RUMOR HAS IT: SENSATIONALISM IN FINANCIAL MEDIA

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Abstract

The business press has an incentive to publish sensational news. We study how this incentive affects asset prices through one form of media sensationalism – merger rumors. Using a novel dataset, we find that newspapers are more likely to publish merger rumors about firms that interest their readers: local firms with recognizable brands that are owned by retail investors. Yet, rumors about these types of firms are less likely to come true. Instead, a rumor's accuracy is predicted by journalists' experience, education, and expertise, but stock returns do not reflect this information. These results suggest that sensational reporting introduces noise in financial markets that is not easily separated from pertinent information.

The business press plays a leading role in financial markets as a distributor of information. This role is not passive, however, as business newspapers actively compete for readership. To win readers' attention, newspapers have an incentive to publish sensational stories, namely attention-grabbing, speculative news with broad readership appeal. Understanding this incentive is important. Media coverage that is skewed towards sensational stories at the expense of less attention-grabbing news could distort investors' beliefs and impact asset prices.

One of the most sensational news stories in the business press is a merger rumor. These stories attract a broad audience because mergers have a dramatic impact on a wide range of corporate stakeholders. For employees, customers, and rivals, mergers lead to layoffs, discontinued products, and increased competition, in addition to the 15-20% abnormal return realized by investors. Further, rumor articles may attract readers because speculation about secret merger negotiations creates drama and suspense. Rumor articles also provide a way for newspapers to outcompete rivals by being the first to break intriguing news.

To illustrate the sensationalism of merger rumors, consider an article that appeared on the front page of the *Seattle Times* on September 2, 1993, entitled, "Could GE Buy Boeing? It's Speculation Now, But Not Entirely Far-Fetched." The article states,

> *A scenario by which fiercely independent Boeing succumbs to an opportunistic corporate raider has been quietly percolating in certain corners of Wall Street for the past year... GE's ambitious Chairman Jack Welch, 57, has been taking steps to position GE to make a major acquisition... Although he hasn't said so explicitly, Welch appears to covet Boeing.*

A letter to the editor in response to this article that was published a few days later provides insight into how this article was received by readers. The letter states,

> *In my opinion, your paper chose to give this story front-page attention only for the purpose of selling newspapers. Unfortunately, judging by the fact that* The Times *newspaper box outside the gate where I work was empty when I left work (this is the first time I've noticed this occurrence), you succeeded. —J.J. Pruss, Bellevue*

This anecdote illustrates a number of interesting features of merger rumors. First, the article is designed to attract readers. Since Boeing is a major corporate presence in Seattle, a merger with GE would impact a large number of potential subscribers to the *Seattle Times*. In addition, the article is written with provocative language that one might find in a paperback novel, such as 'opportunistic raider,' 'Boeing succumbs,' and 'Welch covets.' Second, as the letter to the editor reveals, though not everyone is convinced that the article was factual, the sensational reporting style was highly successful in selling newspapers. In the end, the rumor never materialized — GE never made a bid for Boeing.

In this paper, we exploit the setting of merger rumors to investigate two main questions. First, which characteristics of media reports predict whether a rumor will come true in the future? And second, which characteristics of media reports are picked up by investors and reflected in the stock market response to the publication of a merger rumor? In particular, do investors fully reflect the characteristics that we show determine accuracy?

To answer these questions, we construct a novel and detailed database of merger rumors. Using a multi-step approach, we search Factiva for news articles that mention keywords related to mergers or rumors. Then we follow the citation trail of the articles backward through time to identify the 'scoop' article that first publishes the rumor. To record accuracy, we match targets to the SDC database of formal merger bids, including foreign and private targets. We classify a rumor as accurate if the rumor target receives an official takeover announcement within one year. While we cannot claim that a specific rumor is false if it doesn't come true, it is reasonable that in a sample of merger rumors, the likelihood that a rumor is false is larger in the set of rumors that don't materialize, compared to the set of rumors that do.[1]

Our sampling procedure yields 2,142 articles published in 105 media outlets about 501 unique merger rumors over the period 2000-2011. To our knowledge, this sample represents the most complete dataset on merger rumors in academic research to date. In particular, because we do not restrict rumor articles to be about mergers with a formal bid, our sample is less susceptible to selection bias. Second, our data include a rich set of details about the articles (e.g., the reported information source, the alleged state of negotiations, etc.) and journalists (e.g., age, education, and expertise). These details allow us to precisely test which type of information is indicative of accuracy and whether stock prices reflect such information.

[1]The news articles in our sample are not deceptive: newspapers clearly identify these stories as rumors. Thus, as long as a rumor is being discussed in some setting, the articles are factually accurate. However, this notion of accuracy is much less relevant to readers than is the notion of accuracy based on the likelihood that a merger materializes in the future.

We first document that newspapers are more likely to cover merger rumors when potential targets are more newsworthy: local, large, public firms with higher valuations, recognizable brands, and greater retail ownership. In particular, 88% of targets in merger rumors are publicly traded, compared to 38% of targets in actual mergers announcements. Using data from league tables of brand values, we find that the odds that a newspaper publishes a rumor about a target with a valuable brand is substantially greater than the odds for a firm without a valuable brand. These results are statistically and economically significant.

Next, to address our two main questions, we develop an empirical model that identifies 1) the characteristics of accurate rumors, and 2) the characteristics that affect stock returns following the rumor. First, we estimate logit regressions of the likelihood of rumor accuracy. Then, we control for the target stock returns on the day the rumor is published. If investors correctly identify the characteristics of accurate rumors, the stock returns should precisely predict accuracy. A characteristic that is not fully reflected in stock prices will continue to predict accuracy even after controlling for the rumor-day stock return. Since some rumors likely circulate among traders before being published in a newspaper, in all of our tests we control for stale information using the run-up in the target's stock price during the week before the scoop article is published.

Of the 501 rumors in our sample, 33% are accurate (i.e., come true within one year). Targets of rumors that eventually come true earn an abnormal return of 6.7% on the rumor date, compared to 3.0% for rumors that don't come true. This implies that returns are informative about the accuracy of the rumor. However, for the average firm, we find a significant and meaningful reversal of -1.4% over the ten days following the rumor. This finding suggests that investors appear to overestimate the accuracy of the average rumor.

To identify the determinants of accuracy, we study four sets of factors: the newsworthiness of the target, characteristics of journalists, details in the text of the article, and attributes of newspapers. First, we find that rumors about newsworthy firms (large firms with valuable brands and high valuations) are significantly less likely to come true. However, investors do not correctly account for this inaccuracy. The predictive power of target size, valuation, and brand recognition is virtually unchanged after accounting for the stock price reaction to the rumor article.

Second, we find that some journalists are substantially more accurate than others, but investors do not fully account for a journalist's accuracy. Even controlling for a target's stock returns following the publication of a rumor, accuracy is still explained by journalist fixed effects. To better understand what drives the journalist fixed effects, we show that accuracy improves if a journalist is older, has an undergraduate degree in journalism, and specializes in the target's industry. These results are consistent with the intuitive explanation that journalists with more experience and more relevant educational backgrounds are better able to assess a rumor's accuracy. However, though these traits help to predict a rumor's accuracy, they are not reflected in stock prices.

Third, we investigate the predictive power of the details provided in the text of the article. Articles with more specific details about the rumor could indicate more accurate reporting. For instance, 39% of articles specifically mention a takeover price and 8% name a non-anonymous source. We find that the large majority of details provided in the article do not help to explain whether a rumor will come true. This implies that additional details of the merger rumor are simply cheap talk. Regardless of the accuracy of the rumor, it is costless for a journalist to include details that give the appearance of accuracy. At the same time, investors seem to recognize this, since these details do not influence the rumor-day abnormal returns of the target.

Finally, we find that while newspaper fixed effects predict accuracy, they do not affect stock returns. For example, a rumor article in *Bloomberg* is 50% more likely to come true than an article in the average newspaper, but the announcement return following an article in *Bloomberg* is statistically equivalent to the return following the average article. Newspapers' observable traits, such as circulation, age, and form of ownership, do not help to explain rumor accuracy.

In sum, we find that investors do not perfectly account for all relevant information to predict rumor accuracy. They do not fully discount the inaccuracy of rumors about newsworthy targets, they do not recognize the importance of journalist and newspaper fixed effects, and they do not fully account for the experience and training of journalists. Given the difficulty of observing many of these factors for the average newspaper reader, it is plausible that readers are unaware of these factors, which contributes to a short-run mispricing in targets' stocks.

These results are consistent with the theory that limited attention may lead investors to overlook valuable public information (e.g., Hirshleifer and Teoh (2003); Hirshleifer, Lim, and Teoh (2011)) and empirical evidence that supports these predictions (e.g., Engelberg (2008); Da, Gurun, and Warachka (2013)). While this previous work has focused on the behavior of investors, we show that limited attention has important implications for the media. Because readers' attention is limited, the media competes for their attention by publishing sensational news. These news stories skew the information environment and move asset prices.

In our last set of analyses, we test whether important decisions made by insiders are influenced by the publication of a merger rumor. While imperfectly informed outside investors may have a difficult time correctly adjusting for the accuracy of merger rumors, the actions of perfectly informed insiders should not be swayed by media coverage. Consistent with this, we first show that total takeover premiums are unaffected by rumors, indicating that bidders discount rumor-driven stock returns when negotiating the target price. The publication of a rumor increases a target's stock returns over the two months before the merger's public announcement by about 7%. However, in the period surrounding the official merger announcement, targets in rumored mergers earn about 7% lower returns, erasing the prior run-up. Second, we find that insider trading is unaffected by merger rumors. Though insiders who know that a rumor is false have a strong incentive to sell their shares, such trades on private information are generally illegal.

Our results have several implications. First, we challenge the view that the business press is a passive conduit of financial information. Instead, we highlight an important driver of media coverage – readership appeal – and demonstrate that it is associated with more speculative reporting, particularly for large, well-recognized firms. This underscores the distinction of the business press from other information sources, such as analysts and rating agencies, which typically provide more precise information about large, public firms. Second, our results show that while media articles generate large effects on asset prices, they also introduce additional noise, as investors respond to irrelevant information and ignore pertinent information. Finally, unlike most prior research, which views the financial media as a homogeneous sector, we uncover large cross-sectional variation in the accuracy of reporting and identify journalist biographical characteristics that help to explain it.

This paper contributes to the growing literature on the role of media in capital markets. Previous research shows that individual investors prefer stocks with attention-grabbing news (Barber and Odean, 2008; Da, Engelberg, and Gao, 2011). Our findings suggest that newspapers cater to this preference and skew their coverage to appeal to individual investors. This provides one explanation why investors still trade stocks based on narratives in newspaper articles, despite easy access to firms' press releases, regulated disclosures, and analyst reports (Engelberg and Parsons, 2011). Furthermore, because media speculation is difficult to disprove, our results help explain why media articles affect even the prices of large and widely-followed stocks (Tetlock, 2007). Second, our results extend prior research on textual analysis in finance (Tetlock, Saar-Tsechansky, and Macskassy, 2008; Loughran and McDonald, 2011; Gurun and Butler, 2012; Loughran and McDonald, 2013). Rather than focusing on the tone of the text, as typically done, we focus on details of the text that are expected to signal an article's accuracy.

Finally, we provide novel evidence on the role of journalists in the stock market. In the first article on this topic, Dougal, Engelberg, Garcia, and Parsons (2012) show that the identity of the authors of a popular *Wall Street Journal* column helps to predict next day market returns. We extend this research in two ways. First, we study cross-sectional variation in the accuracy of journalists. This sheds light on one potential underlying mechanism through which a journalist's identity could affect stock returns. Second, we uncover specific characteristics of journalists, including age, education, and expertise, that help to explain why accuracy varies across journalists.

