The Value of Unsolicited Buy Recommendations to Investors:

Can Investors Trade Profitably Based on E-mail Spam?

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Abstract:

This paper explores the possibility of trading profitably based on information contained in email spam messages advertising certain stock trades. Through careful analysis of a basket of sixteen stocks that were recommended to my advisor and myself via unsolicited email spam, I conclude that the most effective way for investors to trade these stocks is to short-sell immediately upon initial receipt of a recommendation to buy.

I. Introduction

With increasing internet literacy across the globe, with particular emphasis in the United States, email spam scams become more popular by the day. According to a recent SEC press release, 100 million email spam stock recommendations, or emails that advertise a company's stock, are sent *per week* (SEC Suspends Trading 2007). With this incredible volume and global reach, spam recommendations have become an oft-discussed topic among not only investors, but also among anyone with an email address that has been plagued by unwelcome messages. Stock recommendation email spam messages and their possible investing benefits for investors are the focus of this study. Spam emails are particularly interesting for study because they are anonymous and often sent from "zombie" computers from all over the world, making it nearly impossible to pinpoint the originators of such messages. Another important characteristic of the specific messages studied in this paper is that they are completely unsolicited – the recipient (myself and Dr. Eraker) never subscribed to a financial email list of any sort. The incentive for anyone to send messages to such recipients who have never shown interest in such list-serves is another interesting aspect of this dataset. This paper takes a closer look at these unsolicited stock "buy" recommendations and through careful analysis of the behavior of stocks that are touted in this way, formulates an on average profitable trading strategy[1] for investors based on the information found in such emails.

[1] Obviously, no trading strategy can be guaranteed to turn a positive strategy all of the time. By describing the final trading strategy as profitable *on average,* I imply that this is a strategy that turns a positive profit in the example explored in depth in this study, which I believe (for reasons discussed later in the paper) should apply to similar portfolios composed of stocks recommended via email spam.

Despite the magnitude of the email spam phenomenon (particularly spam stock recommendations), there have been surprisingly few studies done in this arena. There is extensive literature published concerning the immediate effect of a major event on stock prices and returns, and at least one available working paper that discuss the general effect of email spam messages on the stock market. While the available literature concerning abnormal returns following a major event does touch on analyst recommendations, or recommendations from a reputable source (such as *The Wall Street Journal*), these studies fail to extend their reach into the email spam realm and analyze the period of abnormal returns that could follow an unsolicited recommendation.[2] Also, the Frieder and Zittrain 2006 working paper, which models a form of returns based on spam emails, fails to discuss the implications of their work on investors' possible trading strategies.[3] Thus, the literature leaves two holes: the lack of a paper that uses only unsolicited emails received by the author as the dataset, and also the emphasis on trading possibilities for all investors, and not just the spammers. This paper attempts to fill these gaps by analyzing a dataset made up only of unsolicited emails received directly by the authors (with price data from Yahoo! Finance – another source readily available to anyone with an internet connection), and by maintaining the goal of formulating an on average profitable trading strategy applicable to most investors, not simply the authors of spam emails.

[2] The theory behind the presence of abnormal returns after a major event (artificial demand) is expected to be present in the email spam event as well because this can also be qualified as a major event in the life of a company.
[3] This paper also augments the collection of emails received by an author by gathering data collected by a third party on types of emails received by other internet users than the authors. These authors also do not seem to use a readily available price and volume data source, as this paper does with Yahoo! Finance.

For most individuals, these recommendations are a mere annoyance to be deleted from an email inbox. However, with the number of full-time day-traders climbing by the moment, there is a large audience of captive investors waiting for their next big break to make their first (or perhaps an even higher multiple) million. Thus, in spite of my original assumption that everyone, like me, immediately deletes these emails when they first spot them, these recommendations may be taken seriously by many people and have the ability to move markets. The fact that trading volume does in fact spike for stocks that are recommended in this way on the initial date of email receipt and the following few days, shows that it may be true that many people that take such recommendations seriously.[4] With this these ideas in mind, this paper aims to analyze the market's response to such email recommendations and see if such knowledge can help investors form creative and unique trading strategies.

In this paper I will examine this phenomenon of market movement due to, or perhaps merely coinciding with, the deliverance of a "buy" recommendation by unsolicited email. Incentive theory tells us that an economic agent will not expend time and/or energy on a project without receiving some sort of compensation. For this reason, I hypothesize that the persons responsible for such emails are profiting in some way on investors' reactions to their information dissemination. Analysis of literature on abnormal returns after recommendations extends my hypothesis into the possibility of spammers creating such a period with their emails in order to "sell high" shares that had been previously "bought low." Thus, I believe it is possible for investors to also trade

[4] Volume data from Yahoo! Finance.

profitably on the stocks mentioned in these messages through awareness of the general market's response in trading volume and returns. This paper aims to analyze stocks recommended via unsolicited email and discuss what the best trades would have been on these stocks when they were initially touted. The main assumption I employ is that this trading strategy will work, on average, for the majority of all stocks recommended by such mediums because of not only the incentive theory behind the origination of the messages, but also because of the movements observed stock prices and returns that follow such recommendations.

This paper is organized as follows: Section II gives a brief review of the existing literature that relates to this topic, explains where this literature falls short in its coverage of this issue, and thus where this paper may help address previously unaddressed topics. Section III gives the theoretical framework surrounding my research question. Section IV explains how exactly I collected my dataset, and what precise calculations I employed to reach my conclusions. Section V reviews my findings, the results of said calculations, and how this led to the formation of a profitable trading strategy, with Section VI giving the general conclusions of this paper, including avenues for future research and possible policy recommendations.

II. Literature Review

While there have been extensive studies performed analyzing the effect of different events on stock prices and returns, this study augments existing literature by using the event of specifically email spam recommendations with and the goal of helping average investors form a feasible trading strategy. Different works have employed and analyzed various methodologies used to study the effects of a major event on the stock market and returns, but no authors have yet, as seen in my literature research, employed calculations that I believe to be simple enough to be understood by the average investor. While the subject of email spamming and stock scams have become a more popular topic of literature recently (particularly with a recent SEC regulation dealing with email stock scams), there has yet to be a study with the goal of formulating a profitable trading strategy for investors in addition to describing the incentives and actions of the actual spammers or targeted companies. Moreover, there has yet to be a published study that solely uses messages received by the author as the basis for calculations, thus making the results more applicable to individual investors instead of simply appealing to academic analysis, by the increased high probability that most investors will already possess a similar dataset in their email inbox. This paper takes inspiration from existing literature on both email spam and event studies in the broad stock market and applies these concepts to an arena much more understandable and within reach and interest for most investors as opposed to other economic researchers.

Fama, Fisher, Jensen and Roll (1969) were pioneers in the arena of event study methodology in their study of the effect of a stock split on prices and returns (Fama et al. 1969). The authors' use of the "cumulative effects of abnormal return behavior" (8) when analyzing the magnitude of the effect that an event actually has on stock returns, and how these causal changes can affect the actual monetary value of a position/investment in a particular stock, revolutionized the way researchers model data and how conclusions are drawn from datasets and models. This method of aggregating variables, then, has become convention in research dealing with responses in stocks to different events and is the base from which this paper's specific methodology is drawn. Aggregating returns over a reasonable investment horizon in this paper allows readers to tease out real movements in returns over time, which is of more interest to investors and researchers alike, as opposed to the earlier convention of merely noting daily changes in stock price.

For a relatively comprehensive view of subsequent publishings in event study methodology since this major breakthrough in 1969, Binder's 1998 paper is a valuable resource. Binder discusses various ways researchers can and have tested the null hypothesis that significant changes in stock returns following an event are insignificant (or essentially zero), with a particular emphasis on the perspective of an equity holder in the portfolio companies (Binder 1998). However, the methodologies outlined all introduce many variables that are unnecessary and possibly even bias-inducing for this particular study's dataset, since the goal of this paper is simply to create a trading strategy that increases the wealth of an investor, not to contrast such strategy with other market factors and investment vehicles.

Papers by Mackinlay and Henderson both give clear-cut and eloquent descriptions of the necessary steps to begin setting up an event study. Mackinlay presents a helpful procedure for beginning a study of a mergers effect on both the target and the acquirer's equity, but this methodology is not directly applicable to a study of email spam without slight modification (Mackinlay 1997). Henderson applies a more broad and helpful (to this paper) view of designing an event study by advocating using the most simple set-up a dataset allows. By comparing several formulas used in basic event studies, Henderson concludes that most event studies are conducted in surprisingly similar fashions regardless of superficial differences in calculation formulas, and that even simple models are capable of analyzing complex issues in economics and statistics (Henderson 1990).

