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Telling True from False

Do Markets React Efficiently to Takeover Rumors?

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Abstract

This thesis examines how U.S. markets react to 345 different takeover rumors, and how efficiently the market is capable of distinguishing between true and false rumors. The markets do appear to react differently to true rumors, with a statistically significant difference in the stock price reaction on the day of the rumor, giving weight to the hypothesis that the market can discern true rumors from false. Using this finding, we attempt to create a trading strategy by applying methods previously used for estimating the likelihood of success for takeovers to rumors. With the use of logit classification models and holdout samples we seem to be able to distinguish between true and false rumors with some success, but we cannot profit from trading on the rumors. Using an out-of-sample dataset also on the U.S. market as well as a sample of U.K. rumors, we manage to classify rumors with some degree of precision using the model constructed from estimates from the primary sample. The stock market seems to be reacting efficiently to rumors as we cannot find any evidence to the contrary. We also find a rumor run-up before the rumor publication, which we attribute to the rumor diffusing through the market rather than to insider trading.

Keywords: Takeover Rumors, Market Efficiency, Event Study, Mergers and Acquisitions, Logit Analysis

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1. Introduction

Few corporations in today's information-driven financial markets have not at least once come across rumors about themselves. Rumors can concern almost any business-related matter and vary greatly in how strongly they impact markets. A rumor, when compared to an announcement, often contains little information. Sources are often either not revealed or report anonymously what they know to journalists or other investors. In most cases, details are sparse and investors have to rely on other indicators than the rumor report itself to judge the veracity of the rumor. One common type of rumors in finance concerns takeovers. As the premium for takeovers sometimes go as high as 50 percent[1] above the current market value, and an investor that holds the stock at a point early enough in the process is able to capture a majority of this, takeover rumors can be argued to be of particular interest to researchers. The returns from making the right call can be very large and the ability to correctly estimate the veracity of takeover rumors could potentially prove very profitable.

This thesis investigates the reaction of the U.S. stock market to rumors concerning acquisitions as they are published in the media. First, we examine whether the market appears to be able to distinguish between rumors that are followed by a takeover (hereafter referred to as *true* rumors) and rumors that are not followed by any bids (hereafter referred to as *false* rumors) and find that the market reacts more strongly to the publication of true rumors than to false. We investigate simple strategies such as whether it is profitable to buy and hold the target stock as a rumor surfaces, and what profits are achieved if one would be able to trade either on only true or only false rumors. We show that no abnormal holding period returns can be made from simply buying and holding rumored target firms, but that the difference between the buy-and-hold returns of trading on true rumors and false rumors are noticeable.

Second, we seek potential explanations for the difference in the stock market's reaction to the publication of true and false rumors by examining whether there is any difference in the run-up before the rumor, but do not find any statistically significant difference between the two rumor types. We do, however, find a statistically significant run-up for rumors overall, which could be a signal that the run-up is evidence of the rumor diffusion process (as described by Van Bommel, 2003; based on Kyle, 1985) throughout the market rather than of insider trading. If the rumor run-ups were only caused by insider trading, we would expect a smaller run-up before false rumors which we do not find. The fact that both trading volume and stock price reaction are larger for rumors that are followed by bids tells us that there is some form of information not readily visible in the rumors themselves; even when controlling for the level of detail in the published rumor and how well-reputed the news source is, the difference between true and false rumors changes little.

Third, we attempt to use the information that is publicly available to determine if we can classify rumors depending on whether the rumored target firm is more or less likely to be acquired. Dietrich & Sorensen (1984), Palepu (1986), Walter (1990) and Barnes (1998) are some of a number of papers attempting to use firm-specific characteristics to classify firms as more or less attractive to acquirers.

[1] As established by, among others, Comment and Jarrell (1988).

The notion is that firms that are resource-constrained but exhibit high growth; firms that have an abundance of resources but exhibit low growth; smaller firms; and firms that are badly managed are all more likely to be taken over than the average firm. Variables of interest may thus be market capitalization, sales growth and the price-to-earnings ratio. The technique used is strikingly similar to the bankruptcy prediction models by Altman (1968), Ohlson (1980) and Zmijewski (1984), models that are all in popular use and considered successful in estimating the probability of bankruptcy for firms. All of the papers on acquisition prediction mentioned above find that it is possible to classify firms into targets and non-targets better than chance, but that the technique is unwieldy to apply on the markets. The reason is that the number of non-targets outnumber the number of targets by more than 30-to-1 in the wild (Palepu, 1984), and that the models used only skews the odds in one's favor. Furthermore, the efficient markets hypothesis states that it might not be possible to trade profitably using these models, as stock prices should have already internalized the increased likelihood of an acquisition.

By combining the techniques used by these papers (dichotomous classification models using book values and financial key ratios) with an event, the publication of a rumor, we see whether we can find any systematically different target firm characteristics between true and false rumors and whether these characteristics help explain some of the difference in the reaction to the publication of rumors. The difference between looking at all firms listed on a market and only the firms that have been identified as potential takeover targets in rumors is that instead of non-targets outnumbering targets by 30-to-1 the ratio is closer to 3-to-1. We find a model that, using financial key ratios and other firm-specific characteristics as well as the level of detail of the rumor, manages to classify firms significantly better than chance (while avoiding data snooping biases as the sample is divided into a training set and a validation set). None of the different investment strategies we formulate using the model, some of which are more conservative and some of which are less conservative, yield any statistically significant abnormal one-year holding period returns. However, we find that by adding the abnormal return on the day of publication of the rumor results in a model with a significantly higher degree of explanatory power. This means that we are unable to observe the underlying information that the market uses to distinguish between true or false rumors, but we can use the information inherent in the market reaction in combination with the explanatory power we find in the firm-specific characteristics to identify true rumors. The model specification including the abnormal return on the day the rumor is published manages to classify rumors as true or false even better. However, no profits that are statistically different from zero are achieved using any trading rule based on this model either, implying that the market already has incorporated this information into the stock price.

Fourth, for robustness, we test whether we can replicate the results we found in our U.S. sample (from the M&A database Zephyr) with a dataset from a different source, also containing U.S. acquisition rumors (from Bloomberg). Ascertaining that no target firms are included in both datasets, we estimate the model coefficients on the U.S. Zephyr sample and apply the model with these estimated coefficients to the U.S. Bloomberg sample. The same model with the same coefficients is applied to a U.K. sample, also from Zephyr, and we find that we are able to classify rumors into groups based on the likelihood of them being true better than chance in these two datasets as well.

The thesis is divided as follows: in section 2, we go over the previous literature on the topic. In section 3, we discuss our dataset and initial data generation. In section 4 we present the methodology used and the theoretical framework that lays the foundation for the rest of our thesis. Section 5 lists the results we arrive at, and section 6 sums up our conclusions based on the results. Section 7 concludes with the limitations of the study and some suggestions for potential areas for further research.

Hypothesis 1: Markets are able to distinguish between true and false acquisition rumors, be it using public or private information.

While the opposite could be possible, several aspects point towards the hypothesized outcome being the more likely case. Previous works on the topic have found that some financial key ratios differ systematically between targets and non-targets. The possibility of insider information being traded on also opens up for larger trading volumes and abnormal returns for the rumors that actually hold water. We do not expect, however, to be able to explain the exact causes of a potential difference between true and false rumors quantitatively as we cannot observe variables such as insider information.

Hypothesis 2: It is not possible to profit from following a buy-and-hold strategy based on acquisition rumors.

This is a relatively straightforward test of market efficiency, and given efficient markets a profitable trade on rumors should not on average be possible.

Hypothesis 3a: It is possible, as an uninformed trader, to use public information (including the stock market's reaction pattern) to distinguish between true and false acquisition rumors.

Our hypothesis is that characteristics that make some firms more likely to be taken over than others exist, analogous to some of the papers within the field of takeover prediction. We however also believe that a model based on firm characteristics can be built upon by including some of the private or unobservable information reflected in the target stock price reaction that is not publicly available.

Hypothesis 3b: It is not possible to profit from acquisition rumors using only this public information.

The expectation is that the market's reaction to an acquisition rumor is efficient enough to eliminate any possible profits from trading on the rumors, regardless of whether the stock price reaction is used as an indicator or not.

2. Previous Literature

Before we present our findings it is only natural to look at what has previously been done on the topic at hand and what lessons can be learned from the works of others. We start off by briefly summarizing the research done on rumors. As we use our findings on the stock market's reaction on takeover rumors to predict which rumors are more likely to be true (and result in an acquisition) an understanding of the field of takeover prediction and the tools most commonly used will prove beneficial. Another field where much effort has been made toward finding predictive models is the field of bankruptcy prediction. We take a closer look at some of the papers within this field, both to learn from its long history and some of its missteps along the way, but also to later prove a linkage between the probability of bankruptcy and that of being taken over. Since we look at rumors that are diffused by the media, by large international news outlets as well as smaller online-only publications, rather than by word-of-mouth, the relationship between the media and the stock market is highly relevant. A phenomenon commonly seen before takeovers is a significant run-up in the stock price, for which one potential explanation is rumors. In academia, the run-up is also often linked to insider trading, which is why we conclude this section with some papers which agree with this view and some that do not.

2.1 Rumors in financial markets

One of the earliest empirical papers on the effect of rumors on stock markets is Rose (1951), who hypothesize that trends, unidirectional movements of stock prices in the stock market, are caused by rumors. These trends are named *stickiness* and Rose is able to identify a certain degree of stickiness in the market. While he manages to discard several other explanations for the stickiness, he is unable to ascertain that rumors have an effect on the market.

After Rose, not much significant research was done on rumors until the 1990's when Pound and Zeckhauser (1990) did a study on actual rumors, using 42 takeover rumors published in the Wall Street Journal column *Heard on the Street*. Their findings show that, on average, no excess return can be realized through buying (or selling) rumored target stocks for a holding period of one year, indicating that the market reacts efficiently to rumors. Pound and Zeckhauser's study reveals, however, that there is a significant run-up in prices before the publication of the rumor, indicating that the rumor has already been disseminated in the investment community prior to publication in the column.

Pound and Zeckhauser's research was followed by a similar study by Zivney, Bertin, and Torabzedeh (1996). Zivney et al., however, also study another column in the Wall Street Journal called *Abreast of the Market*, published on the same page of the journal as the *Heard on the Street* column. Analyzing a total of 871 takeover rumors divided between the two columns they find that the market reacts in a much stronger fashion to the rumors published in the *Abreast of the Market* column. They calculate that the cumulative abnormal return of a portfolio of rumored target stocks has a mean of -4.32% in a period of 80 days following the rumor publication and that it is hence possible to make a profit by trading on this overreaction. Contrary to the Pound and Zeckhauser study, Zivney et al. thus conclude that the market is not fully efficient in its reaction to rumors.

Both Pound and Zeckhauser and Zivney et al. find that a majority of the takeovers rumored in the column never take place, but they do not try to determine if there are any differences between true and false rumors. This is where we believe that our study can contribute; by examining the characteristics of the firms appearing in the true and false rumors, respectively, in addition to separating the market reaction on basis of the validity of the rumor we are able to build upon the findings of the two aforementioned studies.

Chou et al. (2010) attempt to predict takeovers based on only cumulative abnormal return around the publication date of the rumor using 74 rumors that led to a takeover announcement and 187 that did not. Thus, their study bears some similarities with our study. Using this approach, contrary to the findings of the present study, Chou et al. are not able to establish a statistically significant difference in the stock price reaction following true and false rumors on the day of publication of the rumor. They are instead able to find differences in the period preceding the rumor publication, a finding that we have been unable to replicate.

There are a great number of psychological studies treating the topic of rumors. While many are beyond the scope of the present, more quantitative, study there are still some interesting considerations in these papers. One example is Kimmel (2004), who finds that rumors that ultimately prove to be true become more credible and precise as they are transmitted, in contrast to false rumors which grow progressively more distorted.

Trading volume and rumors

One of the most recent papers on rumors is Gao and Oler (2012). They find abnormally high trading volumes during the period following a takeover rumor and that the volume consists of both significant buy- and sell-sides. Looking at explanations as to why investors would want to sell on takeover rumors they discard several reasons before concluding that investors act rationally when selling. As so few takeover rumors actually materialize (twelve percent of the rumors in their sample) shorting the rumors becomes a profitable trading strategy.

Credibility of rumors

DiFonzo and Bordia (1997) find, using experimental stock simulations, that people, contrary to their stated opinion that rumors are non-credible, trade on rumors as if they were news. Oberlechner and Hocking (2004) show in a questionnaire-based study find that traders prioritize the speed of news and anticipated impact on the markets above the accuracy of the information. Kosfeld (1998) states that the important characteristic of a rumor is not whether it is true or false, but rather the inability to tell the difference and that a rumor becomes more credible with the extent it is communicated as well as the number of sources reporting it.

Rumors on the Internet

Many of the papers concerning rumors were written before the popularization of the Internet as a source of information, a tool that has simplified and created new ways for the dissemination of rumors. Clarkson et al. (2006) examine whether or not postings about rumored takeovers on Internet Discussion Sites (IDS) affect stock prices. They find that there are significant intraday abnormal returns and volume during a 10 minute posting interval and significant trading volume during the 10 minute interval immediately preceding it, in the predicted direction. Using these findings they discuss whether traders use IDS to manipulate the prices of stocks they already have a position in. Tumarkin and Whitelaw (2001) perform a similar study on the at-the-time leading investment discussion forum *Ragingbull.com* and find that message board activity does not predict returns or trading volume. Their findings refute the possibility that the market can be manipulated by discussion site postings and are instead consistent with market efficiency.

2.2 Takeover prediction

If rumors is an area of study that is still relatively unexplored, the same cannot be said about the research concerning takeovers. A large number of papers have been published on the subject, each introducing a new model aiming to identify firms that are likely to be takeover targets. Among these papers are Simkowitz and Monroe (1971), Castagna and Matolcsy (1976), Belkoui (1978) and Dietrich and Sorensen (1984). The study by Dietrich and Sorensen was the first to apply a logit regression analysis to the question of takeover prediction, an approach that is largely followed by this study. Using this analysis tool on several accounting values they are able to create a model with an accuracy rate of 90 percent.

Palepu (1986) presents some damning criticism toward the earlier work and lay down some ground rules for how to construct a model for takeover prediction. His criticism is mainly focused on the fact that previous studies had not used random sampling of their data (leading to biased estimates and unrealistic error rates) and that the probability cutoff used was often chosen arbitrarily. We have tried to keep his criticism in mind when constructing our model. Palepu then develops a model for takeover prediction himself, but as he was not able to find any specification that made its explanatory power significant he reached the conclusion that it is not possible to robustly predict takeovers beforehand. This finding was later challenged by Powell (1997) who states that Palepu's decision rule to create trading portfolios (to include as many target firms as possible) is erroneous and that the portfolios should instead be formed by maximizing the *proportion* of target firms to non-target firms. This is also the decision rule applied in this thesis. Powell then convincingly shows that by following this rule, it is in fact possible to create a profitable takeover prediction model. Barnes (1998) also tries to improve on the methodology of Palepu (1986) and includes anticipatory share price movements in his model. Unlike Powell (1997), Barnes confirms the findings of Palepu and states that the semi-strong form of the efficient market hypothesis is valid since the market has already accounted for the probability of a firm being a takeover target. More recent work on takeover prediction include Branch and Yang (2003) who look at takeover bids and extend the scope of the model beyond accounting data by using the form and size of proposed payment as determinants and conclude that cash offers are more likely to succeed than equity offers. Branch further improves on the model in Branch and Wang (2009) by using a pairmatched logit regression and including other factors such as stock price, bid competition and target resistance.

Consequently, there is empirical evidence showing both that it is and that it is not possible to predict which firms are more likely to be takeover targets. The present study sides with the views of, among others, Dietrich and Sorensen (1984), Powell (1997) and Branch and Yang (2003): that it is possible to formulate a model that allows classification of firms into those more and less likely to be taken over. None of the papers find conclusive evidence that it is possible to trade profitably using their models, a conclusion that we are hesitant to make as well.

2.3 Bankruptcy prediction

While this thesis deals with the question of takeovers and takeover prediction, the field of bankruptcy prediction is closely related. Both fields try to predict a major event in the lifespan of a company by using publicly available data. Barnes (1998) points out that the major difference between predicating takeovers and predicting bankruptcies is the larger influence of insider trading and rumors, the very topic of this study, on takeover prediction.

The classic paper in this field is Altman (1968), who by using a sample of only 66 firms is able to formulate a model for bankruptcy prediction that has proven to stand the test of time and is still in popular use today. Zmijewski (1984) tries to improve on Altman's model by addressing the biggest concern of all previous work in the field: that the models are constructed using non-random samples. Building upon Altman's model, Zmijewski's model was able to correctly identify 72 percent of the bankrupt firms in his sample. Ohlson (1980) also challenges the conclusions of previous work by arguing that these papers were not careful enough with the timing of the data used. Specifically, that the highly accurate predictions of some papers were reached by using data from after the companies entered bankruptcy. Correcting for this error and adding some additional factors, Ohlson is still able to find a robust prediction model, albeit with a slightly lower accuracy rate than that of earlier works.

2.4 Media and the market

Engelberg and Parsons (2009) and Peress (2012) present strong cases for the role that media plays in relation to the stock market. The former by showing that investors who live in areas where an event was reported in the local newspaper trade significantly more in the concerned stock than investors in other areas and the latter by demonstrating that trading volume falls by twelve percent during newspaper strikes. Tetlock (2007) and Dougal et al. (2011) find that the level of pessimism each day in the Wall Street Journal column *Abreast of the Market* and which journalist writes the column can predict the direction the market takes, findings that clearly demonstrate that not only the information content of media reporting matters but also the way it is framed.

2.5 Pre-announcement run-up and insider trading

Jarrell and Poulsen (1989) present several explanations to the commonly observed pre-announcement run-up in stock prices, including insider trading and investors trying to get a foothold, but find that the presence of rumors is the most significant explaining factor. They establish, however, that investing in rumored takeover targets is very risky; the variance of one-year excess returns after the publication of a takeover rumor is found to be exceptionally high. Sanders and Zdanowicz (1992) are unable to identify significant abnormal trading volume before takeover announcements and use this finding to draw the conclusion that insider trading is not as prevalent as is sometimes believed. Holland and Hodgkinson (1994) find that press reporting prior to announcements explains the run-up and that any potential insider trading is done in such small volumes that it is unable to move the share price. Muelbroek (1992) is, on the contrary, able to show an abnormal return of three percent on insider trading days prior to a takeover announcements and that almost half of the pre-announcement run-up takes place during these days. Bettis (1995) presents a test to gauge the validity of a rumor using a line of thinking based on insider trading activities. Since investors are barred from trading on private information one can use these insiders' trading activity to judge a rumor's validity. If the insider is trading after the publication of the rumor, the rumor is most likely false since the insider otherwise would be committing a crime. On the other hand, if one would expect insider activity and there is none the rumor may be valid. Bettis does not, however, perform a quantitative data analysis of this test but instead presents three cases in support of his hypothesis.

3. Data

The primary data sources used are the M&A database Zephyr and COMPUSTAT. Additionally, data from Yahoo! Finance (FTSE100 historical values), the Bank of England (3-month Treasury bills as proxy for the risk-free rate) and the Ken French Data Library (Fama-French factors for the U.S.) is collected.

3.1 Rumor data

An extensive number of observations on mergers and acquisitions is available through Zephyr, with data on a total of 89 747 acquisitions and institutional buyouts in the U.S. We filter these observations to make sure the target firms are either publicly traded or, in the case of true rumors, have been publicly traded prior to the acquisition. No filters are used for acquiring firms, both since the acquiring firm is often unknown at the rumor stage and also because the acquiring firm seldom shows any noticeable stock price reactions in conjunction with acquisitions (Betton et al., 2008).

The rumors are manually screened to ascertain that they really can be considered to be rumors. Zephyr's rumor categorization is often very broad, and sometimes classifies events such as company press releases concerning signed letters of intent or memorandums of understanding about acquisitions as rumors. Thus, a closer scrutiny of Zephyr's data is required. In addition to filtering the Zephyr data down to rumors only, each rumor record is examined and classified by whether it is reported by a major or minor news source, and whether the initial rumor publication contains what can be deemed to be 'detailed' information. A set of selection criteria are set up for the classification of rumors:

- The rumor may not spring from a press release issued by the firm; if the only source given by Zephyr is an involved company the rumor is not included.
- The firm has not made any public statements (affirmations or denials) regarding the rumor on the days just after the rumor publication.
- The rumor is not based on the event that the firm has hired an investment bank or advisor to look for potential buyers.
- At least three days must pass before any official announcement occurs.

Rumors that are classified as coming from 'major news sources' are rumors that originate from Reuters, Bloomberg, The New York Times, the Wall Street Journal and similar outlets, while non-major news sources are for instance online-only news sources or smaller news networks. Rumors are considered 'detailed' if they contain suggestions for potential bid premiums or suggestions for which the acquiring firm might be, or otherwise provide convincing details. A rumor is considered true if the rumor is followed by an acquisition announcement within a year, or within two years if there is good reason to believe that the rumor has a good connection to the acquisition (for example, rumor information on a potential acquirer is correct) and the completion of the acquisition occurs within a maximum of two years.

3.2 Stock and accounting data

The rumor data is then merged with stock data from COMPUSTAT. Thomson Reuters Datastream and CRSP were both evaluated as potential data sources, but COMPUSTAT was chosen as it had stock price and volume data for the largest number of the securities in our sample. Stock data for one year before and one year after the rumor publication is kept for each rumor to allow for the estimation of normal returns as well as the calculation of potential profits from trading on the rumor. Only rumors where the concerned stock of the target firm is listed in the COMPUSTAT database for our period are included in our study. The data is then complemented with annual report data for the three years preceding the rumor publication, for which COMPUSTAT is used as well. We end up with a dataset consisting of a total of 354 takeover rumors, 104 of them true rumors and 250 false.

3.3 Data for robustness tests

For robustness, data on takeover rumors from the U.K. markets is also downloaded and screened in the same way as the U.S. rumors. The same criteria are used as filters and Zephyr rumor data is used for the U.K. dataset as well. The U.K. rumors are then merged with COMPUSTAT annual report data and COMPUSTAT daily security data. Several noticeable differences can be seen in the U.K. rumor data in Zephyr, compared to the data stemming from the U.S. Zephyr appears to have a larger amount of U.K. rumors recorded compared to the size of the U.K. market, and a slightly different distribution of false and true rumors. The firms are also marginally smaller than for the U.S., which could contribute to differences in the results. In the end we have 290 U.K. rumors of which 79 are true and 211 are false.

Another robustness check is performed by verifying the findings from the primary Zephyr dataset using rumor data also on the U.S. market, provided by Bloomberg. This out-of-sample data contains less information than the primary dataset. Only the date of the rumor is available; no data on the dates for when announcements or completions of takeovers took place is present - only whether the rumor was followed by a takeover or not. The source of the rumor is not listed either. Therefore, the data is of slightly lower quality than the main U.S dataset but still serves well as an out-of-sample dataset to test the external validity of the Zephyr results. The dataset from Bloomberg contains a total of 1875 rumors on 717 companies during the period 2005-2010, and the data is complemented with stock data and annual report data in the same way as the other two datasets. Bloomberg only provides ticker symbols as firm identifiers and we therefore manually verify and match some of the ticker symbols with the corresponding firm in the stock data. We also ensure that no overlap exists between the main dataset and the Bloomberg out-of-sample dataset, considering that they both cover the U.S. market during the same time period. After the filtering, we end up with 1520 rumors from Bloomberg, split between 235 true rumors and 1285 false rumors.

