		**>2.361**	-0.425
	Top500	-0.325		0.246	-0.513		0.452	<-1.295	-0.079
	All	-0.135			-0.199			<-0.678	-0.135
0.5	***Storefront***	-0.135	-0.446		-0.199	0.194		*<-116.200*	-0.581
	Top500	-0.135			-0.199		0.211	***>11.250***	-0.135
	All	0.085			0.092			**>-0.924**	**0.085**
0.75	***Storefront***	0.085	-0.473		0.092			**>4.217**	-0.388
	Top500	0.085		-0.224	0.092			**>1.511**	-0.139
	All	0.238			0.345			**>-0.690**	**0.238**
0.9	***Storefront***	0.238	-0.452		0.345	-0.319		***>8.231***	-0.214
	Top500	0.238		-0.441	0.345		-0.319	***>7.808***	-0.203

Values outside the observed distribution in italics.

Table 13. Total Effects in Model 3 (QR).

Model 3QR	***Seller Type***	***zRdif***	***zTHICK***	***zSFR***
	All		-0.363	
0.1	***Storefront***		0.081	
	Top500	-0.062	0.031	
	All		-0.262	-0.040
0.25	***Storefront***		0.122	-0.040
	Top500	-0.089	0.028	-0.040
	All	0.058	-0.150	-0.096
0.5	***Storefront***	-0.263	0.075	-0.209
	Top500	-0.025	0.082	-0.242
	All	0.109		-0.137
0.75	***Storefront***	-0.114		-0.293
	Top500	0.016	-0.116	-0.137
	All	0.165	0.155	-0.242
0.9	***Storefront***	0.165	0.155	-0.390
	Top500	0.028	-0.087	-0.160

4. DISCUSSION

These results suggest that the number of firms in the market plays an important part in consumer decision making process. The pricing decisions of the firms reflect this. Model 1 suggests that good ratings may provide returns on reputation for storefronts and Top500-sellers. These are, however, contingent on the length of the ratings history. An increase in market thickness lowers the threshold length, but only Top500-sellers seem to be able to set higher prices in very competitive markets. Model 2 examined the effect of an improved rating score on sellers' pricing. The interaction term proved statistically insignificant but a small positive effect for the general seller population surfaced. In Model 3, we included the market variables into the regression equation. The results for reputation variables paralleled the results obtained in Model 1 and Model 2. The market variables indicated that the number of storefronts in a market reduced price levels more than an increase in market thickness. Quantile regression estimates do not change the general results, but they demonstrate that also the general seller population has returns on reputation in the upper tail of the price distribution.

There are few plausible explanations for the results. First, consumers may consider price as a less important decision variable when market thickness increases. If reputation matters in consumer decision making, then price dispersion could emerge. The sellers with better reputations could charge higher prices. This can be demonstrated by a scatter plot with a kernel regression that plots the value of information (*VI*), which measures the monetary value of price information, against market thickness. Figure 3 depicts a kernel fit between market thickness and the value of (price) information which is one measure for price dispersion. We use a relative measure for *VI* given by

$$VI = \frac{\overline{p}_j - p_j^{\min}}{p_j^{\min}}, \tag{8}$$

in which *VI* is a percentage of the difference between the expected price and the minimum price in a market *j* (Baye et. al 2003). Naturally, the value of information is zero in single-seller markets. Figure 3 suggests that *VI* increases rapidly initially and levels off as market thickness reaches approximately 10 (the fit curve decreases again in the right tail but the small number of observations explains this). This means that price dispersion increases even though price information is perfect. These results are comparable to Baye et al. (2003) who discovered a positive correlation between *VI* and the number of firms with similar magnitudes in the online consumer electronics markets. These differences in prices could partially result from the returns on reputation for storefronts and Top500-sellers in the more competitive markets. Second, the likelihood that a consumer encounters a familiar firm increases as the number of firms increases. Thus, earlier successful transactions could weigh in consumer decision making which could give support to price dispersion. According to Grover (et al. 2006) information overload – too much information to process – might cause consumers to buy only at known firms.

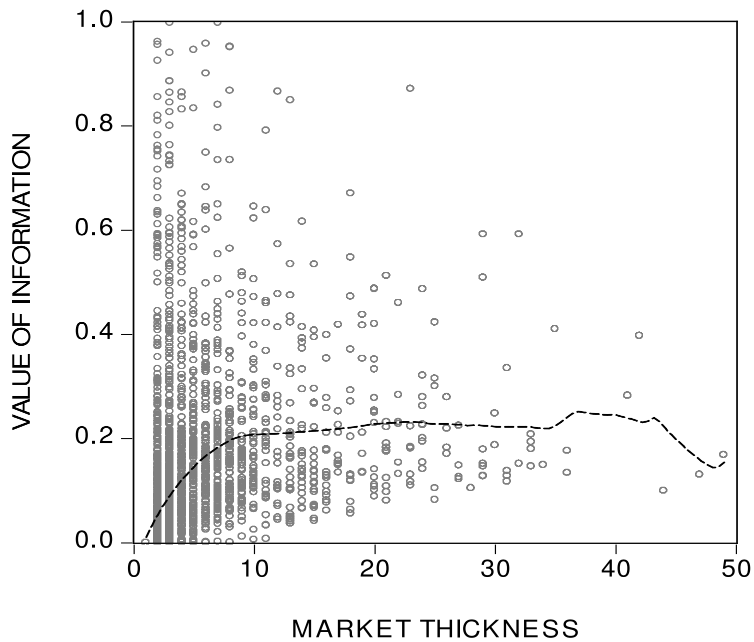

Figure 3. Scatter Plot with Kernel Regression on Value of Information and Market Thickness