Michael Salinger takes Henderson's view a step further and laments the lack of a clear-cut methodology for conducting value event studies, which is the definition of the analysis performed in this paper. After explaining several calculations with numerical examples, Salinger concludes that when studying a major event with a clearly recognized period of information release, specific methodology is likely much less important than initially thought in event study literature, and simply does not matter a great deal to the findings (Salinger 1992). By analyzing these event study guides and the unique characteristics of this particular dataset and research question, I took Salinger's advice and created a simple, seldom-used[5] model for this study.

Frieder and Zittrain's working paper (2007)[6] about email spam uses a somewhat similar dataset as my paper, however uses additional recommendations to augment spam emails collected in an author's personal email account by obtaining third-party records of spam email trends. In this working paper, the authors explore market movements a few days before and after the receipt of an unsolicited email. This paper finds that, as expected, these recommended stocks do increase in price and trading volume on the first day of recommended trading, with a subsequent significant decrease in stock value,

[5] The calculations employed in this paper are described in detail in Section IV. This section labels them as seldom-used because none of the literature related to any topics mentioned in this paper go through the exact calculations this study uses.
[6] My work is independent of the findings in this paper - this paper was not available when I began my study.

referred to earlier as a period of abnormal returns. The work concludes with a discussion of the possibilities for great profits on the part of the people authoring and distributing spam emails, in the form of purchasing stock before the decision to send emails and then selling at the peak of high prices immediately afterward. While this is a central theme of my paper as well, the major focuses of my research are the profit possibilities for investors on the *receiving* end of the messages, not on the authoring end for a longer investment horizon and analysis by a different dataset principle.

There are several articles that describe spam messages, how accurate they may be about stock price increases, and possible explanations for this unexpected accuracy. Michael Dewally gives a possible explanation for positive returns generally observed after a stock recommendation is issued in his article: "Internet investment advice: Investing with a rock of salt." Dewally surmises that these stock recommendations are in fact able to predict upswings in price and thus generate what appear to be abnormal returns because they recognize when stocks are already climbing uphill in price and then "jump on the bandwagon." (Dewally 2003). That could explain most stock recommendations are overwhelmingly positive, in a ratio of approximately 7 to 1 buy to sell recommendations (Sarkar et al / Womack). These two articles give exogenous reasons stock prices could increase just after the issuance of a buy recommendation (reasons mostly unrelated to the effect of the recommendation itself). Many other articles discuss the possibility of a major event being the actual *cause* of an upswing in price, due to a period of abnormal returns following any important announcement or occasion.

Following a positive stock recommendation in the *WSJ*, abnormal trading volumes were more than double the normal prediction for an ordinary trading day for small-cap or penny stocks, which are precisely the types of companies this paper examines in depth (Hirschey et al). Mathur and Waheed (1995) go a step further even and examine abnormal stock returns of 2.35 percentage points in the time after such recommendations were given in *Business Week.* Hirschey, Richardson, and Scholz found 1.62% rise in stock prices on the announcement day with returns of 2.4% from one day before to one day after announcement from *The Motley Fool* (Hirschey at al. 2000). Womack finds abnormal returns when consensus recommendations are changed to "buy" for a particular stock (Womack 1996). Kim and Eum (2006) concur that abnormal returns are definitely present in stocks after a positive recommendation is dispersed to investors in their paper entitled: "The impact of analysts' revisions in their stock recommendation and target prices on stock prices." Berber, Lehavy, McNichols and Trueman also calculate abnormal returns following an analyst recommendation, reporting that this is due to a market inefficiency that allows investors to take advantage of public information, concluding that the most highly recommended stocks outperform the least recommended stocks by approximately 102 basis points per month (Berber et al 2001). Prices also have very significant reactions up to two days before a recommendation is given, and even more so immediately afterward (Sarkar et al). Sarkar and Womack both contribute greatly to the literature by noting that the diminishment in stock value lasts many days (a month was the period studied by Womack, much longer than most papers follow the stocks because this is outside of the conventional abnormal returns window) after a recommendation is issued and is thus not an insignificant, small event for the stock's life. These existing studies then show that abnormal returns due occur following a recommendation, but stop short of showing investors what this information could imply in terms of a profitable trading strategy.

Existing literature and studies have done an excellent job of establishing the convention that buy recommendations (and other major company events) are generally followed by a short period of abnormal returns, even noting that value decrease happens over quite some time after the event, but stop just short of suggesting a profitable trading strategy based on this documented abnormal behavior of stock prices after recommendations. Knowing that a period of abnormal returns is incredibly likely to follow a general buy recommendation is helpful in beginning to formulate trading strategies, however further analysis than these papers perform is needed to apply this principle to the average investor. At least one paper (Frieder and Zittrain 2007) does specifically target email spam recommendations, yet does not recommend a specific trading strategy to investors, instead discusses how the authors of such recommendations *may* be profiting from their endeavors. Overall, existing literature proposes many interesting methods for studying stocks' responses to major events, however it takes a more academic rather than real-life application approach to the findings.

There are two main holes in the existing literature this paper aims to fill. The first is that there has yet to be a study done using only unsolicited email recommendations received by the author in a personal email account, and a widely-available price data source such as Yahoo! Finance that everyone with a computer can access. Using this as the entire dataset for a study, I believe, makes my results more relevant to average investors because it uses only information that any investor could have, not just sophisticated or academic investors, and goes one step further and recommends a trading strategy that might be possible and profitable for all classes of investors (based on such widely available public information). Secondly, the existing literature establishing the presence of abnormal returns after major company events has not yet extended its reach into the realm of spam email recommendations. I intend to add to the literature by showing that it may be possible, on average, to turn an investing profit trading a portfolio of stocks based on unsolicited buy recommendations an individual receives for particular corporations. By analyzing the behavior of returns for touted stocks using the methodology described in Section IV of this paper, I believe a profitable trading strategy will become apparent.

III. Theoretical Framework

According to the accepted convention of incentive theory, rational economic agents will only expend effort, time, or money on an activity if they have a specific incentive (or compensation) to do so. Incentives are such a strong motivator for people that many companies and even cities have set incentive structures in place instead of punitive systems to entice employees and citizens to act in the manner considered preferable by the governing agency (Elswick 2002). Incentive theory is one of the basic foundations of economics and motivates much modern research done in this science, because incentives arguably govern everything people do and has been accepted as economic fact. The role incentives must play in the sending of spam email is the motivating factor behind using only such unsolicited emails as the entire dataset for this study. Since these emails were received without payment for the service or even a subscription to an email stock recommendation service, they count as completely unsolicited. This particular characteristic of the data adds depth to this analysis because the creators of such emails must have some incentive to engage in this activity, since formulating recommendations and emailing them to (assumedly) many addresses takes a good bit of time, effort, and more than likely some money. Thus, in accordance with conventional incentive theory, there must be some way that the masterminds behind this email recommendation scheme are being compensated for their efforts. This theory, when combined with the earlier discussion of abnormal returns theory, leads me to believe that they are probably profiting from a trading strategy based on the market motion the emails incite, which leads to the following discussion of abnormal returns theory.[7]

Abnormal returns theory, as discussed in Section II of this paper, is how I hypothesize spammers formulate their trading strategies, which makes up their incentive or compensation structure. Existing literature has shown that major events, including online recommendations, incite a period of abnormal returns for recommended stocks. The established presence and reliability of abnormal returns in the market give email authors an essentially guaranteed time of unusually high returns to capitalize on, since

[7] Since trading volumes are abnormally high on the day the emails recommend trading and several days thereafter for each stock studied, and in agreement with much of the literature, this paper assumes that there are at least some investors that do in fact trade in accordance with the strategies proposed in these emails.

they can control the start date of such a period with the timing of their messages.[8] Thus, abnormal returns theory together with volume data for the stocks imply that spammers do buy shares in the companies they recommend one or a few days before the sending of the emails, and then unload these shares within a few days of the first sent message.[9]

General incentive theory has driven my suspicion that email spammers are in some way profiting from the effects of their recommendations, and abnormal returns theory has given a plausible vehicle for spammers to do so. These are the theoretical frameworks that not only drive this overall research topic, but also the explanations for specific restrictions imposed on the dataset and calculations.