1. Sample and Summary Statistics

To collect merger rumors, we use a multi-step approach. First, we identify merger rumor targets using a wide filter. Then, we search for the first article to report the rumor, or as we call it, the 'scoop' article. Once the scoop article is identified, we search for all articles that report the rumor in the following week to measure how widespread the rumor was reported.

In the first pass of the search, we manually search the Factiva database using the following filters. First, we limit our sample dates to January 1, 2000 through December 31, 2011. Second, we search within Factiva's set of publications called "Major news and business publications: U.S." This includes the largest 33 newspapers in the US. Within these bounds, we search for articles that include at least one of these words: "acquire," "acquisition," "merger," "deal," "takeover," "buyout," or "bid," and at least one of these words or phrases: "rumor," "rumour," "speculation," "said to be," or "talks." This search provides a noisy sample from which we further refine our search by reading the articles to identify those that report merger rumors. For example, in many cases, this first sample includes articles that refer to a merger and then an unrelated rumor, such as changes in management or product offerings. Once we identify a merger rumor, we record the name of the target, the alleged bidders (if named), the media outlet, and the date of publication. By limiting attention to the largest 33 newspapers in the US, we ensure that the targets of the rumors are at least large enough and important enough to interest a general readership.

Next, we search for the scoop article. Merger rumors are typically re-reported by multiple media outlets and our first-pass search does not usually identify the scoop article. To find the scoop, we first trace backward in time using the source of the rumor stated in the articles we have identified. When a rumor is re-reported, journalists typically cite a newspaper article that reported the story previously. In this second-pass search we place no restriction on the newspaper's size or location. This means our sample includes foreign newspapers and small media outlets. We follow the citation trail until we find an article that does not cite another media source. To verify that it is the scoop article, we search for all articles on the target firm starting one week before this potential scoop to find any previous articles on the rumor. In some cases, articles do not report a source. In these cases, we search backward in time for articles about the target firm until we find the earliest article that reports the rumor, using all sources in Factiva.

Having the scoop article date, we search for all articles that include the target's name in the following week. From this sample, we manually read the articles to identify those that refer to the merger rumor. We identify separate rumors for the same target firm if a year has passed between rumors. Finally, we manually search through all merger bids announced between 2000 and 2012 in the SDC Platinum global merger database to identify any rumors that were followed by a formal public merger announcement. This matching is done first using public firm identifiers and then by hand for private firms, matching on firm name, location, and industry in SDC to ensure accuracy. We record a dummy variable equal to one for rumors where a merger was announced involving the target firm within one year of the scoop article, regardless of whether the bidder in the public announcement was listed as a potential bidder in the rumor.

The final sample includes 2,142 articles covering 501 rumors of 354 target firms. Targets include large, well-known firms, such as American Airlines, Alcoa, Sprint, and US Steel, as well as foreign firms, such as InterContinental Hotels Group, Roche Holding, and Samsung, and private firms, such as Calvin Klein, Skype, and Groupon.

Of the 501 rumors, 167 (33.3%) were followed by a public merger announcement involving the target, whether the deal was completed or not. Though, as stated above, we cannot know for sure whether a rumor is false, we can state that the majority of rumors do not come true.

1.1. Time Series Statistics

Panel A of Table 1 presents the number of all articles, scoop articles, and public announcements by year from 2000 to 2011. There is an overall increasing pattern, with the year 2010 having the most articles and scoops (393 and 75), and the years 2004, 2009, and 2011 having the fewest. There is a positive but insignificant correlation between the number of scoop articles in a given year and the number of formal merger announcements in the SDC database (0.30, p-value=0.34). The correlation between the percent of rumors that emerged and the number of bids in SDC is weaker at 0.17 (p-value= 0.60). These correlations suggest that the prevalence of rumors is not closely tied to actual merger activity. To better reflect the time trend, Fig. 1 presents a three-year rolling average of the number of rumor articles in the sample, normalized by the total number of articles appearing in the *Wall Street Journal* or *The New York Times* that include any of the following words: “merger,” “acquisition,” or “takeover.” This figure shows an increasing time trend in merger rumor articles, controlling for the general volume of media articles about mergers.

In Panel B of Table 1, we find relatively uniform timing in articles across calendar months. In untabulated data, we find no seasonality in total circulation for a set of prominent newspapers, consistent with uniform coverage of merger rumors by month.[2] However, significantly more rumors published in December and significantly fewer rumors published in July come true. Finally, Panel C of Table 1 presents the pattern of media articles by the day of the week. Not surprisingly, few articles appear on Saturday or Sunday. Wednesday and Thursday are slightly more common than other weekdays for rumor articles, but overall, there is not much meaningful variation by day of the week.

1.2. Newsworthiness Variables

To empirically identify the newsworthiness of firms named in merger rumors, we refer to commonly cited characteristics of newsworthiness in journalism studies: breadth, proximity, prominence, and timeliness (Eadie, 2009). First, breadth refers to the size of the audience that would be interested in a specific merger rumor. Large public firms are more likely to interest readers because they employ more people, sell more products, and have more diverse stockholders. Firms that have greater fractions of retail ownership are also likely to appeal to a broader audience of newspaper readers. We use log(book assets) from Compustat to measure firm size. We record institutional ownership from 13-f filings.

Proximity implies that firms located closer to readers are more newsworthy. To record proximity, we use two measures of distance. In the first tests, in which we compare rumored merger targets to actual targets, we record whether a firm is a domestic or foreign firm. In the sample of rumor targets, where we have a newspaper article for each target firm, we calculate the great-circle distance between the headquarters of the firm and the newspaper in kilometers.

Prominence refers to how well-known is a firm. Firms with high brand recognition or firms that sell products to consumers are more likely to interest an average reader than commodity firms or firms that sell intermediate inputs. First, we identify firms with high brand values

[2]We use quarterly circulation data from the Audit Bureau of Circulations for the *Wall Street Journal* and the *New York Times* from 2005 to 2012.

using two data sources. The marketing consultancy firms Interbrand and BrandZ each publish a list of the 100 most valuable brands in the world each year. Data for Interbrand start in 2000 and data for BrandZ start in 2006. Because each firm uses its own methodology, the lists are not identical, though many firms appear on both, such as Coca-Cola, Verizon, and UPS. Because these lists are so selective, we simply record a dummy variable for any target firm that appears on either list in any year from 2000 to 2011. As a second measure of newspaper readers' awareness of a target firm, we record the fraction of total sales by the target's industry that are purchased by consumers. These data are from the 1997 Input-Output tables provided by the Bureau of Economic Analysis and cover all industries in the US and are defined at an industry-level roughly equivalent to 3-digit SIC codes. Thus, this identifies firms that sell products directly to customers, compared to firms that sell intermediate goods in the supply chain.

As alternative measures of prominence, we measure Tobin's Q and R&D/Assets using data from Compustat and CRSP. Firms with high valuations and firms creating new products may attract greater readership. We create a dummy variable for high R&D/Assets if the firm's R&D/Assets is greater than five percent.

Panel A of Table 2 presents summary statistics of the variables related to newsworthiness. Nearly 90% of rumor targets are publicly-traded firms and 16% have valuable brands. About 39% of rumor targets' industry sales are to households and 25% of the sample firms are foreign.

1.3. Journalist Characteristics

Using a variety of sources, we collect data on personal characteristics of journalists that could influence their accuracy. In particular, an older journalist could be better at assessing a rumor's accuracy than a younger journalist. This could be driven by experience or better connections. It could also be driven by selection, in which a journalist who writes less accurate stories does not remain employed as a journalist. Second, a journalist's education could also help to assess the accuracy of information. Reporters who received degrees in journalism or business could be better equipped to assess the likelihood that a merger rumor will come true and the integrity of sources who provide the rumors. Third, a journalist with greater expertise in the industry of the rumor target could also be more accurate than a journalist with expertise in another industry. Finally, there could be gender differences in reporting. For example, it is possible that a female journalist has different connections to business insiders than male journalists.

To measure these journalist characteristics, we manually collect biographical data from a variety of sources on the 368 journalists who authored or coauthored any scoop article in our sample. We begin by collecting journalists' primary and secondary areas of specialization from the social networking site LinkedIn. In some cases, a journalist's specialization is evident from his or her professional job title (e.g., 'Reporter, Automotive'), while in others, it is provided by the newspaper in the journalist's biographical sketch. We verify the reported specialization by reading samples of the journalist's articles. We then match the journalists' industry specializations to the Fama-French 17-industry classifications.

Next, we collect data on journalists' education, following a two-step process. First, we read the journalists' biographical sketches, professional profiles on LinkedIn, and personal web pages. We supplement these sources with web searches, which often bring up helpful academic resources, such as university alumni publications which discuss journalists as alumni and provide their educational background. In the second step, we contact the registrars of the universities attended by journalists to verify their degree, year of graduation, and academic specialization. While many registrars provide this information to us directly, some universities have outsourced the degree verification service to a third-party data repository, the National Student Clearinghouse (NSC). In these cases, we verify the degree by contacting the NSC. For a few observations, we are unable to verify the journalists' undergraduate majors because a small minority of schools, mostly foreign universities in the UK and Canada, require an additional consent form. To verify degrees of female journalists, we also obtain their maiden names from the Lexis Nexis Public Records database (discussed in detail below) if the university registrar is unable to verify the degree under the journalist's current family name.

Finally, to reliably establish a journalist's age and gender, we use the Lexis Nexis Public Records database, which aggregates information on 450 million unique U.S. individuals (both live and deceased) available from various federal, state, and county records, such as drivers' licenses, property tax assessment records, marriage and divorce records, voter registration records, utility connection records, and many others. This information is combined into a comprehensive person report for each individual, which provides the year and month of birth, history of residential addresses, maiden names for women, and information on employment, among many other characteristics. To identify journalists in this database, we use their first, middle, and last name, as well as the approximate age based on the year of college graduation and then verify each match by ensuring that the person's employment record in the Lexis Nexis database matches that of the journalist.

Because some of the articles in our sample include multiple authors, we aggregate the journalist-level information to the article-level. For age, we take the average across co-authors. For gender, we create a dummy variable equal to one if the article has any women co-authors. For industry expertise, we create a dummy variable equal to one if any of the co-authors' primary or secondary industry expertise is the same as the rumored target's industry. For undergraduate majors, we record a dummy variable equal to one if any co-author has an undergraduate minor in one of six fields of study: business, journalism, english, political science, history, and other.[3]

Panel B of Table 2 shows that the average age of journalist co-author teams in our sample is 37 years old, the 25th percentile is 33 and the 75th percentile is 41 years old. Forty-five percent of articles are written by reporter teams that include at least one woman. Fifty-seven percent of articles are written by teams with at least one journalist who claims to be an expert in the industry of the target firm. The most common undergraduate major represented by at least one reporter in a team is journalism (33%), followed by English (31%), history (27%), political science (20%), business (10%), and other (10%).

1.4. Article Characteristics

Using the text of the newspaper article, we record a host of information that may help predict whether a rumor will come true. First, we record the stage of the merger talks in seven categories based on the text of the article. Panel C of Table 2 shows that most rumors are in the 'speculation' stage, accounting for 51% of the 501 rumors in the sample. 'Preliminary

[3]See the appendix for the complete list of fields that are included in each of the six categories.

talks' account for 9%. 'In talks' accounts for 27%, 'preparing a bid' is 4%, 'made offer' is 5%, 'evaluating bids' is 2%, and 3% are categorized as 'for sale.' We also collect the original source of the rumor cited in the article text. The vast majority (92%) are anonymous, with the rest made up of analysts, portfolio managers, bidder and target management, and others. We next collect the targets' comments in response to the rumor. In 38% of scoop articles, there is no mention that the newspaper attempted to contact the target for a comment. In 8% of cases, the article states that the target could not be reached. In 46% of rumors, the target declines to comment on the rumor. In the remaining responses, the target confirms the rumor (3% of cases), denies it (4%), or indicates that it 'has conversations from time to time' (1%). We also record a number of additional variables that may indicate how truthful the rumor is. In particular, we record whether the article mentions the rumor in the headline (85%), reports the number and identity of alleged bidders (1.5 on average), and states the target's price (39%). We also count the number of articles that were published across all sources on the scoop date (1.7 on average).

