Adverse Selection and Reputation in a World of Cheap Talk

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Abstract

Internet message boards are inherently a world of cheap talk due to the anonymity of message authors. This paper investigates whether a pecuniary reputation system influences the adverse selection endemic to message boards. First, we find evidence that authors with high reputation scores are less likely to voluntarily offer a buy-hold-sell sentiment in a particular message. Second, we find that authors with no reputation at stake tend to be more bearish with their sentiment but, after controlling for selection, authors with more reputation at stake tend to be bullish in their sentiment. Third, we find that high-reputation authors tend to offer more accurate sentiments. Our results suggest that reputation, coupled with a small pecuniary reward system, can materially influence the adverse selection problem in a world of cheap talk.

JEL Classifications: *G14, D83*

Keywords: **Internet message board, sentiment, pecuniary reward**

1. Introduction

The Internet has dramatically altered the way information is disseminated. Economies of scale make it possible for information posted in one place to be accessed by thousands of people located in far-flung areas. However, the improved information dissemination technology has not mitigated adverse selection concerning the quality and accuracy of information. One reason for adverse selection on the Internet is the relative ease of anonymously posting potentially misleading or incorrect information; anonymity would seem to make it all too easy for an individual to make false or misleading statements with impunity.

How can the adverse selection problem be overcome? One common approach is to appoint a moderator to screen for obviously misleading or inappropriate content. However, this approach introduces yet additional moral hazard problems and requires considerable resources to be dedicated to monitoring the quality of information. The situation is even worse when the moderator himself participates in the discussion. An alternative is to allow those who consume the information to identify and reward authors for quality information. Such reputation systems have been implemented in a wide range of on-line applications, including auction sites such as *eBay.com* and reseller sites such as *Amazon.com*. However, the vast majority of reputation systems do not directly entail a pecuniary reward; rather, high reputation only provides indirect benefits, perhaps through higher closing prices or more frequent sales.

We investigate an on-line financial message board in which authors can voluntarily offer a buy-hold-sell sentiment with the message and in which readers can offer monetary rewards to authors for high quality or accurate information; we interpret higher aggregated rewards as

a proxy for author reputation. An author's aggregate rewards is public information on every message posted by the author and might mitigate the adverse selection problem by changing the incentives to offer misleading or inaccurate information.

Offering a buy-hold-sell sentiment on an Internet message board would seem a quintessential form of "cheap talk." However, the message board we investigate has two aspects that might mitigate the adverse selection problem. First, readers can add an author to their "watch list," after which all messages by that author are highlighted to the reader. We interpret the number of watch lists to which an author has been added as a non-monetary reputation measure. As the message board indicates the number of watch lists to which each message's author has been added, this simple index of popularity might alter the frequency and quality of information provided by the author.

A second attribute is that readers can purchase credits with real money and award authors for the quality of their information. The author's aggregated number of credits is public information and is revealed with each post. These accumulated credits can be used by the author to reward other authors or to purchase goods and services. We investigate whether such a reward system sufficiently alters incentives to encourage more truthfulness in an otherwise anonymous setting.

Our empirical model is guided by the literature concerning the sentiments offered by professional stock analysts. We relate any sentiment offered on a particular message to characteristics of the author at the time the message was posted, characteristics of the firm to which the message refers, and characteristics of the message itself. We address the obvious

problem of sample selection by allowing the reputation of the author to influence whether a sentiment is offered in the first place.

Our empirical analysis deals with three questions. First, does reputation influence the probability that an author offers a sentiment? Second, does reputation influence an author's revealed sentiment, given that she offers a sentiment? Third, does reputation correlate with more accurate sentiment, given that a sentiment is offered? While it is not immediately clear how a reputation influences the type of sentiment offered, we anticipate that an author's sentiment will be more accurate when she has a reputation at stake.

2. The Potential Influence of a Reader-generated Reputation System on Sentiment

Online message boards are often filled with strong opinions and interesting commentary, see Sabherwal, Sarkar and Zhang (2008). However, these opinions are often considered noise with little useful information for investors, primarily because of the anonymity of the authors, the extremely small amount of constructive information included in any particular message. Furthermore, unlike professional journalism articles or financial reports, messages are often short and written in an informal, dialogue-like format, as pointed out by Admati and Pfleiderer (2001). However, several studies, such as Tumarkin and Whitelaw (2001), Tumarkin (2002), Antweiler and Frank (2004), Das and Chen (2007), Gu, Konana, Liu, Rajagopalan and Ghosh (2007), Koski, Rice and Tarhouni (2007), provide evidence that the general sentiment offered on Internet message boards, measured at the aggregate level, has contemporaneous correlation with short-term abnormal returns, trading volume, and price volatility.

Yet, it is unlikely any individual aggregates the sentiment offered across all of the posts about a particular stock.[1] This suggests that readers might benefit from a signal concerning the quality of the information being offered in a given message. Among the popular stock message boards, such as *Yahoo!Finance*, *RagingBull*, and *Motley Fool*, only *Thelion.com* provides reputation system with which readers can influence an author's reputation in a pecuniary fashion. This reputation system can mitigate the incentive for authors to post under different usernames, might reduce the incentive to "pump and dump" particular stocks, and might increase the incentives to offer accurate information. Similar to Sabherwal, Sarkar and Zhang (2008), we take advantage of *Thelion.com*'s reputation system and assume that authors with higher reader-awarded reputations provide higher quality information on average.