4. Methodology and Theory

In this section we lay out the empirical framework that we use to examine the market's reaction to the publication of rumors and the methods used to create a trading strategy. First, normal and abnormal performances of the target firms' securities are calculated around the publication of the rumor. Once the rumor, pre-rumor and post-rumor reactions have been calculated a variety of regression techniques are used. Ordinary least squares (OLS) models are used in a first attempt to explain the cross-sectional returns on and around the rumor publication date, using both the veracity of the rumor but also other potential explanatory factors as independent variables. Building on this, logit regression models are employed to investigate whether public data available on the rumored target before the rumor date, such as book values, financial key ratios and market capitalization, and rumor-specific information, such as the source, its level of detail and the market reaction, say something about the probability of the rumor leading to a takeover.

Rumor timeline

An overview of the timelines surrounding false and true rumors can be seen in Figure 1 and Figure 2, respectively. A false rumor consists of a pre-rumor period, a post-rumor period and a rumor day, which is the day the rumor is reported by the media. A true rumor also consists of a pre-rumor period and post-rumor period, but is followed by a bid announcement, which is considered a verification of the authenticity of the rumor. If the bid succeeds, the announcement is also followed by a completion of the takeover.

Figure 1. Timeline for false rumors.

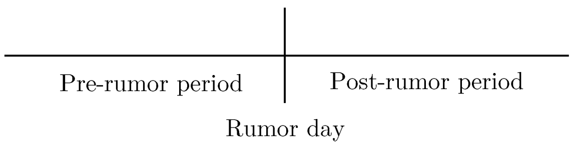
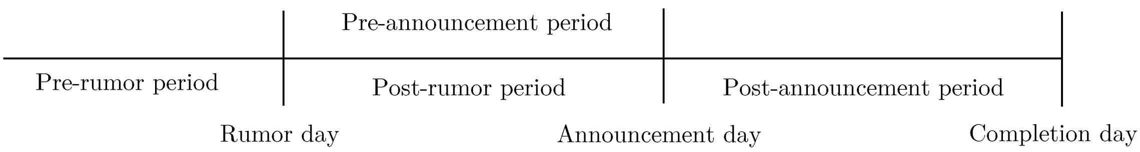


Figure 2. Timeline for true rumors.



4.1 Event study methodology

The dominating methodology used in this study is an event study. MacKinlay (1997) discusses the use and applications of event studies in finance and defines an event study as a study that measures the impact of some event on the value of a firm using security prices observed over a relatively short time period. The methodology has ever since the 1960's been successfully applied to studies on mergers and acquisitions, with Manne (1965) as an early example. An event study requires calculation of the normal performance of a firm's security, from which the abnormal performance of the security around the event can be determined.

The simple market model (the CAPM)

MacKinlay (1997) suggests several different methods for estimating the normal performance of a stock. One of the simpler models for this purpose is the CAPM (Capital Asset Pricing Model) specified as

$$E(r_i) = r_f + \alpha_i + \beta_{mkt,i}(r_{mkt} - r_f) + \varepsilon_i$$

where r_i is the logarithmic stock return for security i, r_{mkt} is the return for the market and r_f is the risk-free rate. $\beta_{mkt,i}$ is a measure of the systematic risk of security i in relation to the market and α_i is the performance of security i after accounting for the systematic risk. For the U.S., a value-weighted index encompassing NASDAQ, Amex and NYSE is used as a proxy for the market return. For the U.K., the FTSE100 is used. The risk-free rate used is the 1-month U.S Treasury and the 3-month U.K. Bank of England Treasury bill rate for the two markets respectively. Abnormal returns are calculated as

$$AR_{i,t} = r_{i,t} - [r_{f,t} + \alpha_i + \beta_{mkt,i}(r_{mkt,t} - r_{f,t})]$$

Where $AR_{i,t}$ is the abnormal return for security i on day t, $r_{i,t}$ is the logarithmic stock return for security i on day t, $r_{mkt,t}$ is the return for the market and $r_{f,t}$ is the risk-free rate. α_i and $\beta_{mkt,i}$ are estimated using the CAPM.

The Fama-French three-factor model

An alternative model, meant to provide more accurate expected returns, is the Fama-French three-factor model, which includes two more factors than the CAPM. It is specified as

$$E(r_i) = r_f + \alpha_i + \beta_{mkt,i}(r_{mkt} - r_f) + \beta_{HML,i}HML + \beta_{SMB,i}SMB + \varepsilon_i$$

where r_i is the logarithmic stock return for security i and r_{mkt} is the return for the market. HML is the return of a portfolio that is long firms with the highest book-to-market ratios and short firms with the lowest book-to-market ratios and SMB is the return on a portfolio that is long firms with low market capitalization (small firms) and short firms with high market capitalization (big firms). $\beta_{HML,i}$ and $\beta_{SMB,i}$ are measures of how the return of security i co-moves with these portfolios. α_i is the performance of security i after accounting for the systematic risk in relation to both the market and these portfolios. A value-weighted index encompassing NASDAQ, Amex and NYSE is used as a proxy for the market return. The risk-free rate used is the 1-month U.S Treasury bill rate. The abnormal returns for this model are calculated as

$$AR_{i,t} = r_{i,t} - (\alpha_i + \beta_{\mathrm{mkt,i}}[R_{mkt,t} - r_{f,t}] + \beta_{\mathrm{HML,i}}HML_t + \beta_{\mathrm{SMB,i}}SMB_t).$$

The Fama-French three-factor model will be used for our main dataset, but as daily HML- and SMB-returns are only readily available for the U.S., the simple CAPM will be used when analyzing the U.K. data in our robustness tests. A comparison between the CAPM and the Fama-French model, using our

U.S. data, showed that the differences between the two are very small. The application of the different models should thus not be a big concern when comparing the U.S. and the U.K. data.

Cumulative abnormal return (CAR) and cross-sectional regression analysis

Abnormal returns are summed over a period of time to achieve a cumulative abnormal return,

$$CAR_i(n,m) = \sum_{t=n}^{m} AR_{i,t}.$$

As suggested by MacKinlay (1997), we will use an event window of 120 days in the span of 180 days to 60 days before the publication of the rumor. This is to make sure that the beta coefficients are not affected by the event itself, and will allow us to look at rumor run-ups as far as 60 days before the rumor without the estimation period overlapping with the run-up returns.

MacKinlay (1997) further discusses how insights can be gained by creating cross-sectional models to examine the association between the magnitude of the abnormal return and characteristics specific to the event observation. A regression model for this should take the form

$$AR_i = \beta_0 + \beta_1 X_{1,i} + \cdots + \beta_m X_{m,i} + \varepsilon_i$$

where $E(\varepsilon_i) = 0$, AR_i is the abnormal return for observation i, $X_{m,i}, m = 1, \dots, M$, are M characteristics for observation i and ε_i is the error term that is uncorrelated with the independent variables. $\beta_m, m = 0, \dots, M$ are the regression coefficients. Since we have no reason to believe that the assumption of homoscedasticity will hold, the regression model is estimated using OLS with homoscedasticity-consistent (robust) standard errors.

Measuring abnormal volume

We also investigate the abnormal trading volume around the rumor publication. Jarrell and Poulsen (1989) and Bajo (2010) find that the *normalized abnormal volume* (NAV) is a suitable measure for this. The NAV for a security i on day t is computed as

$$NAV_{i,t} = \frac{TV_{i,t} - \mu_{i,t}}{\sigma_{i,t}}$$

where $\mu_{i,t} = \frac{1}{N}\sum_{i=1}^{N} TV_{i,t}$ and $\sigma_{i,t} = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left(TV_{i,t} - \mu_{i,t}\right)}$. $TV_{i,t}$ is trading volume, computed as the natural logarithm of (trading volume + 1), for security i on day t; μ and σ are the mean and standard deviation of trading volume in an N day window in a period prior to the observation. Jarrell and Poulsen (1989) use an estimation window of 150 days, looking at a 'clean' period of 170 days before the event to 20 days before the event, while Bajo use a period of the 66 days directly preceding his event. We will use the same estimation window as for our market models, 120 days, a window close to the time span Jarrell and Poulsen (1980) used.

Bajo (2010) finds that the logarithmically transformed trading volume closely follows a normal distribution and as the NAV is similar in construction to a t-statistic we can classify trading volume as *extreme* if the daily trading volume is more than 2.33 standard deviations from the mean.

4.2 Corrections for outliers and missing data

As is always the case when dealing with real-world data there is the issue of outliers, missing data and other impurities in the data. To adjust for this, three different techniques are applied: winsorizing, trimming and imputation.

Winsorizing and trimming

To illustrate the abnormal returns and trading volumes around the rumor publication in graphs, the average cumulative abnormal return and NAV is calculated for each day. Because of a small number of outliers, the graphs are heavily skewed for some days. To make the figures more representative of the sample as a whole, both winsorizing and trimming were considered. Winsorizing, however, appears to provide the best results with the least information lost. Some accounting ratios are nevertheless trimmed; for example, negative dividend payout ratios are treated as missing values. Winsorizing is done at the five percent level, which means that all observations above the 95th percentile are set to the 95th percentile and all observations below the 5th percentile are set to the 5th percentile.

Imputation

When returns are missing on a trading day for some firm, we carry forward the preceding price. The alternative would be to interpolate prices on those days, which would give the day with a missing price an average of the price before and after the day in question. Carrying forward the preceding price is argued to be the most correct method to adjust for missing prices in our dataset, considering that some of the firms in the sample have very low market capitalizations and could be missing prices simply because there were no trades on the days with missing price data.

4.3 Tests for difference

When testing for differences in abnormal returns between true and false rumors, during various time periods, we use Student's t-test. The test compares the means of two samples in order to test equality. We use the variant of the t-test where the sample sizes are allowed to differ but variances are assumed to be approximately equal, since this assumption seems to hold reasonably well for our sample. The simple one-sample t-test is also applied to investigate whether the abnormal returns around the rumor publication differ from zero. To account for some of the non-normality of the abnormal returns we also use the Wilcoxon rank-sum test and Mood’s median test, the latter considered slightly weaker but still useful. The Wilcoxon rank-sum test tests the null hypothesis that two populations are equal against the alternative hypothesis that one population tends to have larger values than the other. Mood’s median test is a simpler alternative to the Wilcoxon rank-sum test, only counting the number observations above or below the median of the combined sample, as opposed to ranking them and adding up their rank-sum.

4.4 Bankruptcy probability formulas

To control for bankruptcy risk, we use three different models: Ohlson's probabilistic bankruptcy model, Zmijewski's probabilistic bankruptcy model and the most popular - Altman's Z-score (Ohlson, 1980; Zmijewski, 1984; Altman, 1968).

The Ohlson model can be calculated as

$$Z = -1.3 - 0.4 \times \log(GNP - Deflated\ Total\ Assets) + 6.0 \times Solvency - 1.4 \times \left(\frac{WC}{Total\ Assets}\right) + 0.1 \times CurrentRatio - 2.4 \times EquityIsNegative - 1.8 \times ROA + 0.3 \times \left(\frac{Funds\ from\ Operations}{Total\ Liabilities}\right) - 1.7 \times NetIncomeNegativePast2Years - 0.5 \times \frac{NI_t - N_{t-1}}{|NI_t| - |NI_{t-1}|}$$

which is transformed into a probability through

$$p = \frac{1}{1 + e^{-z}}.$$

The Zmijewski model is calculated as

$$Z = -4.3 - 4.5 \times \frac{Net\ Income}{Total\ Assets} + 5.7 \times \frac{Total\ Liabilities}{Total\ Assets} - 0.04 \times \frac{Current\ Assets}{Current\ Liabilities}$$

and transformed into a probability in the same way as the Ohlson model.

Altman's Z-score is calculated as

$$Z = 6.56 \times \frac{Working\ Capital}{Total\ Assets} + 3.26 \times \frac{Retained\ Earnings}{Total\ Assets} + 6.72 \times \frac{EBT + Interest}{Total\ Assets} + 1.05 \times \frac{Market\ Value\ of\ Equity}{Total\ Liabilities}$$

Altman's Z-score differs from the other models in that it is not converted into a probability but can take any continuous value. The Z-score has cutoff points above and below which firms are considered healthy or unhealthy. Firms with a Z-score above 2.99 are considered healthy, firms below 2.99 are considered to be in a gray zone and firms below 1.81 are considered to be in financial distress (Altman, 1968).

4.5 Binary logit regression analysis

Binary logit regressions are used to model dichotomous outcome variables such as, which is our case, a rumor, which can be classified as true or false following our definitions. A binary logit regression has the specification

$$\ln\left(\frac{p_i}{1 - p_i}\right) = z_i = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n$$

in which p_i is the probability of a rumor i being followed by a successful bid (being true) and where n independent variables are included. The probability of a rumor being followed by a successful bid can be backed out and is calculated as

$$p_i = 1/(1 + e^{-z_i}) .$$

Dependent variables in logit regressions can just like in other types of regressions be either continuous or categorical. Several different types of model specifications are tried. Once a model is found, our main sample is divided at random into an estimation sample (training set) and a prediction sample (validation set), where we estimate the model parameters - the logit regression coefficients - on the estimation sample and then apply these coefficients to our prediction sample to arrive at estimated probabilities of the rumors in the validation set being true. To get a better indication of how well the model performs, repeated random sub-sampling cross-validation is used[2]. This entails repeatedly shuffling the dataset and splitting it in the same proportions each time, where we, following a common rule of thumb, assign 1/3 of the sample to the validation set and 2/3 to the training set. The model parameters are estimated on the training set and applied to the validation set each time, and the accuracy of the model is recorded for each iteration. This allows us to get a better idea of how well the model performs on an independent dataset. Repeated random sub-sampling cross-validation is usually repeated a few hundred to a few thousand times depending on the complexity of the model, and an average value of the fit is calculated over all the runs. In this respect, the method shares some similarities with Monte Carlo simulations. We perform the process 200 times, providing a reasonable trade-off between computational execution time and precision in the values.

A t-statistic for whether the model outperformed chance can be calculated as

$$t = \frac{z - p}{\sqrt{\frac{z(1-z)}{n}}}$$

where p is the proportional chance criterion, a measure of the expected classification accuracy rate based on chance alone and z is the proportion of total individuals correctly classified. The proportional chance criterion is calculated as

$$p = c^2 + (1 - c)^2$$

where c is the actual proportion of the individuals from the group of interest in the whole sample (Barnes, 1998; Hair et al., 1995).

4.6 Model specifications

Difference between true and false rumors

This is a simple regression run in order to see whether there is any statistically significant difference in the abnormal return reaction caused by true and false rumors on the rumor day. This is equivalent to a t-test of the difference between the true and false rumor samples.

$$AR_{0,i} = \beta_0 + \beta_1 True_i + \varepsilon_i$$

[2] Kohavi (1995) presents a good review of cross-validation methods like this one.

Cross-sectional CAR taking into account detail and source of rumor

In this regression, additional variables are included in order to explore to what extent the rumor effect can be explained by rumor-specific characteristics, such as whether the rumor originates from a major source (see data section) or contains a significant amount of detail. The regression seeks to determine whether the difference in reaction between true and false rumors derive from true rumors being published in more reputable sources or being more detailed than false rumors.

$$AR_{0,i} = \beta_0 + \beta_1 True_i + \beta_2 MajorSource_i + \beta_3 Detailed_i + \varepsilon_i$$

Cross-sectional CAR taking into account firm-specific factors

Additionally, a regression is run containing firm-specific variables and the bankruptcy risk of the firm, to see whether these factors help explain the price jump on the rumor day. If we can eliminate the effect of the categorical variable indicating whether a rumor is true or false, we might be able to extract some of the factors the market uses to estimate the probability of a rumor being true.

$$AR_{0,i} = \beta_0 + \beta_1 True_i + \beta_2 MajorSource_i + \beta_3 Detailed_i + \sum \beta_i FirmSpecificProperty_{i,t-1} + \varepsilon_i$$

Logit regression using rumor- and firm-specific properties and including stock market reaction

The logit regression attempts to classify firms as true or false after the stock market has reacted to the rumor. By determining factors that contribute to explaining whether a rumor is true or false, we can formulate a model for predicting takeover targets from a sample of rumored firms. We include the rumor reaction into the logit model. Ideally, we would be able to include the information the market uses to judge the validity of the rumor as a variable. However, this information is not quantifiable or unobservable; it could be private information, nuances in the rumor report or some other information that leaked to the market but that Zephyr failed to report and that we failed to find. Given that we cannot observe this information, we are instead able to incorporate it indirectly in the regression by including the abnormal rumor day return.

$$p_i(True) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 AR_{i,0} + \sum_j \beta_j FirmSpecificProperty_{ij,t-1} + \sum_k \beta_k RumorSpecificProperty_{ik,t})}}$$

Logit regression using rumor- and firm-specific properties but excluding stock market reaction

The logit regression is re-run without using the stock market reaction on the rumor day in an attempt to test if the classification can be performed using only public information available beforehand and the content of the rumor itself (excluding the information inherent in the reaction of the stock market to the rumor publication).

$$p_i(True) = \frac{1}{1 + e^{-(\beta_0 + \sum_j \beta_j FirmSpecificProperty_{ij,t-1} + \sum_k \beta_k RumorSpecificProperty_{ik,t})}}$$

Using these logit models, we attempt to see whether it is possible to achieve abnormal holding period returns by classifying rumors into true or false and trading on them. Since the rumor day reaction is included in the first model, our strategy will consist of buying at the close price of the rumor day and holding the rumored stock for a period of 365 days or the delisting of the stock, whichever comes first. The abnormal holding period return is the return of the stock during this period compared to the market index for the year, after dividends have been accounted for. The alternative is to use the cumulative abnormal return for the period. However, compounding the abnormal return for such a long period leads to unreasonable discrepancies between the cumulative abnormal return and the holding period return as even small inaccuracies in model alphas are magnified 365 times. Another alternative would be to ignore alphas or re-estimate the model for stocks excluding the alphas. After consideration of the alternatives we concluded that we would use the holding period return and that we would use the value-weighted market index as a benchmark in calculation of excess returns. This was deemed the most appropriate considering that an overwhelming majority of the beta values in our dataset are close to one (see Table 4) and the reduced likelihood of estimation errors due to the simpler nature of these calculations. The holding period return is calculated as

$$HPR_t = \frac{Dividends + (P_{t+1} - P_t)}{P_t}.$$

4.7 The Efficient Markets Hypothesis

Fama (1970) defines an efficient market as a market where security prices fully reflect all available information. The adjustment of security prices differ between three information subsets of the hypothesis. In the weak-form subset, all security prices are assumed to reflect all information contained in historical prices. In the semi-strong subset prices are thought to adjust accordingly and immediately to all other public information as well. Finally, the strong form assumes that prices reflect all public and private information, an assumption that is commonly seen as more of a theoretical scenario.

4.8 Connections between takeover likelihood and book values

There are numerous theories seeking to explain why some firms may be more likely to be taken over than others. Some of the more popular theories are summarized by Barnes (1998) and presented here.

Inefficient management is often suggested as a possible attractant for acquiring firms. Firms which underperform their competitors with low profits are suggested to be more vulnerable to takeovers than firms which outperform their peers. Inefficiently managed firms may also be undervalued. Both these factors are captured in ratios such as profit margins, return on equity, price-to-earnings, the dividend payout ratio and market-to-book.

Growth-resource mismatches are also popular explanations. The theory suggests that low growth-resource rich and high growth-resource poor firms are likely acquisition targets. Firms with low activity ratios or low growth history could also be attractive to acquiring firms. Cash-constrained firms could be easy takeover targets for rich firms, as the rich firms can help fund the expansion of the constrained firm. The capital structure of a firm could also affect how attractive a firm is as a takeover target. A firm with very low leverage can be seen as having unutilized debt capacity. These different notions of why some firms may exhibit properties that make them more attractive as targets than others can be captured in several different accounting ratios. Sales growth over the past few years, the current ratio, the solvency/leverage level and interest coverage ratio could all be indicators for some of these scenarios.

Additionally, a firm with very high leverage may be in some form of distress, and could potentially be saved by a white knight acquirer. Firms in financial distress that are close to bankruptcy could also potentially be more interesting to acquirers, since the value of a revived firm usually exceeds the value of solely liquidating its assets in bankruptcy. We intend to investigate whether such a connection between the bankruptcy risk and the likelihood of a firm being taken over exists, using three measures from the field of bankruptcy prediction: Altman's Z-score, Zmijewski's probability measure and Ohlson's probability measure. All of these measures are tested in different model specifications to determine if there is a connection and if they can help discern between true and false rumors.

The size of the target firm is another variable that could play a role in how likely a firm is to be acquired. Palepu (1986) suggests that the likelihood of acquisitions decreases due to what he calls 'transaction costs' that increase with size. Another simple reason stated by Barnes (1998) is that the larger a firm is, the fewer firms that are larger than the firm itself exists and thus there are fewer potential acquirers. The market capitalization of the firm or the total assets of the firm should be capable of explaining this notion.

4.9 Insider trading in our dataset

Toeholds registered with a 13D SEC filing[3] could have been potential precursors to the rumor, but Zephyr records when a rumor appeared in conjunction with a filing, and no such rumors were included in our sample. Insider trading is also heavily regulated in the U.S. A Form 4 or 5 SEC filing has to be submitted at the latest two days after a change in the ownership share of any director, officer or owner if the ownership is above ten percent. Directors and other employees are required by law to ensure that information about their company is not used unlawfully in the purchase or sale of securities. Any rumors where information regarding insider trading SEC filings is available in Zephyr are dropped, thus hopefully reducing the likelihood of legal insider trading being the cause of the rumor reactions in our sample. That leaves room for word-of-mouth dissemination of the rumor, illegal insider trades or very late or illegal toehold acquisitions to explain any abnormal rumor reaction before the rumor publication.

[3] The Securities and Exchange Commission requires anyone who acquires ownership of more than 5 percent of any class of publicly traded securities in a public company to submit a Schedule 13D filing within 10 days. Any changes in the ownership above 1 percent require additional submissions.

5. Results

The results section is introduced with descriptive statistics on the rumor datasets, including graphs illustrating the different events of interest. The graphs and the accompanying tables indicate some differences between true and false rumors. These differences are then further explored by applying OLS regression techniques and difference testing. Once a difference has been established logit regressions are used to distinguish potential explanatory variables. The results from the logit regressions are applied in the formulation of trading strategies using probability cutoffs with various degrees of conservativeness, after which we present the extent to which the strategies are able to classify true and false rumors as well as the returns these strategies yield. In the robustness test section, we briefly present results for the U.K. and Bloomberg datasets.

5.1 Descriptive statistics on rumors

The rumor publication events are distributed as is shown in Table 1. A large number of false rumors were circulating during the period between 2006 and 2008, most likely created in the turbulent business climate caused by the fall of Lehman Brothers and the consequential financial crisis.

Table 1. Distribution of rumors over the years

This table provides a short summary of how the rumors from the Zephyr U.S. dataset are distributed after the filtering explained in the data section. The rumors are divided based on whether they are followed by an acquisition bid announcement (true) or not (false).

Year	Number of true rumors	Number of false rumors
2000 - 2002	6	20
2003 - 2005	34	67
2006 - 2008	46	123
2009 - 2011	35	47
2012	8	23
Total	129	280

Table 2 shows that a total of 34 out of the 129 true rumors are followed by an announcement within 20 days of the rumor publication day. For nearly all true rumors, less than 300 days pass between the rumor being published and a bid announcement.

Table 2. Days between rumor and subsequent announcement for true rumors

This provides a short summary of how many days pass between the rumor being published and the announcement of a bid. Rumors where less than three days passed before an announcement were not included in our sample, as explained in the data section.

