All Pump, No Dump? The Impact Of Internet Deception On Stock Markets

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ALL PUMP, NO DUMP? THE IMPACT OF INTERNET DECEPTION ON STOCK MARKETS

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Abstract

Internet users are confronted with an increasing amount of deceptive contents. Thereby, especially pump and dump manipulations published via e-mail or within the web represent an important problem. Here, deceivers advertise stocks to profit from an increased price level. Within recent years, market surveillance authorities and software vendors have taken several countermeasures against such fraudulent stock recommendations. At the same time, deceivers have constantly updated their tactics when pursuing their campaigns. Thus, we investigate whether recent suspicious stock recommendations still have an impact on stock markets. We find that current pump and dump campaigns have a positive stock market impact and that they are followed by a decline in stock prices within the subsequent days. We enhance the previous understanding by examining whether spam campaign characteristics also influence the succeeding market reaction. In this context, positive sentiment expressed and the number of stock recommendations published have a positive impact. Consequently, market surveillance authorities and investors should be aware of the related risks and software vendors should consider campaign characteristics within their software to detect suspicious behavior.

Keywords: Internet Deception, Pump and Dump Manipulation, Spam Campaign, Event Study.
1 Introduction

Within recent years, internet users have been confronted with an increasing amount of deceptive contents published in the web and distributed via e-mail (Xiao and Benbasat, 2011). Next to websites aiming to obtain confidential information like credit card data or distributing malicious contents, deceivers also try to sell goods like drugs, replicas or financial products (Abbasi et al., 2010).

Especially with regard to financial products, there is a large risk for investors to lose substantial parts of their investments if they are confronted with a pump and dump market manipulation scheme. In this case, a deceiver first buys a stock, advertises or commissions a promoter to advertise the stock by spreading very positive messages and then sells the stock with profit (Frieder and Zittrain, 2006). Such stock recommendations are particularly suitable to investigate the success of internet deception since the results of such manipulations can be easily measured by assessing their stock market impact. Previous research on suspicious stock recommendations sent via e-mail has found that pump and dump schemes can cause dramatic losses for investors when the scammer closes his position (Böhme and Holz, 2006) and that consequently, trading on pump and dump schemes cannot be recommended.

The Securities and Exchange Commission (SEC) as a regulator has taken legal countermeasures against these stock recommendations by prosecuting manipulators, suspending trading or releasing warnings (Hu et al., 2009; SEC, 2012c). From a technical perspective, spam-filters are constantly being improved to reduce the amount of spam being received (Symantec, 2011). However, deceivers update their tactics and the advent of social media has offered new possibilities to distribute fraudulent contents (Dinev, 2006; Abbasi et al., 2010; SEC, 2012b). Consequently, messages that urge readers to buy specific stocks are also published on blogs or micro blogging services. In contrast to previous spam campaigns where mostly identical e-mails have been sent to a large audience, current campaigns are pursued via different channels and by means of varying messages.

In view of the countermeasures against pump and dump campaigns on the one hand and new possibilities to publish fraudulent stock recommendations on the other hand, we investigate whether such recommendations are still effective. We examine whether there is still a market impact during the campaign or if investors have become more experienced, are aware of the SEC’s warnings and avoid buying the related shares. Furthermore, we also focus on the value for investors when the campaign has ended. In addition to this update of previous studies that have focused on stock spam sent via e-mail, we also consider the novel characteristics of the current market environment in order to examine the impact caused by such fraudulent stock recommendations. While previous studies focus on identical messages sent to the public, we take into account the characteristics of campaigns, represented by dissimilar messages with different contents and publishers. In addition, to the best of our knowledge, we are the first to investigate the impact of another typical message characteristic of pump and dump messages on the market reaction during the spam campaign, i.e. message sentiment. Thus, we contribute to the literature on internet deception in general as well as to the literature on the effectiveness of pump and dump manipulations in specific and provide design recommendations for systems addressing related fraud scenarios.