1.5. Newspaper Characteristics

Finally, we collect additional information about the newspapers that publish the articles in our sample. We record media circulation numbers and founding year from company reports and Audit Bureau of Circulation statistics. The average founding year of newspapers in our sample is 1922. The oldest newspaper in our sample is *The Times of London*, founded in 1785. The average daily circulation is 442,550 copies and the most widely-circulated newspaper is the *Wall Street Journal* with a circulation of 2,092,523 in 2011. We also identify the ultimate owner of each newspaper and record whether it is a family-run firm, which is the case for 74% of articles in the sample.

1.6. Accuracy

It is important to define accuracy in the context of merger rumors. In a literal sense, if a merger rumor is actually spreading among investors and a newspaper reports that there is a merger rumor, the article is accurate. As long as any person, anywhere, with any degree of knowledge suggests to someone else that a firm is ripe for a takeover, a merger rumor article published in the press is accurate in the literal sense. However, this is an extremely low bar for accuracy. It just implies that the journalist is not fabricating the rumor. We define accuracy in a more relevant way. In our setting, a rumor is accurate if it is followed by a public announcement of a proposed merger within one year, whether or not it results in a completed deal. This is the measure that is of ultimate interest to a newspaper's readers. The consequences of the merger, such as the premium paid to target shareholders, the change in control, and employee layoffs and relocations, are what the average reader cares about, not just that someone is making idle speculation.

We acknowledge that this definition of accuracy is not without limitations. An article could accurately report that two firms are in advanced merger negotiations, which then ultimately fail. This would be considered an inaccurate rumor using our definition. However, for our definition to be biased, the likelihood of deal failure would have to be systematically related to a characteristic of the merger negotiations or the firms involved that the journalist does not consider. Given that newspapers select stories to publish from a vast set of new information, it is reasonable that readers expect journalists to consider the likelihood of deal failure when they choose to publish a rumor. Though ideally, we would observe all public and private merger negotiations and all published and unpublished rumors, we believe that our measure provides a reliable estimate that is based on an observable outcome.

2. Which Types of Rumors are Covered by the Business Press?

We first document the characteristics of target firms in merger rumors that attract newspaper coverage. As stated above, we would ideally compare firms mentioned in published rumors to firms mentioned in unpublished rumors. Since it is difficult to observe unpublished rumors, we use actual mergers as a benchmark for comparison. As long as these firm characteristics are unrelated to the likelihood of any merger rumor, published or not, using actual mergers as a comparison group is unbiased. To help ensure this is the case, we use three samples of actual mergers as comparisons: all mergers, mergers of large public targets, and mergers of US targets only. The 'all mergers' group includes all mergers in SDC over the period 2000 to 2011 with a deal value of at least \$250 million. This size threshold is relatively high, since most mergers are for much smaller amounts. Second, in our sample of large and public takeover targets, we include the subsample of all mergers where the target is publicly traded and we set the minimum size of the targets in SDC such that the average of the log book assets is equivalent to the rumor sample. Finally, the third subsample include only US merger targets worth at least \$250 million.

Table 3 presents univariate t-tests between average target characteristics in our rumor sample, compared to the three different samples of target firms in actual mergers. In our sample of rumors, 88% of targets are publicly traded. This is more than double the fraction found in the universe of SDC targets (38%). It is also more than double the fraction found in the sample of US targets (37%). We also find a large and substantial difference in the book assets of rumored targets, compared to actual merger targets. The difference between rumored targets and actual targets is even more stark for brand value. More than 15% of rumored targets have high brand values, compared to less than 1% for all mergers. Even in the size-matched sample, less than 3% of actual merger targets appear on the brand value league tables. Similarly, rumored targets sell 38% of their output to consumers, on average, significantly more than the 31% in all mergers, and 34% in large mergers. These results are consistent with the idea that the media chooses firms that have breadth and prominence with their readers. Consistent with a preference for local reporting, 75% of rumored targets are domestic firms, compared to 44% in the entire SDC sample. We also find that rumored firms spend more on R&D have higher Tobin's Q values than comparable large public merger targets.

In Table 4, we present results from multivariate regressions that test whether newsworthiness explains the likelihood of the publication of a merger rumor. Using the entire sample of rumors, combined with the sample of SDC mergers, we find that US firms that are public and have valuable brands are substantially more likely to be covered in a merger rumor in the press. Restricting attention to public targets, we find that larger domestic targets with valuable brands are significantly more likely to be covered in a merger rumor in the press compared to the full sample of mergers. We also find that firms with high R&D expenditures and high Tobin's Q are more likely to be covered in a rumor. These effects hold using logit models or OLS linear probability models. In addition, these effects are economically meaningful. The odds of a rumor being published in the press if a target firm is public are 11.4 times as large as the odds if the firm is private. The odds of a rumor for firms on the 100 Most Valuable Brand lists are much larger than the odds for firms not on the lists, even after controlling for firm size, industry, and year effects.

These results provide consistent evidence that the financial press skews coverage towards more newsworthy firms. Rumors are more likely to be published for firms that appeal to a broader audience, that have well-known brands, and that are local. These results provide new empirical evidence consistent with the theoretical models of media profit motives in Mullainathan and Shleifer (2005) and Gentzkow and Shapiro (2006).

3. How Do Merger Rumors Affect Stock Prices?

If investors can perfectly infer the likelihood that a rumor will come true in the future, stock returns of targets on the date the rumor is published should be efficient with no systematic under- or over-reaction. However, if investors incorrectly believe rumors are more accurate than they truly are, the average target of a rumor will experience a reversal following the publication of the rumor. To test these predictions, we calculate abnormal stock returns by subtracting the return on the value-weighted CRSP index from each target firm's stock return daily. Cumulative abnormal returns are the time-series sum of the abnormal returns.

In Fig. 2, we find evidence of a run-up in stock returns for all rumored targets before the publication of the rumor and then a substantial increase in prices for rumors that will eventually come true and a substantial decrease in the prices for rumors that don't come true. However, the figure reveals an under-reaction to the accurate rumors and an overreaction to the inaccurate rumors. Targets of accurate rumors continue to experience positive abnormal returns after the rumor has been published, while targets of inaccurate rumors experience persistent negative returns. These results show that investors are adept at identifying accurate from inaccurate rumors immediately, but not perfectly.

The figure also reveals a substantial reversal in stock prices for the average target. This is consistent with the hypothesis that investors do not correctly infer the accuracy of the merger rumor. Specifically, investors appear to systematically overestimate the accuracy of rumors.

Table 5 presents the numerical analysis of the stock returns in event time. On the date of the rumor publication (Day 0), the average target in a rumor experiences a 4.3% abnormal stock return. Targets in rumors that are accurate and will eventually receive a formal takeover bid have abnormal returns of 6.9% on the rumor date, compared to 3.0% for inaccurate rumors, a highly statistically and economically significant difference.[4] All targets experience substantial run-ups of between 2–3% over the period twenty days before the rumor, but there is no significant difference in the run-up between accurate and inaccurate rumors. Importantly, there is a significant and large reversal over the ten days following the merger announcement of -1.4% for all targets. This is driven by a significant reversal in the inaccurate rumors of -2.7%. The post-rumor return in accurate mergers is positive but not statistically significant, except in the five day window following the rumor.

These results show that rumors in the press have large stock price effects. They also show that the market overreacts to the average merger rumor, suggesting that investors cannot perfectly distinguish the accuracy of merger rumors in the press.

4. What Predicts Accuracy in Merger Rumors?

To better understand what drives the reaction of stock prices to merger rumors, we design a set of four tests to identify the factors that predict a rumor's accuracy and the factors that influence the stock price reaction to the rumor. In the first test, we run a logit regression of the likelihood that a rumor comes true within a year on a set of explanatory variables. Using ex post realizations up to a year after the rumor, this test identifies which factors predict a rumor's accuracy. In the second test, we include the abnormal stock returns of the target on the day the rumor is published (day 0 returns) as an explanatory variable in the logit test. This test identifies which explanatory factors are reflected in stock prices and which are not. A variable that remains significantly related to the rumor's accuracy after controlling for the

[4]We use Day 0 returns throughout the paper rather than Day -1,0 to be conservative. This ensures that the responses reflect the rumor article, rather than the run-up.

day 0 returns of the target is not fully reflected in the market reaction to the rumor. Third, we run a regression of the day 0 target abnormal returns on the same explanatory variables. This regression provides a secondary test to identify the factors that influence the market response and also identifies variables that influence the returns, but not the likelihood of accuracy. Finally, in the fourth test, we run a regression on the target cumulative abnormal returns over the 10 days following the rumor publication. This identifies which factors influence the delayed response to the rumor. In all of the tests we control for year and industry fixed effects.

As mentioned above, newspapers are just one link in the diffusion of information from insiders to outsiders. Though our data collection process is designed to ensure that our sample correctly identifies the date and original source of the rumor among all media sources covered in the Factiva data set, we do not claim that the rumors in our sample do not circulate in other venues first. As the theoretical models of Van Bommel (2003) and Brunnermeier (2005) argue, informed traders have an incentive to leak inside information in advance of official announcements. Thus, some rumors may be more stale than others when they are published in the press. Tetlock (2011) shows that stock returns respond less when media reports are more stale. If the staleness of the information varies across our sample firms, then we could make incorrect inferences. For example, we could misinterpret a small stock price reaction to a variable that significantly explains accuracy as investor inattention, when in fact, the price reaction is small because the information has already been incorporated.

Therefore, in all of the tests, we control for staleness and information leakage by using the cumulative abnormal returns of the target in the five days before the rumor is published. If the rumor has been widely circulated before the newspaper article, the pre-publication returns are expected to be higher. In unreported robustness tests, we obtain similar results if we use the cumulative abnormal returns over the twenty days before the article (to control for a longer pre-publication period) and the five days that end two days before the scoop article (to ensure we are not accidentally including a response to the rumor article itself). As a secondary measure, we use the reported stage of merger negotiations discussed in the article (speculation, early talks, advanced talks, etc.). It is reasonable to assume that the amount of information leakage grows as negotiations advance. When we use these alternative proxies for staleness, our main results are unchanged.

We investigate four possible factors that could be used to infer accuracy and influence stock returns: newsworthiness, journalists, the text of the article, and newspapers.

4.1. Does Newsworthiness Influence Stock Returns?

In column 1 of Table 6, we find that rumors about large firms with valuable brands, high Tobin's Q values, and greater sales to households are significantly less likely to come true. The same factors that are associated with greater newspaper coverage are also associated with less accurate reporting. These results are economically substantial. The odds ratio that a rumor comes true about a firm that does not have a valuable brand is twice as large as the odds ratio for a firm with a valuable brand. For a one standard deviation increase in target log(assets), the odds ratio that a rumor comes true decreases by 0.52.

In column 2 of Table 6, we add the target's day zero returns. As expected, the effect of the day zero abnormal returns on accuracy is positive and highly statistically significant. However, even after controlling for the day zero returns, the characteristics of newsworthy firms are still negatively and significantly related to rumor accuracy. In particular, larger firms with more valuable brands that sell more to households are less likely to come true.