The unique aspects of the reputation system utilized by *Thelion.com* facilitate testing hypotheses concerning how the reader-financed reputation system influences the probability that a author will voluntarily offer a buy-hold-sell sentiment on any given post, whether reputation influences the type of sentiment offered, given one was offered, and whether reputation correlates with the accuracy of any sentiment offered.

A post to this message board consists primarily of a message body, comprised of text and possibly links to other sites on the Internet. Each message also identifies which stock or security the author is referring to, the author's username, the number of watch lists to which the author's name has been added, and the aggregate level of credits the author has received

[1] As a practical issue, most Internet message boards show only the most recent posts on the first page, typically twenty-five to fifty posts. Therefore, on a message board with a high level of posting activity, older posts are quickly relegated to "back pages." To the extent that accessing these back pages are costly, individual readers may miss the information provided therein.

up to the time the message was posted, the time of the post, and whether the post is a reply to another post in a thread.[2]

How to measure sentiment on Internet message boards has been the focus of a number of studies. Because not all message boards provide a separate buy-hold-sell sentiment indicator, some studies have focused on messages that include sentiment reflected in the body of the message, considering messages that do not reveal sentiment as noise, for example Tumarkin and Whitelaw (2001) and Gu, Konana, Liu, Rajagopalan and Ghosh (2007). However, other authors have developed techniques which utilize all messages, regardless of whether sentiment was offered, so to retain potentially useful information. One approach is to analyze the words included in the body of the message, gauge whether the message is relatively positive or negative, and generate a "perceived sentiment" score (for example, Antweiler and Frank (2004), and Das and Chen (2003, 2007)). This approach allows all messages to contribute to a proxy for consensus sentiment but is clearly a second-best approach.

Indeed, whether to volunteer a clearly indicated buy-hold-sell sentiment is an active choice by each message's author. One potential problem with researcher-generated sentiment is a sample selection bias. If an author fails to clearly indicate a sentiment yet a researcher attempts to intuit an author's sentiment through her words, it is not clear whether the researcher's proxy will be accurate. The message board we investigate obviates the need to

[2] Internet message boards are often organized by so-called threads. A thread is a group of messages focusing on a particular topic. Depending on the message board's institutions, threads might be introduced only by message board moderator or might be originated by any author. Messages that originate a new thread might contain original information or questions to which other readers respond.

generate a text-based sentiment by providing a separate, optional buy-hold-sell sentiment that the author can provide at the time the message is posted.

Thus, we can address whether voluntary disclosure of sentiment is systematic and what characteristics more strongly correlate with the probability of offering a sentiment. Intuitively, an author with a higher reputation might be less likely to offer sentiment in order to protect her reputation. From the author's point of view, the expected net marginal benefit of offering a sentiment is greater when reputation is low than when it is high. Therefore, we hypothesize that the probability of providing sentiment is higher for low reputation authors than high reputation authors.

Yet, there are other potential influences on the net marginal benefit of voluntarily offering sentiment. An author might only offer sentiment when they are confident they are correct and when there is a high probability that readers will notice the message and reward the author. The more people who have the author on their "watch list," whether the post is a reply to a previous post, whether the post was created while the market was open, and the length of the message in characters are used to proxy for exposure. It is anticipated that messages with greater exposure have a higher probability of being associated with a voluntarily offered sentiment, after controlling for author reputation.

If there is a systematic relationship between author reputation and the odds of sentiment being offered, a natural question is whether author reputation influences the type of sentiment offered. Are high-reputation authors more likely to offer a "buy" or a "sell" sentiment?

The findings of previous studies suggest that stock analysts are generally too optimistic when providing stock recommendations, partly because of conflicts of interest, see Jegadeesh, Kim, Krische and Lee (2004), Carleton, Chen and Steiner (1998), Michaely and Womack (1999), Barber, Lehavy, McNichols and Trueman (2004), and Jackson (2005). Similarly, online traders have been shown to be consistently bullish or buy-side biased and that their sentiments can be treated as a bullishness index, see Antweiler and Frank (2004), Tumarkin and Whitelaw (2001) and Sabherwal, Sarkar and Zhang (2008).

DeMarzo, Vayanos, Zwiebel (2003) and Antweiler and Frank (2004) also posit that traders post about a particular stock only when they have a position in that stock and thus any sentiment offered is influenced by their stake in the stock. It has been documented that 99% of small investors hold long positions and generally do not sell short because of the high costs and risks entailed in short selling (Odean, 1999).[3] Since it is unlikely that a small trader has a short position, and assuming people "put their mouth where their money is," the sentiment disclosed by authors should be consistent with their actual positions, which are expected to be optimistic. If the majority of authors take a buy-and-hold strategy and these authors are unlikely to provide a sentiment in conflict with their own interest, we would expect nearly homogenous sentiment among all authors regardless of their reputation score.

