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Sellers in Online Auction Markets: Introducing a Feedback-Based Classification

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ABSTRACT

Trading in the online consumer-to-consumer (C2C) auction market necessitates buyers and sellers to engage in transactions with anonymous counterparts. The sequence of paying first and then taking delivery introduces a great amount of risk for potential buyers. In order to assist buyers in dealing with this risk, online auction markets (OAMs) are employing reputation-scoring systems and traders can be classified in terms of their online reputation scores. A review of the literature suggests a conspicuous absence of the study on any standard classification of sellers in OAMs. Lack of such a classification hinders systematic research and theory development. Therefore, a classification of sellers, based on the total number of unique feedbacks (a surrogate measure for certainty regarding repetition of past behaviors), negative feedback rate (a surrogate measure for risk based on prior poor performance), and nature of negative feedbacks (a surrogate measure for the degree of risk), is proposed to advance our understanding of the online C2C auction markets. Toward demonstrating the classification's systemic power, we present a propositional inventory developed from the classification and discuss how the classification accommodates current research and furthers theory building.

INTRODUCTION

Growth in the online market has increased the need for buyers and sellers to engage in transactions with unknown counterparts [Houser and Wooders 2000]. Often, in cases of online B2B (Business-to-Business) and B2C (Business-to-Consumer) transactions, the buyers are at least familiar with the sellers. However, in case of C2C (Consumer-to-Consumer) online auction markets (OAMs), both buyers and sellers are total strangers to each other and their true identity is seldom known [Bracker and Smith 2004; Houser and Wooders 2000; Livingston 2002; Zacharia, Moukas, and Maes 2000]. Further, as buyers have no other means of finding the details of products that they are interested in, they have to solely rely on unknown sellers' description of products. Moreover, in such markets, it is not uncommon for payments to precede the delivery of products [Livingston 2002; Melnik and Alm 2002]. The sequence of paying first and then taking the delivery of products, often combined with little or no ability to examine the product in advance, introduces a great amount of risk for potential buyers [Zacharia et al. 2000]. Buyers hardly have any means of preventing the sellers from indulging in opportunistic acts [Shapiro 1983] and, for most part, rely on the information provided by the sellers [Zacharia et al. 2000]. This situation creates asymmetrical distribution of information whereby sellers, when compared to buyers, not only possess far more information about the product but also have the opportunity to withhold information critical to the transaction [Choi, Stahl, and Whinston 1997; Fudenberg and Levine 1989; Houston 2003]. Such an asymmetrical distribution of information reduces the credibility of the signals (about product quality and other transaction related information) sent by sellers and hence, and can lead to market malfunction or even market failure [Akerlof 1970].

The nature of C2C OAMs demands some sort of governance mechanism aimed at mitigating the risks faced by potential buyers [Kollock 1999]. In fact, a variety of risk relief services such as escrow services (by trusted third parties), insurances (provided by the market provider) and warranties do exist in OAMs. However, they impose an additional cost to the buyers, which is often not desired, especially when the worth of the transaction is small [Shapiro 1983]. Therefore, reputation systems have been resorted to as mechanisms to reduce information asymmetries [McDonald & Slawson 2002]. These reputation systems can be used by the buyers without incurring

significant additional costs [Shapiro 1983]. The term reputation has been defined in different ways in different studies [Houston 2003; Mailath and Samuelson 2001; Zacharia et al. 2000]. For the purposes of this study, reputation refers to buyer's estimation of consistency in a seller's behavior over a period of time over any given attribute such as integrity, competence, etc. [Herbig, Milewicz, and Golden 1994].

With the growth in the OAMs, online C2C marketplaces such as ebay, yahoo, and other providers have set up reputation mechanisms whereby buyers and sellers provide feedbacks and rate each other based on their transaction related experiences [Livingston 2002; Resnick and Zeckhauser 2002]. Feedbacks are specific to the parties involved in a particular transaction and are classified into positive, negative, or neutral feedbacks. Further, the difference between the total number of positive and negative feedbacks forms the seller's net reputation score [Standifird 2001]. Potential buyers examine the net reputation ratings of sellers, with the objectives of reducing existing information asymmetries and making better-informed decisions [Livingston 2002]. While extensive literature exists on the differential treatments received by sellers with high and low reputation [Allen 1984; Klein and Leffler 1981; Livingston 2002; McDonald and Slawson 2002; Melnik and Alm 2002; Shapiro 1983], no study has systematically developed a classification of OAM sellers.

Absence of a standardized classification often leads to researchers following their own implicit schema for classifying sellers in an OAM and using that schema to determine gaps in the literature and their area of interest. This leads to major and/or minor overlaps in the phenomenon examined, which makes it difficult to assess the contributions and integrate them with the rest of the research in a systematic manner. Also, the lack of standardized categories makes it difficult to compare and integrate research findings (Engel, Kollat, and Blackwell 1973) and is dysfunctional for any area of research (Hunt 1991). Further, in the absence of a meaningful framework or classification, research in any area cannot be cumulative (Hunt 1991). Furthermore, given the volume of data available on traders in C2C auction markets, an appropriate classification can be used to provide better understanding of the available data and to make predictions regarding future transactions. To sum, absence of a comprehensive classification of such a widely studied phenomenon restricts the prospects for systematically studying the phenomenon and the opportunities for developing related theories. Therefore, in this paper we present a hierarchical classification of sellers in OAMs that can facilitate systematic research. Subsequently, we (i) assess the classification using the evaluative criteria provided by Hunt (1991), (ii) demonstrate the systemic power of the classification by providing a sample propositional inventory, and (iii) discuss how the proposed classification can facilitate further theory building, while accommodating current research.

SELLERS IN ONLINE AUCTION MARKETS: A CLASSIFICATION

Research on the role of reputation in OAMs has focused on a number of important issues some of which have been summarized in Table 1.