Days between rumor and announcement	Frequency
4 - 5 days	12
6 - 10 days	8
11 - 20 days	14
21 - 60 days	26
60 - 180 days	45
181 - 300 days	17
> 300 days	7
Total	129

Returns from trading on rumors

Table 3 displays, consistent with Zivney et al. (1996) and Pound and Zeckhauser (1990), that buying on rumors do not on average allow an investor to make any money, with the average return for our full sample being -1.8%, a result not statistically different from zero due to the high variability in the returns. For true rumors, the average return is 14.0% and for false rumors -8.4%, indicating that an investor capable of distinguishing between the two could potentially use this ability to trade profitably.

As is evident in Figure 3, most firms subject to true rumors exhibit positive returns during the one-year period following the rumor publication while the returns of falsely rumored firms are more evenly split between positive and negative reactions. The span is, however, very large for both true and false rumors, with extremes in both directions, showing that a rumor being true does not guarantee a profit.

Table 3. One-year holding period returns for target firms from close on rumor publication day to close 365 days later

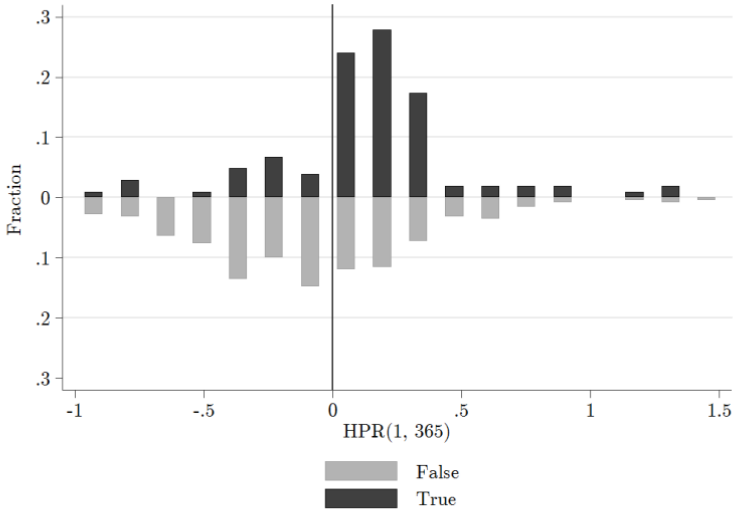
For the whole sample, for true rumors only and for false rumors only, this table provides a summary for the holding period returns that materialize when the target firms are held for one year following the close on the day the rumor is published. This is simply the return you would earn if you bought the rumored target firm after the rumor and held it for one year. Holding period returns are calculated as

$$HPR_n = \frac{Dividends + (P_{n+1} - P_n)}{P_n}.$$

Variable	Obs	Mean	Std. Dev.	Min	Max
Whole Sample	354	-1.8%	42.3%	-99.6%	152.1%
True Rumors	104	14.0%	36.5%	-87.7%	126.7%
False Rumors	250	-8.4%	42.9%	-99.6%	152.1%

Figure 3. Distribution of one-year holding-period returns for target firm from close on rumor publication day to close 365 days later

For true rumors and for false rumors, this histogram shows the distribution of the holding period returns. It is based on 104 true rumors and 250 false rumors, with a total of 354 rumors. The fraction is positive in both directions, making the figure mirrored along the x-axis.



5.2 Stock market reaction around rumor publications

The rumor reaction distribution, shown in Figure 4, is very dense just above the zero mark, with most stocks reacting with less than ten percent and very few with more than 15 percent. The fraction of reactions that are negative is also noticeably larger for false rumors, and there is a visibly higher density of false rumors around the zero mark compared to true rumors. The fraction of rumors that have a comparably significant positive reaction is decidedly larger for true rumors. The difference in the distribution between true and false rumors for the rumor day reaction is nevertheless not as apparent as for the one-year holding period return shown in Figure 3.

Figure 4. Distribution of CARs for target firm from day -1 to +1 based on veracity

This is a histogram showing the distribution of CAR(-1;+1) around the rumor publication date, divided by whether the rumor ends up being true or false. The abnormal returns are calculated using the Fama-French three-factor model. The y-axis shows the fraction that falls within a certain bin. The fraction is positive in both directions, making the figure mirrored along the x-axis. The histogram is based on 112 true rumors and 247 false rumors.

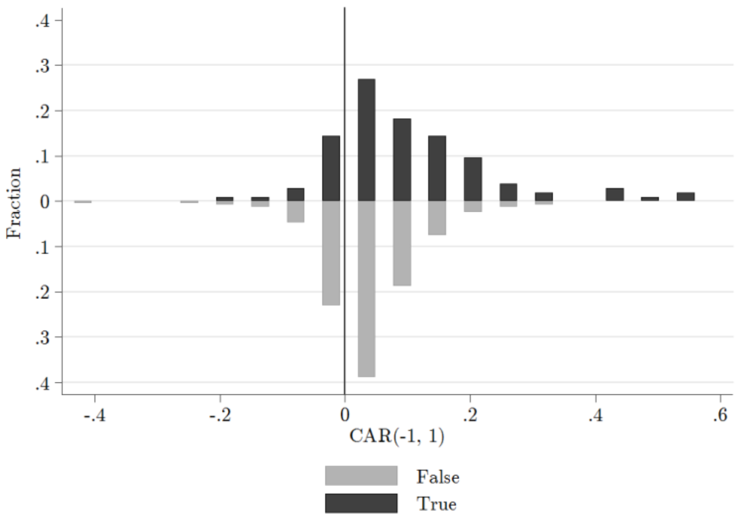


Figure 5, displaying the average cumulative abnormal return (ACAR) for true and false rumors, tells us there is a clear difference in the market reaction between the two rumor types. For both true and false rumors, the increase appears to continue on the day following the rumor publication, but with a more pronounced subsequent jump for the true rumors, corresponding to a few additional percentage units. The observable jump in the winsorized graph is approximately ten percent for true rumors and five percent for false rumors. This difference of five percent between true and false rumors is consistent with the difference found by Zivney et al. (1996).

Figure 6 shows that the reaction to the rumor depends on what news source published the rumor report. Consistent with expectations, major news sources such as the Wall Street Journal and Reuters have a larger impact on markets than smaller, less known news sources. The premium for the rumors coming from a major source appears to be as large as five percent. Figure 7 shows that even when the sample is restricted to rumors from the same type of source, the discrepancy between true and false rumors remains intact.

The existence and the extent of the jump confirm the media's role in diffusing information in the stock market, since one would expect that many of the rumors had spread via word-of-mouth prior to publication. That we observe a stronger reaction to rumors published in more reputable sources indicates that the stock market takes other factors into account than just the information content when processing news or, as in this case, rumors. These findings are in line with the existing literature on the effect on the stock market of media reporting (for example Tetlock, 2007; Dougal et al., 2011).

Figure 5. Winsorized ACAR for target firms day -30 to +30 relative to rumor publication contingent on veracity

This figure shows the average cumulative abnormal return (ACAR) for the days -30 to +30 around the rumor publication day for both rumors that are followed by an acquisition (true) and rumors that are not (false). The figure is based on 129 true rumors and 280 false rumors, where the CARs are winsorized on the 5% level every day before the average is calculated.

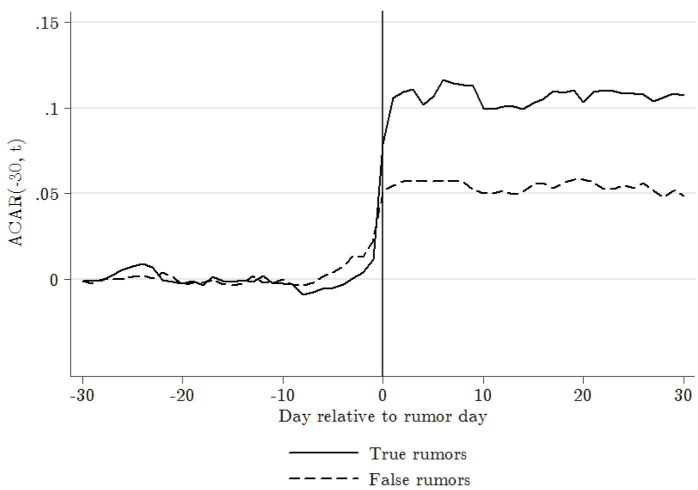


Figure 6. Winsorized ACAR for target firms day -30 to +30 relative to rumor publication contingent on source

This figure shows the average cumulative abnormal return (ACAR) for the days -30 to +30 around the rumor publication day for true and false rumors together, with different lines for only those rumors that come from major sources (see data section for further explanation), those that do not come from major sources and the average altogether. The figure is based on 129 true rumors and 280 false rumors, where the CARs are winsorized on the 5% level every day before the average is calculated.

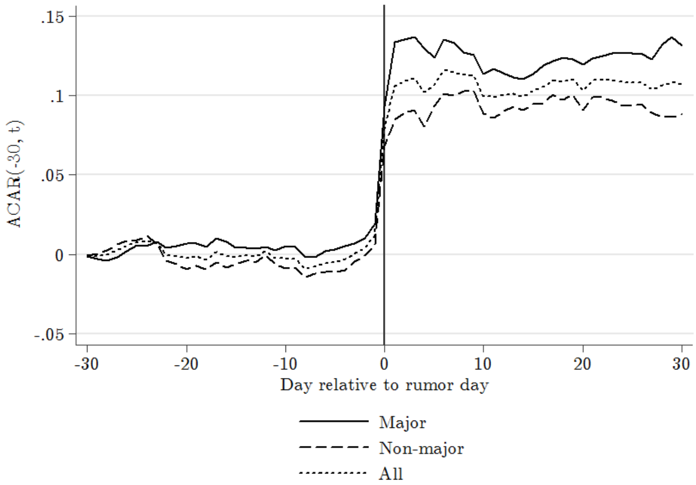


Figure 7. Winsorized ACAR for target firms day -30 to +30 relative to rumor publication contingent on source and veracity

This figure shows the average cumulative abnormal return (ACAR) for the days -30 to +30 around the rumor publication day with different lines for only those rumors that come from major sources (see data section for further explanation) and all rumors, and further divided based on the veracity of the rumor. The figure is based on 129 true rumors and 280 false rumors, where the CARs are winsorized on the 5% level every day before the average is calculated.

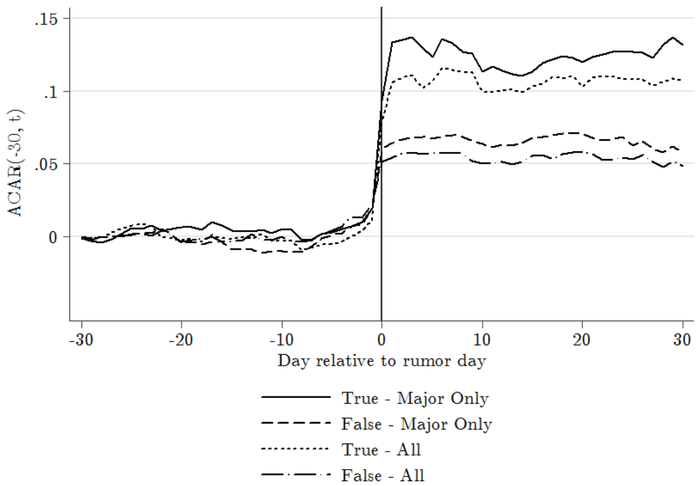


Figure 8 shows the same effect but for rumors with a low level of detail compared to all rumors in the sample. The difference is small here as well, with rumors of less detail generating market movements that are one to two percentage units smaller than otherwise. However, the difference between true and false rumors does not seem to be explained by the level of detail either. Figure 9 shows the normalized abnormal volume, where we can clearly see a difference in the volumes traded on the rumor day between true and false rumors. The normalized abnormal volume on the rumor day is above 2.33 for true rumors on average, which would classify the trading volume as extreme. The same classification cannot be done for the false rumors. No noticeable levels of abnormal volume can be seen in the 30-day window preceding the rumor being published, which tells us that although there is stock price run-up in the pre-rumor period, the volumes traded are small. (The pattern in the period following the rumor publication is a pattern recurring every 7 days and is due to subsequent announcements or bids. Since the rumor reaction has to occur on a trading day, every multiple of 7 days following the rumor day is guaranteed to be a trading day, leading to a disproportionate amount of announcements or bids taking place on these days.)

Figure 10 displays the CAR around the announcement, where the pre-announcement period is significantly affected by rumors. Slightly more than a third of the total acquisition reaction in the period is already incorporated into the price over the two weeks preceding the announcement due to the rumor. This complements the existing empirical body trying to explain run-ups to bid announcements. Figure 11 shows the pattern Betton et al. (2008) found when investigating the reaction to the initial bid on firms in the U.S. The pattern is remarkably similar to the one in our Figure 10, only showing announcements preceded by rumors. This similarity suggests that rumors is a large contributing factor to the general pre-announcement run-up. Betton et al. (2008) find that around one third of the bid premium is incorporated into the price starting 20 to 30 days preceding the bid, which is consistent with the run-up observed in our sample and shown in Figure 10.

Figure 8. Winsorized ACAR for target firms day -30 to +30 relative to rumor publication contingent on detail and veracity

This figure shows the average cumulative abnormal return (ACAR) for the days -30 to +30 around the rumor publication day for rumors that were published with little details against all rumors, divided based on the rumor veracity. The figure is based on 129 true rumors and 280 false rumors, where the CARs are winsorized on the 5% level every day before the average is calculated.

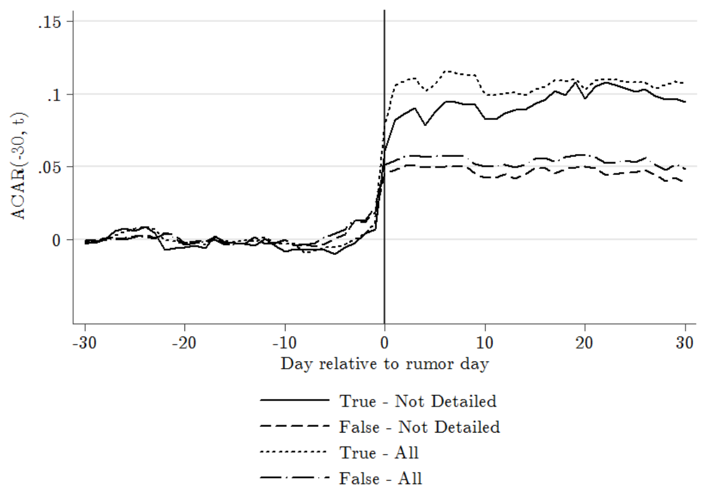


Figure 9. Winsorized NAV for target firms day -30 to +30 relative to rumor publication contingent on rumor veracity

This figure show the average normalized abnormal volume (NAV) for the days -30 to +30 around the rumor publication day for true rumors and for false rumors. The graph includes subsequent bid announcement reactions. The figure is based on 129 true rumors and 280 false rumors, where the NAVs are winsorized on the 5% level every day before the average is calculated.

$$NAV_{i,t} = \frac{TV_{i,t} - \mu_{i,t}}{\sigma_{i,t}}$$

where $\mu_{i,t} = \frac{1}{N}\sum_{i=1}^{N} TV_{i,t}$ and $\sigma_{i,t} = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(TV_{i,t} - \mu_{i,t})}$. $TV_{i,t}$ is trading volume, computed as the natural logarithm of (trading volume + 1), for security i on day t; μ and σ are the mean and standard deviation of trading volume in an N day window in the period prior to the observation.

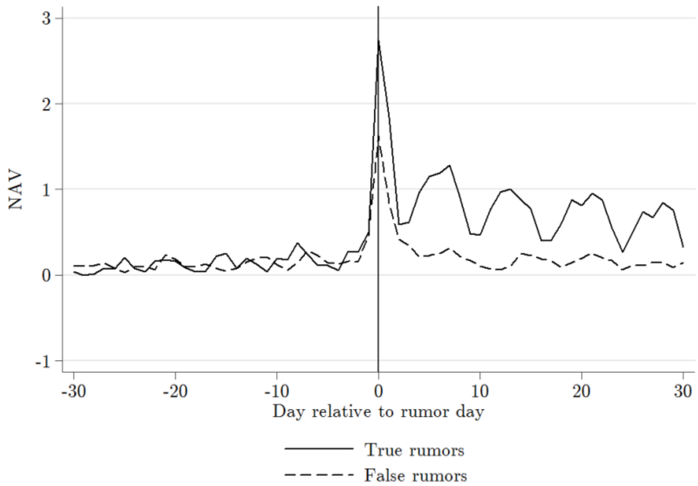


Figure 10. Winsorized ACAR for target firms day -30 to +30 relative to bid announcement

This figure shows the average cumulative abnormal return (ACAR) for the days -30 to +30 around the announcement day for all true rumors in our sample. The figure is based on 129 true rumors, where the CARs are winsorized on the 5% level every day before the average is calculated. The reaction includes the rumor reaction for rumors that had a rumor published less than 30 days before the announcement.

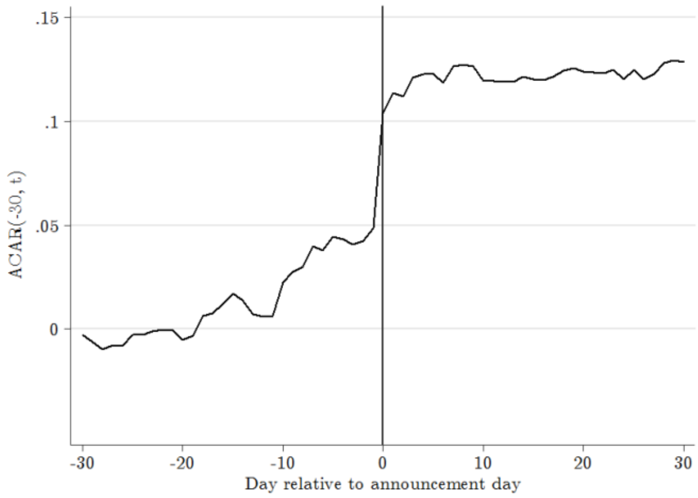
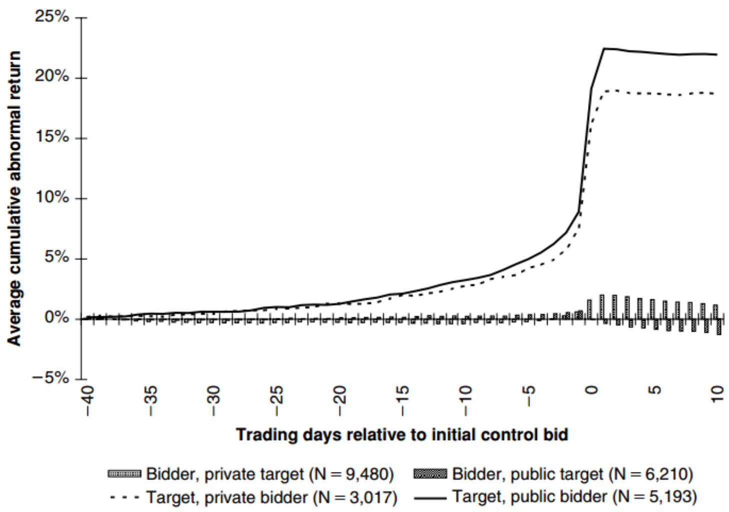


Figure 11. ACAR for target firms and bidding firms from day -40 to day +10 relative to bid announcement

Source: Betton, Eckbo and Thorburn (2008)

This figure from a study of a very large sample of firms by Betton et al. (2008) shows the average cumulative abnormal return (ACAR) for the days -40 to +10 around the announcement day for both bidding firms and target firms. The figure is based on bids between 1980 and 2005.



5.3 Characteristics of firms depending on veracity of rumor

Table 4 shows general firm-specific information on the rumored target firms in the dataset divided depending on whether the rumors ex-post are true or false. There are few striking differences between the two categories. Consistent with theory, the median values for the market capitalization of the firms, the values of their total assets and their annual revenues all indicate that firms that are not acquired seem to be larger than the firms that are acquired. It also appears as if firms in the false rumor category may have a lower bankruptcy probability than firms that are the subject of true rumors. The median value for the Altman Z-score for the firms in the true rumor category is within what Altman denotes a gray zone, below 2.99, while the median value for the firms in the false rumor category is above this level.

We do not observe any clear differences in financial key ratios at this stage, and cannot conclusively say that firms that are acquired suffer from a resource-growth mismatch or are managed worse than the firms that are not acquired. The market beta values for both samples are very close to the beta of the market portfolio ($\beta = 1$) suggesting that our dataset represents a good cross-section of the market. The alpha values are reassuringly close to zero indicating that the Fama-French three-factor model does a good job at explaining the return composition of our sample.

5.4 Difference testing

By performing three different tests (the Wilcoxon Rank-sum test, Student's t-test and Mood's median test) we, in Table 5, investigate whether the cumulative abnormal returns realized around the rumor publication differ between true and false rumors. The tests show that no significant difference in the period preceding the publication can be established. While CAR(-30, -1) is significant in the rank sum test it is not in the other tests, and can thus not with confidence be said to show any difference between the two groups. Additionally, all three tests confirm what we have already seen in the figures; there is a significant difference in the reaction in the stock price on the day of publication between the true and the false rumors. There may also be differences in abnormal return in the few days following the rumor publication, but the tests do not all agree that the difference is significant. CAR(-10, 10) and CAR(-20, 20) both show statistically significant differences between true and false rumors, but primarily because the periods both include the rumor day.

In Table 6, we perform t-tests again, but now testing whether there is a significant reaction in the stock prices for the whole sample in the periods before and after the rumor publication. We find that starting 14 days prior to the rumors publication, there is a statistically significant run-up of about two percentage points. To reduce any possible effects regarding the exact timing of the publication of the rumor we redo the difference test for a period ending two days before the date of publication. Even with this correction we find a statistically significant run-up in the period starting 14 days before the publication. The most obvious explanation to this run-up is that someone with insider information is trading on the target firm before the rumor is published. In that case, however, we would expect a trader with such an information advantage to only trade on true rumors, or at least to trade more on true rumors than on false rumors.

Table 4. Descriptive accounting data for the rumored firms divided on the validity of the rumor

This table provides an overview of the characteristics of the falsely rumored firms and the ones that were eventually taken over in a first attempt to distinguish any differences between the two groups. Some items are shown as they appear in the annual reports while others are calculated financial ratios or measures of bankruptcy. Betas and alphas are estimated using the three-factor model.

