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Determinants of Poster Reputation on Internet Stock Message Boards

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Abstract: Problem statement: I investigate the determinants of poster reputation in a user-rewarding reputation system on Thelion!WallStreetPit stock message board. My empirical analyses deal with two hypotheses: First, is a poster's reputation affected by his/her characteristics at the time the message was posted? Second, is reputation also associated with the characteristics of the stock to which the message refers? **Approach:** To answer these two questions, I tested two sets of explanatory variables in relation to poster reputation in two fixed-effects panel regressions. **Results:** First, the poster's popularity in the community, the poster's sentiment, information quality not quantity and one day follow-up opinion on the stock all have positive impacts on the poster's reputation; Second, recommending stocks with high price to earnings ratio and high institutional investors holding percentage reduce the chance of receiving reputation credits while promoting high liquidity stocks did the opposite. **Conclusion:** This study discarded light on the future construction of a credit-weighted sentiment index should the researchers consider weighing each poster's sentiment based on its reputation. This study also helped us to build a more effective and better functional reputation system in the future. Finally, findings in this study allowed us to better examine the relationship between sentiment and stock returns in future studies.

Key words: Internet, stock message boards, reputation system, online traders, sentiment

INTRODUCTION

The Internet stock message boards serve as an excellent tool for investors to obtain stock information and exchange their opinions easily and almost freely. In addition to the increasing number of sites, such as Finance!Yahoo, RagingBull, MotleyFool and Thelion, growth in the number of participations in these sites has exploded[4,6,9,15]. The impact of the Internet on financial industry and financial market is enormous. On the one hand, the Internet stock message boards dramatically optimize the way that investors acquire information, communicate and initiate trades[2,3,10]. On the other hand, however, the Internet stock message boards are flushed with noise[2,3,5]. One reason for noisy information on the stock message boards is anonymity[5]. How can the anonymity be mitigated on Internet stock message boards? Recent practice is to allow those who consume the information to identify and reward poster for useful information. For example, a rating score or rank which is usually scaled from low to high is attached to a poster so that people can determine the quality of information provided by this person. Such reputation systems have been implemented in a wide range of on-line applications, including auction sites such as eBay.com, reseller sites such as Amazon.com and file sharing sites such as YouTube and Flickr. Recently, many popular internet stock messages also adopt similar reputation system to rank posters based on their information timing, content relevancy and forecast accuracy.

Reputation systems are often useful in large online financial communities in which participants may have the opportunity to interact with posters with whom they have no prior experience. In such a situation, it is helpful to base the trading decision whether or not to follow that user's stock recommendation on the prior experiences of other users. Such reputation system is also often coupled with an incentive system to reward good stock recommendations and punish bad recommendations or irrelevant information. In a stock message board, a typical reputation system is a type of collaborative filtering algorithm which attempts to determine ratings for posters. Many different algorithms can be installed in a reputation system, for example, a feedback system, a fixed formula based on poster's posting statistics, a credit score exclusively assigned by the forum administrator or a user-rewarding system. I investigate an Internet stock message board-Thelion.com, whose reputation system is based upon other users' rewards. This message board has three important aspects that might enhance the reliability of its reputation system. First, readers can add a poster to their "watch list", after which all messages by that poster will be highlighted to the readers. As the message board reports the number of watch lists to which each author belongs, this indicator of popularity might alter the quality of information provided by the poster. A second attribute is that readers can spend real money (through Paypal.com or personal credit/debit card) to purchase electronic credits with which to reward posters who offered stocks recommendations. (A reader can reward a poster between one to three credits each time. The donator's account is deducted each credit awarded to the poster plus a "commission" fee of two credits, which removes the incentive to use different accounts and engage in self-donation. In fact, register multiple accounts to self donate is prohibited within the community. For instance, if awarding one credit to a poster, the donator's account is deducted three credits, the equivalent of fifteen cents and the author's aggregate public reputation score increases by one. Meanwhile, the poster 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 (e.g., Thelion.com provides an all-in-one service to search message boards for a specific stock). Meanwhile, the receiver's aggregate reward credit increases accordingly. Each poster's aggregate reward credit proxy for its reputation measure is also public information which might reduce noisy information by changing the incentives to offer misleading or inaccurate message. A third attribute is that each newly registered user starts with zero score. Register multiple accounts from the same IP (Internet Protocol) address is subject to later deletion by the forum administrator. Such unique structure of the reputation system reduces the probability that forum participants register multiple accounts to self donate in order to boost their reputation credits. If messages written by posters 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 posters have little incentive to register multiple usernames as the reputation of any particular username would be diluted. A higher reward credit reflects a higher reputation of the poster among all users and might also alter the incentives to provide noisy information.