Table 1: Summary of some of the important findings relevant to OAMs from the past literature.

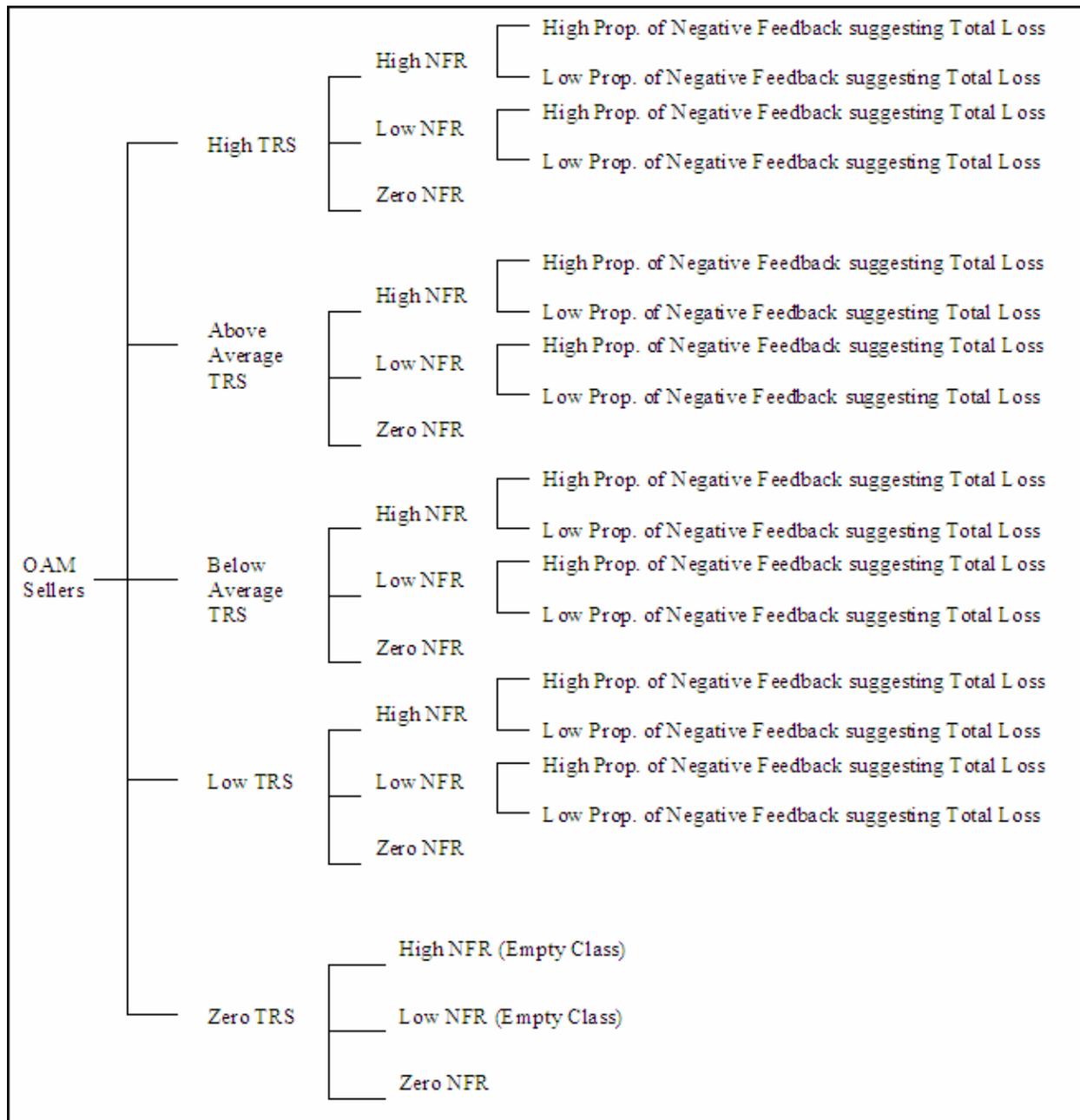
No.	Findings	Citations
1.	A stringent reputation mechanism works effectively towards alleviating information asymmetries and facilitating a market for quality products.	Diamond 1989; Houston 2003; Klien and Leffler 1981; McDonald and Slawson 2002; Shapiro 1983
2.	Anecdotal evidence strongly suggests that reputation greatly matters in OAM and that buyers in this market do actually pay attention to sellers' reputation.	Friedman and Resnick 2001
3.	In OAMs, reputation building is not free of cost. It occurs at a cost to the players i.e. players with low reputation are treated poorly when compared to players with high reputation.	Rao and Ruckert 1994; Shapiro 1983
4.	In the long run participants are rewarded for building reputation and the rewards thus received far outweigh the costs incurred in the process of reputation building.	Kreps and Wilson 1982; Milgrom and Roberts 1982
5.	Several empirical studies have examined the impact of reputation on buyers bidding behaviors and have found that there is a significant relationship between sellers' reputation and the bid prices received by	Friedman and Resnick 2001; Houser and Wooders 2000; McDonald and Slawson 2002; Melnik and Alm

	them.	2002; Shapiro 1983
6.	While the magnitude of impact has differed from study to study, it is evident from theoretical as well as empirical models that higher the reputation of a seller higher the number of bids and prices he receives.	Allen 1984; Camarer and Weigelt 1988; Livingston 2002; Lucking-Reiley et al. 1999; McDonald and Slawson 2002; Melnik and Alm 2002; Shapiro 1983
7.	Negative ratings have highly significant impact on the bid prices, i.e., negative ratings considerably reduce the bid prices received by the seller.	Shapiro 1983; Standifird 2001
8.	New comers or sellers with no reputation or negative reputation are treated poorly during their initial transactions, i.e., they receive low bids or no bids irrespective of the quality of the product they are offering for sale.	Friedman and Resnick 2001; Resnick and Zeckhauser 2002; Shapiro 1983; Zacharia et al. 2000