	False rumors								True rumors							
Variables	Obs.	Mean	SD	Min	1st Q	Median	3rd Q	Max	Obs.	Mean	SD	Min	1st Q	Median	3rd Q	Max
Market Cap	248	8 047.82	27 209.48	0.34	509.56	1 707.87	6 211.79	371 743.10	113	4 137.26	10 216.20	1.30	321.04	1 190.39	3 496.10	90 695.58
Balance sheet items																
Total Assets	241	13 602.27	56 429.27	0.81	593.68	2 204.09	7 296.00	775 410.00	102	8 494.56	27 019.34	11.48	337.10	1 246.66	3 799.67	199 946.20
Total Liabilites	241	10 425.53	51 974.11	0.70	279.09	1 051.20	4 443.47	747 204.00	102	6 957.26	24 652.45	0.54	151.92	715.32	2 632.43	185 628.40
Income statement items																
Revenue	241	5 752.32	19 526.14	0.00	332.76	1 307.08	4 552.40	263 989.00	102	2 862.85	5 479.89	0.00	233.51	765.18	2 394.58	34 115.00
EBIT	239	843.13	3 042.34	-759.50	9.00	149.86	507.07	35 872.00	101	455.22	1 517.88	-190.77	7.41	81.60	283.86	13 467.82
Net Income	241	423.84	1 836.98	-973.69	-3.29	66.30	259.75	25 330.00	102	145.20	553.94	-1 627.60	-4.40	19.29	135.50	2 769.00
Ratios																
Return on Assets	241	-3.43%	32.66%	-375.09%	-1.16%	2.43%	6.42%	39.12%	102	-1.42%	23.42%	-173.09%	-0.89%	2.14%	5.79%	64.92%
Return on Equity	226	-2.89%	68.33%	-637.10%	0.22%	8.72%	16.75%	247.29%	97	0.08%	56.55%	-408.74%	-0.74%	7.21%	12.78%	270.55%
Sales growth	236	14.12%	40.53%	-96.61%	-1.73%	10.16%	23.90%	395.24%	101	10.33%	26.22%	-42.94%	0.00%	7.76%	21.10%	160.55%
Log of Sales Growth	213	10.78%	26.40%	-234.50%	1.58%	9.98%	20.46%	142.54%	93	11.64%	21.27%	-26.43%	1.27%	6.22%	19.67%	132.29%
Solvency	241	0.41	0.30	-0.88	0.22	0.41	0.62	0.98	102	0.36	0.39	-1.82	0.16	0.39	0.60	1.00
Leverage	241	2.23	11.07	-60.45	0.49	1.31	2.56	134.17	102	3.46	6.52	-9.10	0.54	1.42	3.68	37.50
Current Ratio	203	2.82	4.74	0.22	1.13	1.62	2.86	47.86	86	2.59	2.73	0.34	1.31	1.88	2.61	15.30
Interest Coverage	183	15.59	113.23	-920.03	1.16	3.87	13.98	718.87	89	21.43	107.73	-141.98	1.19	3.31	7.41	922.82
Dividend Payout Ratio	239	-0.04	3.97	-60.33	0.00	0.00	0.28	5.53	102	0.23	1.47	-9.89	0.00	0.00	0.17	8.26
Price/Earnings	241	11.04	125.56	-1 136.37	-0.33	13.75	25.04	639.78	102	57.00	385.71	-568.13	-1.46	17.62	30.71	3 671.82
Profit margin	235	-15.54%	165.94%	-1784.32%	2.88%	10.86%	20.85%	89.73%	100	-5.70%	118.02%	-947.85%	3.19%	8.62%	19.90%	77.74%
Market-to-Book	241	1.51	1.98	0.00	0.44	0.93	1.79	14.46	102	1.37	1.38	0.00	0.42	0.96	1.69	6.15
Asset Turnover	241	0.84	0.74	0.00	0.32	0.62	1.20	4.28	102	0.85	0.76	0.00	0.34	0.66	1.18	4.70
Bankruptcy likelihood																
Altman Z-score	200	4.74	12.30	-57.05	1.50	3.06	5.48	119.02	85	3.18	3.77	-13.66	1.66	2.56	4.17	20.39
Zimjewskij probability	203	29.10%	27.53%	0.49%	7.22%	20.50%	41.52%	100.00%	86	33.03%	27.15%	0.44%	10.41%	28.76%	52.68%	100.00%
Ohlson probability	201	55.21%	28.61%	0.01%	31.46%	56.00%	80.20%	100.00%	86	62.23%	27.31%	2.33%	38.71%	66.39%	83.66%	100.00%
Betas and alphas																
Market Beta	246	1.034	0.925	-2.319	0.625	0.994	1.345	6.650	113	0.968	0.829	-4.554	0.545	1.000	1.373	2.560
Beta SMB	246	0.551	1.580	-11.692	-0.076	0.387	1.007	12.677	113	0.300	1.231	-6.364	-0.158	0.312	0.842	3.531
Beta HML	246	0.159	2.094	-7.883	-0.727	0.022	0.665	20.906	113	-0.041	1.322	-5.041	-0.687	-0.022	0.560	3.264
Alpha	246	-0.001	0.006	-0.068	-0.002	0.000	0.001	0.034	113	0.000	0.004	-0.020	-0.002	0.000	0.001	0.009

Ratio calculations: Return on Assets: $\frac{\text{Net Income}}{\text{Total Assets}}$; Return on Equity: $\frac{\text{Net Income}}{\text{Total Equity}}$; Sales Growth: $\frac{\text{Rumor Year Sales}}{\text{Previous Year Sales}}$; Log of Sales Growth: $\frac{1}{3} * \ln(\frac{\text{Rumor Year Sales}}{\text{3Y Before Rumor Sales}})$; Solvency: $\frac{\text{Total Equity}}{\text{Total Assets}}$; Leverage: $\frac{\text{Total Liabilities}}{\text{Total Equity}}$; Current Ratio: $\frac{\text{Total Current Assets}}{\text{Total Current Liabilities}}$

Interest Coverage: $\frac{\text{EBIT}}{\text{Interest Expenses}}$; Dividend Payout Ratio: $\frac{\text{EBIT}}{\text{Interest Expenses}}$; Price/Earnings: $\frac{\text{Market Capitalization}}{\text{Net Income}}$; Profit Margin: $\frac{\text{EBIT}}{\text{Total Sales}}$; Market-to-Book: $\frac{\text{Market Capitalization}}{\text{Total Assets}}$; Asset Turnover: $\frac{\text{Total Sales}}{\text{Total Assets}}$

Table 5. Tests for significant difference between true and false rumors in CAR during various periods

This table shows, using three different tests (the Wilcoxon rank-sum test, Student's t-test and Mood's median test), whether or not the stock price reactions in the true and false sample differ during various time periods around the rumor publication date. The mean values for both true and false rumors are presented together with each standard deviation and their combined standard deviation. For the rank-sum test the z-statistic is presented both as its true value and recalculated as the probability of the CAR of the two samples being the same. For the t-tests, we included both one-sided and two-sided p-values as well as the standard error and the t-statistic. The t-tests assume equal variances, an assumption that seems to hold reasonably well (assuming unequal variances give approximately the same results). The median test is presented as chi-squared values and its corresponding p-values, and complemented with continuity corrected values of both.

								Rank Sum Test		Student's T-test				Median Test			
CAR	Obs (False)	Obs (True)	Std. Dev (False)	Std. Dev (True)	Combined Std. Dev	Mean (False)	Mean (True)	Z-statistic	P-value	One-sided p-value (lower)	Two-sided p-value	Std. Error	T-statistic	Chi-squared	P-value	Chi-squared (cont.-corr.)	Cont.-corr. p-value
CAR(-30,-1)	242	103	18.22%	24.68%	20.34%	1.49%	0.27%	-1.867	0.03**	0.695	0.610	2.39%	0.510	3.239	0.072*	2.830	0.093*
CAR(-21,-1)	242	103	15.22%	17.04%	15.76%	1.63%	1.19%	-0.873	0.19	0.593	0.814	1.86%	0.235	0.737	0.391	0.549	0.459
CAR(-14,-1)	242	103	13.35%	13.23%	13.30%	2.11%	1.71%	-0.015	0.49	0.601	0.799	1.57%	0.255	0.007	0.934	0.001	0.972
CAR(-7,-1)	242	103	11.17%	9.53%	10.69%	2.09%	1.63%	-0.208	0.42	0.643	0.714	1.26%	0.366	0.389	0.533	0.256	0.613
CAR(-6,-1)	242	103	8.59%	8.47%	8.55%	1.87%	1.33%	0.553	0.71	0.704	0.593	1.01%	0.536	0.007	0.934	0.001	0.972
CAR(-5,-1)	242	103	7.55%	7.85%	7.63%	1.80%	1.38%	0.346	0.64	0.681	0.639	0.90%	0.470	0.007	0.934	0.001	0.972
CAR(-4,-1)	242	103	7.13%	7.38%	7.19%	1.55%	1.44%	-0.106	0.46	0.548	0.904	0.85%	0.120	0.151	0.698	0.073	0.787
CAR(-3,-1)	242	103	6.44%	7.12%	6.64%	1.24%	1.51%	-0.846	0.20	0.367	0.734	0.78%	-0.340	1.767	0.184	1.468	0.226
CAR(-2,-1)	242	103	4.60%	6.10%	5.10%	0.81%	1.53%	-0.372	0.36	0.115	0.229	0.60%	-1.205	1.310	0.252	1.052	0.305
CAR(-1,-1)	242	103	3.97%	5.49%	4.47%	0.72%	1.18%	-0.240	0.41	0.189	0.377	0.53%	-0.884	0.669	0.413	0.486	0.486
AR(0)	242	103	6.06%	10.92%	8.14%	2.99%	7.95%	-4.117	0.00***	0.000***	0.000***	0.92%	-5.382	5.155	0.023**	4.635	0.031**
AR(1)	242	103	4.13%	6.36%	4.93%	-0.04%	1.26%	-0.204	0.42	0.013**	0.025**	0.58%	-2.251	0.083	0.773	0.028	0.867
CAR(1,2)	242	103	5.51%	7.38%	6.16%	0.17%	1.66%	-0.212	0.42	0.020**	0.039**	0.72%	-2.072	0.095	0.759	0.035	0.851
CAR(1,3)	242	103	6.57%	8.04%	7.06%	0.27%	1.72%	-0.576	0.28	0.041**	0.082*	0.83%	-1.747	0.003	0.954	0.004	0.952
CAR(-1,1)	242	103	7.71%	13.55%	10.28%	3.67%	10.38%	-4.609	0.00***	0.000***	0.000***	1.16%	-5.815	11.881	0.001***	11.084	0.001***
CAR(-2,2)	242	103	8.83%	13.56%	10.95%	3.97%	11.13%	-4.633	0.00***	0.000***	0.000***	1.23%	-5.824	8.859	0.003***	8.172	0.004***
CAR(-3,3)	242	103	12.51%	13.71%	13.22%	4.50%	11.17%	-4.553	0.00***	0.000***	0.000***	1.52%	-4.400	13.559	0.000***	12.706	0.000***
CAR(-5,5)	242	103	13.34%	15.87%	14.42%	4.75%	11.15%	-4.063	0.00***	0.000***	0.000***	1.66%	-3.849	10.315	0.001***	9.573	0.002***
CAR(-10,10)	242	103	19.36%	21.04%	19.99%	3.59%	8.85%	-2.512	0.01***	0.013**	0.025**	2.34%	-2.247	6.279	0.012**	5.703	0.017**
CAR(-20,20)	242	103	23.20%	28.51%	25.18%	3.47%	12.24%	-3.734	0.00***	0.001***	0.003***	2.93%	-2.994	13.559	0.000***	12.706	0.000***
CAR(-30,30)	242	103	29.27%	37.00%	31.82%	2.64%	8.17%	-3.413	0.00***	0.070*	0.139	3.74%	-1.481	13.559	0.000***	12.706	0.000***

Stars indicating signficance levels: *** p<0.01, ** p<0.05, * p<0.1

However, as we just showed in Table 5, there does not appear to be any difference between true and false rumors during the period running up to the rumor publication. This therefore makes it more likely that what we are seeing is how the rumor is diffusing throughout the market by word-of-mouth and similar channels. Of course, insider information leaking out could still very well be the initial spark of the true rumors.

5.5 Regressions on difference in rumor day reaction based on veracity

Table 7 is a simple univariate regression showing that the abnormal return on the rumor publication day is statistically different from zero, as well as how the rumor day return differs between true and false rumors on average. True rumors have approximately 4.95% higher return on average than false rumors, effectively confirming the results seen in Figure 5. The average return created as an effect of false rumors, without winsorizing applied, is 2.99% on the rumor day, whilst true rumors induce a reaction of 7.94%. When the regression is restricted to rumors where the rumor reaction is positive, as is shown in Table 8, true rumors result in a stock price hike of approximately 10.16% and false rumors a reaction of 5.13%, about the same difference as in the unrestricted regression. In other words, the difference in reaction between the true and false rumors is not an effect of the stock market more frequently reacting positively to rumors that later prove to be true than to false rumors. This is an important finding as we attempt to create a model to determine if a rumor is true or false using the size of the rumor day price reaction as one of the determinants. For this to work there has be a way, on average, to tell the reaction of a true rumor apart from that of a false rumor even if both react positively, which Table 8 suggests is possible. Table 9 reveals that when controlling for the reputation of the source and the level of detail of the rumor report, the difference in reaction between true and false rumors does not change, a confirmation of what Figure 6 and 7 show. That only one of the variables (in this case "Major News Source") is significant in the regression is due to the fact that both variables serve as different proxies for the same aspect – the credibility of the rumor.

In Table 10 the abnormal return on the day of publication is regressed on the categorical variable indicating whether a rumor is true or not while controlling for numerous different factors that could be the real causes of the difference. Despite controlling for these different firm-specific factors we are unable to further explain the difference in the stock price jump on the rumor publication day. The difference in reaction caused by a rumor being true still remains at about five percent, virtually the same as with no control variables. The other variables that are statistically significant (leverage and price-to-earnings ratio) have coefficients so small that they do not add much explanatory power. This serves as evidence that the market also uses other more abstract or non-quantifiable factors than the ones suggested by the theories in Barnes (1998), and the level of detail and source of the rumor itself, when it appraises the probability of a rumor being true. While we are unable to determine what these factors are we can still use the rumor day reaction in order to, indirectly, include the information in the classification of rumors as true or false and subsequently to determine whether the market reacts efficiently to rumors.

Table 6. Test for difference from zero in CAR for all rumors during various time periods

This table shows, using Student's t-test, whether or not the stock price reactions in all rumors in our dataset differ from zero during various time periods around the rumor publication date. The mean values for all rumors are presented together with the standard deviation for each of the time periods. Both one-sided and two-sided p-values as well as the standard error and the t-statistic are included. Two different run-up periods are included, one ending one day before the publication of the rumor and one ending two days prior to publication.

CAR	Obs	Std. Dev	Mean	One-sided p-value (upper)	Two-sided p-value	Std. Error	T-statistic
CAR(-30,-1)	358	22.28%	1.26%	0.142	0.285	1.18%	1.071
CAR(-21,-1)	358	17.82%	1.42%	0.066*	0.132	0.94%	1.509
CAR(-14,-1)	358	15.37%	2.04%	0.006***	0.013**	0.81%	2.509
CAR(-7,-1)	358	12.54%	1.88%	0.002***	0.005***	0.66%	2.835
CAR(-6,-1)	358	9.68%	1.80%	0.000***	0.001***	0.51%	3.510
CAR(-5,-1)	358	7.92%	1.52%	0.000***	0.000***	0.42%	3.621
CAR(-4,-1)	358	7.46%	1.38%	0.000***	0.001***	0.39%	3.489
CAR(-3,-1)	358	6.91%	1.17%	0.001***	0.001***	0.36%	3.203
CAR(-2,-1)	358	4.91%	0.96%	0.000***	0.000***	0.26%	3.684
CAR(-1,-1)	358	6.26%	0.63%	0.029**	0.059*	0.33%	1.896
AR(0)	358	8.00%	4.31%	0.000***	0.000***	0.42%	10.199
CAR(1,1)	358	6.50%	0.66%	0.029**	0.057*	0.34%	1.909
CAR(1,2)	358	7.51%	0.93%	0.010***	0.020**	0.40%	2.342
CAR(1,3)	358	8.23%	1.04%	0.009***	0.017**	0.44%	2.388
CAR(-1,1)	358	10.34%	5.60%	0.000***	0.000***	0.55%	10.239
CAR(-2,2)	358	11.56%	6.20%	0.000***	0.000***	0.61%	10.150
CAR(-3,3)	358	13.12%	6.52%	0.000***	0.000***	0.69%	9.407
CAR(-5,5)	358	14.46%	6.88%	0.000***	0.000***	0.76%	9.006
CAR(-10,10)	358	19.77%	5.39%	0.000***	0.000***	1.04%	5.159
CAR(-20,20)	358	25.33%	6.44%	0.000***	0.000***	1.34%	4.808
CAR(-30,30)	358	33.95%	5.11%	0.002***	0.005***	1.79%	2.849
CAR(-30,-2)	358	21.38%	0.63%	0.287	0.575	1.13%	0.561
CAR(-21,-2)	358	16.45%	0.79%	0.181	0.362	0.87%	0.913
CAR(-14,-2)	358	13.47%	1.41%	0.024**	0.048**	0.71%	1.983
CAR(-7,-2)	358	9.91%	1.25%	0.009***	0.017**	0.52%	2.390
CAR(-6,-2)	358	8.70%	1.17%	0.006***	0.012**	0.46%	2.540
CAR(-5,-2)	358	6.84%	0.89%	0.007***	0.014**	0.36%	2.460
CAR(-4,-2)	358	6.29%	0.75%	0.012**	0.025**	0.33%	2.252
CAR(-3,-2)	358	5.74%	0.54%	0.038**	0.075*	0.30%	1.786
CAR(-2,-2)	358	5.31%	0.33%	0.121	0.243	0.28%	1.171

Stars indicating signficance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 7. Regression of abnormal return difference on rumor day

This regression shows the difference in abnormal return between true and false rumors on the rumor day. (This is equivalent to running a t-test on the difference, but is included in this format to allow comparison to table 9.)

Variables	AR(0)
True	0.0495***
	(0.0114)
Constant	0.0299***
	(0.00390)
Observations	345
R-squared	0.078

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8. Regression of abnormal return difference on rumor day contingent on positive rumor day abnormal return

This regression shows the difference in abnormal return between true and false rumors on the rumor day, contingent on the market reacting favorably to the rumor. (This is equivalent to running a t-test on the difference, but is included in this format to allow comparison to table 9.)

Variables	AR(0)
True	0.0503***
	(0.0121)
Constant	0.0513***
	(0.00390)
Observations	263
R-squared	0.093

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9. Regression of abnormal return on rumor day with control for news source and level of detail

This regression shows the difference in abnormal return between true and false rumors on the rumor day, with controls for the source and the level of detail of the rumor.

Variables	AR(0)
True	0.0485***
	(0.0114)
Major News Source	0.0272***
	(0.0102)
Detailed Rumor	-0.00124
	(0.0116)
Constant	0.0180***
	(0.00464)
Observations	358
R-squared	0.103

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10. The abnormal return on the rumor day as a function of the veracity of the rumor while controlling for various factors

This table shows the regression result when the the abnormal return on the rumor day is regressed on the categorical variable *True* while controlling for a large number of factors, including credibility of the source, level of detail of the rumor, a number of different accounting ratios and the likelihood of the firm going bankrupt. In the different models we vary the variables used to represent bankruptcy probability (Altman's Z-score, Zmijewskij and Ohlson probability), size (Log of Total Assets and Log of Market Capitalization) and profitability (Return on Assets and Return on Equity).

	Dependent variable: Abnormal return on rumor day											
Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
True	0.05193***	0.05286***	0.05270***	0.05310***	0.05342***	0.05327***	0.05325***	0.05431***	0.05408***	0.05384***	0.05365***	0.05402***
	(0.01561)	(0.01522)	(0.01516)	(0.01483)	(0.01459)	(0.01467)	(0.01548)	(0.01496)	(0.01490)	(0.01476)	(0.01435)	(0.01456)
Major News Source	0.01245	0.01352	0.01298	0.01637	0.01657	0.01677	0.01138	0.01254	0.01191	0.01541	0.01610	0.01581
	(0.01450)	(0.01424)	(0.01417)	(0.01426)	(0.01406)	(0.01407)	(0.01421)	(0.01396)	(0.01389)	(0.01395)	(0.01372)	(0.01378)
Detailed Rumor	0.02279	0.02314*	0.02182	0.01159	0.01521	0.01124	0.02221	0.02303	0.02134	0.01112	0.01581	0.01086
	(0.01425)	(0.01399)	(0.01399)	(0.01372)	(0.01360)	(0.01355)	(0.01441)	(0.01400)	(0.01410)	(0.01389)	(0.01354)	(0.01367)
Market-to-Book	-0.00101	-0.00362	-0.00259	-0.00587	-0.00490	-0.00423	0.00352	0.00067	0.00116	-0.00192	-0.00033	-0.00041
	(0.00843)	(0.00533)	(0.00528)	(0.00770)	(0.00498)	(0.00510)	(0.00725)	(0.00523)	(0.00521)	(0.00690)	(0.00501)	(0.00519)
Sales Growth	0.02953	0.02675	0.02728	0.01634	0.01889	0.01640	0.02963	0.02639	0.02721	0.01748	0.01977	0.01744
	(0.02290)	(0.02221)	(0.02267)	(0.02366)	(0.02174)	(0.02310)	(0.02351)	(0.02253)	(0.02319)	(0.02434)	(0.02199)	(0.02378)
Leverage	-0.00297**	-0.00256*	-0.00316**	-0.00155**	-0.00155**	-0.00147*	-0.00312***	-0.00256*	-0.00330***	-0.00159**	-0.00160**	-0.00152**
	(0.00118)	(0.00140)	(0.00127)	(0.00078)	(0.00074)	(0.00077)	(0.00115)	(0.00137)	(0.00124)	(0.00078)	(0.00075)	(0.00077)
Profit Margin	0.00283	0.00002	0.00219	0.00133	-0.00095	0.00161	0.00336	-0.00038	0.00239	0.00158	-0.00173	0.00170
	(0.00681)	(0.00708)	(0.00680)	(0.00604)	(0.00582)	(0.00542)	(0.00692)	(0.00725)	(0.00697)	(0.00609)	(0.00598)	(0.00554)
Asset Turnover	0.00607	0.00440	0.00391	0.00011	0.00216	0.00232	0.00669	0.00448	0.00400	0.00065	0.00201	0.00255
	(0.00715)	(0.00604)	(0.00604)	(0.00700)	(0.00550)	(0.00569)	(0.00734)	(0.00621)	(0.00618)	(0.00709)	(0.00569)	(0.00586)
Dividend Payout	-0.00509	-0.00513	-0.00556	-0.00443	-0.00501	-0.00444	-0.00530	-0.00522	-0.00578	-0.00464	-0.00491	-0.00463
	(0.00488)	(0.00494)	(0.00490)	(0.00462)	(0.00481)	(0.00463)	(0.00473)	(0.00483)	(0.00473)	(0.00449)	(0.00472)	(0.00448)
Current Ratio	-0.00186	-0.00350	-0.00179	-0.00247	-0.00430	-0.00241	-0.00116	-0.00332	-0.00128	-0.00184	-0.00436	-0.00189
	(0.00347)	(0.00293)	(0.00305)	(0.00345)	(0.00265)	(0.00275)	(0.00343)	(0.00300)	(0.00315)	(0.00332)	(0.00267)	(0.00277)
Interest Coverage Ratio	0.00001	-0.00000	0.00001	-0.00002	-0.00002	-0.00001	0.00001	-0.00001	0.00000	-0.00002	-0.00003	-0.00001
	(0.00004)	(0.00003)	(0.00003)	(0.00005)	(0.00004)	(0.00004)	(0.00004)	(0.00003)	(0.00003)	(0.00005)	(0.00004)	(0.00004)
Price-to-Earnings Ratio	-0.00003***	-0.00003***	-0.00003***	-0.00002***	-0.00003***	-0.00002***	-0.00003***	-0.00003***	-0.00003***	-0.00002***	-0.00003***	-0.00002***
	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Altman's Z-score	-0.00171			0.00154			-0.00212			0.00129		
	(0.00429)			(0.00380)			(0.00421)			(0.00369)		
Zmijewski Probability		-0.01449			-0.05353**			-0.02067			-0.06073**	
		(0.03953)			(0.02625)			(0.04127)			(0.02706)	
Ohlson Probability			0.01640			-0.01375			0.01786			-0.01294
			(0.02339)			(0.02263)			(0.02326)			(0.02241)
Return on Equity	0.01194	0.01104	0.01126				0.01272	0.01181	0.01192			
	(0.00847)	(0.00819)	(0.00856)				(0.00882)	(0.00842)	(0.00891)			
Return on Assets				0.04241	0.02720	0.04526				0.04149	0.02835	0.04423
				(0.03524)	(0.03577)	(0.03531)				(0.03546)	(0.03528)	(0.03528)
Log of Total Assets	-0.00681	-0.00734	-0.00643	-0.00628	-0.00698	-0.00648						
	(0.00523)	(0.00495)	(0.00502)	(0.00532)	(0.00489)	(0.00511)						
Log of Market Capitalization							-0.00563	-0.00641	-0.00529	-0.00505	-0.00679	-0.00529
							(0.00454)	(0.00446)	(0.00437)	(0.00435)	(0.00421)	(0.00420)
Constant	0.07923*	0.08859*	0.06572	0.07442	0.10060**	0.08413*	0.06387*	0.07672*	0.05024	0.05866	0.09487**	0.06811
	(0.04478)	(0.04753)	(0.04982)	(0.04601)	(0.04505)	(0.05075)	(0.03736)	(0.04298)	(0.04336)	(0.03563)	(0.03881)	(0.04156)
Observations	220	221	221	236	237	237	220	221	221	236	237	237
R-squared	0.17621	0.17614	0.17702	0.13838	0.15530	0.13936	0.17392	0.17408	0.17474	0.13672	0.15763	0.13779

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

5.6 Logit regressions and trading model specification

Table 11 shows the three logit model specifications that have the best joint explanatory power. The signs of the coefficients are consistent with what theory suggests; larger firms appear to have a smaller likelihood to be taken over, and rumors with a higher level of detail are more likely to be true. Of the three bankruptcy measures, only Altman's Z-score has a significant impact on the probability of a rumor being true, but all measures have signs consistent with theory. Thus, rumors where the target firms have a high risk of bankruptcy are more likely to be true than other rumors. A higher level of leverage also increases the chance of being taken over; a factor that in part captures the same qualities as the bankruptcy measures. While the price-to-earnings ratio is barely statistically significant the miniscule coefficient renders the factor effectively economically insignificant. This indicates a smaller effect than suggested by the theories presented in Barnes (1998), which state that either resource-constrained firms with high growth or resource-rich firms with low growth (captured by the price-to-earnings ratio) are more probable takeover targets. It can be added that extending the model to include sales growth, another factor relevant to the resource-growth mismatch theory, did not result in any significant improvement. The fact that the abnormal return on the rumor day is highly significant even with all other variables included tells us again that the market has access to additional information that we have been unable to identify, and that is not captured by the other variables in the logit regression.