IV. Dataset and Calculations

My dataset is comprised of unsolicited emails I have received to my personal email account and the email account of my advisor, Dr. Bjorn Eraker, during the year 2006. Only those stocks that have historical price lists available for at least twenty-five trading days before the initial recommended trading date for each company, hereafter called "T=0,"[10] and fifty-nine trading days after on Yahoo! Finance were included in the mathematical model, which yields sixteen firms. There are two main motivators behind using strictly unsolicited emails received personally by two parties: incentive and abnormal return theories, and general relevance to most investors. As described in Section III, spam emails are particularly interesting to study because of the significant

[8] Assuming the recommendations are in fact responsible for at least some market movement (which is backed up by volume data for the days surrounding the initial recommendation date from Yahoo! Finance.
[9] As per the Frieder and Zittrain working paper.
[10] T = 0 corresponds to the date that the first spam recommendation for each company recommends to execute the first recommended trade. This is not necessary the same date as the receipt of the email message, because such messages were frequently received on weekends or after the markets closed for the day. For an example of such an email, please see Appendix A.

effects they can have on the market for the stocks they tout, and also because of the possibilities that exist to make money, even on the receiving end of the messages, because of such dramatic movements in price caused (or coinciding with) spam emails.

The overarching goal of this study is to formulate a profitable trading strategy that *any* investor can employ based on previously unwelcome information from of spam emails. The emphasis on formulating a strategy that the average investor can employ in a private portfolio is the main motivation behind using not only emails *personally* received (not simply aggregating by a third party in a database or website) but also price information readily and costlessly available online. I believe this collection of emails to be a representative dataset for most other investors, because neither recipient of the analyzed messages (neither myself nor Dr. Eraker) had at any point signed up for any sort of email recommendation service, ensuring that these emails were completely unsolicited. This implies that the originators of such messages have a way of discovering email addresses, which, combined with conversations I have had with many peers about this topic, leads me to believe that many people worldwide are receiving many of the same, or at least similar, email messages as the ones included in this study. With such a remarkable volume of messages, evidenced by numbers recently released by the SEC, it becomes reasonable to assume that the hundreds of messages received between two parties are fairly representative of emails received by the average investor. This not only makes it possible for investors to use these finding in actuality, but it also makes the findings and calculations presented in this study more relevant to a broad base of investors by the fact that the vast majority of computer owners receive multiple of spam emails per day.

I collected historical daily closing prices from Yahoo! Finance for each of the firms with such data available that had been recommended to either Dr. Eraker or I in the year 2006.[11] The sixteen firms that had available historical prices for the time period in question are: Ever – Glory International Group (EGLY), Trimax Corporation (TMXO), Art4Love, Incorporated (ALVN), Lyric Jeans, Incorporated (LYJN), Las Vegas Central Reservations (LVCC), Capital Reserve Canada (CRSVF), Goldmark Industries (GDKI), Shallbetter Inds, Incorporated (SBNS), Forest Resources MGM (FIRM), PetroSun Drilling (PSUD), Industrial Minerals (IDSM), Infinex Ventures (INFX), Falcon Energy (FCYI), Biogenerics Ltd. (BIGN), China World Trade Corporation (CWTD), and Hollywood Intermediate, Incorporated (HYWI).[12] For these firms, I gathered price data for twenty-five trading days prior to T=0 and the fifty-nine that followed. After compiling the prices, using Microsoft Excel to do all calculations, I computed daily returns for each company by taking the natural log of the ratio of one day's closing price to the closing price for the day before: Daily Return = $\ln(P_t / P_{t-1})$.

I then took the simple average of the return figures for each day over all sixteen companies to get a broad view of daily performance of the entire portfolio, called the AR for "average returns." This series of average returns are the basis for the cumulative

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[11] A large proportion of the recommended stocks did not have historical prices available on this website.

[12] Two of these companies, Biogenerics Ltd. and Goldmark Industries, Inc., were included in 35 firms that the SEC banned trading on March 8, 2007. Many more companies for which I received spam recommendations touting were also included in the trading ban, however they did not have available historical price lists on Yahoo! Finance.

returns which actually lead to the statistical significance calculations described later in this section and then finally to a recommended trading strategy.

In keeping with the Fama et al (1969) paper, and various other event study methodology papers discussed in Section II of this paper, I calculated the cumulative average returns (CARs) from the simple averages for each day. To do so, I simply aggregated the simple average returns for all sixteen companies for every day with available data (which totals eighty-four days). The cumulative average return for day *n* is simply the sum of all the simple average returns from the first day in the time period through *n*. For the first day of the data subset, the CAR for the entire portfolio is simply equal to the simple average on that day, since there is no data on a previous day to aggregate. However, for subsequent time periods, the CAR would be the sum of all of the simple average returns up to the day in question. The CAR formula for day *n* is as follows: $CAR = \Sigma\ (AR_0 \ldots AR_n)$. By graphing out and analyzing the CARs for the stocks in question, I was able to get a picture of the performance of this basket of stocks over the time period in question. CARs allow us to see the portfolio returns as a flow measure instead of simply the overnight change in the stock price. This is clearly the variable of choice when formulating a trading strategy, because it captures overall performance trends rather than daily fluctuations in price.

For the sake of clarity and thoroughness, I analyzed CARs both over the entire time period with data (including twenty-five trading days prior to T=0) and also just beginning at T=0 to get two different viewpoints. The CAR value-set plot using only data from the recommendation date and on gives a picture of what an investor can take advantage of in trading based solely on the recommendation, while the CAR values for the entire time period gives a sense of the magnitude of the effect of such recommendations on the stocks' returns over time, because the changes in stock behavior at T=0 can be noted in accordance with the recommendation date. Both plots are included in Section V, and analysis of the trends pictured in these Figures is the main key to formulating a profitable trading strategy.

After the CARs were calculated, I then ran statistical significance analysis on the results by calculating a confidence band around the CAR trend.[13] To do this, I used Microsoft Excel to form a standard deviation value based on the sample of simple average returns, using all eighty-four trading days measured for each company and then again for the post-recommendation only dataset.[14] I then calculated a standard error value (σ) for each day analyzed by taking the standard deviation, stdev, (which by assumption was constant for each day),[15] multiplied this value by the square root of the day number, $\sqrt{n}$, (which ranged from 1 to 84) and then divided by the square root of the sample size ($\sqrt{16}$) to get 4. This formula mathematically looks as follows: $\sigma = (\text{stdev}*\sqrt{n})/4$. For the upper confidence interval bound, I took the daily CAR and added to it the standard error multiplied by 1.96.[16] The formula for these confidence intervals is as follows: CI = (CAR +/- 1.96(σ)).

[13] Statistical calculations were performed as per conversations and recommendations from my faculty advisor, Dr. Eraker, and are based on general statistics knowledge tweaked to fit with the particular characteristics of this dataset and research question.
[14] Because CARs are simply an aggregate simple average return number, standard deviation calculations should be performed on the simple average return data as per the statistical formula.
[15] Individual stock samples were taken from different time periods, so returns should be uncorrelated.
[16] 1.96 is the value used in constructing confidence intervals at the 5% significance level for a standard normal distribution, which by assumption is a defining characteristic of this dataset.

Although the sample size here (sixteen firms) seems small initially, the results are so dramatic within this basket of stocks, it seems sufficient to discuss the results of analysis on only these companies since this analysis produces such clear conclusions. Also, this paper's aim is to assist individual investors in formulating trading strategies, so constructing a hypothetical portfolio based on sixteen companies seems like more of a reasonable number for an average household then does a portfolio with dozens of different stocks, which would be much more difficult for one individual to manage. Thus, this dataset mimics a feasibly-sized investment vehicle for an individual or a household.

The obvious weakness with my data is that I have no way of knowing what organization (or organizations) sent the emails. Since the sender is unknown, there is also no way of discerning how many people globally have received the same or similar emails. Although the vast majority of people with whom I am acquainted receive frequent unsolicited recommendations, generally multiple messages per day, there is still no way to ensure that the majority of people worldwide receive similar messages with a comparable frequency. The unsolicited aspect of my dataset is one of the elements of this paper that makes the following conclusions interesting and relevant to modern economists and investors, however this is also the aspect that makes it the most difficult to control for or have a solid grasp of the prevalence of such recommendations. Prevalence of these email recommendations could have serious effects on the ability of the buy recommendations to move markets, because the reach of these emails must be broad enough to influence many investors. This fact is the reason it is much easier to study widespread print recommendations, such as columns in *The Wall Street Journal*, because there are relatively precise ways to measure how many people read such columns. Also, since only sixteen recommended companies had historical prices listed on Yahoo! Finance, my sample size was severely limited. But again, since the results are so startlingly clear, as discussed in Section V, this weakness does not seem to muddle my findings, but could possibly provide an avenue of future research with a larger sample size. These issues may limit the certainty and general reliability of my results, however, I still believe this study can produce meaningful conclusions.