Column 3 presents regressions where the dependent variable is the abnormal target return on the rumor date. Though investors seem to partially account for valuable brands and distance, they do not seem to account at all for the importance of firm size, industry sales to households, or R&D expenses in explaining accuracy, as they are unrelated to the day zero returns, but significantly related to accuracy. Column 4 of Table 6 shows that in the reversal period, from one to ten days after the rumor date, larger firms experience more negative abnormal returns. This implies that stock returns incorporate the negative influence of size on accuracy, but with a delay. However, none of the other variables are significant.

As mentioned previously, one concern with our measure of accuracy is that rumors about merger negotiations that do not advance to a public bid could be classified as inaccurate, even if there were actual merger talks happening. This could confound our tests if more newsworthy firms are also more likely to engage in negotiations that ultimately fail. A direct test of this alternative explanation would require a sample of all rumors, both published and unpublished, and their outcomes. Since we cannot observe such a sample, we use a similar setting where we can identify negotiation failures. In particular, we investigate the relation between newsworthiness and the likelihood that a public bid is withdrawn, once it has been made.

Using a large sample of bids from SDC, in Internet Appendix Table 1 we regress our variables of newsworthiness on a dummy variable equal to one if a bid is withdrawn. We find no significant relationship between the likelihood of withdrawal and the fraction of a firm's sales to households or the target's brand value. We find a negative and significant relationship between firm size and withdrawal, and a positive relationship between institutional ownership and withdrawal. Interpreting these results in our setting implies that negotiations involving more newsworthy firms are, if anything, more likely to succeed, compared to less newsworthy firms, suggesting that our results are not driven by rumors of actual negotiations that fail at a higher rate for newsworthy firms.

4.2. Do Journalists' Backgrounds Influence Stock Returns?

In Table 7, we run identical regressions as above, but use journalist biographical information. Column 1 shows that older journalists are significantly more accurate. Second, articles written by reporters that studied journalism in college are significantly more accurate than articles written by journalists who studied other fields. Third, journalists that specialize in the target firm's industry are more likely to write articles that are accurate. Once we control for the target's stock returns following the rumor's publication in column 2, we find no change in these results. Consistent with this, most of the variables are unrelated to stock returns on the rumor date or in the ten days that follow, as indicated in columns 3 and 4.

These findings are intuitive. Older journalists with more experience may be better able to filter out false rumors than less experienced journalists. They may also have culled more reliable sources of rumors with experience. Additionally, an undergraduate degree in journalism may help reporters better identify which rumors are likely to come true. They may have learned how to find reliable sources and verify suspicious claims. At the same time, it is reasonable that many investors would not account for the experience and expertise of journalists, given that this information is not prominently made available.

One possible alternative explanation to our findings is that certain newspapers hire more experienced journalists with more relevant education. If these newspapers were also more accurate, then our findings may be explained by characteristics of the newspaper, rather than the journalist. In Internet Appendix Table 2 we run regressions on journalist characteristics, as above, but include newspaper fixed effects. We find that our results hold. Even within a newspaper, journalists that are older and have undergraduate degrees in journalism are significantly more accurate.

Though we have identified the biographical traits of journalists that we believe are the most important for predicting accuracy, other unobserved characteristics of journalists are likely to be related to accuracy as well. To account for unobserved characteristics of journalists, in Internet Appendix Table 3 we list the number of articles, scoop articles, and accuracy rates for the 26 journalists who have at least four scoop articles in the sample. The most prolific journalist is Dennis Berman of the *Wall Street Journal*, with 24 scoops, followed by Andrew Ross Sorkin of the *New York Times*, with 19 scoops, and Nikhil Deogun and Robert Frank, both of the *Wall Street Journal*, each with 13 scoop articles. The accuracy rate of these journalists is impressive. Berman's accuracy is 62.5%. Sorkin's is 42.1%, Deogun's is 53.8% and Frank's is 23.1%. The first three are well above the average accuracy rate of 33% across all rumors.

In Internet Appendix Table 4, we run journalist fixed effects regressions on accuracy, day zero returns, and post-rumor returns, while controlling for firm size, industry, and year fixed effects, as before. We only include dummy variables for the 26 most prolific journalists, since the total number of journalists is greater than the number of rumors. Consistent with the univariate results, Berman, Sorkin, and Sidel have positive fixed effects on the likelihood that a rumor comes true. For instance, the odds a rumor comes true is 3.8 times higher if the article is written by Berman, compared to all other journalists. In column 2, we find that the journalist fixed effects still have significant predictive power even after controlling for the Day 0 target abnormal returns. In most cases, the magnitude of the fixed effect is only slightly smaller. These results indicate that some journalists are more accurate than others, but that stock prices do not reflect this variation.

It is not surprising that investors do not perfectly account for journalist fixed effects. Given the large number of journalists and limited attention of readers, the cost to a retail investor of accounting for a journalist's historical accuracy rate is likely prohibitive. The marginal effect for Andrew Ross Sorkin illustrates how limited attention is likely to drive these effects. Sorkin is a well-known author of the best-selling book "Too Big To Fail," which was made into a television-movie for HBO, and also is known as the founder of the *New York Times* news service on mergers called *Dealbook*, which uses the masthead, "DealBook with Founder Andrew Ross Sorkin." The odds that a rumor first reported by Sorkin comes true are 3.6 times higher than other rumors. However, once the Day 0 returns are included, the effect drops to 2.5 times higher, indicating that the stock returns account for Sorkin's accuracy, at least partially. Compare this to Dennis Berman, a prolific journalist with high accuracy rates, but not nearly as well-known as Sorkin. Berman's fixed effect on the log-odds ratio of rumor accuracy is 1.325 without controlling for Day 0 returns, and 1.311 after controlling for the returns. Rumors reported by Berman are more accurate than the average rumor, but stock prices do not reflect this additional accuracy.

This evidence is consistent with the theory that limited attention may lead investors to overlook valuable public information and cause distortions in stock prices (e.g., Hirshleifer and Teoh (2003); Hirshleifer, Lim, and Teoh (2011)).[5] Our findings extend this literature by showing that investors' do not fully account for the media's incentive to publish sensational stories, nor the characteristics of journalists that predict accuracy.

4.3. Does the Text of the Rumor Article Influence Stock Returns?

In Table 8, we run a series of identical regressions as before, but using article characteristics as explanatory variables. In the first column, we find that anonymous sources, the target's response to the rumor, the appearance of the rumor in the article headline, the number of

[5]Empirical evidence in support of limited attention has been documented in the context of financial information (Tetlock, 2011; Da, Gurun, and Warachka, 2013), earnings announcements (Engelberg, 2008; DellaVigna and Pollet, 2009; Hirshleifer, Lim, and Teoh, 2009), economic shocks (Cohen and Frazzini, 2008; Cohen and Lou, 2012), and investment choices (Klibanoff, Lamont, and Wizman, 1998; Barber, Odean, and Zheng, 2005).

bidders mentioned, and the mentioning of a specific takeover price are all statistically unrelated to the likelihood that a rumor eventually comes true. Though these characteristics give greater detail and the appearance of credibility to the article, ultimately, they are cheap talk that provides no insight into the article's accuracy. Only the stage of the merger and the number of rumor articles published in the press on the scoop date predict accuracy. Compared to rumors that are solely speculative, the odds that a rumor is true are 4.1 times larger if an article states that firms are in talks.

In column 2, we control for the target's day zero returns. Rumors that mention that the firms are in talks are still more likely to come true, indicating that stock prices do not fully reflect this information. Evidence of this interpretation is shown in column 3 as well. Though the merger stage affects accuracy, it is unrelated to the Day 0 abnormal returns. In contrast, the market appears to correctly price the number of articles published on the scoop date. Once day zero returns are included, this variable is unrelated to the rumor's accuracy.

Since we identify certain specifics of the text cleanly (such as whether a price is mentioned), these results provide powerful evidence that the precise language in the rumor articles is uninformative, for the most part. Even details that would imply greater credibility of the rumor are uninformative. These results also show that investors recognize this. For most article characteristics, the specifics of the text do not influence the target's abnormal returns after controlling for firm size and industry.

4.4. Do Newspaper Characteristics Influence Stock Returns?

In Table 9, we find virtually no significant relations between accuracy or returns and a dummy variable for family-run media, the age of the newspaper, and its circulation. This implies that these characteristics do not help to explain the significant newspaper fixed effects, which are driven by newspaper-specific characteristics.

Analogous to our analysis of journalists, in Internet Appendix Table 5, we present summary statistics for the most prolific newspapers in our sample by number of articles. The *Wall Street Journal* has 448 articles and 158 scoops, the largest number of scoops by far. Next is the *New York Times* with 219 articles and 38 scoops. As with journalists, the most prolific newspapers are also the most accurate. For example, the *Wall Street Journal*'s accuracy rate in scoops is 38.6%. In addition, the accuracy rate of newspapers varies considerably. *Bloomberg* has 10 scoops in the sample, with eight of them coming true. In contrast, the *Los Angeles Times* has six scoops, but only one came true.

Internet Appendix Table 6 presents newspaper fixed effects regressions. Newspapers display fewer statistically significant fixed effects than journalists. This reflects that newspapers aggregate multiple journalists and thus have less cross-sectional variation. Nevertheless, in those cases where the newspaper fixed effects are strongly positive (e.g., *Bloomberg* and *Financial Times*), inclusion of the day zero returns does not diminish the predictive power of the fixed effects to explain accuracy, similar to the case of journalists.

4.5. Summary of Predictive Power and Economic Magnitudes

In summary, though there is good reason to believe that newspapers have an incentive to be more accurate when the stakes are larger, we find no evidence that any of our measures of newsworthiness are positively related to accuracy. In contrast, we find that though newspapers disproportionately cover large firms with brand recognition, they are substantially less accurate when they do so. At the same time, stock returns do not fully account for newspapers' incentives to publish newsworthy articles, even if accuracy is compromised. We also find that the details presented in the text of the article are uninformative to investors. This is consistent with cheap talk, where inaccurate articles can easily pool themselves together with accurate articles by listing unverifiable details that suggest greater credibility. In contrast, we find that journalists have a strong effect on accuracy, but that investors do not correctly account for this in their trading decisions. Older journalists with more relevant education and expertise are significantly more likely to publish accurate merger rumors. Finally, though we find that newspaper fixed effects help to explain accuracy, we are unable to identify the characteristics of more accurate newspapers.

To better understand the economic consequences of price distortions following rumor articles, we calculate the returns of portfolios formed by the likelihood of a rumor's accuracy. In particular, we first run regressions on the likelihood that a rumor comes true within one year, as above. Using the predicted probabilities from the regression results, we classify rumors as "More Likely" if the fitted value is greater than 33% (the unconditional average accuracy rate), and "Less Likely" otherwise. We then use these classifications to form two calendar-time daily portfolios from 2000 through 2012; one for targets in rumors that are more likely to come true, and one for targets in rumors that are less likely to come true. Firms enter a portfolio on the day the rumor was published and stay in the portfolio for up to one year. This means that the firm's first return in the portfolio is on the first day after the date of the rumor's publication. The portfolios are equally-weighted and rebalanced daily. For days in which both portfolios include at least five stocks, we calculate the long-short portfolio returns from holding a long position in the More Likely portfolio and a short position in the Less Likely portfolio.

We estimate three probability models to account for three different sets of variables. First, we run a logit test that only includes newspaper and journalist fixed effects. Though we show above that journalist characteristics help predict the likelihood that a rumor comes true, we do not include these variables since they are not easily observable. Second, we run a test that includes characteristics of the target's newsworthiness, as in Table 6. Finally, the third test includes the characteristics of the article as explanatory variables, as in Table 8. To focus on the characteristics of the rumor article, we omit target size and industry effects in the third regression.