Although Figure 9 seems to indicate that the trading volume on the day of the rumor would be a valuable element to consider when trying to discern true rumors from false, we find that including it in the logit regression contributes little (not shown). This is most likely due to the difference in volume between the two rumor types mirroring the information inherent in the market price reaction, thus making the inclusion of both redundant. Another aspect that could have been relevant to include in the model is a potential run-up before the rumor publication but, consistent with Table 5 where we found no statistically significant difference in the run-up between true and false rumors as well as the similar findings of Barnes (1998), including the run-up does not contribute to the model.

Table 12 shows a logit regression using the model with the best explanatory power in Table 11, Model 1, but excluding the market reaction to the rumor. The regression aims to see if it is possible to categorically identify true and false rumors using only observable information (firm- and rumor-specific properties). While this model performs worse than the model in Table 11, a significant portion of the R-squared value (12%) is retained and most variables are still significant to the same extent as in Table 11. This shows that the identified variables are factors that actively contribute to whether a firm is a likely takeover target or not, and hence factors that can be used, independently and collectively, to estimate the veracity of an acquisition rumor.

Table 11 and 12 both paint a clear picture: apart from the level of detail in the rumor and the unobservable information contained in the price jump the relevant factors to classify rumors as true or false are the size of the firm, its profitability and the likelihood of it going bankrupt. To a smaller extent the indebtedness of a firm the price-to-earnings ratio also hold some explanatory power. The differing signs on the bankruptcy measurements and the return on equity, suggesting that at the same time profitable firms and firms on the verge of bankruptcy are likely takeover candidates, indicate that it is impossible to describe a typical target firm and that there are several reasons to why a firm is more or less likely to be taken over.

Table 11. Logit regression to identify factors determining the veracity of rumors

This table shows the results of a logit regression aiming to find variables that explain whether a rumor is true or false. The specification of the regression is as follows, where *BANKRUPT* is Altman's Z-score, Zmijewski probability or Ohlson probability in each of the three models. Size is the natural logarithm of the total assets of the firm.

$$True = \beta_0 + \beta_1 AR_0 + \beta_2 DETAIL + \beta_3 SIZE + \beta_4 ROE + \beta_5 BANKRUPT + \beta_6 LEVER + \beta_7 PE + \epsilon$$

As the standard R-squared measure is not defined for logit regressions, the commonly used alternative McFadden's R-squared and Adjusted R-squared are instead presented.

	Dependent variable: True		
Variables	Model 1	Model 2	Model 3
AR (0)	7.97722***	8.41956***	8.26838***
	(-2.42733)	(-2.35292)	(-2.3421)
Detailed rumor	0.94759***	0.88857***	0.88739***
	(-0.33166)	(-0.31918)	(-0.31938)
Size	-0.25012**	-0.19512**	-0.18777**
	(-0.10192)	(-0.09345)	(-0.09317)
Return on Equity	0.42044*	0.36400	0.25633
	(-0.24731)	(-0.23945)	(-0.22365)
Altman's Z-score	-0.13481***		
	(-0.04700)		
Zmijewski probability		0.95871	
		(-0.78606)	
Ohlson probability			0.33203
			(-0.54938)
Leverage	0.06573*	0.05912*	0.07432**
	(-0.03634)	(-0.03530)	(-0.03530)
Price/Earnings	0.00067*	0.00067*	0.00064
	(-0.00039)	-0.00039	(-0.00039)
Constant	0.51922	-0.63118	-0.63715
	(-0.79672)	(-0.68007)	(-0.71932)
Observations	269	272	271
McFadden's R-squared	0.169	0.153	0.150
McFadden's Adjusted R-squared	0.12	0.104	0.101

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 12. Logit regression excluding abnormal return

This table shows the results of repeating the logit regression in Table 11 but excluding the abnormal return on the rumor day.

$$True = \beta_0 + \beta_1 DETAIL + \beta_2 SIZE + \beta_3 ROE + \beta_4 ZSCORE + \beta_5 LEVER + \beta_6 PE + \varepsilon$$

Since Altman's Z-score proved to be the best bankruptcy measure in the regression in Table 11 it is the only one used in this one. Size is the natural logarithm of the total assets of the firm.

Variables	True
Detailed rumor	1.24814***
	-0.31851
Size	-0.33291***
	(-0.10034)
Return on Equity	0.54331*
	(-0.28224)
Altman's Z-score	-0.13790***
	(-0.04289)
Leverage	0.04821
	(-0.03661)
Price/Earnings	0.00051
	(-0.00038)
Constant	1.47965**
	(-0.73677)
Observations	269
McFadden's R-squared	0.118
McFadden's Adjusted R-squared	0.075

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

5.7 Classification of rumors and outcome of trading strategy

Using the model specified in Table 11, we divide the sample into a training set and a validation set as explained in the methodology section, estimate the coefficients of the model using the training set, and then use the coefficients on the validation set to calculate probabilities of the different rumors being true. Doing this repeatedly we arrive at the distribution seen in Table 13. By examining the t-statistics presented it is apparent that the model performs significantly better than picking takeover targets at random for all probability cutoffs above 0.3 (when the probability of a rumor being true estimated by the logit regression is higher than 0.3). On average, with a cutoff of 0.5, we select 8.31 true rumors and 5.36 false rumors in the hold-out sample consisting of 75 rumors. Buying these rumors and holding them for one year would yield, on average, a return of 4.16%, or about equal to the market return during the same period. The 0.5 cutoff is the cutoff that maximizes the percentage of rumors correctly identified. However, a slightly better return can be achieved using a 0.6 probability cutoff with only a minute reduction of the success rate and the t-statistic. For any level higher than 0.6 the number of rumors traded on becomes so low that the strategy can no longer be considered viable. While the numbers in Table 13 only represent a third of the total dataset, one must keep in mind that the rumors are spread out over a twelve-year period. For example, applying the 0.7 cutoff would entail investing in, on average, only 1.4 stocks each year whereas a strategy using the 0.5 cutoff represents investments in 3.4 stocks every year.

Table 13. Results from using the logit model including rumor day price reaction with repeated random sub-sampling

This is the results from estimating the coefficients in the logit model

$$True = \beta_0 + \beta_1 AR_0 + \beta_2 DETAIL + \beta_3 SIZE + \beta_4 ROE + \beta_5 BANKRUPT + \beta_6 LEVER + \beta_7 PE + \varepsilon$$

on two thirds of the total U.S. sample and then creating estimated probabilities using these coefficients for the last third of the sample. This is done a total of 200 times, and the holding period return and the excess holding period return for a year after the rumor publication as well as the number of false and true rumors found above a certain cutoff is averaged over all iterations. The C-ratio is the fraction of true rumors above a cutoff level divided by the total number of rumors above the cutoff level, and is a measure of the accuracy of the model. It can also be used determine the most accurate cutoff level. Type I error lists the number of true rumors not included above the cutoff, while the type II column lists the number of false rumors that are, incorrectly, included above the cutoff (a negative value indicates that the classification performs worse than by chance). The number of rumors in the validation set is 75 each time, with 174 rumors in the training set.

Cutoff	False	True	C-ratio	Type I Error	Type II Error	% Correct	HPR(1;365)	Ex.HPR(1;365)	T-stat
0.1 -	47.89	23.33	32.76%	1.42	47.89	40.91%	1.26%	0.22%	-3.71
0.2 -	26.42	18.86	41.66%	5.23	26.42	61.73%	3.23%	2.40%	0.62
0.3 -	15.11	15.12	50.02%	8.80	15.11	71.14%	4.12%	1.58%	2.10
0.4 -	9.60	10.45	52.11%	13.91	9.60	71.57%	2.11%	-0.82%	2.64
0.5 -	**5.36**	**8.31**	**60.81%**	**16.14**	**5.36**	**74.17%**	**4.16%**	**0.07%**	**3.71**
0.6 -	**2.96**	**6.06**	**67.18%**	**18.40**	**2.96**	**74.00%**	**6.32%**	**1.64%**	**3.65**
0.7 -	1.67	3.96	70.31%	19.85	1.67	73.89%	9.82%	2.93%	3.53
0.8 -	0.87	2.30	72.63%	21.99	0.87	72.32%	10.46%	-0.51%	3.15
0.9 -	0.43	1.28	74.85%	23.31	0.43	71.74%	10.02%	-0.38%	3.04
1 -	0.00	0.00	-	24.57	0.00	70.51%	-	-	2.74

Table 14 shows what the same technique yields using the model specification in Table 12, excluding the abnormal return on the rumor day. By examining the number of firms above the different cutoffs and the respective t-statistics it is clear that the model performs slightly worse than the model in Table 13, but is still able to predict takeover targets significantly better than chance. A portfolio where the 0.4 probability cutoff is used earns a better return than any of the portfolios in Table 13, however the returns are not statistically different from zero (as the standard deviation is larger than 40 percent most iterations, resulting in a standard error of above 10 percent.) While insignificant, a larger return could be caused by the exclusion of the rumor day return as a determining factor. Some firms that were included in the portfolios in Table 13 because of their strong rumor day reaction rebound, due to the rumor being proven false or for some other reason, during the following year and hence reduce the return of the investment portfolio. Table 15 investigates a short selling strategy where all firms below a certain cutoff are sold instead of bought. This strategy aims at identifying false firms instead of true firms, which it manages to do with some accuracy. Below the 0.3 cutoff the model identifies 43.47 false rumors and 9.25 true rumors on average, significantly better than chance, which allows us to make a non-risk adjusted average HPR of 2.51% and an average excess return of 2.03%, none of which are statistically different from zero (as standard errors here too are above 10 percent for nearly all iterations.) Figure 12 and 11 provide a more visual presentation of the classification results in Table 12 and 13, clearly showing that a larger fraction of true rumors are identified at higher cutoffs.

All three model variants perform very well at classifying rumors into true or false categories. However, the returns one can earn from trading on these rumors are far too modest (especially since transaction costs are not considered) to justify it as a viable trading strategy, suggesting that the efficient market hypothesis holds for takeover rumors. We have been able to identify factors that contribute to the likelihood of a firm being taken over in addition to the information inherent in the stock market reaction to the rumor. However, that we cannot profit on this ostensible information advantage indicates that the market has already internalized this increased likelihood even before the rumor publication through a higher pre-rumor stock price.

Table 14. Results from using the logit model excluding rumor day price reaction with repeated random sub-sampling

This is the results from estimating the coefficients in the logit model

$$True = \beta_0 + \beta_1 DETAIL + \beta_2 SIZE + \beta_3 ROE + \beta_4 BANKRUPT + \beta_5 LEVER + \beta_6 PE + \varepsilon$$

on two thirds of the total U.S. sample and then creating estimated probabilities using these coefficients for the last third of the sample. This is done a total of 200 times, and the holding period return and the excess holding period return for a year after the rumor publication as well as the number of false and true rumors found above a certain cutoff is averaged over all iterations. Firms above the C-ratio is the fraction of true firms above a cutoff level divided by the total number of rumors above the cutoff level, and is a measure of the accuracy of the model. It can also be used determine the most accurate cutoff level. Type I error lists the number of true rumors not included above the cutoff, while the type II column lists the number of false rumors that are, incorrectly, included above the cutoff. The t-statistic measures whether the classifications above the cutoffs are significantly more accurate than by chance (a negative value indicates that the classification performs worse than by chance). The number of rumors in the validation set is 75 each time, with 174 rumors in the training set.

Cutoff	False	True	C-ratio	Type I Error	Type II Error	% Correct	HPR(1;365)	Ex.HPR(1;365)	T-stat
0.1 -	51.54	22.96	30.81%	1.23	51.54	36.42%	0.59%	-0.65%	-4.73
0.2 -	32.53	19.24	37.16%	4.93	32.53	54.97%	1.30%	0.24%	-0.78
0.3 -	18.52	15.63	45.78%	8.32	18.52	67.46%	2.68%	1.46%	1.91
0.4 -	**10.61**	**11.27**	**51.52%**	**13.25**	**10.61**	**71.20%**	**5.36%**	**4.02%**	**2.95**
0.5 -	**5.54**	**6.07**	**52.26%**	**18.48**	**5.54**	**71.35%**	**2.01%**	**-0.01%**	**2.61**
0.6 -	2.97	2.33	43.96%	21.59	2.97	69.90%	0.37%	-4.27%	2.54
0.7 -	1.39	0.72	34.20%	23.75	1.39	69.70%	0.21%	-4.73%	2.53
0.8 -	0.87	0.26	23.11%	24.08	0.87	70.15%	0.91%	-3.99%	2.59
0.9 -	0.41	0.13	23.36%	24.25	0.41	70.29%	13.92%	4.43%	2.65
1 -	0.00	0.00	-	24.12	0.00	70.92%	-	-	2.79

Table 15. Results from using the logit model including rumor day price reaction with repeated random sub-sampling when shorting firms

This is the results from estimating the coefficients in the logit model

$$True = \beta_0 + \beta_1 AR_0 + \beta_2 DETAIL + \beta_3 SIZE + \beta_4 ROE + \beta_5 BANKRUPT + \beta_6 LEVER + \beta_7 PE + \varepsilon$$

on two thirds of the total U.S. sample and then creating estimated probabilities using these coefficients for the last third of the sample. The firms below different cutoffs are then sold (shorted). This is done a total of 200 times, and the holding period return and the excess holding period return for a year after the rumor publication as well as the number of false and true rumors found below a certain cutoff is averaged over all iterations. The C-ratio is the fraction of true firms above a cutoff level divided by the total number of rumors above the cutoff level, and is a measure of the accuracy of the model. It can also be used determine the most accurate cutoff level. Type I error lists the number of false rumors not included below the cutoff, while the type II column lists the number of true rumors that are, incorrectly, included below the cutoff. The t-statistic measures whether the classifications below the cutoffs are significantly more accurate than by chance (a negative value indicates that the classification performs worse than by chance). The number of rumors in the validation set is 75 each time, with 174 rumors in the training set.

Cutoff	False	True	C-ratio	Type I Error	Type II Error	% Correct	HPR(1;365)	Ex.HPR(1;365)	T-stat
- 0.1	11.26	1.24	90.12%	47.86	1.24	41.14%	5.51%	1.56%	-3.70
- 0.2	31.79	5.08	86.22%	26.60	5.08	61.76%	3.95%	2.29%	0.66
- 0.3	43.47	9.25	82.46%	14.59	9.25	71.05%	2.51%	2.03%	2.86
- 0.4	48.89	13.29	78.63%	9.79	13.29	72.13%	-0.57%	-1.68%	3.09
- 0.5	**52.65**	**16.19**	**76.48%**	**5.89**	**16.19**	**73.32%**	**-0.77%**	**-1.82%**	**3.44**
- 0.6	**55.78**	**17.77**	**75.84%**	**3.15**	**17.77**	**74.72%**	**-0.49%**	**-1.66%**	**3.75**
- 0.7	57.20	20.83	73.31%	1.62	20.83	73.11%	-1.07%	-2.25%	3.46
- 0.8	58.23	22.25	72.35%	0.91	22.25	72.35%	-0.62%	-1.83%	3.14
- 0.9	58.64	23.20	71.65%	0.53	23.20	71.62%	-0.75%	-2.04%	2.99
- 1	59.18	24.54	70.69%	0.00	24.54	70.69%	-0.54%	-2.17%	2.72

Figure 12. Estimated probabilities of rumors being true using the logit model including rumor day price reaction and a single representative random sample

This is the results from estimating the coefficients in the logit model

$$True = \beta_0 + \beta_1 AR_0 + \beta_2 DETAIL + \beta_3 SIZE + \beta_4 ROE + \beta_5 BANKRUPT + \beta_6 LEVER + \beta_7 PE + \varepsilon$$

on two thirds of the total U.S. sample and then creating estimated probabilities using these coefficients for the last third of the sample. This is based on only one such random sampling of the U.S. data that approximated the distribution in table 14. The total number of firms in the validation set shown is 75.

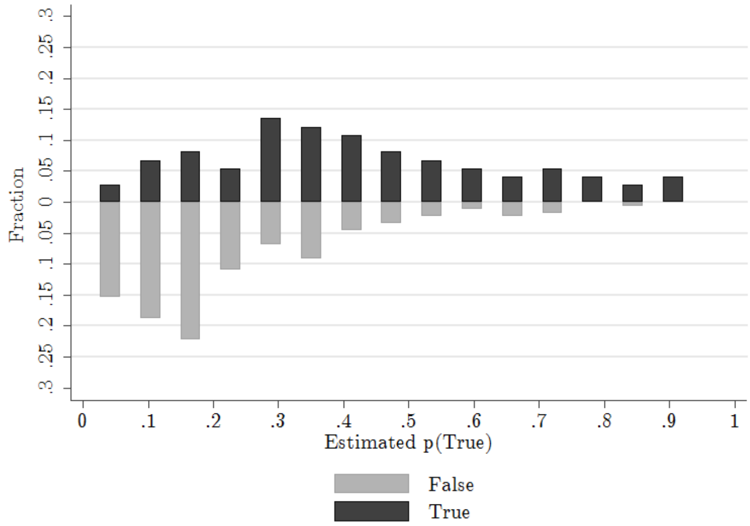
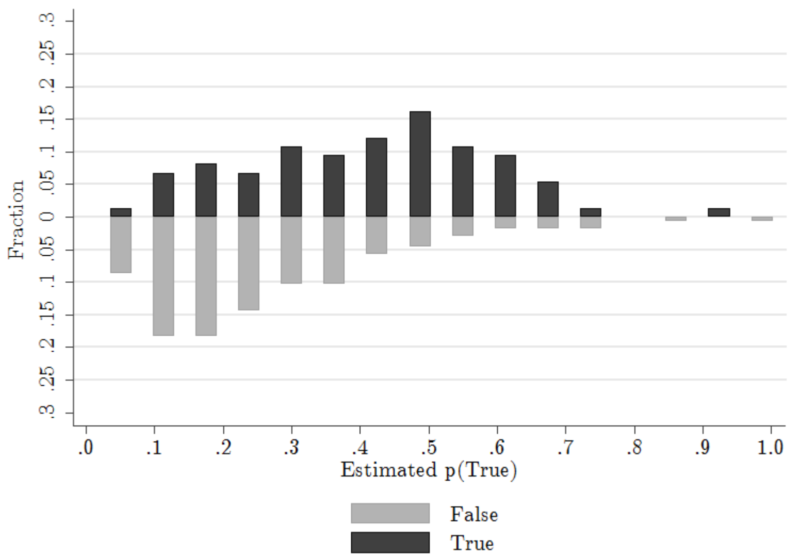


Figure 13. Estimated probabilities of rumors being true using the logit model excluding rumor day price reaction and a single representative random sample

This is the results from estimating the coefficients in the logit model

$$True = \beta_0 + \beta_1 DETAIL + \beta_2 SIZE + \beta_3 ROE + \beta_4 BANKRUPT + \beta_5 LEVER + \beta_6 PE + \varepsilon$$

on two thirds of the total U.S. sample and then creating estimated probabilities using these coefficients for the last third of the sample. This is based on only one such random sampling of the U.S. data that approximated the distribution in table 15. The total number of firms in the validation set shown is 75.



5.8 Robustness tests

For robustness, we redo some of the steps done for the U.S. on a U.K. dataset as well as on an out-of-sample U.S. dataset from Bloomberg to see if our findings hold when using other data. Table 16 is the regression in Table 7 reproduced on the U.K. data, and shows that there is no statistically significant difference in the rumor day reaction between true and false rumors in the U.K. Contingent on the abnormal return being positive, however, the difference is statistically significant and firms subject to true rumors gain on average 12.81%, more than in the U.S., while falsely rumored firms gain 5.5% (compare with Table 9 for the U.S.). In other words, if the market reacts with positive abnormal returns, as is expected since being named a potential takeover target is usually good news, it is possible to tell a difference in the reaction for true and false rumors in the U.K market as well. Table 18, a regression with a country dummy variable for the U.K. and an interaction term between a *True* dummy variable and the U.K. dummy variable is included, tells us that there does not appear to be, on average, any statistically significant difference between the U.S. and the U.K. when it comes to rumor reactions. This is a first indication that we cannot reject that our findings from the U.S. dataset do not hold in the U.K. market as well.

Table 16. U.K. data: regression of abnormal return difference on rumor day

This regression shows the difference in abnormal return between true and false rumors on the rumor day for a U.K. sample, also from Zephyr, selected in similar fashion to the U.S. sample. (This is equivalent to running a t-test on the difference, but is included in this format to allow comparison to table 18.)

Variables	AR(0)
True	0.0307
	(0.0251)
Constant	0.0261***
	(0.00680)
Observations	273
R-squared	0.010

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 17. U.K. data: regression of abnormal return difference on rumor day contingent on positive rumor day abnormal return

This regression shows the difference in abnormal return between true and false rumors on the rumor day for the U.K. contingent on the market reacting favorably to the rumor. (This is equivalent to running a t-test on the difference, but is included in this format to allow comparison to table 18.)

Variables	AR(0)
True	0.0731**
	(0.0303)
Constant	0.0550***
	(0.00566)
Observations	185
R-squared	0.065

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 18. U.K. and U.S. data: regression of abnormal returns on rumor day with country dummy and interaction term

This regression tests whether we can reject the hypothesis that the U.K. rumor reaction differs from the U.S. rumor reaction.