Another explanation for the differences could be that the value of merchandise determines the importance of the seller's reputation in a purchase decision. It is plausible that consumers place a different value on reputation in more valuable items such as televisions than in purchases of a relatively low value such as deodorants. Statistics of sellers' prices in competitive markets are laid out in Table 14. They show that the mean (279.90) and range (8449.01) of storefronts' prices is considerably less than Top500-sellers or sellers in general. The difference in the median prices is less severe but still clear. The statistical tests in Table 15 prove that on average, storefronts focus on items that are of lower value, because the mean and median prices are lower than those of the other two seller types. While the means of Top500-sellers and other sellers are equal, their medians are not. This implies that Top500-sellers sell more valuable items than the other sellers. As the value of a purchased item increases, consumers could become more risk averse and consider a seller's reputation as an insurance against fraudulent behavior. Thus, consumers are willing to pay a price premium for a homogenous item to a more reputable seller.

Table 14. Prices in Competitive Markets.

Statistic	***Other Sellers***	***Storefronts***	***Top500-Sellers***
Mean	423.89	279.90	426.07
Median	111.12	85.00	149.99
Maximum	16797.59	8450.00	16265.20
Minimum	0.01	0.99	0.93
Std. Dev.	962.81	535.48	881.98
Skewness	7.53	4.90	8.08
Kurtosis	91.00	43.09	110.55
Jarque-Bera	3215223.	154222.7	1159607.
Probability	0.000000	0.000000	0.000000
Observations	9681	2173	2353

Table 15. T-Test/Mann-Whitney Test for Prices of Seller Types.

Hypothesis: equal mean/median	***T-test***	***Mann-Whitney***	***Result***
Storefronts Top500-sellers	-6.673***	9.512***	Rejected / Rejected
Storefronts Other Sellers	-6.741***	5.054***	Rejected / Rejected
Top500-sellers Other Sellers	-0.100	6.145***	Accepted / Rejected

*** p-value<0.01; ** p-value<0.05; * p-value<0.1.

Overall, these results show that a reputation score does not enable major price premiums. Unfortunately, it is not possible to compare our results to those obtained from the auction markets because of fundamental differences in retailing and auctions. The closest comparison is Bayliss and Perloff (2002) who find that favorable third party ratings have no effect on prices. They conclude that there is no premium associated with the ratings: "bad firms" charge higher prices than "good firms". Our findings do not agree with this entirely. Since the average rating score is over 4 in a scale of 1 to 5, the number of "bad firms" in the market is not very large. Nevertheless, it is possible that small differences in rating scores and ratings histories do matter. The main effect of the rating score on prices is negative, which could support the findings of Bayliss and Perloff. However, our evidence shows that Top500-sellers and storefronts with better reputations and longer histories charge higher prices than sellers in general. Quantile regression reveals that all sellers benefit from better reputations in the upper quartile of the price distribution. Brand recognition could explain the effect on Top500-sellers but not on storefronts. Specializing in niche product categories might explain it for them, but this study does not differentiate between product categories, nor do we have data to make the distinction.

Our evidence indicates also that the number of sellers in the market have an impact on pricing. More precisely, the number of storefronts seem to affect more than pure number of sellers. There could be a simple explanation for this. As storefronts sell their products only through the comparison shopping website, they have a larger propensity to enter into price competition. For other sellers, a comparison shopping website is a way to attract more price-conscious customers, while they may derive a larger bulk of sales elsewhere. For this reason, they have no interest in entering price competition for the informed consumers who look for bargains by comparison shopping. Instead, the market for them resembles the situations described in Salop and Stiglitz (1977) and Varian (1980), where the informed customers pay lower prices and the uninformed pay higher prices and occasionally a firm charges the lowest price universally by organizing a sale or just by being lucky.

CONCLUSION

In this paper, we examined the effect of reputation on pricing in retail e-commerce. In our model, a seller's reputation is measured by its rating score and ratings history, which are aggregated from the consumer feedback. We controlled for two seller types, storefronts and Top500-sellers, based on their level of sales and choice over a sales channel. Moreover, the variables that characterize competition in markets were included in the regression models. We used OLS and quantile regression to estimate the regression models with different data-sets.

Our findings indicate that there are some positive returns on reputation in retail e-commerce. These are contingent on the length of the seller's ratings history. A long presence in the marketplace seems to allow premium pricing for the controlled seller types Top500-sellers and storefronts. Quantile regression indicates that returns on reputation concentrate to the upper quartile of the price distribution. We also find that the number of sellers in the market seem to affect pricing by decreasing the length of the required ratings history. As price dispersion in markets increases with the number of sellers in the market, seller reputations may be one cause for the emergence of price dispersion in highly competitive markets.

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