If investors perfectly account for the characteristics of rumors, then the long-run returns of the long-short portfolio should be zero. Instead, we find large positive returns. In particular, when we use the newspaper and journalist fixed effects to classify rumors as More Likely or Less Likely, the return on the long-short portfolio is 76 basis points per month. Using the target's newsworthiness to predict accuracy yields a monthly return of 58 basis points. Finally, the information contained in the text of the article yields a monthly return of 36 basis points. Thus, the distortions in stock prices caused by ignoring information are economically meaningful.[6]

[6]It is important to note that we do not claim these results are predictive regressions. We also don't claim that this is an implementable trading strategy, since we have not accounted for transaction costs, and the portfolio sizes are small. Instead, these tests provide an in-sample measure of the economic magnitude of the distortions associated with rumor articles.

5. Do Rumors Affect Insiders?

While we have documented that merger rumors have substantial effects on stock prices and that investors do not fully account for all information, we would like to know if the publication of a merger rumor influences important decisions made by insiders. We look at two such settings: markup pricing in the takeover premium and insider trading.

5.1. Markup Pricing in Premiums

Schwert (1996) shows that takeover premiums include two components: the run-up in the target's stock price before the announcement of a merger, and the markup from the announcement to the close of the merger. If the bidder believes the run-up simply reflects the anticipation of the upcoming merger bid, it would revise its takeover price down accordingly. Schwert finds the opposite: the run-up is an added cost to the bidder and there is no trade-off between the run-up and the markup. Even when the sample is conditioned to include mergers where the run-up is most likely driven by insider information, the run-up still has a substantial impact on the total takeover premium.

Our results above show that rumors are associated with a substantial increase in a target's stock price before an official merger announcement. If bidders do not take the rumor into account when negotiating a takeover price, rumors will contribute to the total premium paid. Alternatively, if it is obvious to both targets and bidders that the target's run-up following a rumor in a major newspaper reflects anticipation about the upcoming merger, not new fundamental information, then premiums will be unaffected.

To test this hypothesis, we include the full sample of official merger bids in SDC over the period 2000-2011 for public targets and record a dummy variable equal to one if the deal was preceded by a merger rumor, identified in our main sample. Following Schwert (1996), we calculate the target's cumulative abnormal stock returns over the period from 42 days before the public announcement of the merger until one day before the announcement. We calculate the second period as the period from the day of the public announcement to five days following the announcement.[7] The total premium is calculated as the target's cumulative abnormal returns from 42 days before the announcement to five days following it. We then regress these returns on the rumor dummy variable, plus a host of factors that might influence the returns, including target size, industry fixed effects, and deal characteristics.

Table 10 presents the results from these regressions. Consistent with our prior findings, rumors increase target returns in the run-up period by 6 to 7 percentage points, on average. This is true after accounting for variables that could affect the accuracy of the rumor, such as brand value and size, as well as deal characteristics, such as payment method and whether any takeover defenses were used by the target. The second set of regressions shows that rumors have a strong and statistically significant negative effect on target returns at the announcement of about 8 percentage points. Thus the markup for rumored deals is substantially reduced. Finally, the third set of regressions shows that rumors have no significant effect on the total takeover premium. The marginal effect of the rumor variable is insignificant and economically minuscule.

These results show that rumors do not contribute to the premium paid in mergers. In contrast to uninformed outsiders who may have limited attention, insiders correctly attribute the additional stock returns caused by the rumor and adjust takeover prices downward accordingly.

5.2. Insider Trading

The significant run-up and reversal in stock prices for inaccurate rumors provides an attractive trading opportunity for those who know the rumor is false. As shown in Table 5, over the ten days following the rumor announcement, targets of inaccurate rumors experience a decline in their stock prices of −2.7%, on average. One set of investors who know for certain whether the rumor is false are the target executives. They have a strong incentive to sell their shares on the rumor news, in anticipation of the reversal. However, insider trading laws create a strong disincentive, since the executives would be trading based on material non-public information.

To test whether insiders act on their knowledge, we collect insider trading data for target officers in our sample from the TFN Insider database. Following prior conventions, we only

[7]Schwert (1996) extends this period for a longer duration, but the vast majority of the returns occur within the first few days of the announcement.

include open market purchases or sales, delete observations marked as inaccurate or incomplete ('cleanse' field of S or A), and only include observations that record all of the following information: the number of shares traded, the date, and the price per share in the transaction. For each day we record the net sales by target insiders. We find no significant change in insider trading in the 40 day window surrounding the rumor date. We also find no statistical difference in trading between accurate and inaccurate rumors.

Cohen, Malloy, and Pomorski (2012) show that insider trading can be split into routine scheduled trades and opportunistic trades and find that only opportunistic trades are informative about future stock returns. If we found that rumors were systematically published immediately before routine insider trading dates, we could conjecture that the rumors are spread by target insiders. On the other hand, opportunistic traders would be more likely to sell immediately after a rumor was published. To check these hypotheses, we follow the procedure in Cohen, Malloy, and Pomorski (2012) to identify routine and opportunistic trades. We still find no significant relation between insider trading and merger rumors. These results are to be expected. Merger rumors are not common occurrences. Insiders who trade around the dates of rumors would easily be the target of an illegal insider trading investigation.

6. Conclusion

This paper presents some of the first evidence to show that the business press skews its coverage towards sensational stories. Using the special case of merger rumors in the financial press over 2000–2011, we show that newspaper coverage of rumors is biased towards newsworthy firms that appeal to a broad audience. At the same time, we find that newsworthiness is a strong predictor of inaccuracy. Rumors about newsworthy firms are substantially less likely to come true, compared to rumors about less newsworthy firms. However, stock returns do not reflect the reduced accuracy related to newsworthiness.

We also provide new evidence that the biographical traits of journalists are strong predictors of accurate reporting, but investors do not fully account for these traits. Older reporters who received degrees in journalism and specialize in the rumor target's industry are significantly more accurate. Since these biographical traits are not easily observed, it is plausible that investors with limited attention do not completely account for their predictive power when setting stock prices. In contrast, newspaper characteristics and many details of the text of the article that could potentially provide relevant information about the rumor's accuracy are unrelated to accuracy and also ignored by investors.

We believe our results have important implications for the role of the financial media in the stock market that extend beyond merger rumors. In particular, by using ex post realizations of rumors reported in the press to separate media coverage from media accuracy, we show that the accuracy of the press is negatively related to newsworthiness. While our results are consistent with the majority of academic research that shows that more information is produced about large, public firms with higher valuations, our evidence shows that this information is likely to be less accurate. This provides new evidence on the effect of media coverage on information asymmetry (Tetlock, 2010). In particular, our results suggest that media coverage could introduce additional noise that is not easily separated from true information.

Appendix: Variable Definitions

Newsworthiness Variables

Public target	Dummy variable equal to one if the rumor target is publicly traded at the time of the rumor.
Valuable brand	Dummy variable equal to one if the target firm was listed in the top 100 most valuable brands by the Interbrand or Brandz data in any year from 2000 to 2011.
Industry sales to households	The fraction of the target industry's total sales that were purchased by households. Data are from the Bureau of Economic Analysis Detailed-level Input Output tables in 1997.
Distance	Great circle distance in kilometers between the headquarters of the newspaper that published the scoop article and the target firm.
Foreign target	Dummy variable equal to one if the rumor target is headquartered outside of the US.
Target book assets	Total book assets as reported in Compustat.
Institutional ownership	The fraction of the target's outstanding shares owned by institutional investors as recorded in 13-f filings.
High R&D/Assets	Dummy variable equal to one if the target firm has R&D/Assets greater than five percent.
Tobin's Q	(Total assets − common equity + market equity)/Total assets. Data from CRSP and Compustat.

Journalist Variables

Age	The average age of all reporters listed as authors of a scoop article.
Gender	Dummy variable equal to one if an article has at least one female coauthor.
Expert in target industry	Dummy variable equal to one if an article is written by a journalist who is an expert in the same industry as the primary industry of the rumor target, using Fama-French 17 industry codes.

Undergraduate major	Dummy variable equal to one if an article is written by a journalist who graduated with a major in one of the following categories:
Business/Economics	Degrees in Business, Economics, Finance, and Management
Journalism	Degrees in Broadcasting, Communication, Journalism, Mass Media, and Media Studies
English	Degrees in Creative Nonfiction, English, Literature, Literary Studies, and Screenwriting
Political Science	Degrees in Government, International Affairs, International Relations, Law, Politics, Political Science, Public Policy, and Public Relations
History	Degrees in Ancient History, American Studies, Art History, Asian History, Chinese History, Classics, History, and Modern History
Other	Degrees in Animals Science, Anthropology, Biology, Biopsychology, Criminal Justice, East Asian Languages, East Asian Studies, Electrical Engineering, Environmental Biology, Film, General Studies, Germanic Studies, Human Development, Liberal Arts, Mathematics, Philosophy, Psychology, Religion, Russian Studies, Sociology, Teaching, Urban Affairs, and Veterinary Medicine.
Article Variables	
Anonymous source	Dummy variable equal to one if an article does not identify a specific source of the rumor.
Target comment	Categorical variable that records the target firm's response to the rumor according to the text of the newspaper article: No comment, Has conversations from time to time, Confirmed rumor, Denied rumor, Couldn't be reached, or Wasn't asked.

Merger stage	Categorical variable that records what stage the rumored talks are in according to the text of the newspaper article: Speculation, Preliminary talks, In talks, Made offer, Preparing a bid, For sale, or Evaluating bids
Articles on scoop date (#)	The total number of articles reporting the rumor published on the same date as the scoop article.
Rumor in headline	Dummy variable equal to one if the rumor article refers to the rumor in the headline of the article.
Number of bidders mentioned	The number of different firms mentioned in the text of the article as potential bidders.
Price mentioned	Dummy variable equal to one if a specific price is mentioned in the text of the article.
Newspaper Variables	
Family-run media company	Dummy variable equal to one if a newspaper is owned by a family-run firm.
Newspaper age	The age of the newspaper in years from its original founding date.
Newspaper circulation	The total daily circulation of the newspaper as recorded in the Audit Bureau of Circulation reports.
Other Control Variables	
Day 0 return	The abnormal stock return of the target firm on the day the scoop article is published. Abnormal returns are calculated as the firm's return minus the CRSP value-weighted index return.
$\text{Returns}_{(-5,-1)}$	The cumulative abnormal stock returns over the period from five days to one day before the scoop article is published. Abnormal returns are calculated as the firm's return minus the CRSP value-weighted index return. Cumulative returns are the sum over five days of the abnormal returns.

Industry fixed effects	Dummy variables for the target firm's primary Fama-French 17 industry code.
Year fixed effects	Dummy variables for the year the scoop article is published.
Target market equity	The target stock price times the number of shares outstanding two days before the announcement of the merger.
Completed	Dummy variable equal to one if a merger bid is successfully completed as reported in SDC.
Majority cash	Dummy variable equal to one if a merger bid using cash as the majority form of payment, using data from SDC.
Tender offer	Dummy variable equal to one if a merger bid is a tender offer, as reported in SDC.
Leveraged buyout	Dummy variable equal to one if a merger bid is classified as a leveraged buyout by SDC.
Cross-border	Dummy variable equal to one if a merger bid is a cross-border bid, as recorded by SDC.
Target takeover defenses	Dummy variable equal to one if a target employed any defensive antitakeover provisions following an unsolicited merger bid, as recorded by SDC.