V. Findings

The pattern of returns and cumulative average returns for the stocks analyzed in this study fit rather well with my predictions. As discussed in the literature review, stocks generally exhibit a period of positive, even abnormal, returns after a major event, such as a merger, acquisition, or buy recommendation. This pattern held true for this particular basket of stocks after the initial unsolicited buy recommendation, in that the cumulative average returns were positive for several days after T=0. However, these positive returns show a clearly diminishing trend in even the initial days following the recommendation (the trend is never positive and increasing at the same time). The decreasing nature of the cumulative average returns continues through the next two months after the recommendation, as evidenced by the following Figure, labeled Figure One.[17] Figure One shows the plot of the cumulative average returns for the basket of sixteen stocks analyzed in this study. As mentioned earlier in the paper, the cumulative

[17] 60 trading days was the maximum amount of time post-recommendation that was available for each company.

abnormal returns for each day are calculated by summing the simple returns for the day in consideration through T=0.[18] The origin of Figure One represents T=0, and no previous trading days, to get a picture of the portfolio choices investors are facing when a recommendation hits.

Figure One – Cumulative Average Returns Plot

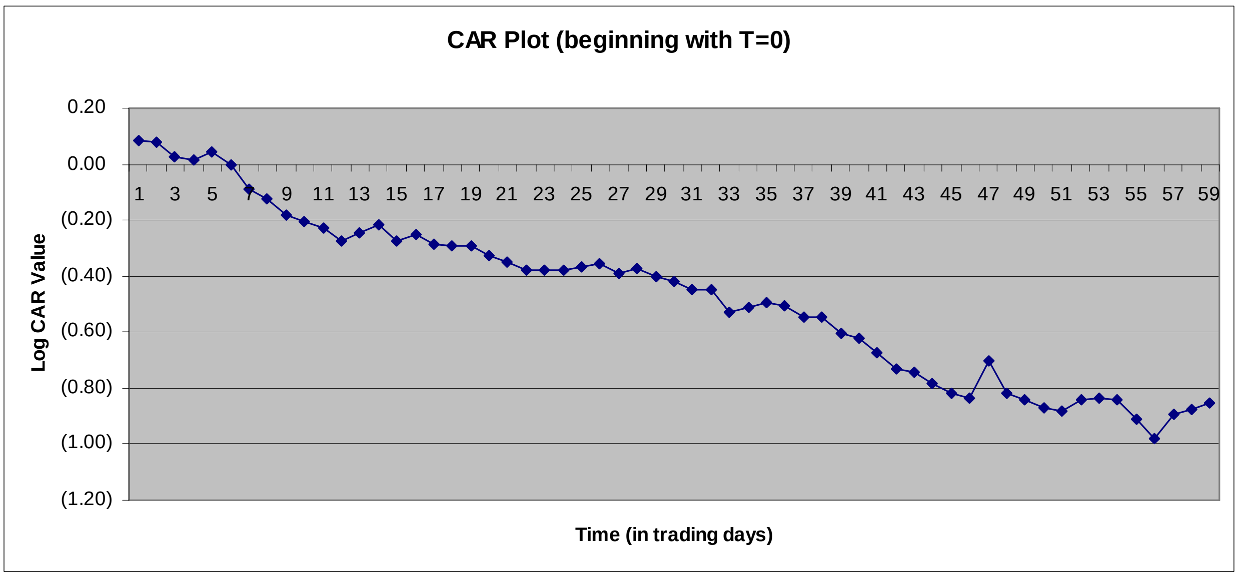


Figure One plots the CARs with days since initial recommendation on the horizontal axis and the actual CAR value (interpreted as percent changes) on the vertical axis, calculated via the aforementioned formula. This particular Figure begins the horizontal time axis with time T=0, which means that the first date on this graph corresponds directly with the first trading date recommended for each company in the first recommendation email received. This graph makes the return pattern for this basket

[18] For example, the CAR on day T = 5 would be the sum of the simple returns for days 0, 1, 2, 3, 4, and 5.

of stocks very clear visually. The shape and data-points of this graph are what dictate the appropriate profitable trading strategy. As is obvious from analyzing this figure, the cumulative average returns begin above zero at T=0, because, as discussed earlier in this paper, a small period of abnormally positive returns was expected immediately after the recommendation was issued, due to increased trading volume, and thus increased demand for the stocks. Then, a mere few days later, the cumulative average returns cross zero and remain negative for the rest of the days analyzed in this paper, which is fifty-nine days total for this particular graph. Thus, this graph and the CARs in general do follow the pattern predicted by the existing literature and my original hypothesis. The CARs exhibit an almost strictly downward trend from T=0 through almost sixty trading days later. The following graph, Figure Two, plots the same calculation, the cumulative average returns, however this data subset begins the CAR calculation and plot twenty-five days prior to the recommendation.

Figure Two – Cumulative Average Returns Plot (over the entire time period analyzed)

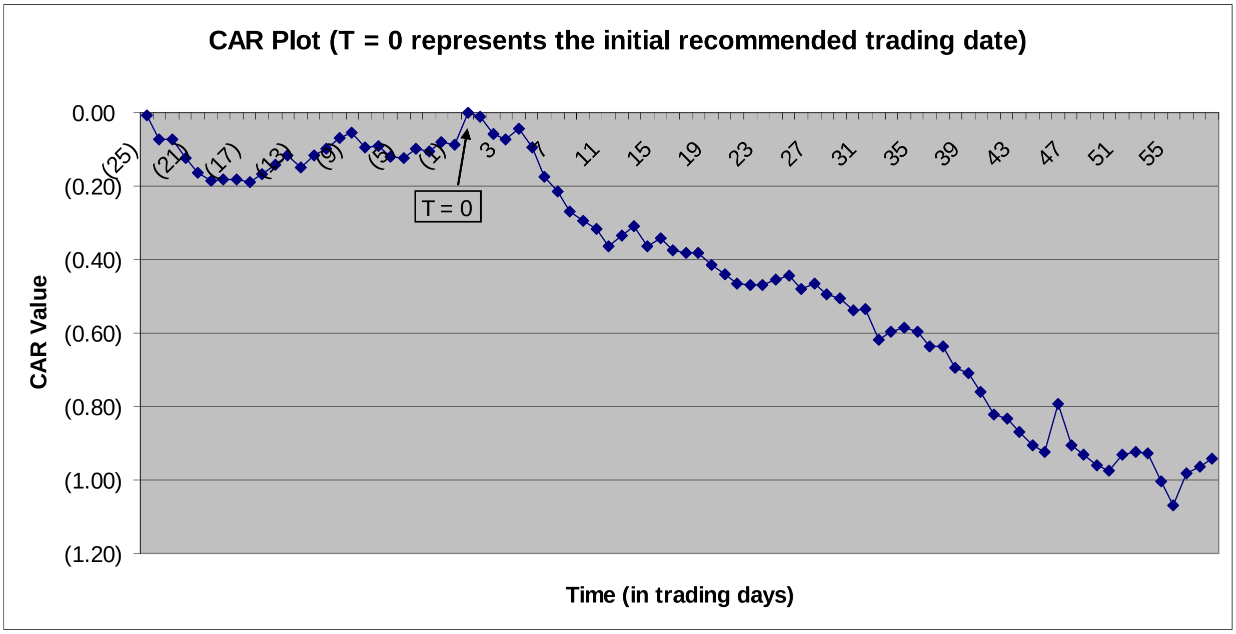


Figure Two is a more comprehensive view of the behavior of this portfolio of stocks around the recommendation date because it encompasses both the response and the preceding behavior to the initial recommendation. This graph begins the CAR calculations twenty-five days before Figure One's data does. The behavior of the trend around T=0 gives evidence that the recommendations actually move the market, because there is such a drastic change in stock behavior around that point. This change obviously alters the absolute cumulative average returns numerical value that corresponds with

Figure One,[19] however, the trend is the exact same shape over the time period common to Figure One, but allows for further analysis into the behavior that precedes recommendation. Figure Two more fully shows the impact that these recommendations have on the stock price and returns.[20] For the twenty-five days prior to recommendation, this basket of stocks exhibits relatively plain and unexciting behavior – nothing drastic enough to formulate a novel trading strategy around. As soon as the recommendations hit, though, this portfolio enters a short period of abnormal returns, with the CARs venturing up to the zero mark exactly on the initial trading day (T=0), and then staying in only the single-digit negative percentages until the CAR hits (18%) on day 32, just six days after the portfolio high on T=0, and then continues its downward spiral until reaching approximately (100%) within fifty-nine trading days.