Variables	AR(0)
True	0.0502***
	(0.0115)
UK	-0.00373
	(0.00783)
True and UK	-0.0111
	(0.0311)
Constant	0.0298***
	(0.00388)
Observations	609
R-squared	0.034

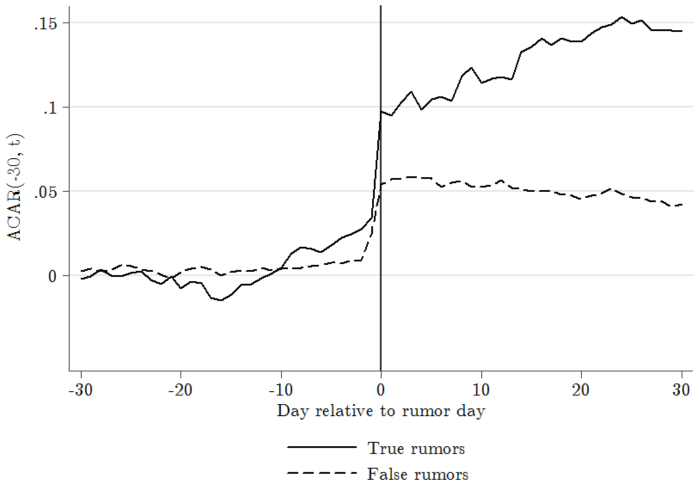
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure 14 shows the rumor day reaction for U.K. market, as Figure 5 illustrated for the U.S. Here, the run-up appears to be distinct for true rumors, but not for false rumors, the 14 days preceding the rumor publication. The U.K. also shows a more distinct upward-sloping ACAR trend after the rumor publication compared with in the U.S. The U.S. sample exhibits a similar trend but only over a longer period. These two differences are difficult to explain, and could be due to structural differences between the markets. It also cannot be ruled out that it is caused by impurities in the U.K. sample or that Zephyr's rumor collection process differs between the U.K. and the U.S. The U.K. reaction is more in line with the diffusion process described by Kimmel (2004), who states that true rumors should become more and more credible with time while the credibility of false rumors deteriorate. The exact causes of this difference remain to be explored, something that is left to future research.

The data for the Bloomberg sample is even more imprecise, and we have reason to believe that the rumor date present in the dataset is in many cases not the first publication date of the rumor but rather the date when it was recorded by Bloomberg. As a consequence, the timing of the reaction is inexact for some rumors and a graph showing the difference between the reaction for true and false rumors may be misleading. Due to the large size of the Bloomberg dataset we have been unable to correct for these imprecisions and therefore choose to not present a graph like Figure 14 for Bloomberg. The imprecise timing also explains the smaller difference for the Bloomberg dataset between the model including the rumor day reaction and the one that does not, compared to the other two datasets.

Figure 14. U.K.: Winsorized ACAR for rumored target firms day -30 to +30 relative to rumor publication, divided by veracity

This figure shows the average cumulative abnormal return (ACAR) for the days -30 to +30 around the rumor publication day for both rumors that are followed by an acquisition (true) and rumors that are not (false). The figure is based on 79 true rumors and 212 false rumors, where the CARs are winsorized on the 5% level every day before the average is calculated.



To test the classification model, we estimate the coefficients in the logit model in Table 11 (including the rumor day reaction) on the full U.S. main data sample, and use the resulting coefficients to estimate a probability for the rumors being true or not in our two external datasets, on U.K. rumors and on other U.S. rumors provided by Bloomberg. Figure 15 and 16 show the distribution of true and false rumors both including and excluding the rumor day reaction on the U.K. dataset, while Figure 17 and 18 give the same graphical presentation for the Bloomberg sample. The model including the rumor day reaction does noticeably better than the one excluding it for both samples, but both still perform decidedly better than chance. The distribution of true rumors is still distinctly skewed toward the right compared to the distribution of false rumors, indicating that the models are able to identify true rumors in these samples as well. The difference in the classification results of the two models is, however, smaller for the Bloomberg sample due to the imprecision of the data causing some rumor day reactions to not be included.

Figure 15. U.K.: probabilities of rumors being true from logit model including rumor day price reaction estimated on U.S. data

This is the results from estimating the coefficients in the logit model

$$True = \beta_0 + \beta_1 AR_0 + \beta_2 SIZE + \beta_3 ROE + \beta_4 BANKRUPT + \beta_5 LEVER + \beta_6 PE + \varepsilon$$

on the full U.S. sample of 249 rumors and then using these coefficients to estimate the probability of a rumor being true in the U.K. sample of 199 rumors. *Detail* is not included as it was not recorded for U.K. rumors.

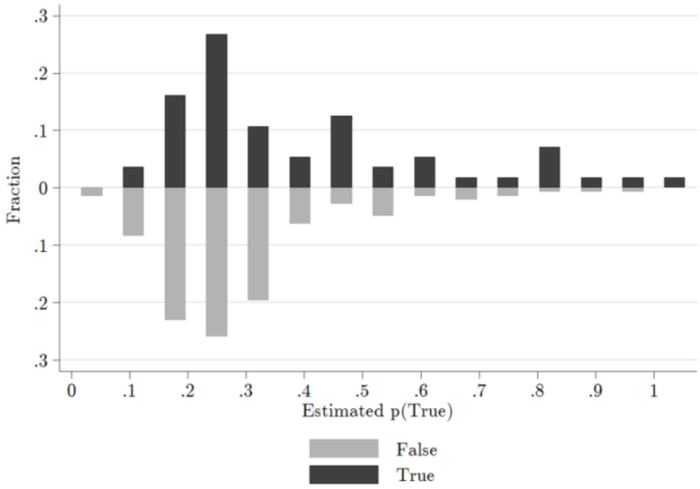


Figure 16. U.K.: probabilities of rumors being true from the logit model excluding rumor day price reaction estimated on U.S. data

This is the results from estimating the coefficients in the logit model

$$True = \beta_0 + \beta_1 SIZE + \beta_2 ROE + \beta_3 BANKRUPT + \beta_4 LEVER + \beta_5 PE + \varepsilon$$

on the full U.S. sample of 249 rumors and then using these coefficients to estimate the probability of a rumor being true in the U.K. sample of 199 rumors. *Detail* is not included as it was not recorded for U.K. rumors.

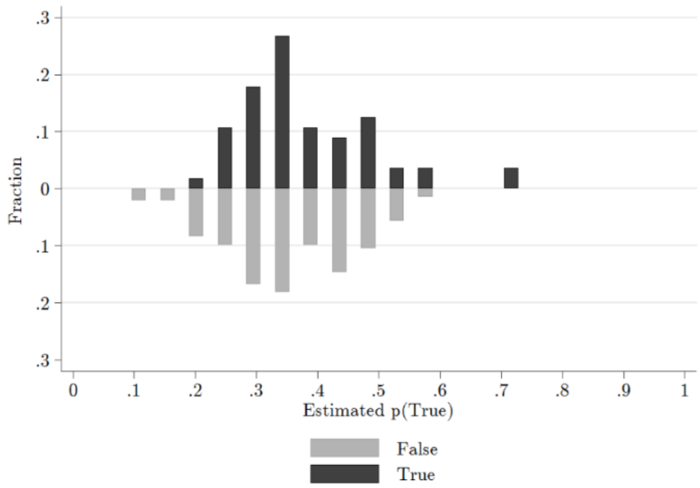


Figure 17. Bloomberg U.S.: probabilities of rumors being true using the logit model including rumor day price reaction estimated on U.S. data

This is the results from estimating the coefficients in the logit model

$$True = \beta_0 + \beta_1 AR_0 + \beta_2 SIZE + \beta_3 ROE + \beta_4 BANKRUPT + \beta_5 LEVER + \beta_6 PE + \varepsilon$$

on the full U.S. (Zephyr) sample of 249 rumors and then using these coefficients to estimate the probability of a rumor being true in the Bloomberg U.S. sample of 783 rumors. DETAIL is not included as it cannot be determined for Bloomberg U.S. rumors.

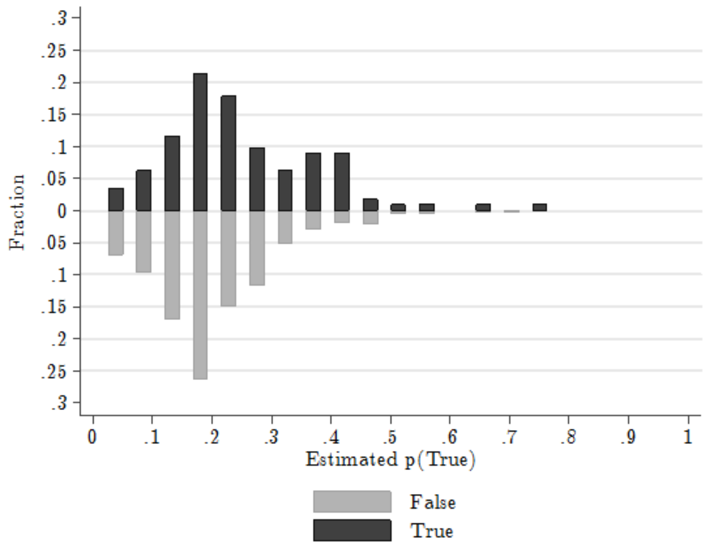
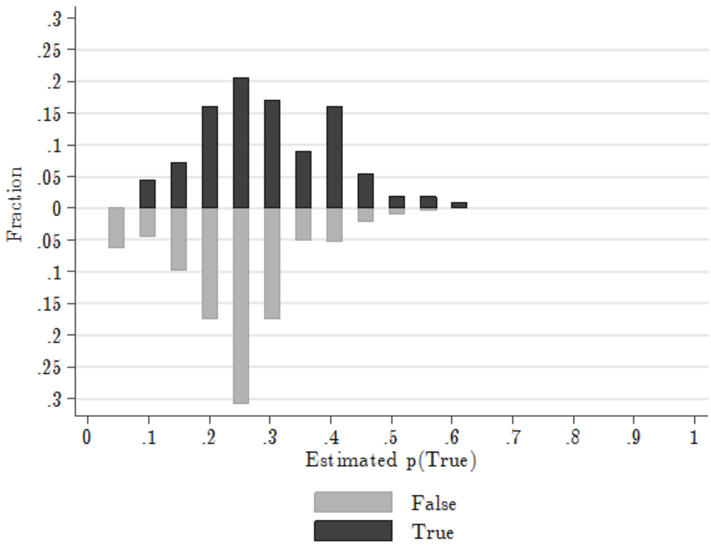


Figure 18. Bloomberg U.S.: probabilities of rumors being true using the logit model excluding rumor day price reaction estimated on U.S. data

This is the results from estimating the coefficients in the logit model

$$True = \beta_0 + \beta_1 SIZE + \beta_2 ROE + \beta_3 BANKRUPT + \beta_4 LEVER + \beta_5 PE + \varepsilon$$

on the full U.S. (Zephyr) sample of 249 rumors and then using these coefficients to estimate the probability of a rumor being true in the Bloomberg U.S. sample of 783 rumors. DETAIL is not included as it cannot be determined for Bloomberg U.S. rumors.



The t-statistics in Table 16 show that all U.K. rumors with an estimated probability of being true that is above 0.4 have been selected significantly better than at random. The model performs, for most cutoffs, significantly better than chance would in the Bloomberg dataset as well, as is shown in Table 17. While the model outperforms chance in the Bloomberg dataset it only manages to classify very few rumors correctly and at very conservative probability levels, most likely due to the reduction of the impact of the rumor day reaction caused by the imprecision of the dates provided in the dataset. As expected, though, both the U.K. sample and the U.S. Bloomberg sample perform worse than the same model does in the U.S. sample. This is partly because of the somewhat lower quality of data in these samples. In particular, Bloomberg's standards for what is required from a rumor in terms of credibility in order for it to be reported appears to be lower than Zephyr's. This is also apparent in the ratio of false to true rumors, where Bloomberg is closer to 10-to-1, compared to the ratio in the Zephyr samples and the distributions seen in papers such as Zivney et al. (1996) and Pound and Zeckhauser (1990) where the ratio is approximately 3-to-1. It is also almost inevitable that differences exist between the U.S. and U.K. markets in some form. Generally, however, it is encouraging to see how well one can classify firms into targets and non-targets using only simple accounting ratios. Holding period returns were not calculated for the Zephyr U.K. and Bloomberg U.S. samples, however, as the stock prices in those datasets required more data processing.

As a last robustness test on both the main U.S. and the U.K. data, we ascertain that the difference in the rumor day reaction between true and false rumors is not solely due to differences in target firm size or other firm characteristics but due to other information available to the market. This was done by matching the true and false rumors on a number of firm characteristics and the results of this procedure can be seen in tables A1 and A2 in the appendix. The difference in rumor day reaction between true and false rumors in the U.S. remains statistically significant while the difference for the U.K. is still statistically insignificant.

Descriptive statistics for the U.K. and Bloomberg datasets are included for sake of comparison with the main dataset in tables A3 and A4 in the appendix.

Table 16. U.K.: results from using the logit model including rumor day price reaction estimated on U.S. data

This is the results from estimating the coefficients in the logit model

$$True = \beta_0 + \beta_1 AR_0 + \beta_2 SIZE + \beta_3 ROE + \beta_4 BANKRUPT + \beta_5 LEVER + \beta_6 PE + \varepsilon$$

on the full U.S. (Zephyr) sample of 249 rumors and then using these coefficients to estimate the probability of a rumor being true in the U.K. sample. DETAIL is not included as it was not recorded for U.K. rumors. The C-ratio is the fraction of true firms above a cutoff level divided by the total number of rumors above the cutoff level, and is a measure of the accuracy of the model. It can also be used determine the most accurate cutoff level. Type I error lists the number of false rumors included above the cutoff, while the type II column lists the number of true rumors that are not included above the cutoff. The t-statistic measures whether the classifications below the cutoffs are significantly more accurate than by chance (a negative value indicates that the classification performs worse than by chance). The model is run on 199 rumors, of which 56 are true and 143 are false.

Cutoff	False	True	C-ratio	Type I Error	Type II Error	% Correct	T-stat
0.1 -	136.00	56.00	29.17%	0.00	136.00	31.66%	-10.56
0.2 -	102.00	49.00	32.45%	7.00	102.00	45.23%	-5.22
0.3 -	52.00	27.00	34.18%	29.00	52.00	59.30%	-0.40
0.4 -	25.00	21.00	45.65%	35.00	25.00	69.85%	3.50
0.5 -	17.00	14.00	45.16%	42.00	17.00	70.35%	3.70
0.6 -	9.00	12.00	57.14%	44.00	9.00	73.37%	4.99
0.7 -	5.00	8.00	61.54%	48.00	5.00	73.37%	4.99
0.8 -	3.00	6.00	66.67%	50.00	3.00	73.37%	4.99
0.9 -	1.00	3.00	75.00%	53.00	1.00	72.86%	4.76
1 -	0.00	0.00	-	56.00	0.00	71.86%	4.33

Table 17. Bloomberg U.S.: results from using the logit model estimated on U.S. data including rumor day price reaction

This is the results from estimating the coefficients in the logit model

$$True = \beta_0 + \beta_1 SIZE + \beta_2 ROE + \beta_3 BANKRUPT + \beta_4 LEVER + \beta_5 PE + \varepsilon$$

on the full U.S. (Zephyr) sample of 249 rumors and then using these coefficients to estimate the probability of a rumor being true in the Bloomberg U.S. sample. DETAIL is not included as it cannot be determined for Bloomberg U.S. rumors. The C-ratio is the fraction of true firms above a cutoff level divided by the total number of rumors above the cutoff level, and is a measure of the accuracy of the model. It can also be used determine the most accurate cutoff level. Type I error lists the number of false rumors included above the cutoff, while the type II column lists the number of true rumors that are not included above the cutoff. The t-statistic measures whether the classifications below the cutoffs are significantly more accurate than by chance (a negative value indicates that the classification performs worse than by chance). Out of the 1520 rumors in the Bloomberg dataset, the required data to run the model was only available for 783 rumors (112 true and 671 false).

Cutoff	False	True	C-ratio	Type I Error	Type II Error	% Correct	T-stat
0.1 -	574.00	102.00	15.09%	10.00	574.00	25.42%	-32.18
0.2 -	279.00	68.00	19.60%	44.00	279.00	58.75%	-9.51
0.3 -	91.00	33.00	26.61%	79.00	91.00	78.29%	1.90
0.4 -	36.00	15.00	29.41%	97.00	36.00	83.01%	5.61
0.5 -	10.00	4.00	28.57%	108.00	10.00	84.93%	7.39
0.6 -	4.00	2.00	33.33%	110.00	4.00	85.44%	7.90
0.7 -	0.00	1.00	100.00%	111.00	0.00	85.82%	8.29
0.8 -	0.00	0.00	-	112.00	0.00	85.70%	8.16
0.9 -	0.00	0.00	-	112.00	0.00	85.70%	8.16
1 -	0.00	0.00	-	112.00	0.00	85.70%	8.16

6. Conclusion

We have examined different hypotheses concerning rumors in financial markets, both in the U.S. and in the U.K. Using rumors between 2000 and 2012, we have studied whether financial markets can tell the difference between true and false rumors; whether markets react efficiently to rumors; whether it is possible to use book values to tell the difference between true and false rumors; and whether the markets have internalized this information or not.

First, we find a statistically significant difference between true and false rumors, where the market reacts, on average, 4.95% stronger to the publication of true rumors than to false rumors. This result stands even when controlling for the source reporting the rumor and the level of detail of the rumor. We find that a rumor from a larger news source induces a rumor day reaction that is around 2.72% stronger than for smaller news sources. This agrees with our first hypothesis, that markets can tell the difference between true and false rumors. We can however only partially explain the information that the market uses to distinguish between the two.

Second, we also find that it is not possible to profit by buying and holding rumors on average, as one would expect; such a strategy would yield a return not statistically different from zero due to the high volatility associated with trading on rumors. This is evidence that markets do appear to react efficiently to rumors, in accordance with our second hypothesis.

Third, using logit models, we find that we are able to successfully classify rumored target firms both in- and out-of-sample using the coefficients estimated in-sample. We find that smaller firms, firms with high return on equity, and firms with high bankruptcy risk are all more likely to be taken over than other firms. We, however, also find that there is a significant amount of information that we are unable to control for that the market uses to distinguish between true and false rumors. We therefore establish that the stock price abnormal return on the rumor publication day has strong explanatory power when added to our model, serving as a proxy for information that cannot be readily observed. This information could be information Zephyr missed to record, such as SEC filings on insider trading or block purchases or further statements by the rumored target or acquiring firm. It could also be due to nuances in the original news report that cannot be captured in a summary of a rumor, in line with how Tetlock (2004) concludes that the way a news item is reported, and not only the content of the report, can make a great difference in what effect it has on the market.

Despite the observed correlation between the rumor day abnormal return and some of the other variables included in the sample, causing some concern about multicollinearity, the inclusion of the rumor day return still contributes significantly to the classification of rumors as true or false. Other statistically significant variables provide explanatory power to the model even when return is included, which leads us to hypothesize that markets perhaps do not take into account all the information available in some of the financial key ratios when judging the veracity of rumors. We therefore try classifying firms by dividing our main sample into a training set and a validation set and can by using this method classify rumors better than at random. While this result is unsurprising when the rumor reaction is included in the logit model, considering the difference in reaction between true and false rumors, the model still does better than chance when only financial key ratios are included. This agrees with our third hypothesis and with the findings of for example Palepu (1986), Barnes (1998) and others that have investigated the differences in characteristics between targets and non-targets (but not in conjunction with rumors). The downfall is that only a fraction of the rumors can be classified, which translates to very few identified rumors if the method were to be applied on future rumors as a trading strategy.

Fourth, we find that it is not possible to profit using either of the two classification strategies in our main sample. The reaction on the rumor publication day appears to be sufficient to capture any potential profits on the rumor day rendering trading of targets after this reaction an unprofitable venture, both in terms of normal and abnormal holding period returns. It is assumed that the stock market reacts nearly instantly to the rumor. If the reaction is not instant, however, profits may be achievable if the model (excluding the rumor day price reaction) is applied before the full reaction has materialized. All strategies were shown unprofitable even without taking transaction costs into account; when controlling for transaction costs, the ability to profit using these methods diminishes even further. These results agree with our last hypothesis.

We compare our findings on the U.S. dataset with another sample of U.S. rumors as well as a sample of U.K. firms and find that the same estimated logit model used in the main U.S. dataset also manages to classify firms significantly better than chance in both the two other datasets. Due to the noisiness of these datasets we have been unable to calculate returns to a buy-and-hold strategy using rumors with any reasonable degree of certainty, but preliminary calculations show a lack of abnormal returns in these markets as well.

We therefore find evidence for weak as well as semi-strong market efficiency in conjunction with rumors. We also find no evidence to contradict strong-form market efficiency for rumors in the U.S., as we do not find any statistically significant differences in the run-up between true and false rumors. We believe that the difference between true and false rumors is likely to be due to public information that we are unable to capture using the summaries available through Zephyr and annual report data. Finally, we have also been able to show that the run-up prior to announcements caused by the rumors in our dataset largely corresponds with the run-up observed in the market as a whole, demonstrated by for example Betton et al. (2008). This finding suggests that rumors may be a large contributing factor to the pre-announcement stock price run-ups and that the part played by insider trading may be overstated.

7. Limitations and Suggestions for Future Research

In the process of selecting the samples used, some assumptions have had to be made. These include that Zephyr is not disproportionately reporting true rumors ahead of false rumors, and that the likelihood of firms being dropped due to missing annual report data or missing stock data is independent of whether the rumors are true or false. While these assumptions are unlikely to hold perfectly, we do not believe that they invalidate the conclusions of this thesis.

Abnormal holding period returns for strategies are calculated by subtracting the market return for the year from the holding period returns. This is done because the estimated daily alphas become severely biased when added up over a period of 365 days as compared to a period of 60 days (the event window used). It is also believed that the systematic risk is very likely to have changed for the target firm with the event, and no period exists to re-estimate the factor betas as the holding period return is calculated starting the day after the rumor publication. An alternative approach would have been to use the pre-rumor factor betas and not include alphas in the normal return calculation, but we instead choose to use the market return as a benchmark (equivalent to assuming market betas of one for all target firms) since this method is less prone to error and provides satisfactory estimates of the abnormal holding period returns.

Since the market reaction to a rumor publication differ quite significantly depending on the source reporting it, controlling more closely for the initial source of the rumor could reveal interesting information about how the market weighs similar news depending on which news outlet the report originates from. Zephyr does not, in most cases, provide enough information to make such research feasible. One way to investigate this better is to collect the rumors manually. Categorizing the rumors further by the exact content and wording of the rumor report would also be possible if the rumors were collected this way. Ideally, the existence of SEC filings concerning toeholds and insider trades in conjunction with the rumor publications would also be manually verified.

Due to the relatively small amount of acquisition rumors, and the high volatility seen for the stocks of rumored target firms, standard errors become very large for any buy-and-hold returns. This is one of the reasons we cannot refute any of the hypotheses that markets react efficiently to takeover rumors. Particularly so since only a small number of true rumors can be identified with confidence, making it difficult to prove that the returns one can earn from trading on them are statistically different from zero. A larger sample would allow for smaller standard errors and consequently improve the investigation of market efficiency in conjunction with rumors. A larger sample could be collected by either manually aggregating rumors, or by increasing the time span investigated.

Henderson (1989) presents common problems with event studies, and solutions to most of them. Some of them include problems common to all regression models that involve stock prices, such as the non-normality and serial correlation of stock returns. As he states, even though returns may not be normally distributed, residuals often end up close enough to normal to ensure that a null hypothesis of normality cannot be rejected. He also exposes the common problems of serial correlation and nonsynchronous trading, which one partially could overcome by averaging leading, lagging and contemporaneous beta values. He states, though, that these methods generally do not manage to overcome the problem of autocorrelated residuals. Other problems could emerge from a larger correlation between the daily residuals in the market model and the market return if the market was in a bear market when betas were estimated and is in a bull market when the event occurs. Some of these matters are not causes of too much concern in our study, while others could potentially introduce biases. Future research could test for these biases and test whether any of them have a noticeable impact on our findings.