Therefore, we first acquire a dataset covering stock recommendations that are suspicious to be part of a pump and dump scheme. Based on event study methodology (MacKinlay, 1997), we determine the market impact of these stock recommendations. Furthermore, we determine the sentiment of these stock recommendations in order to explain the following market reactions taking into account the characteristics of these campaigns. The remainder of this paper is structured as follows. In section 2, we first present recent developments related to internet fraud and summarize the results of previous work related to pump and dump schemes. Additionally, our research hypotheses considering the impact of campaign characteristics on the recommendations’ effectiveness are presented. Section 3 gives an overview on how our dataset was created and presents the research methodology applied. Within section 4, our empirical study is presented and the results are discussed. Finally, section 5 concludes.
2 Background and Research Hypotheses

2.1 Internet deception

Deception can be defined as “form of information manipulation that occurs when an opportunist agent induces a misrepresentation that is designed to influence the behavior of another agent” (Johnson et al., 2001). In specific, internet deception encompasses deception using the internet as a medium (Grazioli and Jarvenpaa, 2003), whereas the rise of the internet has eased deception because of low entry barriers, anonymity and spatial as well as temporal separation of deceiver and target (Xiao and Benbasat, 2011). As a consequence, deception by means of fake websites or fraudulent online shops has become a serious problem (Abbasi et al., 2010).

Related to internet deception, different tactics have been identified that are used by deceivers for information manipulation (Grazioli and Jarvenpaa, 2003). In electronic commerce, deceivers either try to hinder consumers to obtain a correct view of a product by concealment and equivocation of product aspects or foster that consumers get an incorrect view of the product by falsification (Xiao and Benbasat, 2011). In particular, deception focusing on investment products, most frequently stocks, is interesting for researchers. On the one hand, deceivers typically apply tactics like falsification of information, for instance regarding the future prospects of an investment (Grazioli and Jarvenpaa, 2003). On the other hand, the success of deception can easily be measured by considering the financial performance of the investments being advertised – most commonly the stock price impact. However, to the best of our knowledge, previous studies have not investigated the impact of spam campaign characteristics and especially of messages spreading very positive sentiment, measured in the case of deception targeting investment products, i.e. pump and dump stock market manipulations.

2.2 Pump and dump stock market manipulations

Pump and dump stock market manipulations aim at increasing the share price by the publication of false and misleading positive information related to a specific stock (SEC, 2012b). Typically, after “pumping” the price, the initiators then sell their shares with profit at an increased price level (Frieder and Zittrain, 2006). Thereby, pump and dump campaigns are pursued by scammers that are either independent from the targeted company or carried out by company representatives. In some cases, also third parties are hired in order to promote a certain stock (Nelson et al., 2009).

There are several studies investigating the impact of pump and dump campaigns pursued via e-mail. Most of these studies rely on datasets composed of stock spam received by the stock spam effectiveness monitor (SSEM, 2007) that covers recommendations for the period from 2004 to 2007. Based on such datasets, different studies provide evidence for market reactions caused by stock spam. For instance, Böhme and Holz (2006) find that stock spam initially leads to positive abnormal returns but that this effect is reversed when no further spam is sent. Additionally, Hanke and Hauser (2008) also take successive spam days into account and find that stock spam influences turnover as well as the intraday price range. Frieder and Zittrain (2006) confirm the impact of stock spam on stock prices and conclude that spammers follow a “buy low and spam high” strategy. Interestingly, different authors find that positive returns cannot be measured for every campaign. Instead, positive and negative outcomes occur almost equally frequent but the positive abnormal returns are higher than the negative ones (Böhme and Holz, 2006; Nelson et al., 2009). Related to the impact of regulatory countermeasures on the effectiveness of stock spam, Hu et al. (2009) find that spam e-mails following regulatory requirements and revealing conflicts of interest as well as stock spam published after an SEC market intervention are accompanied by reduced market reactions. Based on moderated messages posted in 2008, Delort et al. (2011) find that message boards are also used for market manipulations and that such messages lead to capital market reactions.