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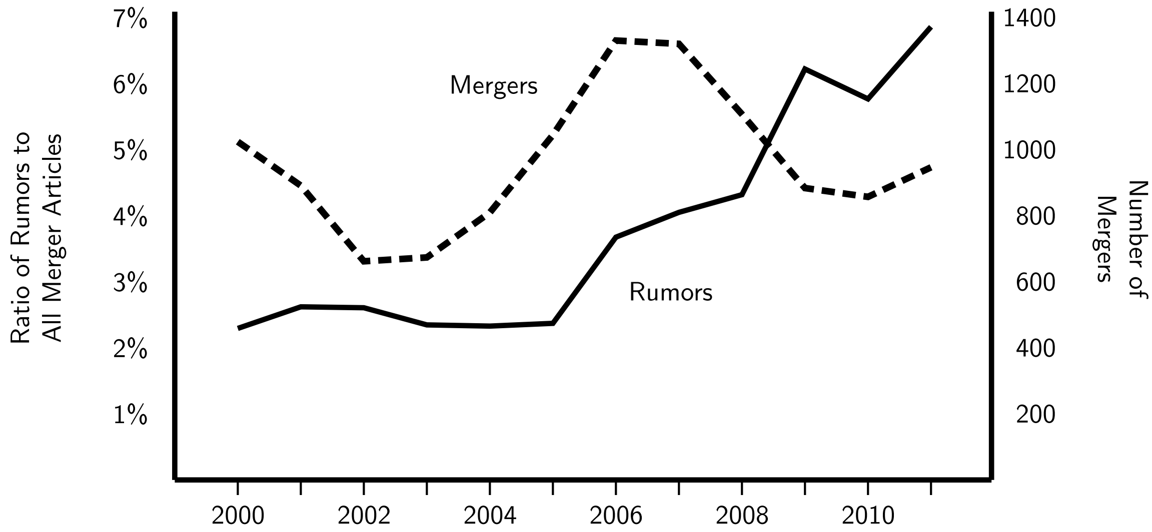

Fig. 1
The Increasing Prevalence of Merger Rumors
This figure presents the time series of rumor articles and actual merger announcements. The solid line represents the ratio of merger rumors in our sample per year to the yearly total number of articles in the *Wall Street Journal* and the *New York Times* that contain any of the words, “merger,” “acquisition,” or “takeover.” The dashed line represents the total number of global mergers in the SDC database where the deal value is greater than $500 million. To illustrate trends, both time series are three-year averages, centered on the observation year.

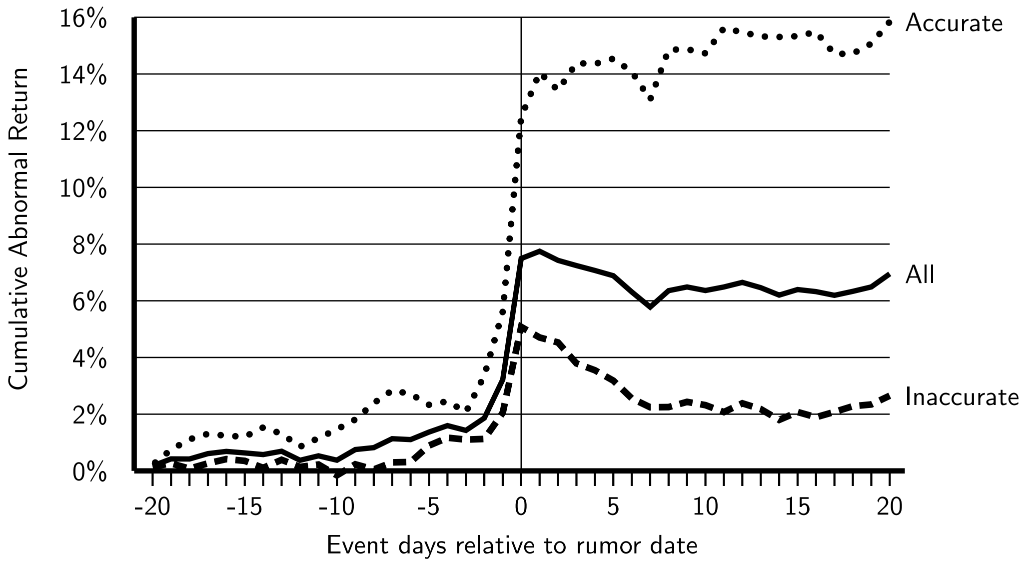

Fig. 2
Abnormal Returns of Accurate and Inaccurate Merger Rumors
This figure presents the time series of cumulative abnormal returns of merger rumor targets for three time series relative to the date of the first publication of a merger rumor. There are 415 rumors with stock price data over 2000-2011. Cumulative abnormal returns are the cumulative sum of daily abnormal returns, calculated as the firm's daily return minus the value-weighted CRSP index. The solid line represents the average of all target firms. The dotted line represents the subsample of merger rumor targets where a public merger announcement was made within one year of the rumor date. The dashed line represents the subsample of merger rumor targets where no public merger announcement was made in the following year.

Table 1
Rumor Articles by Calendar Period
This table presents counts of rumor articles by year, month, and weekday. 'All articles' includes all rumor articles in the sample. 'Scoop articles' is the first article that reports a rumor. 'Percent of scoops' is the fraction of total scoop articles in the sample that were published in a given year, month, or day. 'Percent of bids in SDC' is the fraction of bids in the SDC database where the original public announcement is in a given calendar period. These numbers are based on 129,104 bids worth $5 million or more for targets around the globe, during 2000–2011. 'Rumors that came true' is the number of rumors with a publicly announced bid in the SDC database within one calendar year of the original scoop article. 'Percent that came true' is the number of rumors that came true divided by the number of scoop articles for a given time period.

	All articles	Scoop articles	Percent of scoops	Percent of SDC bids	Rumors that came true	Percent that came true
Panel A: Yearly						
2000	155	35	7.0	9.6	12	34.3
2001	123	40	8.0	6.6	19	47.5
2002	185	60	12.0	6.1	15	25.0
2003	130	37	7.4	6.6	9	24.3
2004	58	14	2.8	7.3	4	28.6
2005	184	37	7.4	8.6	18	48.6
2006	185	56	11.2	9.7	15	26.8
2007	279	70	14.0	11.2	25	35.7
2008	214	31	6.2	9.1	9	29.0
2009	131	25	5.0	7.4	7	28.0
2010	393	75	15.0	8.8	26	34.7
2011	105	21	4.2	9.0	8	38.1
Total	2142	501			167	33.3
Panel B: Monthly						
January	209	46	9.2	7.5	12	26.1
February	134	32	6.4	7.4	12	37.5
March	183	51	10.2	8.9	17	33.3
April	223	47	9.4	8.0	17	36.2
May	246	48	9.6	8.5	20	41.7
June	157	43	8.6	8.9	16	37.2
July	150	36	7.2	8.8	7	19.4
August	100	28	5.6	7.9	4	14.3
September	256	53	10.6	8.0	15	28.3
October	156	42	8.4	8.3	10	23.8
November	185	40	8.0	8.2	17	42.5
December	143	35	7.0	9.6	20	57.1
Panel C: Daily						
Sunday	56	19	3.8	1.5	4	21.1
Monday	364	97	19.4	20.7	28	28.9
Tuesday	366	75	15.0	19.5	16	21.3
Wednesday	416	93	18.6	19.1	36	38.7
Thursday	424	103	20.6	19.2	40	38.8
Friday	388	89	17.8	17.9	29	32.6
Saturday	128	25	5.0	2.0	14	56.0

Table 2
Summary Statistics of Predictive Variables
This table presents summary statistics for the main variables used throughout the paper for 501 merger rumors over the period 2000–2011. Observations are at the scoop article-level. This is the newspaper article that first reports the merger rumor. Journalist characteristics are aggregated from individual journalist characteristics to the scoop article-level as well. Variable definitions are presented in the appendix.

			Percentile		
	Mean	Std. Dev.	25th	50th	75th
Panel A: Target newsworthiness					
Public target	0.884	0.320	1	1	1
Valuable brand	0.156	0.363	0	0	0
Industry sales to households	0.384	0.279	0.102	0.371	0.591
Log(Distance)	1.761	0.734	1.808	2.093	2.214
Foreign target	0.251	0.434	0	0	1
Log(Target book assets)	9.394	1.990	8.056	9.472	10.563
Institutional ownership	0.487	0.311	0.209	0.575	0.706
High R&D/Assets	0.719	0.450	0	1	1
Tobin's Q	1.731	1.471	0.961	1.199	2.007
Panel B: Journalist characteristics					
Log(Journalist age)	3.612	0.190	3.486	3.584	3.714
Gender	0.450	0.498	0	0	1
Expert in target industry	0.574	0.495	0	1	1
Undergraduate major					
Business/Economics	0.095	0.293	0	0	0
Journalism	0.332	0.472	0	0	1
English	0.308	0.462	0	0	1
Political Science	0.195	0.397	0	0	0
History	0.265	0.442	0	0	1
Other	0.095	0.293	0	0	0
Panel C: Article characteristics					
Anonymous source	0.920	0.272	1	1	1
Target Comment					
Declined to comment	0.459	0.499	0	0	1
Has conversations	0.010	0.099	0	0	0
Confirmed rumor	0.032	0.176	0	0	0
Denied rumor	0.038	0.191	0	0	0
Couldn't be reached	0.084	0.277	0	0	0
Wasn't asked	0.377	0.485	0	0	1
Merger Stage					
Speculation	0.507	0.500	0	1	1

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Table 2 - *Continued*

	Mean	Std. Dev.	Percentile 25th	50th	75th
Preliminary talks	0.086	0.280	0	0	0
In talks	0.269	0.444	0	0	1
Made offer	0.050	0.218	0	0	0
Preparing bid	0.036	0.186	0	0	0
For sale	0.032	0.176	0	0	0
Evaluating bids	0.020	0.140	0	0	0
Articles on scoop date (#)	1.729	1.338	1	1	2
Rumor in headline	0.848	0.359	1	1	1
Number of bidders mentioned	1.500	1.517	1	1	2
Price mentioned	0.386	0.492	0	0	1
Panel D: Newspaper characteristics					
Family-run media company	0.735	0.442	0	1	1
Log(Newspaper age)	4.493	0.966	4.718	4.779	4.927
Log(Newspaper circulation)	13.720	1.071	12.902	14.277	14.554

Table 3
Target Characteristics in Rumors Versus Actual Mergers
This table presents average characteristics of target firms in the rumor sample compared to targets in actual mergers. Targets in actual mergers are taken from SDC over the period 2000-2011 and exclude mergers that are in the rumor sample. The column denoted 'All Mergers' includes private, public, and subsidiary mergers of targets across the globe, where deals must be worth at least $250 million. Mergers in the column denoted 'Large, Public Mergers' include the subset of public targets where the minimum target book assets is set such that the average firm in the subsample has the same book assets as the average firm in the rumor sample. The column 'US Merger Targets' only includes targets in the US, but does not constrain size or public status of the target. The numbers in parantheses are p-values from t-tests of the average of each merger column with the rumor column average. Significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *.

	Rumors	All Mergers	Large, Public Mergers	US Merger Targets
Public target (%)	88.42	38.10***	100.00***	36.87***
		(< 0.001)	(< 0.001)	(< 0.001)
Valuable brand (%)	15.57	0.48***	2.27***	0.44***
		(< 0.001)	(< 0.001)	(< 0.001)
Industry sales to households (%)	38.41	30.53***	34.42***	29.83***
		(< 0.001)	(0.003)	(< 0.001)
Foreign (%)	25.15	66.08***	76.99***	0.00***
		(< 0.001)	(< 0.001)	(< 0.001)
Log(Target book assets)	9.39	7.45***	9.39	6.99***
		(< 0.001)	(0.998)	(< 0.001)
Institutional ownership (%)	48.67	44.92*	37.95***	57.24***
		(0.058)	(< 0.001)	(< 0.001)
High R&D/Assets (%)	71.91	11.19***	3.76***	21.75***
		(< 0.001)	(< 0.001)	(< 0.001)
Tobin's Q	1.73	1.64	1.24***	1.85
		(0.299)	(< 0.001)	(0.189)

Table 4
The Likelihood of Rumors
This table presents fixed effects logit and linear probability models of the probability that a rumor article will be published about a potential merger. Observations include 501 targets discussed in merger rumors published in newspapers and actual merger bids that were announced in 2000-2011 and recorded in SDC. The dependent variable equals one if a rumor article was published about the target. The logit models are fixed effects logits with year and industry effects (using Fama-French 17 Industry Definitions). The OLS models are linear probability models. R^2 is the pseudo R^2 in the logit tests and an adjusted R^2 in the OLS regressions. The numbers in parentheses are p-values from standard errors clustered at the industry level. Significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *.