However, "smart money" is often contrarian and many professional money managers use contrarian strategies. Do we expect this to occur in an online financial community? Do high reputation authors behave differently than low reputation authors? To test this, we model the

[3] Taking a short position has infinite risk without hedge while taking long position has finite risk without hedge because the stock price can go no less than zero. Selling short is expensive and comes with many constraints such as the broker must have shares to lend to short seller and stocks can not be short sell under five dollars, see Jones and Lamont (2002) and Reed (2002).

probability that any particular sentiment is offered as a function of the author's reputation, the characteristics of the message, and the fundamentals of the firm about which the message is concerned, controlling for any selection bias.

To determine whether high-reputation users behave differently than low-reputation users in offering sentiment, we measure reputation in three ways. First, we distinguish between those authors who have no reputation, i.e., a zero reputation score, and those with a positive reputation score. We then measure the average reputation per message for each author on a rolling basis, that is, our measure of reputation changes with the number of posts by a particular author. Measuring reputation using the average credits per message penalizes authors who "shot-gun" or post a large number of potentially contradictory messages in hopes of increasing their aggregate reputation. We measure each author's reputation in absolute terms and also in relative terms; the latter being the ratio of an author's average credits per message to the average credit per message across all authors. Specifically, we determine the average credit per post for all authors on a given day and use this to normalize each author's average credits per post.

It has been documented that high-reputation stock analysts, so-called All-star analysts, have greater influence on stock prices and are more accurate in earnings forecasts than those with low or no reputation, see for example Stickel (1992), Park and Stice (2000), and Fang and Yasuda (2005). Recently, Jackson (2005) found that high reputation analysts generate more trades for their brokerage firms and more accurate analysts, in turn, have higher reputations. Further, Resnick and Zeckhauser (2002) and Houser and Wooders (2006), who both study *eBay.com*'s reputation system, find that sellers with higher reputations not only

sell more items, they also sell for a higher price. This finding is also supported by Depken and Gregorius (2008), who investigate the role of seller's reputation in auctions of Apple iPhones on *eBay.com*.

According to Antwailer and Frank (2004), messages are often positively correlated with current-day stock returns but negatively correlated with next-day stock returns. We test whether reputation influences the accuracy of sentiment in terms of intraday and inter-day abnormal returns. Specifically, we test whether current day and inter-day abnormal stock returns are more accurately predicted (rather than caused) by high-reputation authors. If there is no evidence of higher accuracy in predicting intra or inter-day abnormal returns, this would suggest that *Thelion.com*'s readership tends to reward information based on perceived rather than actual value.

3. The Empirical Methodology and Data

The Methodology

The first step in our empirical strategy is to estimate the odds that an author provides a voluntary sentiment for a particular message. We use a standard probit model where the explanatory variables include whether the author has a non-zero reputation, the author's accumulated absolute or relative reputation, the number of watch lists on which the author is listed, whether the post is a reply to a previous post, whether the message was posted while the market was open, and the length of the message.

The second step is to estimate an ordered probit in which sentiment is ranked from most bearish (short sell) to most bullish (strong buy); the ordinal ranking of sentiment therefore

includes five categories. We include whether the author has a zero reputation, the level of the author's reputation, the fundamentals of the firm on which the message focuses, including the firm's market capitalization at the end of the trading day, the firms' book to market ratio, the percentage of the firm's outstanding shares being shorted at the end of the trading day, the percentage of the firm's outstanding shares held by institutional investors, and whether the firm's stocks are offered on option. We estimate the ordered probit using, alternatively, the author's absolute and relative reputation, and, alternatively, including the inverse Mills ratio calculated from the first-stage regression.

Our main empirical results are derived from the second stage of our estimation strategy. If there is substantial selection bias based on author reputation, we expect to see a change in the estimated parameter on author reputation (whether absolute or relative) when the inverse Mills ratio is included in the specification. We also expect that firms with better market fundamentals are more likely to have a buy-side sentiment.

The third step in our empirical strategy is to test whether authors with higher reputations are more accurate in their sentiments. To test this hypothesis, we calculate the abnormal return of the stock referenced in the message on the day the message was posted, and for the three trading days following. We also calculate inter-day abnormal returns between the first trading day and the second, third, and the fifth trading day after the message was posted. We then characterize a sentiment as being accurate if the abnormal return was negative and the sentiment was sell, strong-sell, or short, or if the abnormal return was positive and the sentiment was hold, buy, or strong-buy. We then relate the accuracy of each sentiment to the explanatory variables used in the previous models using a probit estimator.

The Data

Using data gathered from essentially anonymous on-line message boards is fraught with a number of potentially debilitating problems. The first is accurately identifying the author of each message. Because authors can register under a number of different usernames, many researchers treat each username as a different individual even if this is not true (see Antweiler and Frank, 2004, and SEC, 2006). When using data from *Yahoo! Finance* or *Raging Bull*, for example, previous research has not dealt with the problem of multiple user names being registered to the same person.

Why are multiple usernames a potential problem? Consider one scenario in which all posts are provided by a single person with a multitude of different usernames. Under this scenario, any sentiment index generated from the messages provided in the forum is biased because it only represents one person's opinion and not a consensus among investors; the sentiment index would then lose its value as being representative of a community's aggregate opinion. Another scenario is one in which messages are generated by so-called *bots* or computer programs which "write" posts using prescribed language and probabilities. In this case, any sentiment index generated using the composition of the messages is completely arbitrary and any empirical results generated using this index would be suspect.