These studies have provided an understanding of the pump and dump messages’ impact on financial markets. However, they mainly focus on suspicious recommendations distributed via e-mail and rely
on data collected several years ago. Against the background of new spam filtering technologies and regulatory countermeasures (Symantec, 2011; SEC, 2012c) on the one hand and new possibilities to distribute suspicious stock recommendations in social media on the other hand (SEC, 2012b), an understanding of the current impact of such recommendations is necessary. Furthermore, these studies do not take into account the campaign characteristics like the sentiment expressed and different messages published in different time spans, instead, single days are taken into account. With this study, we aim at closing this research gap.

2.3 The impact of pump and dump campaign characteristics on stock market reactions

Due to the characteristics of pump and dump market manipulations, messages are published that urge readers to buy the advertised stock (SEC, 2012b). Because of these characteristics being very similar to classical advertisements (Arens et al., 2012), we focus on marketing research in order to derive research hypotheses about the aspects making pump and dump campaigns effective.

Although different countermeasures against pump and dump manipulations have been applied by market surveillance authorities and enhanced spam filters have been developed (Symantec, 2011; SEC, 2012c), deceivers adapt their strategies and publish messages within the web and within social media (SEC, 2012b). Investors being confronted with these contents possibly rely on the information published or gamble and buy the recommended financial instrument. As follows, we hypothesize: *Pump and dump market manipulations have an impact on stock returns (H1).*

An increased number of deceptive stock recommendations published also increases the reach of the corresponding campaign, especially when these recommendations are sent by different promoters being followed by different groups of investors. In the context of advertising, increasing the reach of a campaign has proven to increase advertising success (Bellman et al., 2010), a pump and dump campaign can be assumed to profit from an increased number of promoters as well. Furthermore, it has been found that an increased number of exposures to an advertising can have a positive impact on consumers (Craig et al., 1976). In the context of advertisements on websites, it has been found that an increased exposure has positive effects on advertising recall and purchase intention for consumers with low product knowledge (Kim et al., 2012). In the context of suspicious stock recommendations, the messages sent deal with less-known stocks that are not traded at well-known exchanges. An increased exposure to these recommendations can have positive effects, i.e. supporting the decision to buy the stock (Zielske, 1959). Thus, we hypothesize: *An increased number of suspicious stock recommendations published positively influences the stock return impact (H2).*

Closely connected to the number of stock recommendations sent is the question for what time span an advertising campaign should last. Previous research has found that a campaign is more effective when it consists of a series of advertisements (Zielske, 1959; Unnava and Burnkrant, 1991). In the case of suspicious stock recommendations, advertising success should depend on the question of whether all messages are published during one day or whether different days are covered. Thus, we hypothesize: *An increased spam campaign length positively influences the stock return impact (H3).*

From the perspective of advertising campaign effectiveness, previous research has found that emotions play an important role to increase consumers’ product attention as well as product recall (Chandy et al., 2001). This especially holds in comparison to advertisements with low emotional contents (Heath and Hyder, 2005). In general, advertisers aim at communicating a positive view related to a product in order to have an impact on consumers and to achieve the purchase of the product (Sonnier et al., 2011). For instance, an analysis of stock fund ads showed that evaluations of past returns were included in case of good performance but excluded after a market crash (Mullainathan et al., 2008). In the financial context, Behavioral Finance theory also supports the role of sentiments on financial markets since it assumes that investors also trade because of irrational expectations that are evoked by factors like sentiment (de Bondt, 1998). In this case, it has already been found for non-suspicious
messages that investors are influenced by the tone of the discussions related to certain financial instruments either expressed in mainstream media (Tetlock, 2007), message boards (Antweiler and Frank, 2004) or twitter (Bollen and Huina, 2011). Thus, we formulate: *Positive sentiment expressed within suspicious stock recommendations positively influences the stock return impact (H4).*

3 Research Methodology

3.1 Dataset acquisition

As a source for stock recommendations, we make use of the “Newsletters Hub” of the website http://newsletter.hotstocked.com/newsletters. This website does not publish own stock recommendations, but collects and aggregates different third party stock recommendations published via e-mail but also in the web and in social media which ensures that an adequate audience is covered.