While different groups of sellers such as new comers, sellers with low or high net reputation scores, sellers with or without negative reputation ratings, have been individually identified in the literature, a review of the literature reveals no standard classification of OAM sellers based on feedbacks or reputation scores. Since classification schema play a significant role in organizing phenomena into classes that are amenable to systematic investigation and theory development (Hunt, 1991), we propose a classification of OAM sellers that could potentially lead to substantive theoretical development, facilitate meaningful comparisons between different groups of sellers, help in developing a holistic perspective about the impact of reputation on bid prices, and provide other research opportunities. While recognizing that sellers can be categorized on the basis of product types, price range of the products, homogeneity and heterogeneity of products, innocence and malice in intentions, etc., in this paper, we present a parsimonious but adequate classification of sellers based on online traders' feedbacks, because the feedbacks and the reputation ratings that are calculated based on the feedbacks have been extensively studied as determinants of the prices and number of bids received by an OAM seller during subsequent transactions. Resnick and Zeckhauser (2002) report, based on the online transaction data from eBay, that the feedback rate is 52.1% from buyers to sellers and 60.6% from sellers to buyers. As majority of traders contribute to the online reputation feedbacks, the online data are instrumentally valid and effective to study the classification of online sellers. Since we are developing the classification before analyzing any specific set of data, i.e. "a priori," the procedure employed here is called logical partitioning (Harvey 1969). This way of classifying schema is also called "deductive classification" or "classification from above" (Hunt 1991).

Developing a classification schema involves three main steps: (i) specifying the phenomena to be categorized, (ii) delineating the categorial term(s), which are properties of the phenomena on which the classification schema is to be based, and (iii) labeling the various categories that emerge from applying the categorial terms to the phenomena (Hunt 1991). The phenomenon that we are attempting to categorize is OAM sellers. The categorial terms must be such that they help in developing a meaningful and useful classification. The primary concern in OAMs is the *risk* involved in dealing with unknown sellers and the leading focus of research in this area is to provide mechanisms that will help the users in assessing the *certainty* with which a seller will behave in a particular manner in future transactions (Zacharia et al. 2000). Therefore, the categorial variables used in this study are: (i) estimate of certainty regarding repetition of past behaviors in future transactions; and (ii) estimate of risk involved in dealing with the OAM seller. We also introduce a third categorial term which is a measure of the *degree of risk* involved in dealing with the OAM seller. The procedure employed to create the classification has resulted in a hierarchical classification represented in Figure 1. The advantage of such a classification is that it has greater power in systematically organizing the phenomenon under investigation (Hunt 1991). We now describe each category in the classification that was briefly introduced here.

Figure 1: Feedback Based Classification of Sellers in OAMs.



Level I: Categorization Based on Total Reputation Score (TRS) – A Surrogate Measure for Certainty Regarding Repetition of Past Behaviors in Future Transactions

An integral part of the definition of the term reputation is the consistency in the seller's behaviors over a period of time. Therefore, a surrogate measure of reputation should allow the buyer to estimate the certainty with which the seller will behave in a manner consistent with his past behaviors. Often net reputation score (total number of positive feedbacks minus total number of negative feedbacks) is used for this purpose (Standifird 2001). However, net reputation score throws little light on how consistent the seller's behaviors are likely to be. Two sellers, A and B, could have the same net reputation score of 50. It is possible that seller A has received only 50 times of positive feedbacks without any negative feedbacks, whereas seller B has traded 150 times (received 100 positive and 50 negative feedbacks). The net reputation score provides little information about which seller is more likely to behave in a manner consistent with his past behavior. Therefore, as a surrogate measure for the certainty regarding the consistency in seller's behaviors, we used a measure called *the total reputation score* (TRS). It is defined as the total number of feedbacks - positive, negative and neutral - that a seller has received so far from unique trading partners. The higher the seller's TRS, the higher the chance that he will act in a manner consistent with his past behavior, because the larger the sample size the more probable it is that the sample mean comes arbitrarily close to the population mean according to the *Law of Large Numbers* (Hays and Winkler, 1971; See Appendix I for a detailed explanation). This means that the larger the TRS, the more accurate the negative feedback rate reflects the risk when buying from the seller. Similarly, we can demonstrate that the larger the TRS, the more consistent will be the rate of positive feedbacks received by the seller.

Therefore, TRS can be used by researchers as well as potential buyers to determine the certainty with which the seller is likely to behave in a specific manner in future. Based on the TRS we suggest that sellers be classified into five groups: (i) Sellers with high TRS, (ii) Sellers with above-average TRS, (iii) Sellers with below-average TRS, (iv) Sellers with low TRS, and (v) Sellers with zero TRS (inactive sellers or new sellers who have never received any feedback).

Sellers with high TRS are the most active sellers and are likely to account for the majority of the transactions in the market. Given the situation that they are frequently traded with buyers, a potential buyer can expect the seller of this type to repeat his past performance with greater certainty. Sellers with Above-Average TRS are those whose total reputation score is equal to the average reputation score of a given market. While contemplating to deal with sellers in this category, buyers can be reasonably certain that the seller will demonstrate past behavior in future transactions. Sellers with below-average TRS are those about whom the buyers cannot be certain in terms of consistency in behaviors. However, there is a chance that the sellers might behave in a manner consistent with their previous behaviors. While dealing with sellers with low TRS there is a very low degree of certainty that these sellers will repeat past behaviors. The buyers cannot be certain while contemplating to deal with sellers belonging to this group since these sellers have not been very active in the market. Sellers with Zero TRS refer to inactive sellers who have been registered as sellers but not engaged in any transaction or engaged rarely in transactions but did not receive any reputation feedback. Since no buyer has had any experience in the past with this seller or no one has left any feedback for this seller, there is no clue to the potential buyer and there is no justified way for the buyer to assess the certainty with which the seller will behave in a particular manner. Section 4 will detail how this classification is done with the support of empirical data.