Thelion.com mitigates the incentive to register multiple usernames through its reputation system. First, *Thelion.com* publicizes the number of readers who have put a particular author on their watch list (although it does not report the number of "ignore" lists). Second, each newly registered user starts with a zero reputation points and can purchase credits at a price

of five cents each with which to reward other authors.[4] The author's aggregate number of credits is displayed next to the author's username in each message.

The unique structure of the reputation system of *Thelion.com* reduces the probability that forum participants abuse electronic money or register multiple accounts to self donate in order to boost their reward points. If posts written by authors with more aggregate credits are more likely to be read, and if registering multiple accounts would reduce the accumulated reputation for any particular account, then authors have little incentive to register multiple usernames as the reputation of any particular username would be diluted.

We gathered every message posted at *Thelion!WallStreetPit* from July 18, 2005 to July 18, 2006, collected correspondent financial data from CRSP (Center for Research in Security Prices), CompuStat, CapitalIQ and Yahoo! Finance. Since this study focuses on the impact of reputation on the frequency and accuracy of sentiment, we drop messages not associated with a specific stock symbol.[5] We also removed messages posted during weekends and holidays and messages concerning stocks that trade less than $5 and any over the counter stocks. [6]

The descriptive statistics of our sample are reported in Table 1. The sample is comprised of 48,647 different messages, of which 8,705 (23%) were associated with a buy-hold-sell sentiment. Amongst all messages, approximately 5% were posted by an author with zero reputation. Amongst those messages posted by authors with a non-zero credit, the average

[4] A reader can reward an author between one to three credits. The awarder's account is deducted the credits awarded to the author plus a "commission" of two credits, which removes the incentive to use different accounts and engage in self-donation. For instance, if awarding one credit to an author, the giver's account is deducted three credits, the equivalent of fifteen cents, and the author's aggregate credits increases by one. In addition, the author also receives one credit of electronic money which can be used to award other authors (at the same two-credit cost) or for online services (*Thelion.com* provides an all-in-one service to search message boards for a specific stock).

[5] Each message can only specify one stock symbol, displayed with the message's title on the forum webpage.

[6] Stocks priced below five dollars cannot be sold short. Excluding stocks priced less than five dollars allows us to include "short sell" sentiments.

credits-per-message was 0.14. Approximately 75% of the messages were posted while the market was open, the average message was written by an author on 60 different watch lists, approximately 21% of the messages were replies to another message, and the average message length was 230 characters.

Sentiment was coded as -3 for short sell, -2 for strong sell, -1 for sell, 0 for hold, 1 for buy, and 2 for strong buy. For the 8,705 messages with a sentiment, the average sentiment was 1.19 or slightly buy-side biased.[7] The average credit per post among these messages was approximately 0.067 and the relative average credit was 0.65, suggesting that those who offered sentiment were, on average, lower reputation authors. Approximately 15% of the sample messages were replies to another message, and 79% were posted while the market was open. The average firm referred to in a message had a book to market value ratio of 0.36, a market capitalization of approximately $3.9 billion, had approximately 36% of outstanding shares held by institutional investors, and had approximately 10% of outstanding shares being sold short.

The bottom panel of Table 1 reports the average accuracy of the sentiments relative to intra and inter-day abnormal returns. Approximately 65% of the sentiments offered matched the same day abnormal return, about 42% matched the following day's abnormal return, about 42% matched the second day's abnormal return, and approximately 40% matched the third day's abnormal return. About the same proportion of sentiments matched the abnormal returns between the first and second, first and third, and first and fifth trading days after the message was posted.

[7] The mean sentiment score is in line with the 1.56 reported by Tumarkin and Whitelaw (2001).

4. Empirical Results

Table 2 reports the results of the first step of the empirical analysis using the entire sample of 48,647 observations. Model (1) includes the absolute level of the author's reputation, as measured by the average credits per message posted, whereas Model (2) includes the relative reputation, as measured by the ratio of the author's reputation to the average of all author reputations.

Messages posted while the market was open, messages by authors who were listed on more reader watch lists, and longer messages were more likely to have a sentiment offered. However, if the message was a reply to another message, the reply was less likely to have a sentiment offered. Of primary interest in this study, authors with no reputation did not offer sentiment at a statistically different rate than those with reputations. However, amongst those with non-zero accumulated reputation scores, those with greater reputations were less likely to voluntarily offer a buy-hold-sell sentiment of any kind. Whether reputation is measured in absolute or relative terms, the results suggest that the reputation system of *Thelinon.com* motivated individuals with accumulated reputations to offer sentiment less often, perhaps improving the quality of the sentiments that were offered.

The ordered probit results are reported in Table 3. Model (1) and Model (2) use the absolute reputation, with Model (2) including the Inverse Mills Ratio from the first-stage regression. Model (3) and Model (4) use the relative measure of reputation, with Model (4) including the Inverse Mills Ratio from the first-stage regression.

In general, we find that those individuals with a zero reputation offer stronger sell-sentiments. This bearish attitude seems inconsistent with other studies which suggest that on-

line traders tend to buy long. While the market was generally increasing in value during the sample period, it is plausible that the average author with no reputation would offer bearish sentiments in the hopes of generating a greater reputation, even if that reputation was earned through simple correlation and "luck" rather than for keen insights.