In contrast to pump and dump market manipulations solely distributed via e-mail, where each undesired message received is often seen as suspicious, identifying suspicious documents in the web and social media is more difficult. In this case, the intention of the corresponding author, i.e. the question of whether the stock price shall be manipulated or not, cannot be observed directly. To identify suspicious messages in the newsletters hub, we follow the SEC guidelines that warn investors of pump and dump stock recommendations (SEC, 2012a, 2012b). In this context, the recommendation has to deal with stocks that are traded on low-regulated markets like Pink Sheets or OTC Bulletin Board (Hanke and Hauser, 2008) and each message has to urge readers to buy the stock which is indicated by statements such as “another winner to buy now” or “new spotlight stock”. Furthermore, the messages shall contain vague disclaimers matching the SEC criteria. Here, the SEC gives the following examples: “From time to time, XYZ Newsletter may receive compensation from companies we write about.”, “From time to time, XYZ Newsletter or its officers, directors, or staff may hold stock in some of the companies we write about.”, or “XYZ Newsletter receives fees from the companies we write about in our newsletter.” (SEC, 2012a).

Finally, we select only those messages for which corresponding daily stock closing prices from Yahoo! Finance can be retrieved. This reduces the total number of available suspicious stock recommendations since for some stocks, no daily prices are available. Our sample contains 1,299 suspicious stock recommendations covering 221 stocks recommended in 252 campaigns by 156 publishers in the period from 12/16/2010 to 04/09/2012. A campaign covers several suspicious stock recommendations sent within a maximum time-span of one trading week.

3.2 Event study

To determine the stock market reaction caused by pump and dump market manipulations, we make use of event study methodology (MacKinlay, 1997) which determines the impact of a certain event on stock returns. In this context, the event window denotes the period where the event takes place, i.e. within this study, the time when suspicious stock recommendations are published. We require that the stock recommendations are published within a maximum period of one trading week to discard cases with too much temporal distance between the different recommendations published.

The market impact during the event window is determined by calculating abnormal returns which are defined as “the actual ex post return of the security over the event window minus the normal return of the firm over the window” (MacKinlay, 1997). Thus, the proportion of the return is calculated that can be attributed to the event. Therefore, the normal return, which is defined as “the expected return without conditioning on the event taking place” (MacKinlay, 1997) is determined. In this study, we estimate normal returns by means of the constant mean return model (MacKinlay, 1997) which assumes that the normal return equals the mean return of the security during the estimation window. To specify the estimation window, we follow Böhme and Holz (2006) and skip the 3 trading days preceding the spam campaign and select the previous 30 trading days to estimate the mean returns.
This avoids that the event is included in the estimation window. In addition, we only analyze stocks that have not been targeted by a pump and dump campaign within the preceding 4 months in order to eliminate interdependencies between different campaigns.

Although more sophisticated methods for estimating normal returns do exist, the constant mean return model is selected since previous research, also in the context of pump and dump market manipulations, has found this to be appropriate (MacKinlay, 1997; Böhme and Holz, 2006). As our event covers several days, we aggregate the daily abnormal returns during the event window \( \text{car_event} \). To calculate the impact after the pump and dump campaign has ended, we further calculate the average cumulated abnormal returns for the next 20 trading days following the event.

In equation 1-3, \( R_{it} \) denotes the actual return for stock \( i \) on day \( t \) which is determined by taking into account the closing prices \( P \) for stock \( i \) on day \( t \) and \( t-1 \). \( AR_{it} \) is the abnormal return for stock \( i \) on day \( t \), taking into account the mean return over the estimation window \( \bar{R}_i \). \( CAR_i(T_1, T_2) \) is the cumulative abnormal return between day \( T_1 \) and day \( T_2 \). Thereby, we define \( \text{car_event} \) as \( CAR_i(T_1, T_2) \) with \( T_i \) defined as the first day of the campaign and \( T_2 \) defined as the last day of the campaign.

\[
R_{it} = \frac{P_{it} - P_{it-1}}{P_{it-1}} \quad (1) \quad AR_{it} = R_{it} - \bar{R}_i \quad (2) \quad CAR_i(T_1, T_2) = \sum_{t=T_1}^{T_2} AR_{it} \quad (3)
\]

As a robustness check, we also evaluated different parameterizations of the event study. For instance, our results remain robust when a gap of 10 days between estimation window and event window is chosen or when the gap to a previous pump and dump campaign is set to 1, 2 or 3 months. However, if the gap between two advertising campaigns is diminished, the significance of the results is reduced, which may be caused due to the fact that the advertised stocks are well-known to investors and that interested investors already possess the related stocks and abnormal returns are reduced.