Figure Two is of particular interest to this paper because it so clearly shows that the returns for this basket of stocks react very sensitively to the receipt of the first email stock recommendation.[21] This is exemplified through the way that the cumulative average returns are relatively steady for the twenty-five days preceding T=0 and then radically alter their previous pattern. Although the CAR values do remain in the negative range for the entire period analyzed before the recommendation date, they exhibit the trend behavior that one would expect from an average stock not experiencing any sort of

[19] Actual number CAR values would be different in this case because I aggregated over more days, which introduced more numbers into the overall summation. This does not change the shape of the plot and should be interpreted the same way as Figure One.

[20] Clearly, we cannot attribute all of the movement in prices and returns to these recommendation without running further statistical significance tests. This paper does not claim that these unsolicited buy recommendations are the cause of these price changes, this paper simply looks for a profitable trading strategy based on the general behavior of stocks around the time a buy recommendation is issued.

[21] The mention of the initial receipt of a recommendation refers to the first recommendation I received in my inbox for a particular company. There is no way to verify this was the same date for other investors.

extraordinary event (such as T=0), in that there are no major disruption to prices or returns, and returns follow an almost horizontal path. However, as soon as trading can begin based on information contained in these emails, these stocks reach an 84-day high at an exactly 0% CAR. This is due to the entrance of the portfolio into a distinct period of abnormal returns, whose trend seems to begin two trading days before T=0, and last approximately eight days, as was hypothesized in Section II of this paper.

There are obviously an infinite number of possible explanations for this behavior that are unrelated to the presence of unsolicited buy recommendations for these companies. Regardless, this pattern is so clear that it is still very significant for my analysis. After this "high" period for the portfolio,[22] beginning slightly before the initial recommendation and pursuing for six days afterward, the CAR plot begins an unmistakable plummet to end at almost (100%) CAR after fifty-nine days of post-recommendation trading. While the standard abnormal return model predicts abnormally high returns following a major company event, it also predicts that trading will resume normal value levels soon afterward. This dataset, however, dramatically exaggerates (outperforms) this model. This data does exhibit classic signs of abnormal returns following the event of investors' receipt of an unsolicited buy recommendation, but instead of returning to normal trading levels within a short number of trading days, this particular portfolio continues to devalue for a very extended period of time, with the stock prices not bouncing back in more than two months after the period of abnormal returns began and very frequently becoming nearly worthless. This clarity in stock price

[22] Which I describe by exhibiting cumulative average returns that are only negative to the single-digit percent.

performance allows for simple analysis and the formulation of a clear optimal trading strategy.

Figure Three – CAR Plot Bound by a 95% Confidence Level Band (Figure Two plus a 5% significance level confidence interval)

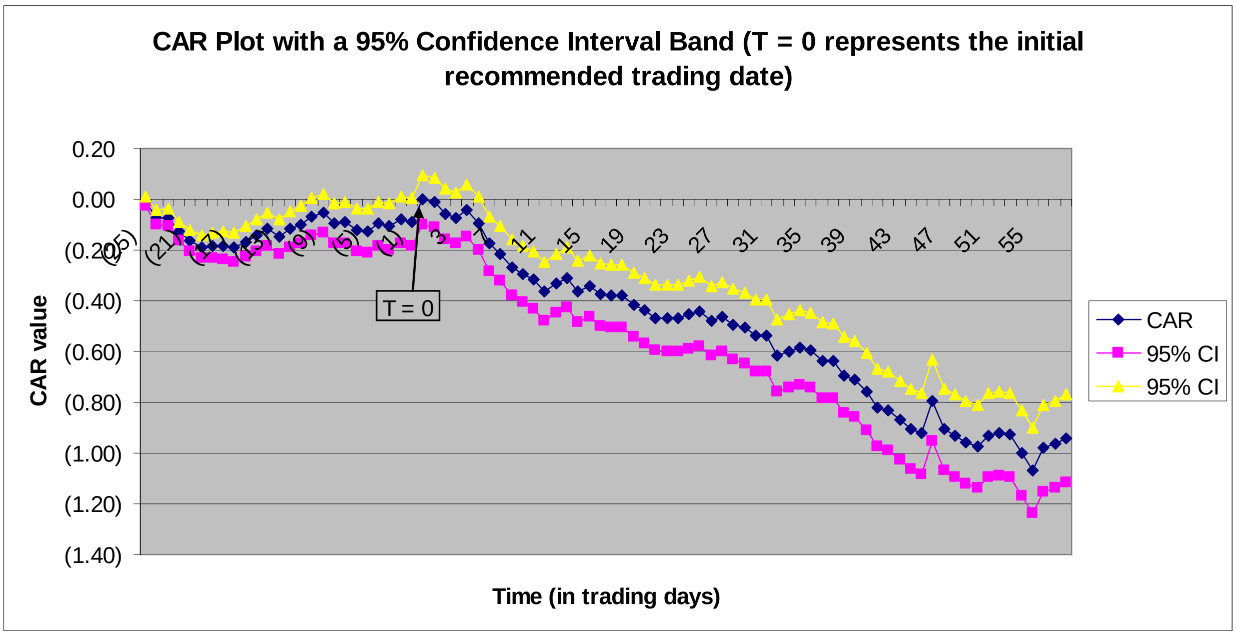


Figure Three is evidence to support the statistical significance of the findings derived from Figure Two. Figure Three plots a confidence interval for the cumulative average returns, calculated to the 5% significance level using the methodology described in Section IV. This band shows that at the 5% significance level we can reject the null hypothesis that the trend seen in the CARs is simply coincidence. The probability of seeing cumulative average returns so far from zero by chance (as predicted by a theoretical random walk model) under the null hypothesis is then less than 5%. The tightness of this confidence band shows how small this area is, meaning that these results are very significantly different from zero, at the 5% (a relatively certain) significance level. Thus, the returns that we see in this graph that lend themselves so clearly to a profitable trading strategy are most likely not a random coincidence, and in fact extremely helpful in portfolio management strategies for individual investors.

Figure Four – CAR Plot beginning at T=0 Bound by a 95% Confidence Level Band (Figure One plus a 5% significance level confidence interval)