Skipping the results concerning the marginal effect of author reputation, given that the author has a reputation, the fundamentals of the firm on which the post focuses suggest that firms with greater market capitalization are more likely to receive a sell-side sentiment, book to market ratio did not have a statistically significant impact on voluntary sentiment (although its parameter estimate is consistently negative), the greater the percentage of the firm's outstanding shares sold short the greater the buy-side sentiment, and if the firm's shares were option listed the greater the odds of a sell-side sentiment.

These results are supported by the following intuition. Firms with smaller market capitalization are more likely to receive buy-side sentiment because online traders are more likely to be attracted to small cap stocks which usually trade at a lower price per share. The greater the percentage of a firm's outstanding shares sold short, the stronger the buy-side sentiment because the higher short ratio implies a greater chance for a stock buy-back, which in turn would cause the stock price to increase. If a firm's shares are optioned, then many traders will switch to option trading instead of trading the stock itself, which could cause a reduction in the stock's price, *ceteris paribus,* and therefore encourage a sell-side sentiment.

Returning to the author reputation variables, in Model (1) the absolute level of an author's reputation correlates with a stronger sell-sentiment which seems to indicate that authors with higher reputations tend to be more bearish in their sentiments. However, after

controlling for selection the parameter estimate on author reputation changes sign and indicates a higher probability of expressing a stronger buy sentiment, when sentiment is offered. The other parameter estimates maintain their sign and significance, especially the bearish sentiment offered by those authors who have no reputation at stake. These results are duplicated in Model (3) and Model (4); after controlling for selection authors with higher reputations have a higher probability of offering buy-side sentiments, all else equal.

Thus far the empirical results suggest that reputation has a statistically significant impact on whether a particular message is associated with a voluntarily offered sentiment and that, after controlling for selection bias, authors with higher reputation have a higher probability of offering a buy sentiment while those authors with no reputation at stake tend to be more bearish in their sentiment. However, an important remaining question is whether the sentiments offered are accurate in the short to medium term and whether reputation tends to encourage more accurate sentiments. In other words, do readers award authors who are more accurate on average?

Table 4 reports probit estimation results wherein sentiments are compared to single-day abnormal returns. For each abnormal return we estimate two specifications, one including the absolute measure and one including the relative measure of author reputation. Model (1) and Model (2) model the same-day accuracy of sentiments. In general, author reputation is not strongly correlated with same-day accuracy. However, larger market capitalization, a greater proportion of outstanding shares sold short, and whether the firm's stocks can be optioned all correlate with a lower probability of an accurate sentiment. In Model (3) and Model (4), authors with higher reputation tend to be more accurate the day after the message was posted,

although the evidence is still rather weak. In these two models, the parameter on book to market is negative and statistically significant. Furthermore, messages posted while the market is open tend to be less accurate in predicting next trading day abnormal returns.

Models (5) and (6) model sentiment accuracy relative to abnormal returns two trading days after the message was posted. In these two models, authors with higher absolute reputations are more accurate than those with lower reputations. However, we find that more watch lists and the longer the message, the lower the accuracy. These results are replicated in Model (7) and Model (8), which model sentiment accuracy relative to abnormal returns three trading days after the message was posted: higher reputation authors tend to be more accurate, all else equal, but messages posted while the market is open, longer messages, and messages posted by those who are on more watch lists tend to be less accurate.

The ability to predict single-day abnormal returns might just be a statistical anomaly. We further test sentiment accuracy relative to inter-day abnormal returns between the first trading day and the second, third and fifth trading days after the message was posted. The probit results are reported in Table 5. We find that the greater the absolute reputation of the message author, the more accurate the sentiment in all three combinations (although relative reputation is not a significant predictor of sentiment accuracy). We find that those authors without a reputation are slightly more accurate in their sentiments when compared to three-day abnormal returns; however the evidence of strong sentiment accuracy amongst these message authors is not strong overall.

Sentiments offered about stocks with a greater proportion of shorted shares and a higher book to market ratio are generally less accurate, as are sentiments offered while the market is

open, when there are more users who have the author on their watch list, and when the message is longer. On the other hand, messages concerning stocks with a greater proportion held by institutions and reply messages tend to be more accurate, all else equal.

In general, it seems that those authors with higher reputations are generally more accurate in their offered sentiments, which is consistent with our previous results. Authors who have a higher reputation at stake are less likely to offer sentiment, but when they do they are more likely to offer a buy-side sentiment and are generally more accurate in their sentiments. These results combine to suggest that the reputation system used by *Thelion.com* seems to have the desired effect of reducing noise in proffered sentiment and providing incentive for individuals to post accurate information.

5. Conclusions

This paper provides an empirical examination of how a reader-generated reputation system influences adverse selection on an Internet message board. Most message boards are inherently plagued by an adverse selection problem because of author anonymity. However, the message board we investigate has a reputation system in which readers can grant pecuniary rewards, in the form of credits, to authors of their choice. We interpret an author's average credits per message as a measure of reputation and test whether reputation influences the frequency and accuracy of voluntarily offered buy-hold-sell sentiments.