### 3.3 Sentiment analysis

To be able to measure the impact of the sentiment expressed, we follow a dictionary-based sentiment analysis approach that determines sentiment by incorporating a dictionary of sentiment bearing words. Within the financial domain, such dictionary-based approaches have often been applied and have proven to be promising (Tetlock, 2007; Tetlock et al., 2008; Loughran and McDonald, 2011). Furthermore, in comparison to a machine learning-based approach, no gold standard corpus of labeled documents for classifier training is necessary.

We make use of the well-established dictionary of the General Inquirer (Stone et al., 1962) including word lists of positive and negative expressions. This is advantageous due to the dictionary’s extensive previous validation (Weber, 1990). Furthermore, since the dictionary is publicly available, automated coding of documents is transparent and results can be reproduced easily.

To calculate the sentiment for each pump and dump campaign, we first determine the sentiment of the suspicious stock recommendations. We obtain the occurrences of positive and negative words by comparing each document with the positive and negative word lists. Examples for positive and negative terms are “rally” and “volatile”, respectively. We follow Loughran and McDonald (2011) and reverse the interpretation of a word if it is preceded by a negation. Then, we adapt three document-level sentiment measures (equation 4-6), positivity and negativity, representing ratios of positive \( (pos) \) and negative \( (neg) \) words related to the total words \( (n) \) of a document and polarity that determines the sentiment direction (i.e. from negative to positive) and its strength (Zhang and Skiena, 2010; Tetlock et al., 2008). If a document neither contains positive nor negative words, polarity is defined as zero. Thereafter, for each campaign, the average of these measures related to the documents contained is calculated and used within the following analysis.

\[
\text{positivity} = \frac{\text{pos}}{n} \quad \text{(4)} \quad \text{negativity} = \frac{\text{neg}}{n} \quad \text{(5)} \quad \text{polarity} = \frac{\text{pos} - \text{neg}}{\text{pos} + \text{neg}} \quad \text{(6)}
\]
3.4 Regression analysis

In order to explain which factors determine the cumulative abnormal returns measured during the event window \((\text{car\_event})\), we estimate different ordinary least squares (OLS) regressions using robust standard errors clustered at stock level. As explanatory variables we include \(\text{count}\) which is defined as the number of recommendations published within the campaign, \(\text{no\_promoters}\) which denotes the number of distinct promoters publishing the recommendations, \(\text{days}\) which denotes the difference between the beginning and the end of the campaign in days (e.g. \(\text{days} = 0\) denotes a spam campaign lasting for 1 day) and \(\text{polarity}, \text{positivity}\) as well as \(\text{negativity}\) which denote the different sentiment measures. We also estimate the regressions by including day-of-week dummy variables as well as by a dummy variable indicating that the stock is also recommended within twitter to exemplarily investigate whether increased social media coverage also has an impact on \(\text{car\_event}\).