Previous literature has provided extensive examinations in whether higher poster reputation correlates with higher information quality and their findings are significantly positive[8,11]. However, the analysis of the reputation itself is nonexistent. It is obvious that the understanding of the construction of poster reputation allows us to analyze how online posters interact with each other within a financial community. Furthermore, understanding the pros and cons of an existing online reputation system directly helps us to build a more efficient and better functional reputation system in the future which ultimately will add value to the entire online financial community. To fill the literature gap, I investigate the determinants of poster reputation under a user-rewarding reputation system. My empirical analyses deal with two hypotheses: First, is a poster's reputation affected by the characteristics of the poster at the time the message was posted, such as the poster's average number of messages posted and average length of each message? Second, is the reputation also associated with the characteristics of the stock which the poster recommends, such as the stock's fundamental and technical aspects? While it is not immediately clear how a reputation is built, according to previous literature, I anticipate that some factors from both hypotheses will have significant contribution to one's reputation on the Internet stock message board.

MATERIALS AND METHODS

Similar to prior studies, I choose Thelion!WallStreetPit message board that provides a user-rewarding reputation system with which readers can affect a poster's reputation in a pecuniary fashion[5,12]. (Thelion!WallStreetPit (http://thelion.com/bin/forum.cgi?tf=wall_street_pit) is a stock trading forum that allows people to post their opinions for any stock. Unlike Finance!Yahoo and RagingBull which allocate messages under the stock symbol, Thelion!WallStreetPit shows all the messages in the same platform and sorts them by time. Messages posted on Thelion!WallStreetPit include both self-disclosed and non-self-disclosed sentiment messages. For information of Thelion.com, see http://www.thelion.com/aboutus/ and http://thelion.com/aboutus/ir/). This reputation system might mitigate the incentive for poster to post under different accounts, might reduce the incentive to hype particular stocks and might increase the incentives to offer quality information. The unique aspects of this reputation system facilitate testing hypotheses concerning how the attributes of a poster itself and the characteristics of an underlying stock that the poster is recommending will influence the poster's reputation. Each message posted on Thelion!WallStreetPit from July 18th, 2005 to July 18th, 2006 was downloaded. A post to Thelion!WallStreetPit forum consists primarily of a text body, a self-disclosed sentiment on a voluntary basis, such as buy or sell, a symbol as to which stock the poster is referring, the poster's username, the number of watch lists to which the poster's name has been added, the aggregate reputation score the poster has received up to the time the message was posted, the time of the post and whether the post is a reply to an older message. (Thelion!WallStreetPit, a chat room like message board that differs from online message boards such as Yahoo! Finance and Raging Bull in many ways. For instance, Thelion!WallStreetPit lists messages reverse chronologically on a single front page. In contrast, Yahoo! Finance, Raging Bull and many other forums list messages under each stock's separate webpage) Furthermore, these data were merged through stock symbol with corresponding financial data from CRSP (Center for Research in Security Prices), CompuStat, CapitalIQ and Yahoo! Finance. Since this study focuses on the impacts of potential forum and stock variables on the poster's reputation, messages not associated with any explicit stock symbol were excluded from the sample. As a standard procedure[1,13,14,18], self-disclosed 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. Since not all the messages are with self-disclosed sentiment, I assign a 0 sentiment score as neutral opinion for messages with no explicit self-disclosed sentiment. This practice accords with prior studies that treat messages that do not reveal sentiment as noise[7,14]. I also removed messages posted during weekends and holidays and messages concerning stocks that traded less than $5 or their symbols end with. OB or PK. (Stocks priced below five dollars cannot be sold short. Excluding stocks priced less than five dollars allows us to include "short sell" sentiments. Also share price lower than $1 will excessively increase a trader's transaction costs). Totally 6,729 observations meet above requirements.