The order in which the categories have been presented should theoretically suggest which sellers are more desirable than others when compared to each other on the basis of certainty regarding future behaviors. The sellers in the earlier categories are likely to be more desirable than the later ones. Further, it is important to note that the proposed categorization uses TRS of sellers and the average TRS of sellers in a given product market to classify them into one of the five categories mentioned above. That is, the categorization is specific to a product market. For example, let's assume that a seller's TRS is 50. When he attempts to sell a book, the average TRS in that market could be 100 and hence, he could be treated as a seller with low TRS in that market. But when the same seller attempts to sell a laptop, he might be considered as a seller with high TRS because the average reputation scores in that market is say 25. Thus, the categorization is flexible enough to accommodate the changing status of a seller.

Level II: Categorization Based on Negative Feedback Rate (NFR) – Surrogate Measure for Risk Based on Prior Negative Performance

An important concern for buyers in OAMs is the potential for being cheated in a transaction (Choi et al. 1997; Zacharia et al. 2000). Reputation mechanisms attempt to assist buyers in gauging the risk that arises while dealing with a seller (Livingston 2002). A common measure used to gauge this risk is the number of negative feedbacks received by a seller (Standifird 2002). However, the number of negative feedbacks left for a seller is often not very high. This hinders the process of gathering data for research in order to make reasonable predictions. Also, absolute numbers can give little information to enhance the understanding of the risks facing the buyers. It might lead the buyer to treat 2 sellers with 10 negative feedbacks each as same in terms of the risk involved even though one buyer might have 10 negative feedbacks out of a TRS of 1000 while the other might have a TRS of 100. Therefore, the rate at which the seller receives negative feedback is a better predictor of the risk involved in dealing with the seller in future transactions (Li and Lin 2004).

Negative feedback rate or NFR is defined as the ratio between the number of negative feedbacks and the total reputation score in the same period. NFR as an indicator of risk has been mostly ignored in the past literature. Given its potential to signal risks involved in a transaction, it is essential that NFR be included in the classification as a surrogate measure of risk. Therefore, sellers in each category at level 1 of the classification are further classified as sellers with high, low, or zero NFR. On the basis of our analysis of a number of datasets from eBay, we suggest that sellers with an NFR greater than the median NFR for a given product market be treated as sellers with high NFR and sellers with NFR below the median but greater than zero be treated as sellers with low NFR. It is important to note that a number of sellers might have no negative feedbacks and, hence, no NFR (hereafter referred to as sellers with zero NFR for convenience). Other things being equal, a seller with zero NFR should be preferred over others and sellers with low NFR should be preferred over sellers with high NFR. However, when other things are not equal it may be advisable for buyers to look at both TRS and NFR in conjunction to get a better picture of the risks involved. Further studies directed at this level of categorization are essential given its importance in making predictions about future behaviors of sellers and the inadequacy of research on NFR.

Level III: Categorization Based On Nature of the Feedback – A Surrogate Measure for the Degree of Risk Involved in a Transaction

Buyers are not likely to interpret all feedbacks simply as positive, negative or neutral feedbacks. Let's consider for instance two positive feedbacks: (a) "Great seller, great transaction. Thank You!" (b) "Got what I wanted but delivery was late by a week." Though both are positive feedbacks they clearly do not suggest the same information about the sellers. In the first case, the buyer is totally satisfied and hence perceives "total gain" whereas in the second case the buyer is not totally satisfied and, hence, perceives only "partial gain" that might vary in degree from buyer to buyer.

Next, consider two negative feedbacks: (a) "Sent the money, did not get the product." (b) "Got the product after one month!" In the first case, the buyer perceives "total loss" since he did not get anything in return for his payment. In the second case, the buyer does get the product but is not satisfied due to the delayed delivery and, hence, perceives "partial loss". A close observation highlights the similarity between partial loss and partial gain. The only difference between them is how the buyer perceived the case. If the buyer classifies such a feedback as positive, it means he/she perceives the transaction to be a transaction fetching partial gain or else he considers it to be a transaction resulting in partial loss, i.e., not getting everything he/she expected from the transaction.

Generally, based on the nature of the feedbacks, sellers can be classified as the sellers with high or low proportion of positive or negative feedbacks suggesting total or partial gain or total or partial loss. However, according to Standifird (2001, p. 293), "... positive reputational rating emerged as only mildly significant in determining the final bid price ... whereas a negative reputational rating emerged as highly significant and detrimental." Therefore, we consider only the nature of negative feedbacks and propose that it can be used as an indicator of the degree of risk involved in a transaction. Accordingly, we further classify sellers in level II who have received negative feedback in the past as sellers with high or low proportion of negative feedbacks suggesting total loss or partial loss. This measure is defined as the ratio between the total number of negative feedbacks suggesting total or partial loss and total number of negative feedbacks. Sellers with 50% or more negative feedbacks suggesting

total loss are considered as sellers with a 'high proportion of negative feedbacks suggesting total loss' else they are classified as sellers with a 'high proportion of negative feedbacks suggesting partial loss.'

Empty Classes

An important observation relating to logical partitioning is the scope for empty classes (Hunt, 1991). According to Hunt (1991, p. 180), "... proper application of categorial terms may generate a class to which no phenomenon belongs." Our classification has certain empty classes precisely for the reason suggested by Hunt (1991). Sellers with zero TRS cannot be classified any further as sellers with high or low NFR because they have not received any feedback at all. They will always belong to the category of sellers with zero NFR. Also, sellers with zero NFR cannot be classified any further based on the nature of the negative feedback.