4 Empirical Study

4.1 Descriptive results

Table 1 shows the descriptive statistics of our sample. The 252 advertising campaigns in our sample are on average composed of 5 different messages sent out by approximately 2 promoters during a period of 1.869 days, whereas the longest advertising campaign in the sample covers a period of 5 days. Furthermore, the most comprehensive advertising campaign consists of 42 different messages and is carried out by 14 different promoters. In addition, we also checked whether the related campaigns have also been carried out within the micro blogging service twitter representing a popular social media service by searching for the related ticker symbol and assessing the resulting tweets, which is the case for 41.67% of the campaigns.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>SD</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
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</thead>
<tbody>
<tr>
<td>1 car_event</td>
<td>0.087</td>
<td>0.410</td>
<td>1</td>
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<td></td>
<td></td>
<td></td>
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<td>2 count</td>
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<td>6.187</td>
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<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3 no_promoters</td>
<td>2.706</td>
<td>2.601</td>
<td>0.195</td>
<td>0.829</td>
<td>1</td>
<td></td>
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<td>4 days</td>
<td>0.869</td>
<td>1.209</td>
<td>0.137</td>
<td>0.422</td>
<td>0.350</td>
<td>1</td>
<td></td>
<td></td>
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<tr>
<td>5 polarity</td>
<td>0.459</td>
<td>0.185</td>
<td>0.166</td>
<td>-0.019</td>
<td>0.016</td>
<td>-0.075</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>6 positivity</td>
<td>0.057</td>
<td>0.017</td>
<td>0.165</td>
<td>-0.018</td>
<td>0.011</td>
<td>-0.092</td>
<td>0.448</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>7 negativity</td>
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<td>0.011</td>
<td>-0.049</td>
<td>-0.034</td>
<td>-0.059</td>
<td>-0.034</td>
<td>-0.634</td>
<td>0.184</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 1. Means, standard deviations (SD) and correlations.

As a consequence, taking into account the number of messages sent as well as the number of promoters carrying out an advertising campaign seems to be appropriate to explain the advertising campaign impact. Considering the different sentiment measures, it can be noted that the average sentiment \(\text{polarity}\) is 0.459. This shows that the messages sent contain a very positive sentiment which is also indicated by the \(\text{positivity}\) score of 0.057 which exceeds the amount of \(\text{negativity}\) contained in the pump and dump messages (0.020).

Table 1 also shows the correlations of the different variables. It can be observed that the number of promoters being active in an advertising campaign \((\text{no\_promoters})\) and the number of messages sent \((\text{count})\) are highly correlated. Thus, we only include one of these variables at the same time within our further analysis. In addition, high correlations between \(\text{polarity}\) as well as \(\text{positivity}\) and \(\text{negativity}\) can be observed as these variables each measure the advertising campaign sentiment.
4.2 Event study results

The distribution of the cumulative abnormal returns during the event window is depicted on the left hand side of Figure 1. Thereby, we first confirm a result that has also been reported for stock spam sent via e-mail (Böhme and Holz, 2006; Nelson et al., 2009): although the mean cumulative abnormal event window return ($car_event$) is above zero (mean: 8.7%, median: 2.0%), there are also cases where $car_event$ is negative, probably caused by market participants selling the stocks already during the spam campaign.

Overall, since a Wilcoxon signed-rank test for equality of medians reports that the median of $car_event$ is statistically different from zero at a 1% level of significance, the campaigns of our sample still have an impact on capital markets although the SEC has issued several warnings and spam filters have been constantly improved. Thus, hypothesis H1 can be accepted.

![Distribution of cumulative abnormal returns during the pump and dump campaign event window (car_event) and time series of average cumulative abnormal returns (CAR) after the end of the campaign.](image)

Furthermore, we also take into account the developments after the event window when the pump and dump campaign has ended. Therefore, we calculate the average cumulative abnormal returns beginning from the last message published for the following 20 trading days. As shown on the right hand side of Figure 1, we find on average cumulative abnormal returns of -20.60% within the first 5 days, -30.11% within the first 10 days and -47.40% within the first 20 trading days after the pump and dump campaign has ended. These values are different from zero at a 1% level of significance. Thus, we find a massive price decrease after the campaign has ended, which may be caused by manipulators or private investors selling the advertised stocks.