I test two groups of explanatory variables in relation to poster reputation surrogated by their credit scores through two panel regressions. The fixed-effects panel regression models are as follow (The fixed effect model is chosen because it controls within stock effect and Hausman test favors it over the random effect model. Results are not tabulated but available from authors upon request):

$$Credit_i = \beta_0+\mu_i+\beta_1 U_{1i}+\beta_2 S_{2i}+\beta_3 M_{3i}+\beta_4 L_{4i}+\beta_5 R0_{5i}+\beta_6 R\_1_{6i}+\beta_7 ES_{7i}+\varepsilon_i \quad (1)$$

$$Credit_i = \theta_0+\nu_i+\theta_1 TPE_{1i}+\theta_2 ROE_{2i}+\theta_3 DTE_{3i}+\theta_4 VOL_{4i}+\theta_5 HBI_{5i}+\theta_6 SSR_{6i}+\theta_7 TEC_{7i}+\varepsilon'_i \quad (2)$$

Where:

i = 1,..., n
$Credit_i$ = Poster i's mean reputation score on day t
β_0 = A constant
μ_i or ν_i = A fixed-effects dummy variable controlling for the poster i

Sequent posting days are treated as TimeID in the panel regression.

In Eq. 1 which is to test the relation between credit scores and posters' attributes, U is the average cumulative number of watch lists to which the poster has been added on day t; S is the poster i's mean sentiment on all recommended stocks which ranges from -3 to 2 on day t; M is the average number of message posted by the poster i on day t; L is the average length, measured by the number of characters, of messages posted by the poster i on day t; R0 represents the probability of same-day sentiment accuracy, from 0-1, of the poster i's contemporaneous recommendation on day t. R0 is calculated as follow:

$$R0 = \frac{\sum_{j=1}^{n} r_j}{n} \quad (3)$$

Where:

n = The total number of messages that each recommends a specific stock on day t
r = A binary function to measure if a poster's average sentiment on the stock during day t accords with the stock's same day return:

$$r \begin{cases} =1, & \text{if } \dfrac{s_t^k}{Rt_t^k} > 0 \text{ or } s_t^k = Rt_t^k = 0 \\ =0, & \text{otherwise} \end{cases} \quad (4)$$

where, s is the message's associated sentiment $(s \in \{-3,-2,-1,0,1,2\})$ on stock k on day t while Rt represents the stock k's daily return when the market is closed on day t. In a similar vein, R_1 represents the average probability of consistency, also ranges from 0-1, between the poster i's mean sentiment on day t and the recommended stocks' returns from previous trading day t-1. R_1 captures the effect that whether the poster's current recommendation follows a stock's previous return. Similar to the calculation of R0 and R_1, I define ES as the average earnings surprise effects, which is designed to examine whether the poster is simply using an earnings announcement drift strategy. For instance, a poster could easily initiate a buy recommendation according to the most recent positive earnings shock, vice versa. ES is calculated as:

$$ES = \frac{\sum_{j=1}^{n} c_j}{n} \quad (5)$$

where, c is also a binary function to measure whether a poster's average sentiment on the stock k during day t accords with the stock's most recent earnings surprise:

$$c\begin{cases} =1, \text{ if } \dfrac{s_t^k}{es_q^k} > 0 \text{ or } s_t^k = eps_t^k = 0 \\ =0, \text{ otherwise} \end{cases} \quad (6)$$

where, es is the most recent price-deflated earnings surprise for stock k at quarter q on or before it is recommended by the poster i. It is measured by the following four-quarter Seasonal Random Walk (SRW) model without drift:

$$es_q^k = \frac{(ae_q^k - ef_q^k)}{p_q^k} \quad (7)$$

Where:

ae = The actual earnings per share of stock k reported in quarter q

ef = The forecasted earnings per share which is $ae_{q,q-4}$ for stock k in quarter q-4

p = Stock k's closing price 10 trading days before earnings release for quarter q

Wysocki provides evidence that online talk is related to firm's fundamental characteristics[17]. In Eq. 2 which is to correlate credit scores with the recommended stock (firm)'s characteristics, I include three fundamental variables: TPE, as a valuation measure, represents the average firm' trailing price to earnings ratio; ROE represents the average firm's return on equity which is a management effectiveness measure; DTE represents the average debt to equity ratio from firms' balance sheets. In addition, I include four technical variables: VOL represents the logarithm form of average prior 3 month volume; HBI represents the average institutional investors holding proportion, SSR represents the average short-sell ratio and TEC is the proportion of recommended stocks that belong to technology sector. (According to previous literature that technology stocks occupy a large portion of the online message board sample, it is necessary to control for technology sector stocks in the sample[14,17]).