	All Targets		Public Targets	
	Logit	OLS	Logit	OLS
Public target	2.436***	0.048***		
	(< 0.001)	(< 0.001)		
Valuable brand	3.050***	0.412***	1.813***	0.283***
	(< 0.001)	(< 0.001)	(< 0.001)	(0.003)
Industry sales to households	0.743*	0.017	−1.319*	−0.033
	(0.086)	(0.224)	(0.085)	(0.172)
Foreign	−1.925***	−0.047***	−1.494**	−0.058**
	(< 0.001)	(< 0.001)	(0.030)	(0.046)
Log(Target book assets)			0.739***	0.030***
			(< 0.001)	(0.001)
Institutional ownership			−0.681	−0.044*
			(0.143)	(0.059)
High R&D/Assets			1.785***	0.065***
			(< 0.001)	(< 0.001)
Tobin's Q			0.478***	0.024***
			(< 0.001)	(0.006)
Observations	18,325	18,325	1,712	1,712
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Pseudo/Adjusted R^2	0.274	0.114	0.355	0.172

Table 5
Target Abnormal Event Returns and Reversals
The cells report average cumulative abnormal returns in percentages. Abnormal returns are raw returns minus the CRSP value-weighted index. Rumors that came true are those in which an official takeover announcement was made within one year of the first report of the rumor in the press. The numbers in parentheses are p-values from t-tests of the average of each merger column with the rumor column average. Significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *.

		Rumor Came True		
	All	Yes	No	Difference
Day 0	4.271***	6.865***	3.029***	3.835***
	(< 0.001)	(< 0.001)	(< 0.001)	(0.001)
Days $[-20, -1]$	3.093***	5.267***	2.045**	3.222
	(< 0.001)	(0.003)	(0.041)	(0.112)
Days $[-10, -1]$	2.483***	3.850***	1.824**	2.026
	(< 0.001)	(0.005)	(0.029)	(0.205)
Days $[-5, -1]$	2.116***	2.903***	1.736***	1.167
	(< 0.001)	(0.005)	(0.003)	(0.320)
Days $[+1, +5]$	−0.850	1.313*	−1.885**	3.198***
	(0.177)	(0.090)	(0.027)	(0.005)
Days $[+1, +10]$	−1.395*	1.422	−2.743***	4.165***
	(0.062)	(0.107)	(0.007)	(0.002)
Days $[+1, +20]$	−0.849	2.480	−2.442**	4.922**
	(0.371)	(0.114)	(0.039)	(0.012)

Table 6
Rumor Accuracy and Stock Returns: Target Newsworthiness
This table presents results of the relationship between target newsworthiness and 1) the likelihood that a rumor comes true and 2) the target stock returns following the publication of the rumor. Columns 1 and 2 present fixed effect logit regression coefficients in which the dependent variable is a dummy variable equal to one if a merger rumor came true within one year of the first rumor date. Columns 3 and 4 present OLS regression coefficients. The dependent variable in column 3 is the rumor target's abnormal stock return on the date the first rumor article is published. The dependent variable in column 4 is the cumulative abnormal return over the days +1 to +10, relative to the rumor date. Abnormal returns are calculated as the target returns minus the CRSP value-weighted index return. Variables are defined in the appendix. Industry fixed effects include Fama-French 17 industry codes. Standard errors are clustered at the industry level and p-values are reported in parentheses. Significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *.

Dependent variable:	Rumor Comes True		Return Day 0	Returns $(+1,+10)$
	(1)	(2)	(3)	(4)
Day 0 Return		4.352***		
		(0.006)		
Valuable brand	−0.699**	−0.460**	−0.062***	0.028
	(0.022)	(0.034)	(0.001)	(0.209)
Log(Target book assets)	−0.322***	−0.335***	0.000	−0.015***
	(0.002)	(< 0.001)	(0.958)	(0.001)
Tobin's Q	−0.103*	−0.085	−0.005	0.000
	(0.062)	(0.222)	(0.228)	(0.984)
Industry sales to households	−0.878**	−0.821**	−0.005	−0.001
	(0.017)	(0.030)	(0.915)	(0.981)
Log(Distance)	−0.009	−0.113	0.023**	0.000
	(0.954)	(0.483)	(0.025)	(0.988)
Institutional ownership	−0.857*	−0.987	0.008	−0.066
	(0.099)	(0.108)	(0.710)	(0.236)
High R&D/Assets	−4.768	−6.574***	0.290	0.004
	(0.106)	(0.001)	(0.102)	(0.977)
$\text{Returns}_{(-5,-1)}$	−0.359	0.818	−0.309	0.077
	(0.841)	(0.766)	(0.128)	(0.263)
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	234	234	234	234

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Table 6 - *Continued*

Dependent variable:	Rumor Comes True		Return Day 0	Returns $(+1, +10)$
	(1)	(2)	(3)	(4)
Pseudo/Adjusted R^2	0.088	0.126	0.084	0.036

Table 7
Rumor Accuracy and Stock Returns: Journalist Characteristics
This table presents results of the relationship between journalist characteristics and 1) the likelihood that a rumor comes true and 2) the target stock returns following the publication of the rumor. Columns 1 and 2 present fixed effect logit regression coefficients in which the dependent variable is a dummy variable equal to one if a merger rumor came true within one year of the first rumor date. Columns 3 and 4 present OLS regression coefficients. The dependent variable in column 3 is the rumor target's abnormal stock return on the date the first rumor article is published. The dependent variable in column 4 is the cumulative abnormal return over the days +1 to +10, relative to the rumor date. Abnormal returns are calculated as the target returns minus the CRSP value-weighted index return. Variables are defined in the appendix. Industry fixed effects include Fama-French 17 industry codes. Standard errors are clustered at the industry level and p-values are reported in parentheses. Significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *.

Dependent variable:	Rumor Comes True		Return Day 0	Returns (+1, +10)
	(1)	(2)	(3)	(4)
Day 0 Return		8.485		
		(0.167)		
Log(Journalist age)	1.922***	2.040***	0.028	0.003
	(0.008)	(0.005)	(0.709)	(0.962)
Gender	−0.784	−0.610	−0.011	−0.038**
	(0.194)	(0.289)	(0.702)	(0.018)
UG degree: Business/Econ	1.481	1.204	0.043*	−0.023
	(0.204)	(0.304)	(0.086)	(0.354)
UG degree: Journalism	1.453***	1.495**	0.031	0.001
	(< 0.001)	(0.013)	(0.332)	(0.970)
UG degree: English	−0.077	−0.226	0.022	0.011
	(0.886)	(0.689)	(0.396)	(0.554)
UG degree: Poli-Sci	0.008	−0.214	0.019	−0.036*
	(0.989)	(0.626)	(0.434)	(0.058)
UG degree: History	0.704	0.533	0.057**	−0.035
	(0.361)	(0.541)	(0.048)	(0.228)
UG degree: Other	0.135	0.032	0.030	−0.042*
	(0.818)	(0.956)	(0.484)	(0.092)
Expert in target industry	0.983**	1.056***	−0.007	0.014
	(0.031)	(0.001)	(0.742)	(0.340)
$\text{Returns}_{(-5,-1)}$	2.417	3.791*	−0.166**	0.158

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Table 7 - *Continued*

Dependent variable:	Rumor Comes True		Return Day 0	Returns $(+1, +10)$
	(1)	(2)	(3)	(4)
	(0.136)	(0.063)	(0.022)	(0.262)
Log(Target book assets)	-0.488^{**}	-0.440^{***}	-0.001	-0.004
	(0.017)	(0.002)	(0.809)	(0.382)
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	159	159	159	159
Pseudo/Adjusted R^2	0.316	0.374	0.088	-0.025

Table 8
Rumor Accuracy and Stock Returns: Article Characteristics
This table presents results of the relationship between article characteristics and 1) the likelihood that a rumor comes true and 2) the target stock returns following the publication of the rumor. Columns 1 and 2 present fixed effect logit regression coefficients in which the dependent variable is a dummy variable equal to one if a merger rumor came true within one year of the first rumor date. Columns 3 and 4 present OLS regression coefficients. The dependent variable in column 3 is the rumor target's abnormal stock return on the date the first rumor article is published. The dependent variable in column 4 is the cumulative abnormal return over the days +1 to +10, relative to the rumor date. Abnormal returns are calculated as the target returns minus the CRSP value-weighted index return. Variables are defined in the appendix. Industry fixed effects include Fama-French 17 industry codes. Standard errors are clustered at the industry level and p-values are reported in parentheses. Significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *.

Dependent variable:	Rumor Comes True		Return Day 0	Returns $(+1, +10)$
	(1)	(2)	(3)	(4)
Day 0 Return		3.512***		
		(< 0.001)		
Anonymous source	−0.041	−0.151	0.037***	−0.050*
	(0.956)	(0.843)	(0.008)	(0.064)
Target response				
Has conversations	0.510	0.559	−0.010	−0.023
	(0.424)	(0.405)	(0.611)	(0.511)
Confirmed rumor	1.420	1.277	0.068**	−0.006
	(0.155)	(0.238)	(0.015)	(0.898)
Denied rumor	−0.098	−0.175	0.014	0.019*
	(0.901)	(0.835)	(0.527)	(0.077)
Couldn't be reached	0.354	0.218	0.045***	0.020
	(0.184)	(0.475)	(< 0.001)	(0.279)
Wasn't asked	−0.011	−0.049	0.009	−0.002
	(0.983)	(0.922)	(0.659)	(0.827)
Merger stage				
Preliminary talks	−0.077	−0.183	0.020*	0.027
	(0.886)	(0.734)	(0.076)	(0.552)
In talks	1.407***	1.432***	−0.009	0.018
	(0.001)	(< 0.001)	(0.677)	(0.375)
Made offer	0.908	0.974	−0.011	−0.067**

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Table 8 - *Continued*

Dependent variable:	Rumor Comes True		Return Day 0	Returns $(+1, +10)$
	(1)	(2)	(3)	(4)
	(0.519)	(0.472)	(0.389)	(0.043)
Preparing bid	0.855	0.842	0.017	0.029
	(0.299)	(0.225)	(0.730)	(0.379)
For sale	−0.038	0.049	−0.034	0.026
	(0.918)	(0.909)	(0.104)	(0.748)
Evaluating bids	2.839**	3.056**	−0.028	0.066**
	(0.038)	(0.032)	(0.146)	(0.024)
Articles on scoop date (#)	0.316**	0.221	0.027**	−0.003
	(0.011)	(0.145)	(0.011)	(0.296)
Rumor in headline	−0.364	−0.349	−0.013	−0.022
	(0.453)	(0.448)	(0.488)	(0.326)
Number of bidders mentioned	0.031	0.016	0.003	−0.007
	(0.652)	(0.833)	(0.494)	(0.181)
Price mentioned	0.524	0.428	0.034***	0.030*
	(0.281)	(0.413)	(0.007)	(0.085)
$\text{Returns}_{(-5,-1)}$	−0.097	0.937	−0.337*	0.049
	(0.916)	(0.359)	(0.059)	(0.370)
Log(Target book assets)	−0.292***	−0.272***	−0.005*	−0.004
	(0.001)	(0.005)	(0.088)	(0.267)
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	284	284	284	284
Pseudo/Adjusted R^2	0.257	0.269	0.301	0.044

Table 9
Rumor Accuracy and Stock Returns: Newspaper Characteristics
This table presents results of the relationship between newspaper characteristics and 1) the likelihood that a rumor comes true and 2) the target stock returns following the publication of the rumor. Columns 1 and 2 present fixed effect logit regression coefficients in which the dependent variable is a dummy variable equal to one if a merger rumor came true within one year of the first rumor date. Columns 3 and 4 present OLS regression coefficients. The dependent variable in column 3 is the rumor target's abnormal stock return on the date the first rumor article is published. The dependent variable in column 4 is the cumulative abnormal return over the days +1 to +10, relative to the rumor date. Abnormal returns are calculated as the target returns minus the CRSP value-weighted index return. Variables are defined in the appendix. Industry fixed effects include Fama-French 17 industry codes. Standard errors are clustered at the industry level and p-values are reported in parentheses. Significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *.