We find that authors with no reputation tend to offer sentiment more often and authors with higher reputation offer sentiment less often. This selection process has important implications for testing how reputation influences the type of sentiment offered. When not controlling for selection, we find that higher reputation is correlated with a higher probability

of offering a sell-side sentiment. However, after controlling for selection, we obtain the opposite result: not only do authors with greater reputation offer sentiment less often, when they do offer sentiment there is a higher probability that it will be a buy-side sentiment.

We also test whether authors with higher reputations are more accurate in their sentiment, when sentiment is offered. We find some evidence that high-reputation authors are more accurate in predicting inter-day abnormal returns up to five trading days after a message was posted. Our results suggest that in a world of "cheap talk" even small pecuniary rewards can significantly reduce an adverse selection problem in a statistically meaningful way.

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Table 1: Descriptive Statistics of the Sample

Panel A: Message characteristics (N=48,647)

Variable	Description	Mean	Std. Dev.	Min	Max
SENTIMENTYES	Sentiment was offered	0.229	0.420	0	1
ZEROCRED	Author has no credit (1=Yes)	0.048	0.214	0	1
AVECREDIT	Author's average credit per message posted	0.142	1.535	0	156.67
RELAVECREDIT	Author's relative average credit per message posted	1.000	1.951	0	89.175
MKTOPEN	Message was posted while market open (Yes=1)	0.756	0.429	0	1
USERSWATCH	Number of users who have author on their watch list.	60.11	108.106	0	70
REPLY	Message is a reply to a previous message (Yes=1)	0.213	0.409	0	1
MSGLENGTH	Message Length in Characters	230.829	833.558	0	43,698

Panel B: Sentiment, Stock Fundamentals and Technical Statistics (N=8,705)

SENTIMENT	Buy-Hold-Sell Sentiment *	1.190	1.628	-3	2
ZEROCRD	Author has no credit (1=Yes)	0.048	0.214	0	1
AVECREDIT	Author's average credit per post	0.067	0.133	0	6.048
RELAVECREDIT	Author's relative average credit per post	0.654	0.746	0	17.237
BME	Book value to market value ratio	0.361	0.293	0.002	2.159
MARKETCAP	Market capitalization	3.905	20.287	0.007	381.99
MKTOPEN	Posted while market open	0.794	0.404	0	1
HELDBYINST	Pct. of outstanding shares owned by institutional investors	36.062	37.781	0	133.33
SHORTOFFLOAT	Pct. of outstanding float that has been shorted	9.854	11.917	0	88.70
REPLY	Message is a reply to a previous message (Yes=1)	0.154	0.361	0	1

Panel C: Sentiment Accuracy (N=8,705)

RIGHT0	Sentiment matches abnormal return the day the message was posted	0.652	0.476	0	1
RIGHT1	Sentiment matches abnormal return one trading day after the message was posted	0.420	0.493	0	1
RIGHT2	Sentiment matches abnormal return two trading days after the message was post	0.424	0.494	0	1
RIGHT3	Sentiment matches abnormal return three trading days after the message was posted	0.399	0.489	0	1
RIGHT12	Sentiment matches abnormal returns between one day after and two days after the message was posted	0.421	0.494	0	1
RIGHT13	Sentiment matches abnormal returns between one day after and three days after the message was posted	0.430	0.495	0	1
RIGHT15	Sentiment matches abnormal returns between one day after and five days after the message was posted	0.438	0.496	0	1

Notes: * Buy-Hold-Sell sentiment is coded as: -3 short-sell; -2 strong sell; -1 sell; 0 hold; 1 buy; 2 strong buy. Data obtained from *TheLion.com* and entail a full sample of 48,647 messages of which 8,705 contained a voluntarily offered buy-hold-sell sentiment. Panel A reports descriptive statistics of the full sample, used in a sample selection model. Panel B reports descriptive statistics of the messages with sentiment, including market fundamentals of the firms to which the messages refer. Panel C reports descriptive statistics of the intraday and inter-day accuracy of sentiments offered.

Table 2: Probit Results of Whether Sentiment is Offered

	(1) Sentiment Offered	(2) Sentiment Offered
ZEROCRED	0.0213	-0.0466
	(0.029)	(0.029)
AVECREDIT	-1.264***	
	(0.055)	
RELAVECRED		-0.227***
		(0.0083)
MKTOPEN	0.0818***	0.0731***
	(0.015)	(0.015)
REPLY	-0.238***	-0.226***
	(0.016)	(0.016)
USERSWATCH	0.000540***	0.000705***
	(0.000057)	(0.000058)
MSGLENGTH	0.0000309***	0.0000275***
	(0.0000072)	(0.0000073)
Constant	-0.684***	-0.610***
	(0.016)	(0.016)

Notes: Dependent variable is whether voluntarily offered buy-hold-sell sentiment was provided. Independent variables as described in Table 1. Both models include 48,647 observations. A negative parameter estimate indicates that the covariate reduces the probability that a sentiment was offered. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3: Ordered Probit Results of Buy-Hold-Sell Sentiment