In recent years, other techniques have shown that they might do a better job at a task such as the one at hand than the logit model applied in this thesis. Both support vector machines (SVMs) and artificial neural networks have shown to be at least as good as the simpler dichotomous probit[4] or logit regression techniques at tasks such as estimating bankruptcy risk and identifying or classifying merger and acquisition targets (Tan and Dihardjo, 2001; Min and Lee, 2005). Applying the same techniques to this more niche topic of rumors could potentially provide even more promising results. The advantage to using probit and logit regressions is their relative simplicity and how the estimated coefficients have a simpler economic interpretation, while neural networks and support vector machines can be harder to translate into relationships that can easily be explained.

Further investigations into other characteristics of the firms involved could also be conducted, such as changes in the volatility of the stock before and after the rumor, and whether the systematic risk or alpha of the firm shift with the rumor. Since the ability to profit from the rumor depends on how efficiently, and especially how quickly, markets adjust to new news, examining intra-day stock reaction to the rumor could reveal, for example, whether the market instantly reacted to the new information or whether the adjustment takes place over a longer timespan.

[4] Probit regression models are very similar to logit models and serve, effectively, the same purpose. Instead of a using a logistic function, probit is based on the normal cumulative distribution function.

8. References

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A. Appendix

Table A1. Using matching to confirm the difference in reaction between true and false rumors

Matching of the two samples (true and false) using as firm-specific variables: Major News Source, Return on Equity, Size (Log of Total Assets), Leverage, Sales Growth and Probability of Bankruptcy (Zmijewskij). ATT ("Average Treatment Effect on the Treated") is the matched sample, "Treated" are the true rumors and "Controls" are the false rumors. "Difference" is the difference between the two.

Variable	Sample	Treated	Controls	Difference	Std. Error	T-stat
AR (0)	Unmatched	0.08823	0.02940	0.05883	0.01070	5.5
	ATT	0.08823	0.03323	0.05501	0.01556	3.54

Table A2. Using matching to confirm the difference in reaction between true and false rumors

Matching the two samples (true and false) using as firm-specific variables: Major News Source, Return on Equity, Size (Log of Total Assets), Leverage, Sales Growth and Probability of Bankruptcy (Zmijewskij). ATT ("Average Treatment Effect on the Treated") is the matched sample, "Treated" are the true rumors and "Controls" are the false rumors. "Difference" is the difference between the two.

Variable	Sample	Treated	Controls	Difference	Std. Error	T-stat
AR(0)	Unmatched	0.07192	0.02656	0.04536	0.02655	1.71
	ATT	0.07192	0.04440	0.02752	0.03822	0.72

Table A3. Descriptive accounting data for the rumored firms divided on the veracity of the rumor for the U.K. dataset

This table provides an overview of the characteristics of the falsely rumored firms and the ones that were eventually taken over. Some items are shown as they appear in the annual reports while others are used to calculate ratios or measurements of bankruptcy. Betas and alphas are calculated using the CAPM. All book values and the market capitalization are expressed in GBP.

	False rumors								True rumors							
Variables	Obs.	Mean	SD	Min	1st Q	Median	3rd Q	Max	Obs.	Mean	SD	Min	1st Q	Median	3rd Q	Max
Market Cap	194	3 540.97	8 354.75	1.48	110.74	624.92	3 041.45	76 030.63	70	1 945.88	3 943.93	0.46	77.86	574.42	1 878.70	25 649.97
Balance sheet items																
Total Assets	153	4 778.27	20 536.29	0.08	127.92	633.60	2 320.00	235 968.00	57	2 017.29	3 294.20	3.04	140.78	639.00	2 009.40	15 205.00
Total Liabilites	153	2 753.05	11 611.61	0.16	61.49	390.30	1 242.74	133 855.00	57	1 176.62	1 847.22	0.10	76.31	245.73	1 466.30	9 213.00
Income statement items																
Revenue	153	4 277.63	20 036.49	0.00	96.62	582.30	2 075.10	239 272.00	57	1 499.75	2 310.15	0.00	81.50	542.00	1 889.80	10 140.00
EBIT	153	470.60	2 006.60	-1 298.70	4.89	47.40	201.70	22 004.00	57	138.74	225.23	-202.81	5.33	50.77	182.20	1 039.00
Net Income	151	284.95	1 476.14	-1 188.90	-0.84	15.10	148.10	16 576.00	57	64.41	143.13	-400.50	0.39	21.80	84.60	531.00
Ratios																
Return on Assets	150	-3.26%	34.60%	-295.07%	-1.60%	4.59%	7.50%	33.43%	57	-5.07%	48.68%	-359.11%	0.76%	3.81%	5.11%	23.47%
Return on Equity	143	-3.90%	103.23%	-765.16%	-1.09%	10.52%	19.10%	427.02%	53	0.46%	30.07%	-166.02%	2.15%	8.98%	13.38%	42.50%
Sales growth	142	15.30%	76.49%	-98.85%	-0.80%	6.86%	18.96%	849.87%	54	28.87%	82.02%	-37.77%	-1.89%	5.42%	13.85%	438.16%
Log of sales growth	120	10.51%	26.61%	-161.39%	1.00%	9.25%	18.69%	159.59%	39	9.41%	16.48%	-41.13%	1.51%	7.28%	14.88%	59.44%
Solvency	153	0.38	0.38	-2.91	0.27	0.41	0.53	0.99	57	0.44	0.24	-0.44	0.30	0.47	0.58	0.97
Leverage	153	2.57	12.93	-69.24	0.85	1.36	2.34	137.57	57	3.25	14.19	-23.69	0.65	1.14	2.12	99.99
Current Ratio	153	2.24	5.13	0.21	0.93	1.22	1.72	53.59	57	1.59	1.62	0.17	0.85	1.13	1.59	9.27
Interest Coverage	144	9.06	84.14	-649.50	2.06	4.68	9.28	561.29	54	-0.49	56.25	-368.71	2.00	3.80	5.79	105.38
Dividend Payout Ratio	112	0.71	3.30	-5.00	0.16	0.38	0.57	32.72	46	0.41	2.66	-13.33	0.23	0.42	0.67	11.46
Price/Earnings	151	14.36	94.79	-350.40	-0.86	10.85	19.10	730.04	57	5.72	74.19	-526.78	6.51	15.39	22.53	90.67
Profit margin	147	-12.91%	103.20%	-624.17%	3.44%	9.12%	16.97%	100.00%	55	-0.75%	52.54%	-302.76%	3.10%	8.21%	14.33%	47.25%
Market-to-Book	153	1.88	4.54	0.01	0.47	0.89	1.51	41.92	57	0.96	0.85	0.02	0.54	0.79	1.06	5.59
Asset Turnover	153	1.13	1.15	0.00	0.47	0.89	1.58	10.90	57	1.05	0.87	0.00	0.41	0.79	1.41	3.44
Bankruptcy likelihood																
Altman Z-score	153	4.42	28.99	-160.29	1.57	2.67	3.93	284.56	57	3.48	8.83	-11.37	1.64	2.45	3.51	66.28
Zimjewskij probability	151	31.41%	25.57%	0.19%	11.95%	22.90%	44.95%	100.00%	57	28.15%	24.96%	3.19%	9.27%	20.54%	37.93%	100.00%
Ohlson probability	145	65.38%	28.44%	1.16%	46.07%	75.22%	89.14%	100.00%	56	67.55%	25.10%	5.78%	50.61%	74.84%	85.86%	100.00%
Betas and alphas																
Market Beta	194	0.871	0.933	-0.895	0.447	0.814	1.083	10.676	69	0.666	1.470	-2.602	0.214	0.605	0.997	10.253
Alpha	194	-0.001	0.010	-0.030	-0.002	0.000	0.002	0.107	69	-0.005	0.033	-0.271	-0.004	-0.001	0.001	0.020

Ratio calculations: Return on Assets: $\frac{\text{Net Income}}{\text{Total Assets}}$; Return on Equity: $\frac{\text{Net Income}}{\text{Total Equity}}$; Sales Growth: $\frac{\text{Rumor Year Sales}}{\text{Previous Year Sales}}$; Log of Sales Growth: $\frac{1}{3} * \ln(\frac{\text{Rumor Year Sales}}{\text{3Y Before Rumor Sales}})$; Solvency: $\frac{\text{Total Equity}}{\text{Total Assets}}$; Leverage: $\frac{\text{Total Liabilities}}{\text{Total Equity}}$; Current Ratio: $\frac{\text{Total Current Assets}}{\text{Total Current Liabilities}}$

Interest Coverage: $\frac{\text{EBIT}}{\text{Interest Expenses}}$; Dividend Payout Ratio: $\frac{\text{EBIT}}{\text{Interest Expenses}}$; Price/Earnings: $\frac{\text{Market Capitalization}}{\text{Net Income}}$; Profit Margin: $\frac{\text{EBIT}}{\text{Total Sales}}$; Market-to-Book: $\frac{\text{Market Capitalization}}{\text{Total Assets}}$; Asset Turnover: $\frac{\text{Total Sales}}{\text{Total Assets}}$

Table A4. Descriptive accounting data for the rumored firms divided on the veracity of the rumor for the U.S. Bloomberg dataset

This table provides an overview of the characteristics of the falsely rumored firms and the ones that were eventually taken over in. Some items are shown as they appear in the annual reports while others are used to calculate ratios or measurements of bankruptcy. Betas and alphas are calculating using the three-factor model. All book values and the market capitalization are expressed in GBP.

	Rumor and no acquisition								Rumor and acquisiton							
Variables	Obs.	Mean	SD	Min	1st Q	Median	3rd Q	Max	Obs.	Mean	SD	Min	1st Q	Median	3rd Q	Max
Market Cap	1285	7 509.78	27 786.85	41.10	1 246.98	3 142.32	7 562.71	858 353.10	235	3 532.82	6 531.56	18.20	910.74	2 191.31	4 105.63	79 956.04
Balance sheet items																
Total Assets	1285	12 507.17	74 466.56	8.46	705.08	2 460.20	7 239.00	2 364 452.00	227	9 886.22	73 779.68	26.51	498.26	1 304.31	2 953.20	782 896.00
Total Liabilites	1285	9 708.30	69 951.90	0.98	231.85	1 139.08	3 959.30	2 228 791.00	218	8 452.09	67 629.11	4.28	179.67	747.47	1 485.47	702 689.00
Income statement																
Revenue	1285	4 629.40	7 679.83	-288.95	455.70	1 614.09	5 577.60	89 328.00	227	2 730.69	7 461.70	3.10	193.09	774.00	1 974.55	55 528.00
EBIT	1281	496.05	1 396.97	-8 851.00	15.93	146.80	658.50	30 156.35	227	317.53	1 225.76	-461.04	0.14	76.01	318.76	12 531.00
Net Income	1285	187.82	800.93	-6 453.29	-6.84	76.67	328.00	7 438.00	227	170.92	713.99	-732.19	-7.20	46.78	206.00	6 312.00
Ratios																
Return on Assets	1285	1.07%	19.52%	-156.89%	-0.43%	4.41%	8.96%	52.45%	227	-1.86%	27.09%	-138.33%	-0.81%	4.15%	8.57%	43.13%
Return on Equity	1238	4.20%	43.92%	-349.39%	-0.93%	8.80%	18.55%	292.98%	200	6.19%	50.12%	-320.12%	1.21%	8.31%	22.45%	200.25%
Sales growth	1275	16.34%	50.29%	-230.71%	-5.64%	8.94%	29.19%	722.27%	226	40.37%	95.13%	-63.26%	1.59%	12.28%	37.82%	514.26%
Log of sales growth	1240	16.38%	29.10%	-153.19%	1.79%	11.78%	28.40%	197.31%	219	23.15%	28.59%	-25.44%	6.63%	18.25%	33.47%	204.27%
Solvency	1285	0.48	0.28	-1.84	0.32	0.50	0.70	0.96	218	0.46	0.29	-0.48	0.29	0.51	0.69	0.97
Leverage	1285	1.07	17.91	-592.56	0.39	0.91	1.84	50.84	218	1.11	3.68	-15.13	0.36	0.84	1.50	17.56
Current Ratio	1177	3.00	2.95	0.21	1.34	2.16	3.53	42.01	210	3.24	2.78	0.50	1.84	2.54	3.79	19.14
Interest Coverage	1032	29.39	113.62	-932.20	1.10	5.48	19.26	998.59	182	23.87	69.19	-248.80	0.12	7.59	49.06	350.13
Dividend Payout Ratio	1283	0.04	2.16	-52.20	0.00	0.00	0.10	9.65	227	0.06	0.28	-1.78	0.00	0.00	0.02	3.14
Price/Earnings	1285	60.65	729.95	-3 169.09	-2.44	14.99	29.87	12 504.52	227	40.75	216.97	-1 178.11	-1.56	14.58	33.61	1 364.63
Profit margin	1244	5.44%	56.71%	-669.28%	3.67%	10.62%	20.25%	517.40%	225	-20.96%	124.40%	-757.06%	1.16%	7.82%	19.04%	74.51%
Market-to-Book	1285	2.91	21.23	0.01	0.69	1.48	2.87	744.26	227	2.39	2.44	0.03	0.95	1.64	3.05	17.17
Asset Turnover	1285	0.83	0.66	-0.01	0.40	0.63	1.12	4.05	227	0.88	0.96	0.06	0.37	0.63	0.96	6.73
Bankruptcy																
Altman Z-score	1177	8.02	34.48	-28.83	2.25	4.03	6.84	999.63	201	5.28	10.12	-6.69	1.89	3.33	6.67	95.86
Zimjewskij probability	1177	23.02%	23.41%	0.40%	4.88%	15.53%	33.33%	100.00%	201	25.68%	29.87%	0.75%	5.25%	14.53%	32.60%	99.94%
Ohlson probability	1176	47.96%	27.58%	0.57%	22.22%	47.81%	71.40%	100.00%	201	47.92%	28.55%	0.81%	22.67%	44.86%	71.30%	99.45%
Betas and alphas																
Market Beta	1285	1.151	0.706	-5.505	0.815	1.134	1.470	9.273	235	1.137	0.724	-3.274	0.727	1.115	1.529	3.549
Beta SMB	1285	0.479	0.993	-7.249	-0.077	0.389	0.926	10.551	235	0.565	1.094	-2.388	-0.051	0.454	1.074	7.765
Beta HML	1285	-0.094	1.417	-11.069	-0.740	-0.131	0.598	7.246	235	-0.110	1.342	-4.141	-0.817	-0.181	0.454	5.293

Ratio calculations: Return on Assets: $\frac{\text{Net Income}}{\text{Total Assets}}$; Return on Equity: $\frac{\text{Net Income}}{\text{Total Equity}}$; Sales Growth: $\frac{\text{Rumor Year Sales}}{\text{Previous Year Sales}}$; Log of Sales Growth: $\frac{1}{3} * \ln(\frac{\text{Rumor Year Sales}}{\text{3Y Before Rumor Sales}})$; Solvency: $\frac{\text{Total Equity}}{\text{Total Assets}}$; Leverage: $\frac{\text{Total Liabilities}}{\text{Total Equity}}$; Current Ratio: $\frac{\text{Total Current Assets}}{\text{Total Current Liabilities}}$

Interest Coverage: $\frac{\text{EBIT}}{\text{Interest Expenses}}$; Dividend Payout Ratio: $\frac{\text{EBIT}}{\text{Interest Expenses}}$; Price/Earnings: $\frac{\text{Market Capitalization}}{\text{Net Income}}$; Profit Margin: $\frac{\text{EBIT}}{\text{Total Sales}}$; Market-to-Book: $\frac{\text{Market Capitalization}}{\text{Total Assets}}$; Asset Turnover: $\frac{\text{Total Sales}}{\text{Total Assets}}$

Table A5. False rumors in the U.S. main dataset

Target Name	Rumor date	CAR(-1;1)	HPR (1;365)	Market Cap (M$)
99 Cents Only Store	June 30, 2005	-5.14%	-17.70%	827.7172
Adobe Systems Inc.	October 7, 2010	4.59%	-11.89%	14800.32
Akamai Technologies Inc.	October 12, 2011	4.09%	62.13%	4452.108
All-American Sportpark Inc.	April 24, 2002	-25.80%	18.18%	0.1216643
Allegheny Technologies Inc.	April 4, 2008	8.57%	-68.90%	7708.139
America First Apartment Investors Inc.	April 12, 2007	-0.59%	14.67%	232.7726
Ameristar Casinos Inc.	October 22, 2007	16.40%	-76.79%	1661.223
Asiainfo Holdings Inc.	February 3, 2003	13.51%	63.66%	216.1471
Bally Technologies Inc.	February 22, 2007	6.24%	89.35%	1123.451
Bally Total Fitness Holding Corporation	January 27, 2003	5.51%	-7.47%	225.9763
Bj's Wholesale Club Inc.	April 11, 2003	8.37%	79.28%	933.9271
Bmb Munai Inc.	September 9, 2005	6.43%	-26.95%	207.1705
Boise Cascade Corporation	November 10, 2003	1.64%	8.25%	2070.856
Boyd Gaming Corporation	November 22, 2006	1.94%	-15.36%	3716.683
Brink's Company, The	November 22, 2006	0.67%	5.35%	2737.898
Bristol-Myers Squibb Company	April 1, 2002	-4.65%	-45.92%	73393.02
Bristol-Myers Squibb Company	March 22, 2006	10.90%	10.10%	46593.59
Brocade Communications Systems Inc.	October 5, 2009	10.36%	-36.63%	3412.342
Cabg Medical Inc.	February 9, 2006	-5.58%	20.33%	23.21118
Cadence Design Systems Inc.	June 4, 2007	5.44%	-53.63%	6211.558
Cal-Maine Foods Inc.	July 14, 2003	10.89%	143.83%	64.69117
Cambridge Heart Inc.	October 19, 2007	-5.99%	-86.81%	157.8348
Capital One Financial Corporation	November 25, 2002	7.44%	74.05%	7125.485
Capital Senior Living Corporation	March 24, 2008	-2.37%	-70.02%	211.4895
Capitalsource Inc.	January 5, 2011	6.61%	-9.00%	2335.473
Cboe Holdings Inc.	February 9, 2011	10.34%	3.76%	1107.945
Cedar Fair Lp	July 2, 2007	0.81%	-36.60%	1526.724
Cedar Shopping Centers Inc.	January 23, 2008	5.13%	-43.95%	490.1977
Charles & Colvard Ltd	March 4, 2008	8.05%	-76.56%	26.1897
Charles River Laboratories International Inc.	December 9, 2010	3.75%	-20.45%	2060.866
Children's Place Retail Stores Inc, The	October 12, 2007	3.51%	33.24%	759.1672
Ciphergen Biosystems Inc.	November 2, 2001	14.47%	-39.36%	119.286
Cit Group Inc.	September 25, 2012	5.11%	7.57%	7734.171
Citizens Communications Company	April 28, 2004	0.92%	-0.31%	3690.385
Cleco Corporation	September 28, 2005	3.14%	11.62%	1120.048
Cleveland-Cliffs Inc.	May 14, 2007	2.60%	150.62%	3027.086
Cnet Networks Inc.	May 11, 2001	11.22%	-76.55%	1345.519
Coinstar Inc.	August 16, 2012	7.60%	12.61%	1695.717
Colgate-Palmolive Company	November 18, 2009	2.51%	-8.92%	40248.06
Comerica Inc.	June 23, 2003	0.33%	18.34%	8167.474
Commercial Metals Company	July 31, 2006	2.01%	35.92%	2682.92
Compass Minerals International Inc.	March 3, 2009	14.57%	33.72%	1814.84
Comtech Telecommunications Corporation	October 5, 2011	4.75%	-1.42%	721.1029
Comverse Technology Inc.	July 10, 2007	5.02%	-23.74%	4147.75
Consolidated Freightways Corporation	December 11, 2002	17.33%	-50.48%	0.2941695
Cooper Tire & Rubber Company	October 11, 2012	4.27%	29.73%	1345.401
Cousins Properties Inc.	September 7, 2007	2.67%	-9.30%	1442.824
Cullen/Frost Bankers Inc.	March 18, 2003	-3.19%	40.33%	1600.574
Curagen Corporation	July 11, 2005	-0.22%	-45.53%	256.3229
Cv Therapeutics Inc.	June 19, 2007	12.92%	-38.73%	634.5278
Cysive Inc.	May 13, 2003	13.63%	12.98%	83.17525
Da Consulting Group Inc	May 16, 2003	-6.10%	-97.27%	1.642707
Devon Energy Corporation	April 5, 2007	1.81%	49.33%	31536.29
Diamond Foods Inc.	October 9, 2007	3.64%	37.45%	304.1201
Dick's Sporting Goods Inc.	December 17, 2010	2.99%	-4.02%	3153.071
Dillard's Inc.	May 31, 2005	-1.44%	13.80%	1931.282
Dish Network Corporation	January 11, 2012	-0.91%	28.70%	5762.471
Dish Network Corporation	October 18, 2007	-2.57%	-69.03%	9205.226
Dow Chemical Company, The	February 26, 2007	4.10%	-13.31%	41451.65
E*Trade Financial Corporation	July 20, 2011	17.71%	-46.88%	3712.02
Earthlink Inc.	August 6, 2007	-8.83%	41.42%	917.7663
Eastman Kodak Company	July 14, 2005	4.17%	-22.86%	7626.689
Ebay Inc.	May 26, 2006	9.68%	-4.53%	45330.13
Edgar Online Inc.	November 11, 2002	14.04%	-1.51%	27.05318
Electronic Arts Inc.	August 25, 2004	1.01%	11.42%	14876.06
Eli Lilly And Company	July 22, 2002	0.77%	35.35%	64009.61
Emc Corporation	June 2, 2011	2.01%	-18.27%	55959.25
Endologix Inc.	September 29, 2006	-1.67%	-1.75%	164.5266
Entertainment Distribution Company Inc.(Old)	May 3, 2007	7.67%	-77.72%	148.0772
EstE Lauder Companies Inc.	September 21, 2007	3.27%	19.68%	4845.849
Euronet Worldwide Inc.	September 10, 2007	1.60%	-31.47%	1371.494
Euroweb International Corporation	April 3, 2002	-1.02%	-31.48%	10.64495
Exelixis Inc.	April 12, 2011	7.30%	-56.05%	1367.934
Expedia Inc.	June 15, 2007	3.14%	-15.49%	7282.587
Extreme Networks Inc.	March 20, 2006	2.22%	-18.34%	581.3388
Exxon Mobil Corporation	October 31, 2005	-1.31%	27.22%	371547.4
Fair Isaac Corporation	July 6, 2007	0.20%	-51.85%	2132.241
Falconstor Software Inc.	April 11, 2007	0.27%	-34.56%	529.8777
Federal-Mogul Corporation	March 7, 2011	8.11%	-34.28%	2339.88
Fifth Third Bancorp	March 6, 2008	0.49%	-94.06%	12362.22
First Community Bancorp Inc. (California)	September 10, 2007	1.71%	-43.64%	1546.672
Fountain Powerboat Industries Inc.	June 11, 2009	15.30%	-68.75%	0.4116991
Freeport-Mcmoran Copper & Gold Inc.	June 27, 2007	0.14%	40.93%	31259.44
Gap Inc.	January 6, 2006	-0.96%	7.27%	15609.56
General Mills Inc.	June 4, 2004	4.41%	5.73%	17612.87
Genzyme Corporation	November 15, 2007	0.92%	-5.08%	19057.7
Georgia Gulf Corporation	December 20, 2006	1.52%	-65.53%	706.9996
Gramercy Capital Corporation	September 14, 2011	-0.71%	-22.85%	147.2048
Granite City Food & Brewery Ltd	January 23, 2009	18.85%	-	5.083861
Greenbrier Companies Inc., The	February 4, 2008	30.75%	-76.61%	385.873
Harley Davidson Inc.	June 22, 2007	5.58%	-40.46%	15505.8
Health Net Inc.	July 7, 2005	3.54%	15.03%	4336.829
Herley Industries Inc.	September 2, 2008	4.22%	-38.12%	215.555
Hershey Company, The	April 14, 2008	0.18%	-1.71%	6206.004
Hollywood Casino Corporation	March 18, 2002	-2.26%	-20.25%	357.4806
Home Depot Inc., The	December 1, 2006	4.25%	-26.71%	78873.28
Honeywell International Inc.	May 6, 2005	4.07%	19.73%	31463.71
Hudson United Bancorp	August 5, 2003	10.42%	-10.13%	1621.655
Humana Inc.	July 7, 2005	3.26%	31.31%	6573.905
Huntington Bancshares Inc.	April 26, 2005	1.96%	1.03%	5461.896
Impax Laboratories Inc.	January 6, 2005	12.47%	-39.26%	908.4077
Independence Federal Savings Bank	May 28, 2003	-3.27%	20.26%	24.08214
Instinet Group Inc.	April 2, 2002	9.18%	-45.06%	1784.564
International Coal Group Inc.	December 6, 2006	8.71%	-2.08%	763.969