EVALUATION OF THE PROPOSED CONCEPTUAL MODEL

Although alternative classifications of sellers in OAMs are not available, we can validate our classification by evaluating it based on five important criteria provided by Hunt (1991):

Does the schema adequately specify the phenomenon to be classified? As there seems to be a consensus among researchers about the definition of an OAM seller, this schema does well on criterion 1 referring to what is being categorized.

Does the schema adequately specify the properties or characteristics that will be doing the classifying? Throughout the classification, we uniformly use TRS as the indicator of certainty, NFR as the indicator of risk level, and nature of negative feedbacks as the indicator of the degree of risk involved in trading with a seller. Given that each categorial term has been precisely defined and consistently used, the schema is structurally sound and does not produce different and inconsistent systems of classes. Also, our classification procedures are inter-subjectively unambiguous, i.e., given our categorial terms different people would classify the phenomena into the same categories.

Does the schema have categories that are mutually exclusive? Since one seller who belongs to one category or class does not fit into any other category or class at a given point in time in a given product market, all categories are mutually exclusive. For example, a seller who belongs to high TRS class for one product does not fit into low TRS class for the same product at a given point in time.

Does the schema have categories that are collectively exhaustive? As every seller that needs to be classified does have a home in our classification, our classification is collectively exhaustive. A review of the literature reveals that the classifications that are implicit in the works of many researchers fit into our proposed classification.

Is the schema useful? Our classification is devised to explicate buyer behavior with reference to various sellers that are present in OAMs. To that extent, our classification adequately classifies sellers and generates intellectual discourse for further conceptual and empirical work as demonstrated in the following section.

Based on the above discussions, we conclude that our classification of sellers is valid and effective.¹ We will further demonstrate the usefulness of the proposed conceptual model in the next two sections.

EMPIRICAL FINDINGS TO ASSESS THE ASSUMPTIONS MADE IN DEVELOPING THE CLASSIFICATION

The proposed classification classifies sellers according to three different dimensions that majority of the buyers are concerned about: the certainty with which past behaviors are likely to be repeated, the risk involved in trading with a seller, and the degree of risk involved. In order to assess the three dimensions, the proposed classification uses TRS as a surrogate measure for the certainty with which past behaviors are likely to be repeated,

¹ We encourage researchers to critically evaluate our work toward a better understanding of OAMs.

NFR as a surrogate measure for risk, and the nature of negative feedbacks (partial or total loss) as a surrogate measure for the degree of risk. In this section, we provide empirical findings related to the three dimensions of the classification schema. The objective of reporting these findings is to throw more light on the categorical variables and not to validate any set of hypotheses. Therefore, we focus on the findings rather than the analysis of the dataset.

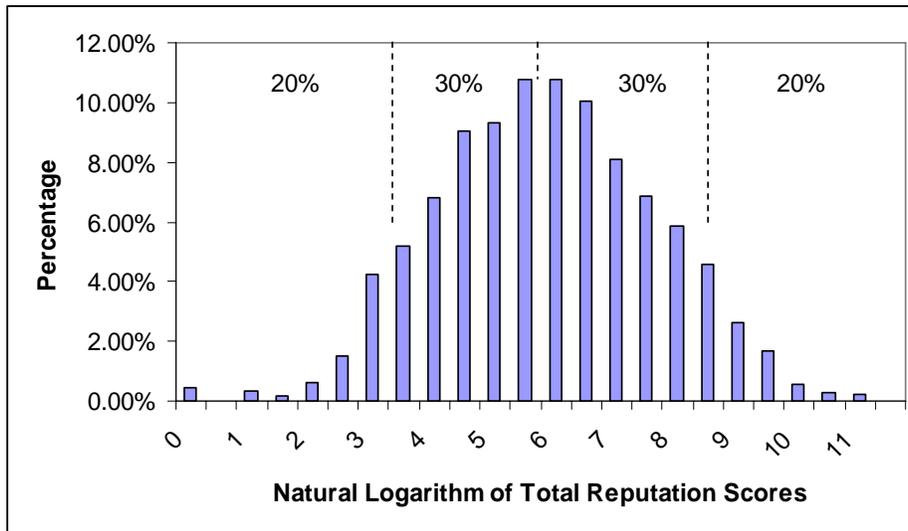
Data Collection

The data analysis presented in this section is based on seller’s reputation data collected from eBay’s website. Reputation data includes data on feedback scores including positive, negative and neutral reputation scores, and the feedback itself to analyze the nature of the feedback. The data set was gathered for different categories of products through a process of ID sampling which allows the researcher to manually collect the information on sellers while allowing for removal of duplicates. This process was followed by a data retrieving process that allows for collection of relevant information on the sellers selected through the process of ID sampling (see Lin et al. (2004) for more details on the data collection process). The final dataset contains randomly sampled positive, neutral, and negative reputation scores of 2000 sellers. 1967 (98.9% out of 2000) of them have non-zero TRS, 1953 (97.7%) of them have received feedbacks in a period of 6 months, 1126 (56.3%) of them have ever received one or more negative feedbacks since they started the online business, and 752 (37.6%) of them received one or more negative feedbacks in a period of 6 months.

Findings Pertaining to TRS

In order to assess the distribution of TRS and its ability to predict future behaviors with a certain level of certainty, we compared TRS scores of sellers with their total feedback score over the last six months. On analyzing the data collected on TRS, which refers to the total number of unique feedbacks received from sellers’ unique trading partners, we found that the distribution of TRS is lognormal (Wald-statistic is $2.556 < \text{the critical value } \chi^2_{(d=2, \alpha=0.05)} = 5.99$). Also the distribution of 6-month TRS is lognormal (Wald-statistic is $1.986 < \text{the critical value } \chi^2_{(d=2, \alpha=0.05)} = 5.99$ (Lin et al (2004a) has reported this finding)). This shows to some extent that the past behavior of sellers in an OAM is a representative of their recent behaviors. Figure 2 shows the normal-like distribution of the logarithm of TRS.