	(1) SENTIMENT	(2) SENTIMENT	(3) SENTIMENT	(4) SENTIMENT
ZEROCRED	-0.271***	-0.259***	-0.347***	-0.278***
	(0.062)	(0.062)	(0.063)	(0.064)
AVECREDIT	-0.423***	0.825***		
	(0.094)	(0.19)		
RELAVECRED			-0.150***	0.0550*
			(0.018)	(0.031)
MARKETCAP	-0.00234***	-0.00227***	-0.00229***	-0.00222***
	(0.00061)	(0.00061)	(0.00061)	(0.00061)
BME	-0.0479	-0.0558	-0.0417	-0.0537
	(0.048)	(0.048)	(0.048)	(0.048)
SHORTOFFLOAT	0.00382***	0.00338***	0.00353***	0.00293**
	(0.0013)	(0.0013)	(0.0013)	(0.0013)
HELDBYINST	-0.00397***	-0.00395***	-0.00394***	-0.00387***
	(0.00058)	(0.00058)	(0.00058)	(0.00058)
ISOPTIONS	-0.438***	-0.441***	-0.430***	-0.431***
	(0.036)	(0.036)	(0.036)	(0.036)
INVMILLS		-1.144***		-1.197***
		(0.16)		(0.15)
Cut 1	-1.715***	-3.122***	-1.790***	-3.205***
	(0.033)	(0.19)	(0.034)	(0.18)
Cut 2	-1.569***	-2.975***	-1.643***	-3.057***
	(0.032)	(0.19)	(0.034)	(0.18)
Cut 3	-1.513***	-2.920***	-1.587***	-3.002***
	(0.032)	(0.19)	(0.033)	(0.18)
Cut 4	-1.401***	-2.807***	-1.474***	-2.888***
	(0.031)	(0.19)	(0.033)	(0.18)
Cut 5	-1.024***	-2.428***	-1.094***	-2.506***
	(0.030)	(0.19)	(0.032)	(0.18)

Notes: Dependent variable is buy-hold-sell sentiment coded as: -3 short-sell; -2 strong sell; -1 sell; 0 hold; 1 buy; 2 strong buy. Cut points reflect data-determined thresholds at which author sentiment, a latent variable, falls in a particular sentiment category. The variable INVMILLS is the Inverse Mills Ratio calculated from Model (1) or Model (2) reported in Table 2 and controls for sample selection bias. A significant parameter on the variable INVMILLS indicates the presence of selection bias. The remaining explanatory variables are as described in Table 1. All specifications include 8,705 observations. Robust standard errors reported in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table 4: Probit Estimates of Single Day Sentiment Accuracy

	(1) RIGHT0	(2) RIGHT0	(3) RIGHT1	(4) RIGHT1
ZEROCRED	-0.153**	-0.156	0.0229	0.138
	(0.067)	(0.10)	(0.066)	(0.096)
AVECREDIT	1.957		5.551***	
	(1.75)		(1.66)	
RELAVECRED		-0.141		0.333
		(0.35)		(0.32)
MARKETCAP	-0.00154**	-0.00151**	-0.000874	-0.000835
	(0.00069)	(0.00069)	(0.00069)	(0.00069)
BME	-0.0212	-0.0226	-0.112**	-0.115**
	(0.051)	(0.051)	(0.050)	(0.050)
SHORTOFFLOAT	-0.00829***	-0.00830***	-0.00679***	-0.00692***
	(0.0012)	(0.0012)	(0.0012)	(0.0012)
HELDBYINST	0.000324	0.000350	0.00344***	0.00347***
	(0.00059)	(0.00059)	(0.00058)	(0.00058)
ISOPTIONS	-0.147***	-0.145***	0.0612*	0.0648*
	(0.036)	(0.036)	(0.035)	(0.035)
MKTOPEN	-0.0370	0.131	-0.385***	-0.174*
	(0.10)	(0.11)	(0.098)	(0.10)
REPLY	0.422	-0.0720	0.864***	0.254
	(0.29)	(0.33)	(0.28)	(0.30)
USERSWATCH	-0.000831	0.000385	-0.00214***	-0.000984
	(0.00068)	(0.0010)	(0.00065)	(0.00094)
MSGLENGTH	-0.0000532	0.00000395	-0.000115***	-0.0000374
	(0.000040)	(0.000043)	(0.000039)	(0.000040)
INVMILLS	-1.955	0.783	-4.895***	-1.625
	(1.59)	(1.89)	(1.51)	(1.71)
Constant	2.974	-0.479	6.032***	1.784
	(2.02)	(2.30)	(1.91)	(2.08)

Notes: Dependent variable equals one if sentiment matches abnormal returns on the day the message was posted (RIGHT0) or the trading day after the message was posted (RIGHT1). The variable INVMILLS is the Inverse Mills Ratio calculated from Model (1) or Model (2) in Table 2 and controls for potential selection bias as not all messages had a sentiment offered. The remaining explanatory variables are as described in Table 1. All models have 8,705 observations. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 4 (cont.): Probit Estimates of Single Day Sentiment Accuracy