These two models are used for testing the factors that affect the change of poster reputation in a panel structure. The t-statistics are adjusted based on the heteroskedasticity-consistent covariance matrix developed by White[16]. As a robustness test, I save the residual ε_i from the Eq. 1 which represents the unexplainable portion of $Credit_i$. I then replace the dependent variable $Credit_i$ in Eq. 2 with ε_i in order to orthogonalize two groups of independent variables to avoid potential multicollinearity problems by compounding all exogenous variables in one long equation. I find no inconsistent results between this robust method and the presented approach stated in Eq. 1 and 2. For brevity, robustness tests results are not tabulated.

RESULTS

The descriptive statistics are reported in Table 1. Table 1 discloses couple interesting aspects of online posting and characteristics of stocks recommended by posters. Summaries related to posters' and stocks' characteristics are presented in Panels A and B of the Table 1 respectively.

Table 1: Descriptive statistics

	Mean	SD	Minimum	Median	Maximum
Panel A: Posters related characteristics					
U	55.24	115.90	0	11.00	720
S	0.91	1.69	-3	2.00	2
M	1.38	0.92	1	1.00	18
L	283.05	783.15	2	89.00	18085
R0	0.60	0.46	0	1.00	1
R_1	0.51	0.47	0	0.50	1
ES	0.60	0.45	0	1.00	1
Panel B: Stock's Fundamental and technical aspects					
TPE	47.25	78.78	2.07	29.33	1980.00
ROE (%)	-0.91	100.83	-2630.83	8.91	3505.26
DTE	1.20	10.91	-28.77	0.18	347.87
VOL (in millions)	13.38	1.55	8.19	13.37	18.10
HBI (%)	45.91	28.27	0.20	44.10	168.30
SSR	4.59	4.89	0.00	3.20	49.70
TEC	0.36	0.45	0.00	0.00	1.00

Totally 6,729 messages posted at Thelion!WallStreetPit from July 18th, 2005 to July 18th, 2006 are presented. In Panel A, U: Is the average number of watch lists to which the poster has been added; S Is the poster's mean sentiment on all recommended stocks; M: is the average cumulative number of message posted by the poster; L: is the average length, measured by the number of characters, of messages posted by the poster; R0: Represents the probability of average contemporaneous sentiment accuracy. R_1: Represents the probability of average consistency between the poster's mean sentiment on day t and the recommended stocks' return on previous day t-1. ES: Is the likelihood that the poster's stock recommendation follows the stock's most recent earnings shock. In Panel B, TPE: Represents the average firm' trailing price to earnings ratios; ROE: Represents the average firm's return on equity; DTE: Represents the average debt to equity ratio; VOL: Represents the logarithm form of average prior 3 month volume; HBI Represents the average institutional investors holding percentage, SSR: represents the average short-sell ratio and TEC: Is the proportion of recommended stocks that belong to technology sector. SD: Represents the standard deviation

In Panel A, I observe that the average number of watch lists to which the poster has been added is about 55 users with minimum of 11 users and maximum of 720 users. Average sentiment among all posters is 0.91 which is close to opinion of "Buy". Such bullish sentiment among posters is in line with prior studies that online posters are on average optimistic[13,14,18]. Number of messages posted by an author is about 1.38 per day with minimum of merely 1 post and maximum of 18 posts a day. The average length of a message is about 283 characters. The shortest message contains 2 characters while the longest message conveys a total 18,085 characters. Interestingly, 60% of chance that (100% as the median) poster sentiments are in the same direction as the contemporaneous stock returns which might imply that people simply express what they see from the stock market. However, the consistency between poster's current sentiment and previous stock returns drops to about 50% which might signal the chance that a poster's sentiment agrees with yesterday's stock return is just half-and-half. Surprisingly, 60% of chance that (100% as the median) poster sentiments follow the most recent earnings shock for the stock. This supports the earnings announcement drift argument and tells us that a positive (negative) earnings shock is likely to be followed by bullish (bearish) words from investors. From a different angle in Panel B, I observe many strong characteristics of stocks recommended by online posters. Average TPE ratio of 47.25 is way above the normal fair value range of 10-17, suggesting that these stocks are likely to be characterized as overvalued stocks. In line with TPE ratio, the average ROE is negative which suggests an average unpleasant return on equity of these firms. Moreover, the average DTE is 1.20 which is also considered as a high debt to equity ratio to a conservative investor. The average trading volume in the past 3 month is reported as 13.38 million shares which indicates some liquidity for these stocks. The HBI is unexpectedly high with a mean of 46% which tells us that about half of the shares are held by the institutional investors. High HBI shows strong interests from institutional investors which is a positive signal to conservative investors. The average SSR is 4.59 which illustrates that it takes investors 4.59 days to cover the current short position. High SSR means low liquidity for short-sellers. Finally, over one-third of the sample stocks are in technology sector.