Figure 2: The histogram of logarithm of total reputation scores.



In addition, we found three interesting results:

- 1) 20% active sellers with the highest TRS contributed to 80.69% of the feedbacks received;

- 2) 20% sellers who were active in the last 6 months had the highest 6-month total reputation score and contributed to approximately 80% of the feedbacks (79.66%) in the same period; and
- 3) Sellers' 6-month total reputation scores are positively correlated to their TRS. Regression analyses led to an R-square of 73.32%.

These results provide strong support to the contention that the higher the TRS, the more consistent are the sellers' future behaviors with their past behaviors. The first two findings discussed in this paragraph demonstrate that the distribution of seller's TRS follows the 80/20 principle (80% of the trade is conducted by 20% of the sellers with high TRS, while the last finding clearly implies that the TRS of sellers can well predict the future TRS of those sellers. Further analysis of the TRS data demonstrated that the manner in which sellers were proposed to be classified in the earlier sections (based on their TRS and the average TRS of the market) was reasonable. Table 2 summarizes the findings in supports of this statement.

Table 2: Statistics based on TRS.

Total reputation scores	Activeness status	% of the active sellers	The range of total reputation score	The ratio of the ranges	% of total reputation scores
High	98.4% of the total	20%	> 1362	$1362/262 = 5.198$ $262/56 = 4.679$	79.66%
Above average		30%	262-1362		15.86%
Below the average		30%	56-262		3.93%
Low		20%	1-56		0.55%
Inactive (zero scores)	1.6% of the total		0		0%

When the sellers were classified simply based on the average TRS in the market, clearly 50 % of the sellers were above the average TRS and 50 % were below. Among the sellers who had scores above the average, clearly two groups emerged. The first group was composed of sellers with the highest TRS in the market. This group formed 20% of all the sellers, who were the most active sellers both in the overall past and in the last six months. Also, this group accounted for approximately 80% of all the feedbacks received in the market. The second group accounted for 30% of the sellers in the market. This group clearly was less active than sellers with high TRS but was significantly more active than the other groups of sellers. They received close to 16% of all the feedbacks from the market. Similar grouping emerged among sellers who had scores below the average TRS of the market. 30 % of sellers with TRS below the average TRS of the market accounted for 3.93% of the trades and 20% of the sellers with the lowest TRS in the market accounted for merely 0.55% of the feedbacks received in the market.

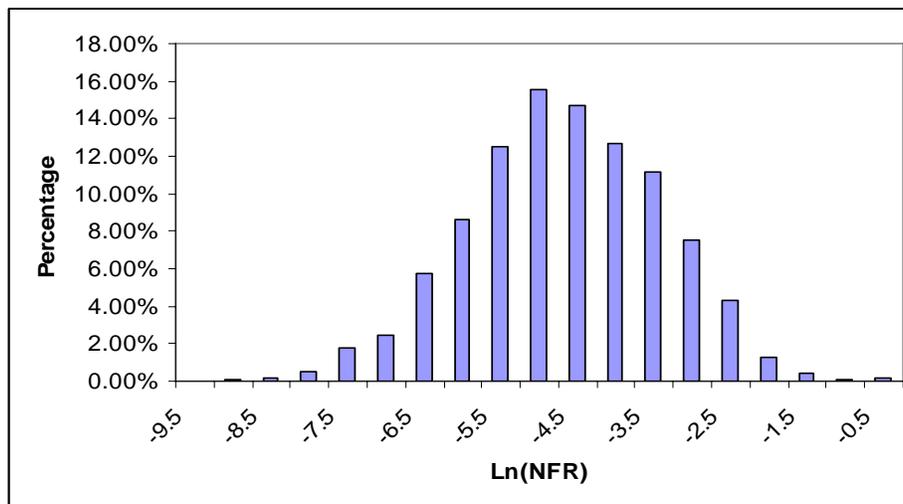
The results of this analysis provide some important insights besides providing support to the cutoffs used in this study to classify sellers based on TRS. It demonstrates an important phenomenon: 50% of active sellers (sellers who have TRS less than the average TRS) account for less than 4.5% of the transactions conducted by sellers with unique buyers. And even among the other 50% of sellers, 20% of sellers with high TRS account for 80% of the transactions which means that a small group of sellers who have a long track record conduct most of the businesses. Analyzing the track record of such sellers along with their NFRs can allow buyers to make more informed decisions regarding risks involved in a transaction.

Yet another interesting finding was regarding inactive sellers. Inactive sellers account for 1.6% of the total number of sellers in a given market. According to prior literature, sellers belonging to this group are usually treated very poorly by buyers since they have no track records. Given that new sellers and inactive sellers need to become active sellers in the market for the market to flourish, more research in providing equitable treatment to the inactive sellers is warranted. Similar analyses were conducted on two other data sets (not reported in this study) and the results were quite similar to the ones presented in this section. This provides certain degree of generalizability to the findings discussed in this section.

Findings Pertaining to NFR

An analysis of the dataset showed that a little more than half (56.3%, 1126 out of 2000) of sellers have received negative feedbacks. So, generally we can divide sellers in two groups, sellers with negative feedbacks and sellers without negative feedbacks (Seller with zero NFR). Analysis of sellers with negative feedbacks showed that both the total and 6-month NFRs fit lognormal distribution very well (Figure 3), although theoretically the distribution of NFR cannot be a lognormal distribution since its upper range is not infinitum. The Wald-statistics of for both logarithmic-transformed 6-month NFRs and total NFRs are significant with values of 0.429 and 1.938 respectively (critical value $\chi^2_{(d=2, \alpha=0.05)} = 5.99$).

Figure 3: A histogram of Ln(NFR).