4.3 The impact of pump and dump campaign characteristics on stock market reactions

After having confirmed that currently published suspicious stock recommendations still have an impact on stock prices, we investigate the determinants of this stock price impact. As already stated, we therefore run four different regressions, taking into account campaign characteristics including the sentiment of the related messages to explain the cumulative abnormal return during the campaign ($car_event$). We run these regressions to evaluate H2 by incorporating either the number of messages sent or the number of promoters publishing a stock recommendation (due to a high correlation of both variables, we only include one at the same time). Furthermore, we test H3 by including the number of days of each advertising campaign. Finally, for examining H4, we consider the sentiment $polarity$ measure as well as the $positivity$ and $negativity$ measures to investigate the campaign sentiment impact on the capital market reaction.
As illustrated in Table 2, regression (1) to (4) indicate that a high number of messages sent or an increased number of promoters publishing suspicious stock recommendations has a positive influence on the contemporary capital market reactions. In this context, the coefficients are significant at a 10% level of significance. Thus, research hypothesis H2 can be accepted and results of previous studies in the context of stock spam sent via e-mail are confirmed (Nelson et al., 2009). Taking into account the number of days the advertising campaign lasts, we find no significant influence on the following capital market reaction, although the coefficients are positive in every case. As a result, research hypothesis H3 has to be rejected.

In case of the sentiment expressed within the advertising campaigns, we find that the more positive the sentiment is, the higher the cumulative abnormal returns during the event window are. As a consequence, research hypothesis H4 can be accepted. This is indicated by the polarity measure included in regression (1) and (2) as well as by the positivity and negativity measures in regressions (3) and (4). Interestingly, if positivity and negativity are taken into account, we find that mainly the use of positive sentiment bearing words leads to a positive impact which is significant at the 5% level, whereas the coefficients of negativity are negative but not significant.

To further evaluate the goodness of our results and to test for multicollinearity, we calculated the variance inflation factor for each independent variable. Thereby, no multicollinearity was detected since the highest score of 1.23 is below common thresholds of 4 or 10 (O'Brien, 2007). Furthermore, the F-scores of regressions (1) to (4) show that the hypothesis that none of the independent variables has an influence on the cumulative abnormal return during the event window can be rejected at a 5% level of significance. Finally, the adjusted R² of the different regressions shows that 5.91% to 6.27% of the variance of car_event can be explained. This indicates that although the different independent variables contribute to car_event, they do not have a substantial influence. This result is not uncommon due to the complex nature of returns and is also indicated in related studies, where R² is comparably low as well when abnormal returns are explained (Tetlock et al., 2008; Loughran and McDonald, 2010, 2011).

The conclusions from these regressions remain robust when we include daily dummy variables instead of controlling for the number of days (days) and if we include dummy variables for each promoter in order to control for promoter specific aspects instead of the number of promoters (no_promoters). Furthermore, we also evaluated different parameterizations of the event study which did not affect the results. Finally, we also run the regressions by including a dummy indicating whether a campaign is also carried out in twitter. In this case, the results remain robust but the dummy is not significant.

### Table 2

<table>
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<tr>
<th></th>
<th>Coeff.</th>
<th>p-value</th>
<th>Coeff.</th>
<th>p-value</th>
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<td>0.038**</td>
<td>-0.185</td>
<td>0.123</td>
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<td>H3: days</td>
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<td>0.032</td>
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<td>0.029</td>
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<td>0.135</td>
</tr>
<tr>
<td>H4: polarity</td>
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<td>positivity</td>
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<td>0.017**</td>
<td>0.378</td>
<td>0.020**</td>
<td>4.462</td>
<td>0.016**</td>
<td>4.357</td>
<td>0.021**</td>
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<tr>
<td>negativity</td>
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<td>F</td>
<td>3.27</td>
<td>0.022**</td>
<td>3.19</td>
<td>0.025**</td>
<td>3.12</td>
<td>0.016**</td>
<td>2.96</td>
<td>0.021**</td>
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<tr>
<td>Adjusted R²</td>
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<td>0.0611</td>
<td>0.0610</td>
<td>0.0627</td>
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**OLS regression results (n=252 campaigns) for explaining cumulative abnormal returns (car_event) during the pump and dump campaign. Standard errors clustered by stock. * p < 10%; ** p < 5%.**
4.4 Discussion

Our results reveal that stock recommendations being suspicious to be part of pump and dump schemes published within the web and in social media still cause stock market reactions. During the campaigns, we measure on average a cumulative abnormal return of 8.7%. However, there are also cases where negative cumulative abnormal returns occur already during the campaign. One explanation could be that scammers already “dump” their stocks when a stock is still “pumped”. If the cumulative abnormal return within the next trading days after the end of the campaign is taken into account, we find that on average, investors having invested during the campaign are confronted with negative cumulative abnormal returns and lose money if they sell their stocks.