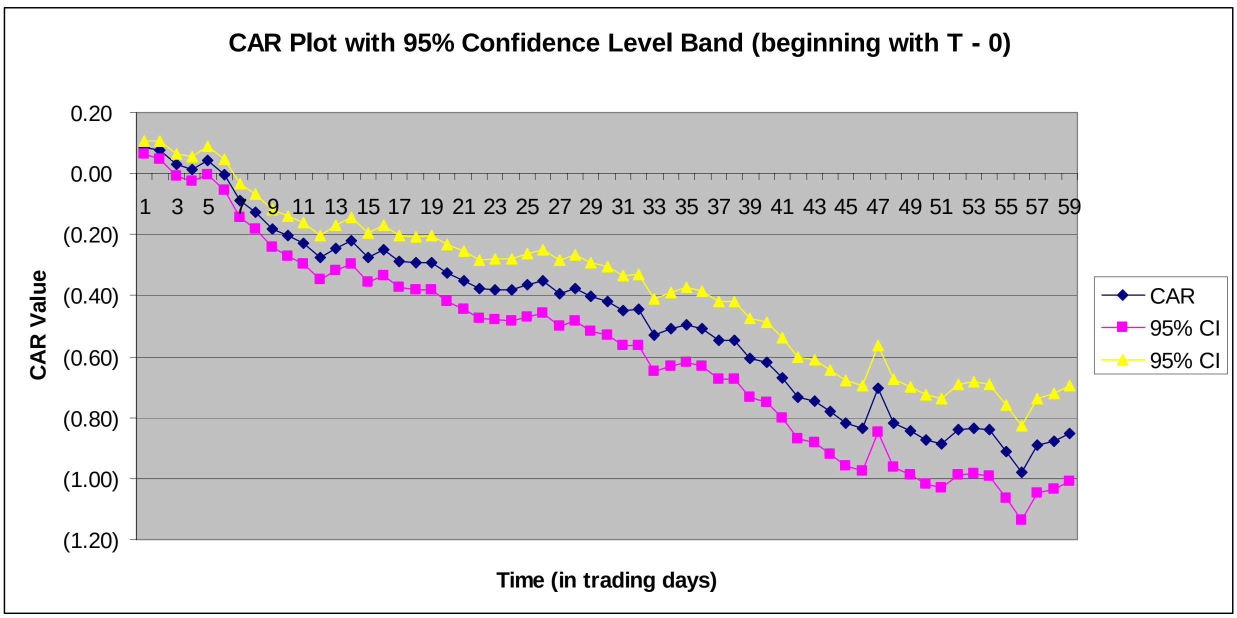
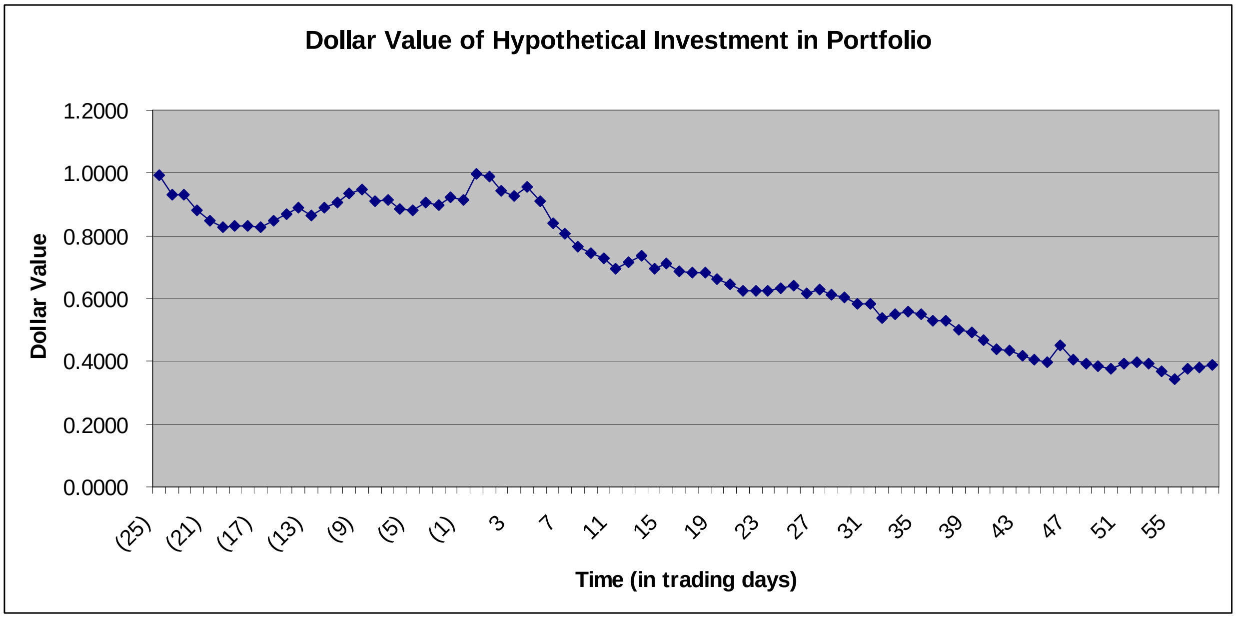


Figure Four runs the same standard error and confidence interval calculations as the data subset used in Figure Three, however the following graph uses only the data from T=0 and onward; i.e. this confidence interval was run only on CAR data from the initial recommendation date and fifty-nine trading days following (or the last fifty-nine trading days of Figure Three). The purpose of this graph is to get a more focused view on the behavior of the portfolio after trading becomes possible based on information contained in unsolicited email recommendations, which represents the trading opportunity an actual investor would face upon receipt of a spam message. This is a very useful plot for investors because it shows the portfolio performance and also the significance of such cumulative average returns in the time period in which traders would be able to trade based on spam messages. This subset of CARs also exhibits a very tight confidence interval, showing that at a 5% significance level we can also reject the null hypothesis that the CAR trend is actually zero with some ease.

Figure Five takes the basic cumulative average return plot and applies the exponent function to each data-point, to obtain a plot of the value of a hypothetical investment of one dollar ($1.00) in this portfolio of sixteen stocks.

Figure Five – Plot of the Value of a Hypothetical Investment in the Analyzed Portfolio



This Figure again begins twenty-five trading days before the initial recommendation date, and runs fifty-nine trading days after T=0. This Figure has the same underlying message as the plot of the cumulative average returns, however the vertical axis of this Figure is in dollar values instead of a natural log cumulative return values. This Figure should be interpreted as what would have happened to a $1.00 investment in this portfolio of sixteen chosen stocks made before T=0 – which clearly decreases approximately 60% over the total eighty-four trading days.[23] This decrease in investment value is just another way of showing that taking a long position[24] in this

[23] Essentially, this chart assumes that an investor put $1/16 in each stock recommended, denoted by an overall $1 investment.
[24] A long position simply means purchasing the stock outright, as opposed to buying on margin or short-selling. Generally, a long position is connoted as having a long-term investment horizon, or at least not

portfolio would have been a poor decision on the part of an investor. The profitable way to have traded on this portfolio would have been to short-sell[25] each stock as soon after receiving the unsolicited recommendation as possible, and then buying the shares back at least two months afterward, when the share value reached 40% of the initial value.[26] Figure Six plots the value of a long position in this portfolio taken the moment the initial recommendation was received, which is the equivalent of plotting simply the last fifty-nine trading days of Figure Five.

Figure Six – Plot of the Value of a Long Position in the Portfolio

having plans to immediately sell the purchased shares. A long position is what the spam emails studied in this paper suggest investors should take in these particular stocks.

[25] Selling-short involves borrowing shares from a third-party and selling them in the open market, with the promise to return the shares in a prespecified amount of time. This strategy is generally employed when the share price is believed to decrease after the initial open-market sale.

[26] This particular graph plots out the basket of stocks, with T=0 varying with time for each particular company. Figure Seven breaks it down by stock to see how a long position in each individual stock would have performed if purchased on T=0 and reevaluated fifty-nine days later. Thus, short-selling would have given gains approximately equal to the losses portrayed in this graph.