The distribution showed that, based on NFR, sellers can be clearly divided into two groups: Sellers with high NFR when the sellers have NFRs above the median NFR for all the sellers put together and as sellers with low NFR when sellers have NFR greater than zero but less than the median NFR. Some interesting findings that came up during this analysis are as follows:

- 1) 50% of sellers (376 out of 752) having the highest 6-month NFR are responsible for about 80% (actually 79.62%) of the negative feedbacks received during the same period. They have an aggregate 6-month NFR of 2.55%, which is about 3 times the overall 6-month NFR of all other sellers (0.84%).
- 2) 50% of sellers (563 out of 1126) having the highest total NFR are responsible for about 80% (82.06%) of the negative feedbacks during the same period. They have an aggregate total NFR 1.94%, about 2.3 times of total NFR of other sellers (0.85%).
- 3) 6-month NFRs are positively correlated to total NFRs according to the regression model $Ln(6\text{-month NFR}) = \beta Ln(\text{total NFR})$, where *total NFR* is the NFR calculated by excluding the most recent 6-month transactions. The regression analysis resulted in an R-square of 0.47. This finding suggests that total NFR can well predict the NFR in the next 6-month period. A corollary of this analysis is that it supports the stance that past behaviors are a good indicator of future behaviors and hence TRS is a good measure of certainty of repeating past behaviors.

The first two findings suggest that we can indeed meaningfully classify sellers by their NFRs into three groups: Top 50% of the sellers having negative feedbacks, lower 50% of the sellers having negative reputation feedbacks, and the sellers without any negative feedbacks.

The major implication of this data analysis is that NFR could be beneficially used to identify sellers who are more likely to default. Further analysis showed that the same sellers are more likely to cause problems in the

future too (this part of the analysis has been explained in Lin, Li and Browne 2004). Also, these results reiterate the importance of level II categorization (based on NFR) of the proposed classification.

Findings Related to Nature of Negative Feedback

Li and Lin 2004 (2004) report that about one third of negative comments are not about the merchandises that have been purchased but are typically about the service. This implies that two thirds of complaints may be related to total losses. Although sellers' responses show the possibility that many of these complaints are not necessarily total losses for the buyers, they do signal higher risk levels. So, we can conclude that sellers with a high proportion of negative feedback suggesting partial loss are lesser than sellers with high proportion of negative feedback suggesting total loss, and the former group of sellers gets more complaints regarding the services they provide whereas the later group receive more complaints regarding the non-delivery of merchandise.

To sum, the findings presented here provide valuable information regarding the various categories of sellers in the proposed classification schema. It also helps in identifying areas that are crucial for the buyers and the overall functioning of the OAM. The analyses draw attention to an important factor that has been ignored in the past (i.e. NFR). These findings can be used in conjunction with the proposed classification to recognize gaps in the literature and develop a research stream that is of use to both practitioners as well as researchers. In the next section, we demonstrate the systemic power of the classification by presenting a propositional inventory developed on the basis of our classification.

A DEMONSTRATION OF THE SYSTEMIC POWER OF THE CONCEPTUAL MODEL: A PROPOSITIONAL INVENTORY

An important use of classifications is its ability to systematically generate meaningful propositions. A number of propositions can be put forward based on the proposed classification of sellers in OAMs. Due to space limitations, we present five interesting propositions that can be used to study how prospective buyers are likely to treat the different categories of sellers. These are propositions that have not received adequate attention in the literature and the classification helps us in identifying the same. In this section we use some of the categories from levels I, II and III of the proposed classification to demonstrate the ability of the classification to generate propositions and systematic research. In the next section, we present some interesting findings regarding categories I and II to explicate how the proposed categories can trigger an interesting stream of research. In the rest of this paper, we attempt to demonstrate the ability of the classification to generate systematic research.

A number of other propositions can be developed by meaningfully comparing sellers in a given category or across different categories. For example, if there are two sellers in the same class of Low TRS, and one with higher NFR and another with lower NFR, we propose that the former will receive lower prices than the later. Though the low TRS suggests uncertainty regarding the sellers' future behaviors, for a given level of uncertainty, buyers are likely to choose the seller who projects lesser risk (low NFR) than others. Therefore, we propose that under the condition of high uncertainty (low TRS), lower NFR will be perceived to be better than higher NFR.

If there are two sellers in the class of High TRS, one with higher NFR and another with lower NFR, we propose that the former will receive lower prices than the later. Since a high TRS suggests the high degree of certainty regarding the probable repetition of past behavior, in the same class of High TRS, the sellers with higher NFR will be expected to repeat their poor performance and, hence, will receive lower prices than the sellers with lower NFR. Thus,

Proposition One: *For sellers belonging to a given class of TRS, sellers with higher NFR are likely to receive lower prices on their products than sellers with lower NFR, ceteris paribus.*

Negative reputation increases the risks for potential buyers [Shapiro 1983]. Low TRS of sellers suggests to the buyers that the given seller has done very few transactions and, hence, there is uncertainty regarding how they are likely to behave while sellers with high TRS are likely to suggest that they are very likely to repeat past behaviors. Therefore, a seller with high NFR and high TRS will be expected to repeat his poor performance with greater certainty than a seller with high NFR and low TRS and vice versa in case of low NFR.