	(5) RIGHT2	(6) RIGHT2	(7) RIGHT3	(8) RIGHT3
ZEROCRED	0.0173	-0.0312	0.0498	0.489***
	(0.066)	(0.098)	(0.067)	(0.11)
AVECREDIT	4.383***		9.615***	
	(1.62)		(2.08)	
RELAVECRED		-0.330		1.614***
		(0.33)		(0.42)
MARKETCAP	-0.00117*	-0.00110	0.000600	0.000608
	(0.00070)	(0.00070)	(0.00069)	(0.00069)
BME	-0.0867*	-0.0892*	-0.0252	-0.0315
	(0.050)	(0.050)	(0.050)	(0.050)
SHORTOFFLOAT	-0.00565***	-0.00595***	-0.00509***	-0.00510***
	(0.0012)	(0.0012)	(0.0012)	(0.0012)
HELDBYINST	0.00344***	0.00353***	0.00294***	0.00291***
	(0.00058)	(0.00058)	(0.00058)	(0.00058)
ISOPTIONS	0.106***	0.110***	-0.0640*	-0.0586*
	(0.035)	(0.035)	(0.036)	(0.036)
MKTOPEN	-0.297***	0.0392	-0.607***	-0.546***
	(0.095)	(0.11)	(0.12)	(0.13)
REPLY	0.791***	-0.229	1.536***	1.443***
	(0.27)	(0.32)	(0.36)	(0.41)
USERSWATCH	-0.00160**	0.00103	-0.00355***	-0.00459***
	(0.00063)	(0.00099)	(0.00082)	(0.0013)
MSGLENGTH	-0.0000833**	0.0000421	-0.000200***	-0.000179***
	(0.000037)	(0.000041)	(0.000049)	(0.000051)
INVMILLS	-3.850***	1.841	-8.620***	-8.502***
	(1.46)	(1.80)	(1.95)	(2.32)
Constant	4.634**	-2.490	10.72***	10.10***
	(1.85)	(2.20)	(2.48)	(2.83)

Notes: Dependent variable equals one if sentiment matches abnormal returns two trading days after the message was posted (RIGHT3) or three trading days after the message was posted (RIGHT3). The variable INVMILLS is the Inverse Mills Ratio calculated from Model (1) or Model (2) in Table 2 and controls for potential selection bias as not all messages had a sentiment offered. The remaining explanatory variables are as described in Table 1. All models have 8,705 observations. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Probit Estimates of Inter-day Sentiment Accuracy

	(1) RIGHT12	(2) RIGHT12	(3) RIGHT13	(4) RIGHT13	(5) RIGHT15	(6) RIGHT15
ZEROCRED	0.0488	0.168*	0.152**	0.206**	0.0630	0.0114
	(0.065)	(0.097)	(0.065)	(0.096)	(0.065)	(0.11)
AVECREDIT	8.179***		3.694**		5.800***	
	(1.68)		(1.66)		(1.61)	
RELAVECRED		0.274		0.117		-0.435
		(0.33)		(0.32)		(0.39)
MARKETCAP	-0.000578	-0.000508	-0.000362	-0.000329	0.0000881	0.000165
	(0.00069)	(0.00069)	(0.00069)	(0.00069)	(0.00069)	(0.00069)
BME	-0.250***	-0.254***	-0.189***	-0.191***	0.0231	0.0197
	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)
SHORTOFFLOAT	-0.00634***	-0.00660***	-0.00677***	-0.00689***	-0.00733***	-0.00758***
	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)
HELDBYINST	0.00378***	0.00383***	0.00413***	0.00417***	0.00307***	0.00315***
	(0.00058)	(0.00058)	(0.00058)	(0.00058)	(0.00058)	(0.00058)
ISOPTIONS	0.0210	0.0264	-0.0416	-0.0387	0.0127	0.0166
	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)
MKTOPEN	-0.516***	-0.144	-0.342***	-0.170*	-0.408***	0.0500
	(0.100)	(0.10)	(0.098)	(0.10)	(0.095)	(0.12)
REPLY	1.358***	0.262	0.602**	0.0981	0.826***	-0.558
	(0.28)	(0.31)	(0.28)	(0.30)	(0.27)	(0.37)
USERSWATCH	-0.00310***	-0.000763	-0.00171***	-0.000633	-0.00246***	0.00107
	(0.00065)	(0.00097)	(0.00064)	(0.00094)	(0.00062)	(0.0012)
MSGLENGTH	-0.000156***	-0.0000181	-0.0000631	-0.000000755	-0.000110***	0.0000596
	(0.000039)	(0.000041)	(0.000038)	(0.000040)	(0.000037)	(0.000047)
INVMILLS	-7.164***	-1.206	-3.332**	-0.594	-5.073***	2.634
	(1.53)	(1.77)	(1.50)	(1.71)	(1.45)	(2.13)
Constant	8.934***	1.292	4.174**	0.662	6.321***	-3.342
	(1.94)	(2.15)	(1.91)	(2.08)	(1.84)	(2.59)

Notes: Dependent variable equals one if sentiment matches abnormal returns between one and two trading days after the message was posted (RIGHT12), between one and three trading days after the message was posted (RIGHT13), and one and five trading days after the message (RIGHT115). The variable INVMILLS is the Inverse Mills Ratio calculated from Model (1) or Model (2) in Table 2 and controls for potential selection bias as not all messages had a sentiment offered. The remaining explanatory variables are as described in Table 1. All models have 8,705 observations. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1