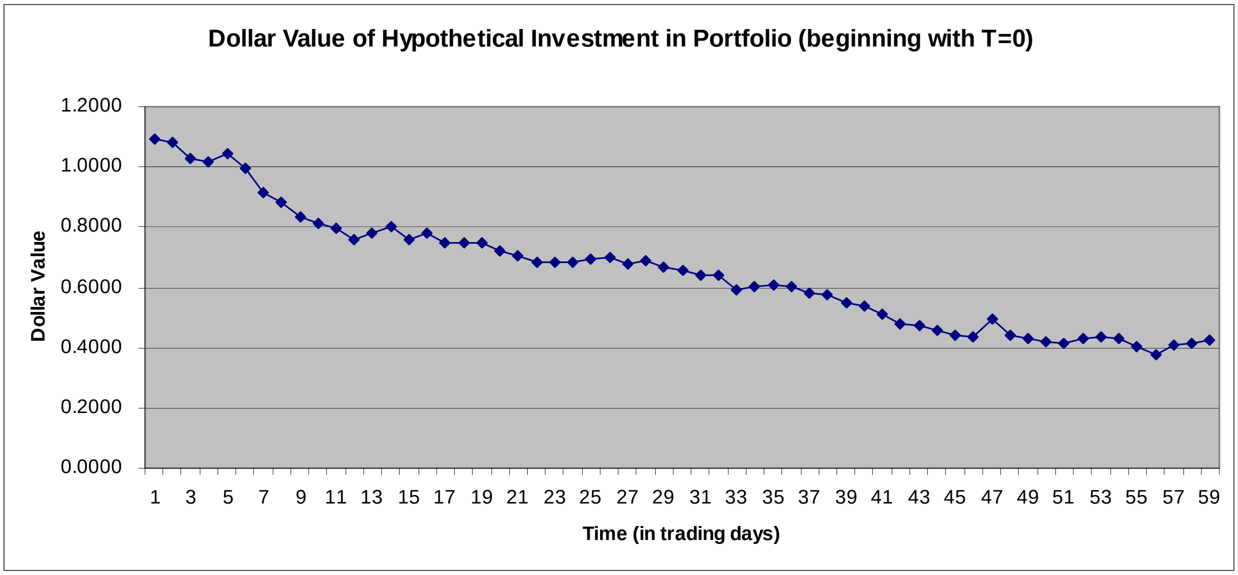


Figure Six coveys the same basic idea as Figure Five and should be interpreted very similarly, however this analysis begins on the day when trading was possible based only on information contained in spam emails. Thus, this graph gives the perspective of a long position taken in each stock on the day the first buy recommendation was received for each company – which is what the spam messages advised recipients to do. As evidenced by this graph, buying into the stocks at the recommendation date makes the loss over fifty-nine trading days even larger then 60%, which is obviously a poorly performing investment vehicle. The results of Figures Five and Six clearly rule out the possibility of forming a profitable trading strategy on only the advice of email spammers. In fact, a long position is so clearly a bad idea that this Figure seems to support doing just the opposite and short-selling this basket of stocks, to get the inverse of this graph as the payoff function. Short-selling this basket of stocks at T=0, or even the next trading day, would have resulted in gains of over \$.60 for each \$1.00 share sold short. Employing this strategy on these sixteen stocks, then, would have generated over 60% returns in less than sixty trading days, which is a phenomenal result considering reports that investors can expect to earn 6.3% on a general S&P 500 portfolio of stocks at this point in time (Tully 2007).

Figure Seven is also a value graph representing the value of a long position in the portfolio; however, this graph calculates the end value per stock instead of averaged over all sixteen firms. These calculations assume that a hypothetical investor invested $1.00 in *each* company's stock on T=0. Thus, the following bar graph simply shows how much an investment of this value would be worth after the fifty-nine trading days following T=0. Each bar represents a different firm, arranged in ascending order, with the label "1" representing the firm whose share value declined the most, and the label "sixteen" representing the company whose shares performed the best of the group over this time period (the numerical labels have no mathematical importance – they were only assigned based on ending stock value).

Figure Seven – Plot of the Value of a Long Position Taken on T=0 in Each Portfolio Stock

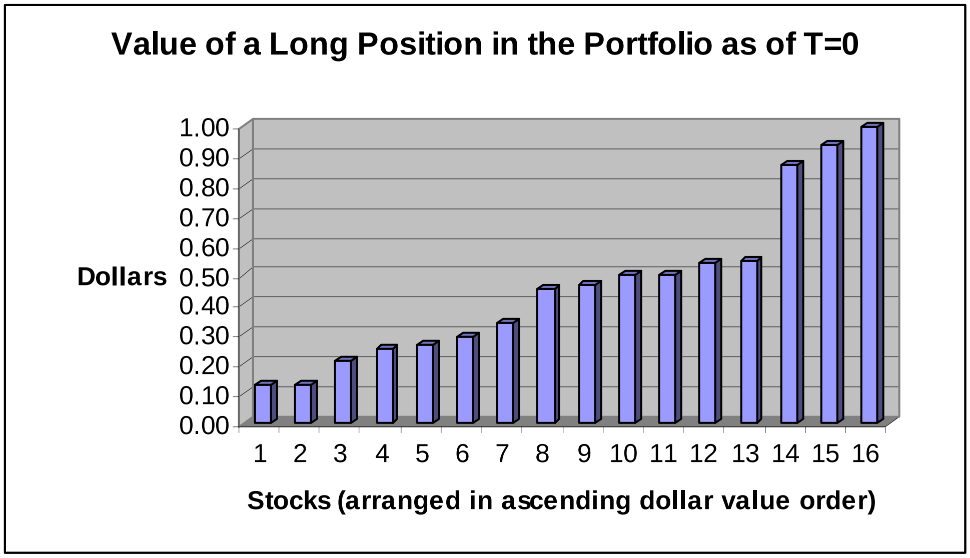


Figure Seven shows the value that would be left after fifty-nine trading days if an investor had invested $1.00 in each of the sixteen portfolio stocks on their respective T=0's. This Figure is useful in seeing what would happen to a person's investment value if he or she actually took the advice of unsolicited email buy recommendations for each individual company included in this study[27] and bought shares when recommended for each firm. Obviously, this would have been a losing strategy in the case of every stock except for one, INFX, whose value ended up exactly equaling its initial value on the day before the initial recommendation.[28] For each of the other stocks, purchasing shares on

[27] Again, the requirements for being included in this study are not only the receipt of a spam recommendation, but also having historical and current price information available free of charge on Yahoo! Finance, so that theoretically any investor could access this same information.
[28] This particular stock follows the traditional abnormal returns model of exhibiting unusually high returns for a short period after the recommendation event and then returning to it's normal (or pre-recommendation)

the recommendation date would have led to a strict decline in value, of almost 90% in some cases. This Figure is simply another way of presenting the results of Figures One through Six, separated into a long position by each company individually instead of the overall averaged basket. This trend eliminates the possibility of a long trading strategy being profitable in this case, because not a single stock increased in value over this time period.

These findings together support the idea of short-selling stocks that are recommended via unsolicited email services. As this graph shows, if an investor had short-sold this particular basket of stocks, he or she could have taken advantage of a very clear decline in returns and general stock value after a couple of months. Had an investor short-sold this basket of stocks on T=0 for each company and bought back fifty-nine trading days later, the portfolio value would have fallen 60%, allowing the investor to buy back at a significantly lower price than that of the initial sale. The actual feasibility of such a strategy will be further explored in Section VI (or could prove to be an interesting future project), but it becomes obvious after viewing the data that the on average profitable trading strategy that emerges is definitely short-selling as soon as possible after the initial buy recommendation.

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trading level. Taking a long position in this stock for more than a few days would be a break-even, rather than strictly losing, strategy in this case, which still does not support the adherence to the strategy published in these emails. This clearly does not overcome the vast negative results seen for the rest of the stocks.

VI. Conclusions

The overarching goal of this study is to formulate an on average profitable trading strategy based only on information contained in unsolicited email stock recommendations. To do so, I collected spam emails sent to my and Dr. Eraker's personal email accounts. Since neither party had previously signed up for such a subscription service, these emails were completely unsolicited, which we can assume is representative of the sort of emails investors receive all over the globe since this is such widespread phenomenon. Analysis on returns generated by hypothetical investments made in the recommended stocks clearly showed that investors would have uniformly lost money by taking the advice contained in the email messages and bought (or taken a long position in) the touted stocks. This leads to the main finding of this study, what has emerged as the appropriate way to trade the stocks recommended in spam messages: investors should *always* short-sell stocks immediately upon receipt of an unsolicited buy recommendation for a particular firm.

Returns and dollar values for the portfolio of sixteen companies averaged together began a clear descent immediately beginning on T=0, as seen in the results presented in Section V of this paper. These trends help show that there is no real value to be found in a long position taken in the basket of stocks when the spam messages recommend one be taken. This theory applies not only to the average basket analyzed, but also to each individual firm's stock. As Figure Seven shows, there was not a single stock whose value increased over the period analyzed. Thus, in aggregate and at the individual level, taking the advice of spam recommendations is a losing strategy.

The simplest way for investors to take advantage of such facts is to take the opposite of the losing strategy and short-sell each time. By short-selling, an investor would have to borrow another person or institution's shares and sell them in the open market as soon as possible after T=0, and then return the shares (by buying back the same number of shares in the market) later on, when the price has uniformly not increased. The requirements to execute such a trade are only that there is another party willing to participate, and obviously that there is demand to purchase the shorted shares in the market, which is generally assumed to always be present. With the breadth of online brokerage houses, that charge only a flat, relatively small, fee per trade regardless of the actual number of shares traded, and importantly, regardless of the type of trade or the type of equity. This means that any investor theoretically has the opportunity to simply go online upon receiving a spam message touting a firm's stock, and short-sell without even having to speak to another person.[29]

Hopefully this paper can pique the curiosity of other researchers and perhaps incite more studies similar in topic to this paper. It would be useful to look at similar data and calculations from different people that may receive emails from different recommendation services. The more emails that are analyzed, the more broadly applicable the results will be. Broader results increase the likelihood of encompassing similar data to the emails received by actual investors, and thus making the results of such studies more helpful and accurate for readers. Also, it would be useful to do these same calculations on a larger sample size, if available. Larger sample sizes allow for

[29] Clearly, the real-life feasibility of short-selling shares in each of these companies will depend on both the investor and the company, and must be determined on a case-by-case basis.

more certainty in results and calculations. Along with this theme of increasing the sample size, another possibility for a future study would be to take samples over a longer period of time, to try and adjust for possible seasonality trends in the stock market as a whole.