In order to check the multicollinearity and the correlation among explanatory variables within groups, I set forth the pairwise correlation among exogenous variables in Table 2. Pairwise correlation among factors related to posters' and stocks' characteristics are reported in Panels A and B of the Table 2 respectively.

Table 2: Pairwise correlation among exogenous variables

Panel A: Posters related characteristics

	U	S	M	L	R0	R_1	ES
U							
S	-0.04						
M	-0.01	-0.02					
L	0.02	0.02	-0.01				
R0	-0.02	0.10	0.00	-0.02			
R_1	-0.01	0.05	0.02	0.04	0.08		
ES	-0.01	0.28	0.01	-0.01	0.06	0.04	

Panel B: Stock's Fundamental and Technical Aspects

	TPE	ROE	DTE	VOL	HBI	SSR	TEC
TPE							
ROE	-0.03						
DTE	-0.03	0.04					
VOL	0.05	0.05	0.06				
HBI	-0.10	0.02	0.02	-0.33			
SSR	-0.03	-0.01	0.02	-0.09	0.29		
TEC	0.09	0.05	-0.09	0.28	-0.02	-0.08	

U: Is the average number of watch lists to which the poster has been added; S: Is the poster's mean sentiment on all recommended stocks; M: Is the average cumulative number of message posted by the poster; L: Is the average length, measured by the number of characters, of messages posted by the poster; R0: Represents the probability of average contemporaneous sentiment accuracy. R_1: Represents the probability of average consistency between the poster's mean sentiment on day t and the recommended stocks' return on previous day t-1. ES: Is the likelihood that the poster's stock recommendation follows the stock's most recent earnings shock; TPE: Represents the average firm' trailing price to earnings ratios; ROE: Represents the average firm's return on equity; DTE: Represents the average debt to equity ratio; VOL: Represents the logarithm form of average prior 3 month volume; HBI represents the average institutional investors holding percentage, SSR: Represents the average short-sell ratio and TEC: Is the proportion of recommended stocks that belong to technology sector

Overall correlation between any pair of exogenous variables in both Panel A and B is small with the lowest is 0.00 between R0 and M while the highest is -0.33 between HBI and VOL. Panel B also contains some interesting results: 1. Average sentiment S is positively correlated with R0, R_1 and ES ($Corr_{R0,R\_1}$ = 0.08, $Corr_{R0,ES}$ = 0.06, $Corr_{ES,R\_1}$ = 0.04), which tells us that poster sentiments are in the same direction of contemporaneous and one-day lagged stock returns and also the most recent earnings announcement shock. Also noticeable positive correlation among R0, R_1 and ES raises the question of possible autocorrelation. I conduct Durbin-Watson d-statistic on these three variables and no significant sign for autocorrelation is found. For brevity, Durbin-Watson tests results are not tabulated. Positive correlation between ES and R0, R_1 accords with earnings announcement drift argument supported earlier in Table 1. In Panel B, although overall correlations are low, some interesting points, especially among technical factors (VOL, HBI, SSR and TEC) are worth the discussion. First, VOL is negatively correlated with HBI ($Corr_{VOL,HBI}$ = -0.33) which suggests that stocks with high intuitional holdings are less likely to be traded by online investors. In other words, popular stocks traded by online investors are less likely to have high institutional occupations. VOL is positively correlated with TEC ($Corr_{VOL,TEC}$ = 0.28) which shows that technical stocks are popular among traders and provide relatively high liquidity. Second, HBI is positively correlated with SSR ($Corr_{SSR,HBI}$ = 0.29). Since a high SSR implies a low liquidity or buy-to-cover difficulty for short-sellers, high institutional holdings prevent online traders from short selling. On the contrary, the negative relation between SSR and TEC ($Corr_{SSR,TEC}$ = -0.08) discloses the chance that a technical stock being sold short is high since technical stocks in general carry high liquidity regardless long or short positions. Last, the negative correlation between HBI and TEC propounds that technical stocks recommended by online posters are not braced by institutional investors ($Corr_{TEC,HBI}$ = -0.02). Moreover, TPE ratio also brings some interesting stories when interacting with other technical factors: 1. High TPE stocks have larger trading volume ($Corr_{VOL,PE}$ = 0.05); 2. Institutional investors prefer relatively low price to earnings (undervalued) stocks ($Corr_{HBI,TPE}$ = -0.10); 3. High TPE (overvalued) stocks have low liquidity pressure for short-sellers ($Corr_{SSR,TPE}$ = -0.03); 4. Technical stocks have high TPE ratio ($Corr_{TEC,TPE}$ = 0.09).