Table A5 continued. False rumors in the U.S. main dataset

Target Name	Rumor date	CAR(-1;1)	HPR (1;365)	Market Cap (M$)
Interplay Entertainment Corporation	May 29, 2001	-9.12%	-86.49%	76.89841
Jc Penney Company Inc.	March 31, 2005	6.35%	16.35%	13117.53
Jds Uniphase Corporation	January 20, 2004	0.70%	-53.93%	5913.879
Jefferies Group Inc.	April 18, 2007	1.49%	-51.32%	3593.31
Jetblue Airways Corporation	July 10, 2012	5.31%	22.99%	1448.721
Jo-Ann Stores Inc.	May 31, 2007	6.73%	-33.44%	718.5946
Jones Lang Lasalle Inc.	February 26, 2007	-0.92%	-23.39%	3747
Journal Register Company	June 19, 2008	5.35%	-97.50%	6.483086
Juniper Networks Inc.	August 18, 2006	0.51%	126.16%	8526.784
Keycorp	June 23, 2003	-0.55%	18.18%	10971.94
Krispy Kreme Doughnuts Inc.	October 4, 2004	2.36%	-51.03%	745.699
Laboratory Corporation Of America Holdings	July 31, 2012	4.28%	7.27%	8558.503
Leap Wireless International Inc.	February 1, 2010	12.24%	-4.34%	1203.52
Leap Wireless International Inc.	May 11, 2012	0.68%	1.99%	542.5701
Ligand Pharmaceuticals Inc.	September 23, 2005	10.81%	26.53%	612.8892
Lighting Science Group Corporation	October 27, 2010	-1.39%	13.60%	131.1354
Local.Com Corporation	July 2, 2007	25.22%	-59.93%	60.63439
Longs Drug Stores Corporation	May 19, 2003	-1.57%	36.06%	601.1633
M&T Bank Corporation	May 19, 2010	-4.55%	6.93%	10057.28
Macromedia Inc.	December 26, 2002	-3.21%	56.79%	751.7538
Magna-Lab Inc.	March 17, 2003	-7.58%	6.25%	0.8686644
Marriott International Inc.	October 16, 2007	1.41%	-57.76%	14946.64
Marsh & Mclennan Companies Inc.	July 8, 2005	3.88%	-9.32%	15176.46
Mcclatchy Company, The	December 14, 2007	-1.10%	-83.33%	767.3744
Mccormick & Schmicks Seafood Restaurants Inc.	January 2, 2008	5.37%	-67.37%	197.6478
Meristar Hospitality Corporation	June 19, 2002	-0.62%	-65.80%	663.1859
Midway Games Inc.	June 9, 2004	-0.96%	-14.66%	707.4907
Monster Beverage Corporation	April 30, 2012	2.36%	-26.55%	11721.35
Monster Worldwide Inc.	January 6, 2006	5.06%	8.68%	5107.349
Morgan Stanley	March 31, 2005	5.48%	9.73%	60277.12
Morgans Hotel Group Company	August 13, 2008	-2.22%	-70.33%	418.6651
Motorola Mobility Holdings Inc.	April 10, 2012	1.07%	1.55%	11709.9
Mpg Office Trust Inc.	August 21, 2012	9.93%	-15.38%	164.6775
Nanometrics Inc.	August 17, 2010	7.32%	22.65%	263.5624
Nasdaq Omx Group Inc., The	February 23, 2011	-0.06%	-6.21%	4908.56
Nbty Inc.	March 28, 2007	2.69%	-42.12%	3421.245
Net Perceptions Inc.	February 24, 2003	0.08%	-72.26%	38.21073
New York Community Bancorp Inc.	May 18, 2004	-4.75%	-19.40%	6565.139
New York Times Company, The	October 19, 2006	-3.43%	-20.05%	3343.193
New York Times Company, The	May 12, 2009	11.43%	37.77%	801.9557
Newmont Mining Corporation	March 19, 2007	0.33%	17.69%	18442.45
Nitromed Inc.	March 22, 2006	6.70%	-60.74%	315.3832
North Coast Energy Inc.	February 14, 2003	2.16%	115.86%	77.41266
Nui Corporation	October 28, 2003	-1.41%	-20.76%	261.7609
Nyse Euronext Inc.	December 8, 2008	20.42%	-6.94%	6614.749
Officemax Inc.	October 26, 2005	-3.39%	74.95%	2083.497
Optical Communication Products Inc.	September 29, 2003	2.22%	-19.07%	117.0242
Optionsxpress Holdings Inc.	May 21, 2007	7.05%	-9.26%	1579.728
Overseas Shipholding Group Inc.	March 25, 2008	-0.62%	-64.05%	2168.522
Palm Inc.	November 8, 2005	6.41%	-42.83%	1455.535
Par Pharmaceutical Companies Inc.	September 18, 2007	7.93%	-37.60%	729.8829
Parametric Technology Corporation	September 10, 2008	-4.39%	-32.28%	2039.829
Peabody Energy Corporation	September 7, 2007	6.24%	18.16%	12457.75
Pegasus Communications Corporation	May 20, 2003	-16.70%	-51.02%	120.8541
Pennichuck Corporation	February 6, 2003	-5.27%	20.30%	58.63942
Pennsylvania Real Estate Investment Trust	May 30, 2007	6.78%	-43.04%	1667.452
Pep Boys - Manny, Moe And Jack, The	January 21, 2011	16.47%	-19.58%	692.7322
Pioneer Railcorp	February 4, 2005	3.84%	-9.52%	13.59446
Plains Exploration & Production Company Lp	September 21, 2010	-2.83%	0.27%	3643.589
Planet Hollywood International Inc.	December 20, 2001	-11.65%	83.33%	0.24644
Playboy Enterprises Inc.	July 24, 2007	1.45%	-56.15%	312.5903
Pnc Financial Services Group Inc., The	June 23, 2003	0.01%	11.95%	13519.62
Polaris Industries Inc.	October 4, 2007	8.04%	-14.74%	1676.567
Polycom Inc.	March 17, 2010	2.48%	47.80%	2410.148
Pricesmart Inc.	June 20, 2005	0.38%	34.63%	190.8445
Pride International Inc.	April 23, 2008	6.26%	-48.55%	6761.249
Primedia Inc.	October 24, 2005	-44.73%	-43.61%	763.8406
Protalix Biotherapeutics Inc.	November 2, 2009	9.92%	-4.12%	664.8285
Publix Super Markets Inc.	January 7, 2002	0.07%	-36.36%	10334.01
Quest Diagnostics Inc.	July 5, 2007	8.73%	-12.25%	10141.44
Quest Software Inc.	March 12, 2003	2.53%	65.89%	928.6266
Quicksilver Resources Inc.	July 19, 2010	16.70%	10.60%	2087.566
Quicksilver Resources Inc.	May 6, 2004	-7.31%	16.40%	1178.474
Rackable Systems Inc.	April 11, 2007	3.60%	-30.50%	418.0634
Radioshack Corporation	March 26, 2010	6.80%	-39.53%	2665.941
Radioshack Corporation	May 14, 2007	3.46%	-51.12%	4156.162
Rambus Inc.	September 12, 2007	9.70%	-7.60%	1784.35
Ramco-Gershenson Properties Trust	April 7, 2008	3.17%	-67.73%	412.4045
Resmed Inc.	June 30, 2008	9.50%	13.96%	3061.929
Rockwood Holdings Inc.	March 7, 2008	5.83%	-85.27%	2381.097
Rpc Inc.	August 8, 2011	12.35%	-28.60%	3378.956
Saks Inc.	August 30, 2010	15.38%	47.88%	1364.691
Saks Inc.	October 16, 2007	11.81%	-72.90%	2651.849
Salesforce.Com Inc.	February 11, 2008	4.06%	-51.00%	6793.792
Sangamo Biosciences Inc.	November 22, 2006	13.00%	67.15%	207.6969
Santarus Inc.	July 2, 2007	5.92%	-63.59%	252.765
Sara Lee Corporation	October 4, 2006	1.78%	1.78%	12395.53
Scientific Atlanta Llc	December 19, 2005	0.50%	-0.37%	6357.854
Sherwin-Williams Company, The	September 26, 2007	2.73%	-9.37%	8512.926
Siebel Systems Inc.	March 31, 2005	9.96%	16.21%	4587.599
Siebel Systems Inc.	July 15, 2003	-3.57%	-21.38%	4841.158
Signature Bank	March 15, 2005	-10.36%	31.57%	817.3923
Skechers Usa Inc.	May 21, 2007	4.35%	-33.42%	1026.485
Smithfield Foods Inc.	June 29, 2010	3.16%	45.89%	2640.729
Sonicblue Inc.	January 17, 2003	-20.04%	-99.56%	45.22466
Sonus Networks Inc.	July 20, 2007	3.73%	-60.10%	1892.055
Southern Union Company Inc.	July 24, 2006	-2.54%	21.84%	2950.576
Spark Networks Inc.	January 4, 2008	12.59%	-52.78%	126.5971
Sprint Nextel Corporation	November 10, 2006	3.88%	-19.93%	52489.19
St Jude Medical Inc.	January 27, 2006	-1.90%	-17.90%	17928.54
Staples Inc.	September 13, 2012	5.63%	12.21%	8081.014
Starwood Hotels & Resorts Worldwide Inc.	January 2, 2009	12.66%	75.82%	2915.87
Starwood Hotels & Resorts Worldwide Inc.	November 29, 2006	0.42%	-17.85%	13251.65
Steel Dynamics Inc.	July 31, 2006	0.36%	-27.73%	2729.219

Table A5 continued. False rumors in the U.S. main dataset

Target Name	Rumor date	CAR(-1;1)	HPR (1;365)	Market Cap (M$)
Stillwater Mining Company	April 7, 2010	4.02%	56.61%	1347.312
Strategic Hotels & Resorts Inc.	March 9, 2007	8.65%	-39.05%	1645.63
Student Loan Corporation, The	December 28, 2007	2.12%	-68.45%	2495.395
Sun Microsystems Inc.	May 12, 2003	6.60%	-10.93%	13164.13
Sunoco Inc.	October 15, 2008	-12.63%	22.66%	4102.687
Suntrust Banks Inc.	August 6, 2007	4.64%	-43.38%	28806.78
Synovus Financial Corporation	February 23, 2011	-3.64%	-20.00%	2082.122
Take Two Interactive Software Inc.	March 19, 2007	10.73%	11.81%	1429.898
Teco Energy Inc.	April 12, 2002	0.50%	-60.29%	3714.397
Tellabs Inc.	July 20, 2007	2.29%	-61.69%	4759.812
Textron Inc.	April 9, 2009	31.61%	62.91%	2215.653
Tibco Software Inc.	June 25, 2008	4.77%	-9.45%	1443.763
Tiffany & Company International Inc.	June 25, 2007	5.60%	-17.70%	6832.384
Timberland Company Inc., The	November 15, 2006	1.30%	-47.63%	1552.34
Tivo Inc.	February 23, 2005	13.80%	27.63%	387.4873
Todhunter International Inc.	March 19, 2003	22.59%	58.67%	50.68347
Transmeta Corporation	February 7, 2005	4.69%	8.53%	226.5834
Travelzoo Inc.	May 12, 2005	2.20%	15.41%	578.8992
Travelzoo Inc.	September 9, 2011	-1.23%	-27.66%	648.4885
Travelzoo Inc.	April 11, 2012	24.33%	-21.03%	388.0479
True Religion Apparel Inc.	October 10, 2012	18.95%	1.56%	616.4705
Tyson Foods Inc.	June 21, 2007	0.48%	-38.21%	6266.676
Unisys Corporation	February 16, 2001	7.40%	-36.81%	4914.448
United Bancshares Inc.	May 30, 2002	0.79%	17.11%	44.63625
United Industrial Corporation	January 31, 2002	7.82%	-20.80%	233.582
United States Cellular Corporation	September 13, 2011	-1.23%	-3.18%	2132.667
Unumprovident Corporation	October 16, 2006	-3.70%	15.05%	6800.871
Us 1 Industries Inc.	September 15, 2010	20.49%	35.00%	15.03491
Us Bancorp	June 23, 2003	0.21%	17.92%	45935.8
Valassis Communications Inc.	June 27, 2006	-10.82%	-26.59%	1161.617
Valueclick Inc.	January 5, 2011	-0.04%	1.53%	1244.97
Valueclick Inc.	June 14, 2007	-0.59%	-39.60%	2840.617
Valuevision Media Inc.	November 26, 2008	10.16%	-	21.7552
Verint Systems Inc.	August 22, 2007	-10.70%	-13.84%	953.8877
Verint Systems Inc.	November 20, 2006	5.07%	-40.04%	1064.596
Verizon Communications Inc.	July 16, 2007	1.74%	-18.05%	122556.4
Vitacost.Com Inc.	May 26, 2010	5.64%	-43.40%	276.6812
Vsi Holdings Inc.	February 25, 2002	1.06%	-90.00%	19.69732
Websense Inc.	March 17, 2011	9.05%	-7.81%	906.1583
Wellcare Management Group Inc., The	May 17, 2002	24.34%	0.00%	8.002338
Wendy's/Arby's Group Inc.	June 10, 2010	10.23%	4.15%	1975.531
Whole Foods Market Inc.	August 17, 2011	4.89%	54.63%	11331.44
Wr Grace & Company	July 30, 2008	8.10%	-32.50%	1723.122
Zimmer Holdings Inc.	July 17, 2007	3.99%	-19.96%	19678.79
Zonagen Inc.	March 17, 2006	0.19%	2.98%	89.55711

Table A6. True rumors in the U.S. main dataset

Target Name	Rumor date	CAR(-1;1)	HPR (1;365)	Market Cap (M$)
24/7 Real Media Inc.	April 25, 2007	19.48%	38.84%	529.7132
7-Eleven Inc.	February 22, 2005	-0.75%	53.69%	3261.596
Abgenix Inc.	November 29, 2005	4.54%	71.36%	1473.393
Accredited Home Lenders Holding Company	April 3, 2007	2.18%	38.68%	318.0284
American Community Bancshares Inc.	September 6, 2007	6.27%	-41.38%	69.24164
Amerus Group Company	January 11, 2006	-1.15%	10.88%	2351.761
Aviat Networks Inc.'S Wimax Business	May 5, 2011	-4.94%	-42.68%	232.6627
Bj's Wholesale Club Inc.	November 10, 2010	9.80%	21.91%	2572.945
Blockbuster Inc.	September 19, 2003	2.22%	-64.47%	605.1014
Burlington Industries Inc.	March 6, 2003	45.71%	-77.50%	1.309659
Catalina Marketing Corporation	December 8, 2006	18.12%	34.01%	1372.061
China Security And Surveillance Technology Inc.	January 28, 2011	6.92%	31.15%	434.7623
Collateral Therapeutics Inc.	March 1, 2002	3.44%	139.87%	102.3452
Commerce Bancorp Inc.	June 29, 2007	10.66%	3.52%	7024.566
Compellent Technologies Inc.	October 26, 2010	34.01%	56.16%	754.3556
Concord Efs Inc.	March 10, 2003	-21.41%	44.15%	6391.829
Continental Airlines Inc.	April 15, 2010	0.68%	6.84%	3015.974
Countrywide Financial Corporation (Old)	January 26, 2007	3.47%	-85.06%	17014.09
Crown American Realty Trust	March 19, 2003	1.63%	28.95%	320.4267
Csk Auto Corporation	February 1, 2008	42.49%	81.18%	396.9593
Deltek Inc.	July 18, 2012	13.42%	5.44%	848.3578
Dobson Communications Corporation	June 25, 2007	7.85%	28.25%	1715.528
Double-Take Software Inc.	April 12, 2010	16.92%	21.13%	209.3054
Drs Technologies Inc.	May 8, 2008	17.71%	26.06%	2861.313
Efunds Corporation	May 9, 2007	9.88%	28.04%	1527.757
Encysive Pharmaceuticals Inc.	June 26, 2007	-10.09%	24.34%	159.8668
Equity Inns Inc.	June 6, 2007	9.90%	10.41%	1109.252
Genentech Inc.	July 21, 2008	12.78%	16.07%	90695.58
Grey Global Group Inc.	June 28, 2004	5.48%	12.30%	1042.935
Guitar Center Inc.	May 31, 2007	-1.27%	17.51%	1558.586
Heelys Inc.	October 23, 2012	20.58%	21.62%	56.50957
Heritage Property Investment Trust Inc.	September 15, 2005	1.44%	2.76%	1655.168
Hilton Hotels Corporation	November 22, 2006	5.56%	44.45%	13910.64
Hollywood Casino Corporation	March 18, 2002	-2.26%	-20.20%	316.751
Hughes Communications Inc.	January 20, 2011	30.79%	30.67%	1142.353
Hughes Supply Inc.	December 1, 2005	-2.91%	19.93%	2662.952
Human Genome Sciences Inc.	October 18, 2011	28.94%	26.58%	2344.991
Ivillage Inc.	February 15, 2006	7.70%	10.10%	591.015
J Jill Group Inc.	August 24, 2005	5.27%	36.88%	380.7249
John Hancock Financial Services Inc.	May 16, 2003	-0.33%	55.14%	9048.035
Kinetic Concepts Inc.	July 6, 2011	7.84%	16.49%	4544.383
Kraft Foods Inc.	August 30, 2006	2.74%	-4.75%	15763.84
Legato Systems Inc.	March 3, 2003	4.57%	94.77%	845.0216
Lincare Holdings Inc.	June 27, 2012	24.95%	64.25%	2718.69
Lucent Technologies Inc.	March 24, 2006	8.77%	-9.57%	12549.83
Lyondell Chemical Company	July 12, 2007	3.50%	24.66%	10514.95
Macdermid Inc.	September 18, 2006	1.04%	7.97%	987.5436
Main Street Restaurant Group Inc.	October 12, 2005	9.26%	25.10%	93.36954
Marketwatch Inc.	November 1, 2004	6.81%	35.72%	393.2064
Massey Energy Company	October 18, 2010	6.40%	84.95%	4994.943
May Department Stores Company, The	January 19, 2005	21.60%	23.41%	9621.99
Meadow Valley Corporation	November 20, 2007	-0.28%	-22.55%	57.67405
Medimmune Inc.	December 13, 2006	-3.09%	75.40%	9452.938
Mercury Interactive Corporation	May 1, 2006	7.89%	44.36%	3498.368
Meristar Hospitality Corporation	November 11, 2005	15.17%	20.23%	841.6212
Mgi Pharma Inc.	November 29, 2007	12.67%	41.76%	2828.419
Microislet Inc.	March 1, 2002	-16.28%	-38.46%	20.26605
Millipore Corporation	February 23, 2010	27.61%	22.44%	5020.498
Mips Technologies Inc.	April 12, 2012	19.88%	53.17%	364.6586
Mission Resources Corporation	July 20, 2004	-3.65%	34.72%	256.216
National City Corporation	March 13, 2008	-9.98%	-87.70%	5947.458
Nautica Enterprises Inc.	June 20, 2003	8.90%	41.62%	458.4336
Neuberger Berman Inc.(Old)	June 25, 2003	14.10%	25.91%	2627.812
Nextel Communications Inc.	December 9, 2004	4.10%	19.13%	30601.6
Nextel Partners Inc.	June 27, 2005	-3.62%	6.27%	4876.315
Nicor Inc.	December 2, 2010	-0.15%	27.09%	2197.04
North Coast Energy Inc.	May 22, 2003	5.16%	19.31%	147.4038
Nymex Holdings Inc.	June 15, 2007	4.88%	-37.11%	10481.93
Optical Communication Products Inc.	April 25, 2007	1.66%	9.35%	71.18235
Pactiv Corporation Inc.	May 17, 2010	16.09%	38.63%	3909.882
Pegasus Solutions Inc.	June 30, 2005	3.95%	-10.21%	198.6401
Pharmaceutical Product Development Inc.	July 18, 2011	10.44%	19.31%	3372.397
Pixar Animation Studios Inc.	January 19, 2006	0.72%	18.22%	7002.646
Polymer Group Inc.	April 7, 2010	15.89%	-5.22%	383.2423
Pride International Inc.	November 2, 2010	5.23%	33.14%	6048.77
Protection One Inc.	January 27, 2003	2.84%	-77.24%	113.018
Pulitzer Inc.	December 9, 2004	-0.44%	0.99%	608.7298
Pyr Energy Corporation	January 29, 2007	16.79%	36.17%	42.56527
Ralcorp Holdings Inc.	August 23, 2012	2.82%	31.61%	4126.036
Rawlings Sporting Goods Co. Inc.	December 11, 2002	0.97%	7.58%	63.06609
Remington Oil And Gas Corporation	October 6, 2005	3.99%	19.91%	1119.058
Renaissance Worldwide Inc.	August 28, 2001	6.91%	56.69%	77.17155
Ribapharm Inc.	March 10, 2003	-0.21%	31.16%	820.2964
Riskmetrics Group Inc.	January 22, 2010	13.17%	39.88%	1194.208
Savvis Inc.	March 4, 2011	-1.33%	17.56%	2005.99
Sicor Inc.	October 22, 2003	21.20%	32.28%	2826.763
Simtek Corporation	February 4, 2008	3.24%	41.76%	37.96828
Solar Power Inc.	September 29, 2010	-10.63%	43.48%	22.54592
Sonosite Inc.	November 3, 2011	25.29%	75.47%	585.9553
Stearns & Lehman Inc.	December 20, 2001	45.10%	95.23%	18.44874
Sterling Bancshares Inc.	January 14, 2011	1.41%	3.34%	797.5196
Sun Microsystems Inc.	March 18, 2009	57.30%	90.95%	5271.531
Talbots Inc., The	August 2, 2011	16.19%	-32.92%	202.0084
Ticketmaster Entertainment Inc.	February 4, 2009	18.42%	150.81%	300.808
Timco Aviation Services Inc.	June 30, 2006	49.94%	56.08%	67.1414
Tpc Group Inc.	July 25, 2012	6.40%	34.45%	644.0045
Unocal Corporation	March 3, 2005	11.10%	23.55%	15469.92
Usf Corporation	February 23, 2005	14.44%	38.79%	1157.896
Ust Inc.	September 4, 2008	23.12%	28.53%	8882.869
Wendy's International Inc.	April 25, 2007	13.90%	-17.79%	2896.495
Wfs Financial Inc.	August 23, 2005	14.61%	37.49%	2597.492
Whitehall Jewelers Inc.	September 29, 2005	53.00%	16.18%	30.48585
Williams Pipeline Partners Lp	January 19, 2010	17.60%	36.45%	645.9511
Wilmington Trust Corporation	October 22, 2010	8.22%	-44.86%	595.9098
Zareba Systems Inc.	September 10, 2009	18.39%	127.27%	13.24516