On March 8, 2007 the SEC banned trading for ten day in the stocks of thirty-five OTC companies (SEC Suspends Trading 2007). Two stocks included in the ban, Goldmark Industries, Inc. and Biogenerics Ltd., were included in this study. The reasons behind such an action as stated in the press release centered around the recent growth in weekly spam stock touts and the possibility of a scam involving brokers or people affiliated with the companies making money from investors' losses. A great future study would be to analyze what effects, if any, this ban has on the penny stock market and the flow of email recommendations in the future, and also analyze any such future regulations and their effects on the market.

Future studies could also be conducted within the very dataset used in this paper. One option could be to explore the legal, or less than legal, standing of the companies involved. The knowledge of which are fraudulent companies and which are legitimate enterprises could add depth to the results and ease in foreshadowing future return and price trends – or in other words, compare the performances of legitimate enterprises with those, if there are any, companies are actually fraudulent. Research into what kinds of brokers hold reserves of these shares to market them to investors would also be an interesting study. Knowing whether trades made in shares o such touted stocks are 100% legal or moral could also influence the actions of possible investors. These are several possible avenues for further research that I believe could add great depth and understanding to this particular field of research and general interest.

Future policy implications of the issues described in this paper are surprisingly simple – if investors do begin to short-sell touted stocks with this new information, the market will tend to become more efficient, which would actually negate the need for new policy implementation. If investors begin to short-sell during the short period of abnormal returns following T=0 (which is where we hypothesize spammers are being compensated, but unloading their shares during this period of artificially high demand), then the shares would be less artificially scarce, which drives down the price. This would lessen, and hopefully eventually completely undo, the abnormal return period seen for several days following T=0, which would unravel the spammers' compensation schemes. If the abnormal returns are lessened and eventually cancelled altogether, spammers would have no incentive to send out these emails, because they would lose their informational advantage over investors. If investors were to use the tricks of the spammers to short-sell in the same window, spammers no longer have a competitive advantage, which leads to a more efficient overall market, which would imply less profit possibilities for the spammers. Thus, as soon as returns were normalized once again, all incentive to send spam messages would be gone since there would no longer be any sort of compensation possibilities, and it is logical to assume that the emails would eventually stop. Hence, there would be no real need for the SEC to govern spamming because there would be no incentive for the originators to continue their scam.

Short-selling spam-advertised stocks is not only a way that investors could theoretically make money, but it is also an interesting way of stopping annoying emails. While it would take a decent amount of time for investors to gather the necessary momentum to completely normalize returns, the results of this study make it very clear that investors should take short positions in all stocks supported by the receipt of an unsolicited email message. Not only does this strategy make logical and analytical sense, but it also becomes easier to execute everyday with the exponential increases in technology we perpetually see in the world.

Appendix A: Example Email Spam Stock Recommendation[30]

[30] Received to angela.aldrich@duke.edu on Wednesday, November 1, 2006 at 7:06 PM, with a T=0 of Thursday, November 2, 2006.

Works Cited

Acharya, Sankarshan (1993). Value of Latent Information: Alternative Event Study Methods. *The Journal of Finance, 48(1),* 363-385. Retrieved March 28, 2007, from JSTOR database.

Barber, Brad; Lehavy, Reuven; Marureen McNichols, & Brett Trueman (2001). Can Investors Profit from the Prophets? Security Analyst Recommendations and Stock Returns. *The Journal of Finance, 56(2),* 531-563. Retrieved October 3, 2006, from JSTOR database.

Binder, John J. (1998). The Event Study Methodology Since 1969. *Review of Quantitative Finance and Accounting. 11,* 111-137.

Brooke, Jesse, & Oliver, Barry (2004). The Source of Abnormal Returns from Strategic Alliance Announcements. *Pacific-Basin Finance Journal, 13(2),* 145-161. Retrieved September 25, 2006, from ScienceDirect database.

Dewally, Michael (2003). Internet Investment Advice: Investing with a Rock of Salt. *Financial Analysts Journal, 59(4)*, 65. Retrieved October 4, 2006, from ProQuest database.

Elswick, Jill. More Plans Test Patient Incentives / Disincentives. *Employee Benefit News*, October 1, 2002. Retrieved November 7, 2006 from Info Trac OneFile database.

Fama, Eugene F.; Fisher, Lawrence; Jensen, Michael C., & Roll Richard (1969). The The Adjustment of Stock Prices to New Information. *International Economic Review, 10(1),* 1-21. Retrieved February 6, 2007 from JSTOR database.

Frieder, Laura L., & Zittrain, Jonathan L. (2007). Spam Works: Evidence from Stock Touts and Corresponding Market Activity. Retrieved April 1, 2007, from Google Scholar database.

Gompers, Paul & Loerner, Josh (1999). An Analysis of Compensation in the U.S. Venture Capital Partnership. *Journal of Financial Economics. 51(1),* 3-44.

Green, T. Clifton (2006). The Value of client Access to Analyst Recommendations. *Journal of Financial and Quantitative Analysis*, *41(1),* 1-24. Retrieved October 18, 2006 from Business Source Complete database.

Henderrson, Glenn V. Jr. (1990). Problems and Solutions in Conducting Event Studies. *The Journal of Risk and Insurance, 57(2),* 282-306. Retrieved March 28, 2007, from JSTOR database.

Hirschey, Mark; Richardson, Vernon J., & Scholz, Susan (2000). How 'Foolish' are Internet Investors. *Financial Analysts Journal, 56(1),* 62-70. Retrieved October 4, 2006 from Business Source Complete database.

Hirschey, Mark; Richardson, Vernon J., & Scholz, Susan (2000). Stock-Price Effects of Internet Buy-Sell Recommendations: *The Motley Fool* Case. *The Financial Review 35(1),* 147-174. Retrieved October 4, 2006 from Proquest database.

Jegadeesh, Narasimhan, & Livnat, Joshua (2006). Post-Earnings-Announcement Drift: The Role of Revenue Surprises. *Financial Analysts Journal, 62(2),* 22-35. Retrieved September 28, 2006, from ProQuest database.

Kim, DS., & Eum, SS. (2006). The Impact of Analysts' Revisions in their Stock Recommendation and Target Prices on Stock Prices. *Asia-Pacific Journal of*

Financial Studies, 35(2), 75-108. Abstract retrieved September 28, 2006, from Web of Science database.

MacKinlay, A. Craig (1997). Event Studies in Economics and Finance. *Journal of Economic Literaturer, 35(1),* 13-39. Retrieved March 28, 2007, from JSTOR database.

Park, Jinwoo (1995). A Market Microstructure Explanation for Predictable Variations in Stock Returns following Large Price Changes. *The Journal of Financial and Quantitative Analysis, 30(2),* 241-256. Retrieved September 25, 2006, from JSTOR database.

Pump&Dump.con: Tips for Avoiding Stock Scams on the Internet. http://www.sec.gov/investor/pubs/pump.htm. Retrieved April 1, 2007.

Salinger, Michael (1992). Value Event Studies. *The Review of Economics and Statistics, 74(4),* 671-677. Retrieved March 28, 2007 from JSTOR database.

Sarkar, Salil K.; Jordan, Douglas J. (2001). Stock Price Reactions to Regional Wall Street Journal Securities Recommendations. *Quarterly Journal of Business & Economics, 39(2),* 50-62. Retrieved October 3, 2006, from Business Source Complete database.

SEC Suspends Trading of 35 Companies Touted In Spam Email Campaigns (Press Release). Retrieved April 8, 2007, from www.sec.gov/news/press/2007/2007-34.htm.

SEC Trading Freeze Likely Won't Slow Email Spam Campaigns. *FinancialWire, 3/12/2007*, 1. Retrieved April 7, 2007, from ProQuest database.

Tully, Shawn (2007). Big Profits = Danger Ahead! *Fortune, 155(5),* 196. Retrieved April 12, 2007, from ProQuest database.

Wallace, N. Davidson III, & Worell, Dan L. (1988). The Impact of Announcements of Corporate Illegalities on Shareholder Returns. *The Academy of Management Journal, 31(1),* 195-200. Retrieved March, 28, 2007, from JSTOR database.

Womack, Kent L. (1996). Do Brokerage Analysts' Recommendations Have Investment Value? *The Journal of Finance, 51(1)*, 137. Retrieved October 18, 2006 from Business Source Complete database.