Table 3 unveils my major findings in this study which are the empirical test results based on Eq. 1 and 2.

In Panel A, I find that the higher number of watch lists to which the poster has been added, the higher the poster's reputation ($Coefficient_U$ = 3.4363, $T\text{-}test_U$ = 36.84). Meanwhile, optimistic sentiment is also significantly helping a poster's reputation ($Coefficient_S$ = 0.6427, $T\text{-}test_S$ = 1.87). Surprisingly, posting more messages actually reduce reputation ($Coefficient_M$ = -1.1137, $T\text{-}test_M$ = -3.09), which suggests that hyping a stock with multiple posts within a day is not favored by other users. The possible explanation is that rewarding incentives are not based on the quantity but the quality of information. The quality of information might be reflected in the length of a message. We can see that the longer the length of a message the higher the chance a poster will receive higher reputation ($Coefficient_L$ = 0.0019, $T\text{-}test_L$ = 3.04).This finding is consistent with prior argument that the longer the length of a message, the more information it conveys[1]. R0 turns out to be insignificant ($Coefficient_{R0}$ = 0.3391, $T\text{-}test_{R0}$ = 0.39), which tells us that just by saying what you see in the market won't reinforce your reputation. On the contrary,

Table 3: Determinant of reputation credits

Panel A: Posters related determinants

$Credit_i$	Coefficient	Robust std. err.	T-test
β_0	185.0192	5.03	36.80***
U	3.4362	0.09	36.84***
S	0.6427	0.34	1.87*
M	-1.1137	0.36	-3.09***
L	0.0019	0.00	3.04***
R0	0.3391	0.88	0.39
R_1	2.6424	0.83	3.17***
ES	0.3423	0.93	0.37
F-test	210.64***	Pro (F-test)	0.00

Panel B: Stocks related determinants

$Credit_i$	Coefficient	Robust std. err.	T-test
θ_0	344.5342	12.39	27.81***
TPE	-0.0205	0.01	-2.49**
ROE	-0.0008	0.00	-0.24
DTE	0.3405	0.24	1.42
VOL	4.3665	0.95	4.58***
HBI	-0.1744	0.05	-3.50***
SSR	0.2820	0.31	0.90
TEC	-2.9518	2.78	-1.06
F-test	4.7800***	Pro (F-test)	0.00

Two groups of explanatory variables in relation to posters' credit scores through two panel regressions are presented in this table. The fixed-effects panel regression models are as Eq. 1 and 2. Credit measures the poster's mean reputation score. U: Is the average number of watch lists to which the poster has been added; S: Is the poster's mean sentiment on all recommended stocks; M: Is the average cumulative number of message posted by the poster; L: Is the average length, measured by the number of characters, of messages posted by the poster; R0: Represents the probability of average contemporaneous sentiment accuracy. R_1: Represents the probability of average consistency between the poster's mean sentiment on day t and the recommended stocks' return on previous day t-1. ES: Is the likelihood that the poster's stock recommendation follows the stock's most recent earnings shock; TPE: Represents the average firm' trailing price to earnings ratios; ROE: Represents the average firm's return on equity; DTE: Represents the average debt to equity ratio; VOL: represents the logarithm form of average prior 3 month volume; HBI: represents the average institutional investors holding percentage, SSR represents the average short-sell ratio and TEC: Is the proportion of recommended stocks that belong to technology sector. Corresponding t-statistics, adjusted for heteroscedasticity, are shown in Italic. Pro(F-test): Is F-test statistics of the model