In addition, our results indicate that an increased spread of suspicious stock recommendations increases the market reaction. Although this result might encourage scammers to raise the number of sources where these stock recommendations are published, this also provides useful insights for market surveillance authorities that might especially take care of stocks that are frequently recommended. Furthermore, this also applies to stocks that are subject to a very positive sentiment as indicated by the effect of sentiment on the market reaction during the spam campaign.

We also confirm that social media is actually used to distribute pump and dump market manipulations. A search for the ticker symbols of the advertised stocks in the micro blogging service twitter revealed that 41.67% of the campaigns analyzed are also accompanied by recommendations of the related stocks in twitter. However, the question of whether a stock is also recommended in twitter has no significant influence on the following capital market reaction.

The stock recommendations at hand are published by different promoters. It is possible that the impact of a campaign depends on a single promoters’ outreach. Thus, campaigns which are carried out by promoters followed by many investors may have an increased impact when compared to messages published by promoters with a small number of followers which might bias the results. We take this into account by controlling for the number of promoters being involved in an advertising campaign. To cover these promoter-specific properties more accurately, we rerun our regressions by taking into account promoter-specific dummy variables. In this context, our results remain robust.

Furthermore, our data set is acquired by selecting documents from an aggregator that match criteria published by the SEC. We do not claim that our study covers the whole amount of suspicious stock recommendations and all aspects of advertising campaigns available. For instance, our data source is not likely to cover every message published. However, the stock recommendations obtained lead to capital market reactions and cover a substantial amount of promoters and stocks. This leads us to assume that we have covered a representative amount of suspicious stock recommendations. Furthermore, due to the event study design, we leave a gap between the estimation and event windows so that the influence of potential messages not covered by our data source is minimized.

5 Conclusion

With this study, we contribute to the literature on internet deception in general and pump and dump stock market manipulations in specific. We focus on information manipulation in the case of pump and dump market manipulations which are especially suitable to evaluate the impact of internet deception. Thereby, we confirm that currently, pump and dump campaigns can still be effective although different countermeasures have been taken to prevent investors from losing substantial parts of their investments. We observe positive mean cumulative abnormal returns during the campaign and negative mean cumulative abnormal returns after the campaign. In this context, we are among the first taking into account advertising campaign characteristics to explain the success of information manipulation. We find that the number of unique stock recommendations sent as well as the number of different promoters recommending a specific stock positively affects the subsequent market reaction and that the number of days the campaign lasts has a positive but not significant influence on advertising efficiency. Most important, we further enhance the previous understanding by taking into
account an important characteristic of pump and dump stock recommendations: the sentiment expressed within the messages. Thereby, we find that the more positive the sentiment within the campaign, the higher the following cumulative abnormal return.

From a practical perspective, our study has implications for market surveillance authorities, retail investors and software vendors. Market surveillance authorities shall still be aware of information manipulation and foster activities for monitoring the web and especially social media to investigate whether deceivers try manipulating the market by distributing false positive information. Market surveillance authorities and retail investors shall especially take care of messages which express a very positive sentiment or avoid negative sentiment. Finally, software vendors can incorporate the results of this study in order to detect suspicious contents. In this context, fraud detection systems might incorporate message sentiment related to a certain stock to detect suspicious behavior.

Next to information manipulation, also manipulating the information's presentation may have an influence on a deceiver's success (Xiao and Benbasat, 2011). As follows, within future research, we want to explore whether different presentations used in pump and dump messages have an influence on the following market reactions. Therefore, we want to take into account the layout of the corresponding websites including images displayed or fonts used. Furthermore, we plan to analyze and to compare the impact of pump and dump market manipulations in different countries to examine whether cultural aspects influence the effectiveness of pump and dump campaigns. Finally, we also aim at analyzing whether suspicious stock recommendations are also spread and discussed by private investors in social media and whether this influences the effectiveness of the related campaigns.

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References