Proposition Two (a): *For sellers belonging to a given class of high NFR, sellers with higher TRS are likely to receive lower prices on their products than sellers with low TRS, ceteris paribus.*

Proposition Two (b): *For sellers belonging to a given class of low NFR, sellers with high TRS are likely to receive higher prices on their products than to sellers with low TRS, ceteris paribus.*

Sellers with negative feedbacks suggesting complete loss can be expected to send stronger negative signals to buyers about the seller's credibility when compared to sellers with negative feedbacks suggesting partial loss. Therefore, the effects of negative feedbacks suggesting total loss and partial loss are predicted to be unequal. Drawing from probability theory, we propose that buyers will place greater negative weights on sellers with feedbacks suggesting total loss when compared to sellers with feedbacks suggesting partial loss. Thus,

Proposition Three: *For sellers belonging to a given class of NFR and TRS, sellers with a high proportion of negative feedbacks suggesting total loss are likely to receive lower prices on their products than sellers with high proportion of negative feedbacks significantly suggesting partial loss, ceteris paribus.*

While a seller with high NFR and high TRS sends strong negative signals to buyers, a new seller has no means of sending any positive or negative signal. In this case, buyers can either choose between sellers who are more likely to default or choose sellers whose behavior is not much known, in whose case, there is a possibility that the buyer might honor the agreement. It is more like the dilemma where a choice needs to be made between a known devil and an unknown angel. Drawing from prospect theory, we argue that in cases of expected losses, individuals are willing to take chances and explore the unknown. Therefore,

Proposition Four: *New sellers and inactive sellers are likely to receive better prices than low reputation sellers with negative feedbacks significantly suggesting total loss to the buyer, ceteris paribus.*

While comparing new sellers and inactive sellers (both with zero TRS) with any category of sellers except for sellers with high NFR, it is likely that new and inactive sellers will receive poor treatment. This is because other categories have demonstrated some kind of positive behavior in the past, which makes them more desirable than a seller who has no track record. This explains the poor treatment that new comers often receive from buyers when they enter an OAM. Thus,

Proposition Five: *New sellers and inactive sellers are likely to receive lower prices than sellers with zero or low NFR irrespective of their TRS or the nature of their negative feedbacks, ceteris paribus.*

The propositions briefly discussed here are only a few of the propositions that can be explored using the classification. Systematically generating propositions from the classification and empirically testing them can throw more light on the nature of OAMs and the treatment doled out to different types of sellers and the attitudes (risk averse versus risk seeking behaviors) of buyers. Next, with reference to accommodating current research and facilitating further theory building, we discuss some of the other uses of our classification.

DISCUSSION

Given that OAMs are relatively immature, there is immense scope for both empirical and conceptual work. We hope that our endeavor provides a small but significant thrust in that direction. Our work could stimulate researchers' interest to come up with (1) newer classifications that could then be validated and (2) systematic empirical investigations using our classification. The classification presented in this paper highlights the need for including information such as mean reputation scores in a product market as it can provide buyers with useful information in evaluating a seller's reputation. It also draws attention toward more closely examining feedbacks in terms of total and partial loss. Empirical studies in this area could have important implications for building more sophisticated and useful reputation reporting systems. It is important to note that our classification does not undermine the research that has been done so far. In fact, our classification accommodates research that compares sellers with high and low reputation. In addition, our classification highlights the need to pay greater attention to the

process of reputation building by introducing sub-classes that could bring greater explanatory power with reference to buyer behavior that reflects in number of bids and bid prices received by a seller.

Also, it is important to make use of the huge volumes and wide variety of data regarding traders as well as transactions that are freely available to all. Available data includes feedback score of traders which is the net reputation score, percentage of positive feedbacks received by the trader, number of positive, negative and neutral feedbacks received by a trader during the past 12 months, 6 months, and 1 month, number of bids retracted during the last 6 months, actual feedbacks received from and left for trading counterparts, and membership duration. Market participants are often deluged with voluminous data that they are rarely able to use because of limited time and attentional resources (Gray 2001). Given such limitations, the proposed classification helps in identifying areas that need further research and help in providing a better understanding of the categories and guide predictions regarding future behaviors of sellers. Simple data mining tools like Microsoft Excel, or more sophisticated ones like SAS, can be used in conjunction with the proposed classification to acquire a better understanding of the categories of the proposed classification. Not only can such analyses provide a better understanding of the market in general and a deeper insight into the characteristics of each category of the proposed classification, but also help in making meaningful predictions [Han and Kamber 2001]. Predictions become more valuable and relevant when they help in drawing conclusions about well established categories based on systematic classification of a given phenomenon. Therefore, it would be highly beneficial for researchers to analyze existing data with the help of the proposed classification in conjunction with data analysis and mining tools to draw meaningful conclusions regarding C2C online market sellers.

As we have argued earlier in this article, classifications are important for developing good research traditions in our discipline, because classifications are amenable to systematic investigation and, thereby, theory development. With our proposed classification, we have demonstrated that (i) new propositions and hypotheses concerning various categories can be developed, (ii) a sound foundation that provides the basis for cumulative conceptual and empirical research can be provided, and (iii) last but not the least, the concept or theory driven work that could potentially stimulate the intellectual curiosity of researchers can be initiated. Toward an intellectual discourse that can facilitate stronger theory informed empirical research, we wait!

APPENDIX I

Assume that a seller has a probability of p to receive a negative feedback after a transaction, given that the corresponding buyer will send back a feedback. When the seller has totally received N feedbacks from unique buyers, the probability that he will receive x negative feedbacks complies with the Bernoulli distribution (Hays and Winkler, 1971):

$$P(x|N, p) = \binom{N}{x} p^x (1-p)^{N-x} = N! p^x (1-p)^{N-x} / [x!(N-x)!], \quad 0 \leq x \leq N \quad (1)$$

The mean of the number of negative scores is: $E(x) = Np$, and its variance is $var(x) = Np(1-p)$. According to the *Law of Large Numbers*, the larger the sample size, the more probable it is that the sample mean comes arbitrarily close to the population mean. Since $NFR = x/N$, we can derive the mean of NFR: $\lim_{N \rightarrow \infty} E(NFR) = \lim_{N \rightarrow \infty} E(x)/N = p$. This means that larger the TRS, the more accurate the NFR reflects the risk when buying from the seller. Similarly we can demonstrate that larger the TRS, more consistent will be the positive feedbacks received by the seller.

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