R_1 is significantly and positively affecting the reputation ($Coefficient_{R\_1}$ = 2.6424, $T\text{-}test_{R\_1}$ = 3.17). A one day follow-up opinion on yesterday's stock return can earn more reputation. Finally, the most recent earnings shock of the recommended stock is irrelevant to the poster's reputation ($Coefficient_{ES}$ = 0.3423, $T\text{-}test_{ES}$ = 0.37). At the bottom of Panel A shows the effectiveness of model 1 (F-test = 210.64, P-value = 0.0000) and I find that this model is significantly useful when seeking determents of posters' reputations on the Internet stock message board. Nonetheless, the significant intercept β_0 propounds that the reputation is not exclusively explained by the components included in Eq. 1. Therefore, in Panel B, I continue to search for other factors that might also affect the reputation.

In Panel B, I further examine the determinants of poster reputation by including technical and fundamental variables of the recommended stocks. Previous researchers document that stocks' technical and fundamental attributions affect online investors' trading preference[14,17]. Therefore, I argue that recommending different types of stocks will also affect poster popularity among other users and therefore affect their reputations. My empirical results in Panel B support this argument. Recommending a stock with a high TPE ratio will significantly decrease the chance of receiving credits ($\text{Coefficient}_{\text{TPE}}$ = -0.0205, $\text{T-test}_{\text{TPE}}$ = -2.49). In addition, recommending a stock with high HBI will also negatively affect the reputation ($\text{Coefficient}_{\text{HBI}}$ = -0.1744, $\text{T-test}_{\text{HBI}}$ = -3.50). On the contrary, promoting a stock with high average trading volume (liquidity) is welcome by online traders since higher trading volume implies higher chance of receiving credit ($\text{Coefficient}_{\text{VOL}}$ = 4.3665, $\text{T-test}_{\text{VOL}}$ = 4.58). Similar to what is shown in Panel A, at the bottom of Panel B shows the effectiveness of model 2 (F-test = 4.78, P-value = 0.0000). Although model 2 is less effective than model 1, variables in model 2 significantly complement model 1 in terms of explaining poster reputation. Together, I conclude that posters' reputations on Thelion!WallStreetPit message board are affected by multiple factors from both the poster's own attributes and the referring stock's fundamental and technical characteristics.

DISCUSSION

In the present study, I investigate the determinants of poster reputation on Thelion!WallStreetPit stock message board. My empirical analyses reach the following two conclusions: First, a poster's reputation among other users is affected by the characteristics of the poster. Specifically, the poster's popularity in the community, the poster's average sentiments on the stocks, information quality not quantity and one day follow-up opinion on the stock have significantly impacts on the poster's reputation in a positive way. Second, reputation is also influenced by the recommended stocks' characteristics. In detail, recommending stocks with high price to earnings ratio and high institutional investors holding percentage reduce the chance of receiving credits while promoting high liquidity stocks does the opposite. I also find that online posters in general are promoting risky, weak-fundamental and overvalued stocks. Such phenomenon advises general especially conservative investors who base their trading decisions on online stock message board information that extra care is needed when following other posters' recommendations.

The present study fills the literature gap by decomposing posters reputation on Internet stock message boards. Understanding the components of the poster reputation sheds light on the future construction of a credit-weighted sentiment index should researchers consider weighing each poster's sentiment contribution based on its reputation. Understanding the determinants of poster reputation allows us to analyze how online posters interact with each other within a financial community. Understanding the advantages and disadvantages of Thelion!WallStreetPit's reputation system directly helps us build a more efficient and better functional reputation system in the future which ultimately will benefit the entire online financial community. Moreover, an extant interesting question is the relationship between posters' sentiment and stock returns. However, the model to study such relationship falls into a simultaneous estimation procedure.

CONCLUSION

Findings in this study suggest that reputation variable might serve as an instrumental variable candidate in a two stage least square model which can be used to examine the relationship between sentiment and stock returns.

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