Dependent variable:	Rumor Comes True		Return Day 0	Returns $(+1, +10)$
	(1)	(2)	(3)	(4)
Day 0 Return		5.825**		
		(0.014)		
Family-run media company	−0.717	−0.759	−0.004	0.001
	(0.256)	(0.195)	(0.877)	(0.828)
Log(Newspaper age)	−0.370	−0.430	0.009	0.002
	(0.417)	(0.277)	(0.476)	(0.742)
Log(Newspaper circulation)	−0.093	−0.125	0.005	−0.016**
	(0.573)	(0.452)	(0.269)	(0.019)
$\text{Returns}_{(-5,-1)}$	−0.998	−0.053	−0.236**	−0.033
	(0.415)	(0.964)	(0.014)	(0.850)
Log(Target book assets)	−0.248***	−0.246***	0.000	−0.005**
	(< 0.001)	(0.001)	(0.953)	(0.047)
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	198	198	198	198
Pseudo/Adjusted R^2	0.169	0.211	0.064	0.031

Table 10
Runup and Total Premium
This table presents fixed effects OLS models of the cumulative abnormal stock returns of merger targets in the three windows: runup (event window $(-42, -1)$ relative to the public announcement date), announcement $(0, +5)$, and the combined period $(-42, +5)$. Observations include mergers for public US targets that were announced in 2000-2011. Variables are defined in the appendix. The numbers in parentheses are p-values from standard errors clustered at the Fama-French 17 industry level. Significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *.

	Target CAR (-42,-1)		Target CAR (0,+5)		Target CAR (-42,+5)	
Rumor	0.062***	0.069***	−0.080***	−0.078***	0.001	0.006
	(0.001)	(0.002)	(<.001)	(<.001)	(0.966)	(0.735)
Log(Target market equity)	0.009**	0.011**	−0.021***	−0.027***	−0.023***	−0.027***
	(0.037)	(0.022)	(<.001)	(<.001)	(0.001)	(0.001)
Industry sales to households		−0.040***		0.015**		−0.034***
		(0.002)		(0.041)		(0.002)
Institutional ownership		0.008		0.123***		0.107**
		(0.729)		(0.008)		(0.036)
Valuable brand		−0.138***		−0.034		−0.167**
		(0.010)		(0.321)		(0.039)
Completed		0.037***		0.045***		0.085***
		(0.008)		(0.001)		(<.001)
Majority cash		−0.013		−0.016		−0.017
		(0.192)		(0.319)		(0.287)
Tender offer		0.043***		0.087***		0.116***
		(<.001)		(<.001)		(<.001)
Leveraged buyout		−0.014		0.000		−0.019**
		(0.182)		(0.978)		(0.050)
Cross-border		0.022**		0.009		0.017
		(0.016)		(0.366)		(0.231)
Target takeover defenses		−0.017		0.008		−0.008
		(0.247)		(0.671)		(0.661)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2652	2280	2583	2231	2583	2231
Adjusted R^2	0.037	0.049	0.061	0.110	0.056	0.112

Internet Appendix for

"Rumor Has It: Sensationalism in Financial Media"

Internet Appendix Table 1
Likelihood of Withdrawal

This table presents fixed effects linear probability models estimated using OLS. The dependent variable is a dummy variable equal to one if a merger bid is withdrawn and zero otherwise. Observations include mergers that were announced in 2000-2011 for public US targets. The numbers in parentheses are p-values from standard errors clustered at the Fama-French 17 industry level. Significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *.

	Dependent variable: Bid Withdrawn			
log(Target market equity)	−0.003	−0.003	−0.010**	−0.010**
		(0.597)	(0.016)	(0.044)
Rumor		−0.012		−0.019
		(0.732)		(0.593)
Industry sales to households			0.024	0.025
			(0.624)	(0.618)
Institutional ownership			0.063***	0.062***
			(0.006)	(0.008)
Valuable brand			−0.019	−0.021
			(0.476)	(0.422)
Majority cash			0.011	0.011
			(0.550)	(0.558)
Tender offer			−0.037	−0.036
			(0.279)	(0.274)
Leveraged buyout			0.088***	0.090***
			(0.009)	(0.006)
Cross-border			−0.006	−0.005
			(0.636)	(0.645)
Target takeover defenses			0.282***	0.281***
			(0.001)	(0.001)
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	2,652	2,652	2,280	2,280
Adjusted R^2	0.004	0.004	0.034	0.033

Internet Appendix Table 2
Rumor Accuracy and Stock Returns: Journalist Characteristics and Newspaper Fixed Effects

This table presents results of the relationship between newspaper characteristics and 1) the likelihood that a rumor comes true and 2) the target stock returns following the publication of the rumor. Columns 1 and 2 present fixed effect logit regression coefficients in which the dependent variable is a dummy variable equal to one if a merger rumor came true within one year of the first rumor date. Columns 3 and 4 present OLS regression coefficients. The dependent variable in column 3 is the rumor target's abnormal stock return on the date the first rumor article is published. The dependent variable in column 4 is the cumulative abnormal return over the days +1 to +10, relative to the rumor date. Abnormal returns are calculated as the target returns minus the CRSP value-weighted index return. Variables are defined in the appendix. Industry fixed effects include Fama-French 17 industry codes. Standard errors are clustered at the industry level and p-values are reported in parentheses. Significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *.

Dependent variable:	Rumor Comes True		Return Day 0	Returns (+1, +10)
	(1)	(2)	(3)	(4)
Day 0 Return		8.008		
		(0.149)		
Log(Journalist age)	1.953**	2.156***	0.021	0.004
	(0.048)	(0.006)	(0.785)	(0.959)
Gender	−1.008	−0.881	−0.006	−0.040*
	(0.145)	(0.274)	(0.855)	(0.061)
UG degree: business/econ	1.559	1.135	0.069**	−0.067
	(0.276)	(0.417)	(0.050)	(0.181)
UG degree: journalism	2.046***	1.842***	0.035	0.013
	(< 0.001)	(0.003)	(0.301)	(0.694)
UG degree: english	−0.522	−0.321	0.011	0.019
	(0.484)	(0.631)	(0.677)	(0.513)
UG degree: poli sci	−0.297	−0.445	0.014	−0.025
	(0.697)	(0.533)	(0.545)	(0.390)
UG degree: history	−0.884	−0.784	−0.001	−0.030
	(0.190)	(0.319)	(0.964)	(0.419)
UG degree: other	0.488	0.239	0.049	−0.022
	(0.558)	(0.753)	(0.138)	(0.492)
Expert in target industry	0.797	0.826	0.005	0.011
	(0.200)	(0.123)	(0.686)	(0.629)
The Wall Street Journal	0.965	1.043	−0.002	−0.013
	(0.163)	(0.148)	(0.935)	(0.701)
Dow Jones News Service	1.495	1.406	0.026*	0.067*

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Internet Appendix Table 2 - *Continued*

Dependent variable:	Rumor Comes True		Return Day 0	Returns $(+1, +10)$
	(1)	(2)	(3)	(4)
	(0.114)	(0.127)	(0.094)	(0.097)
New York Times	0.339	−0.262	0.068	0.012
	(0.832)	(0.891)	(0.120)	(0.729)
Reuters News	−1.677	−1.749	−0.066	0.003
	(0.275)	(0.365)	(0.492)	(0.958)
New York Post	0.082	0.341	−0.038	0.111**
	(0.926)	(0.628)	(0.431)	(0.042)
Barron's	−1.991	−1.621	−0.140**	0.007
	(0.249)	(0.494)	(0.020)	(0.807)
NYT Blogs	−2.265	−2.791	−0.063	−0.038
	(0.268)	(0.388)	(0.197)	(0.590)
Bloomberg	3.118***	3.078***	0.079	0.009
	(< 0.001)	(0.001)	(0.157)	(0.762)
The Boston Globe	−15.740***	−13.990***	−0.014	−0.045
	(< 0.001)	(< 0.001)	(0.743)	(0.313)
Financial Times	3.507**	2.627	0.072	−0.028
	(0.015)	(0.118)	(0.135)	(0.601)
Denver Post	0.534	1.126	−0.042	−0.020
	(0.771)	(0.538)	(0.270)	(0.780)
Associated Press Newswires	−14.490***	−13.250***	0.022	0.037
	(< 0.001)	(< 0.001)	(0.586)	(0.166)
Pittsburgh Post-Gazette	−14.760***	−13.320***	0.015	0.041
	(< 0.001)	(< 0.001)	(0.577)	(0.186)
The Globe and Mail	2.674**	1.400	0.110*	0.055
	(0.028)	(0.286)	(0.099)	(0.480)
Returns$_{(-5,-1)}$	3.214*	5.006*	−0.149**	0.168
	(0.090)	(0.082)	(0.044)	(0.243)
Log(Target book assets)	−0.375**	−0.358***	0.000	−0.005
	(0.011)	(0.001)	(0.953)	(0.285)
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	159	159	159	159
Pseudo/Adjusted R^2	0.396	0.439	0.095	−0.101

Internet Appendix Table 3
Journalists' Accuracy Rates

This table presents publishing activity for journalists in the sample from 2000-2011. Media source is the most recent media company that published an article by the journalist. Scoop articles are the first reporting of the merger rumor. Accuracy rate is the fraction of scoop articles written by a journalist in which a formal takeover bid is made for the target firm within one year. Some articles are written by more than one journalist, which leads to more bylines than rumors. Journalists with fewer than four scoops in the sample are included in the 772 others.

Journalist	Media Company	All Articles	Scoop Articles	Accuracy Rate
Dennis K. Berman	WSJ	71	24	62.5
Andrew Ross Sorkin	NYT	67	19	42.1
Nikhil Deogun	WSJ	27	13	53.8
Robert Frank	WSJ	20	13	23.1
Robin Sidel	WSJ	23	9	55.6
Anupreeta Das	WSJ	21	7	42.9
Michael J. De La Merced	NYT	32	6	16.7
Jeffrey Mccracken	Bloomberg	19	6	50.0
Anita Raghavan	Dealbook	19	6	16.7
Suzanne Kapner	NYT	18	6	33.3
Sarah Ellison	DJNS	16	6	33.3
Erica Copulsky	NY Post	14	6	33.3
Gina Chon	WSJ	17	5	80.0
Peter Lattman	NYT	13	5	40.0
David Enrich	WSJ	10	5	20.0
Tennille Tracy	WSJ	9	5	0.0
John Carreyrou	WSJ-Europe	8	5	0.0
Leslie P. Norton	Barron's	7	5	20.0
Matthew Karnitschnig	WSJ	19	4	75.0
Susan Carey	WSJ	18	4	50.0
Jason Singer	DJNS	15	4	75.0
Tim Arango	NY Post	14	4	25.0
Martin Peers	WSJ	11	4	50.0
Mohammed Hadi	WSJ	8	4	25.0
Michael Arrington	TechCrunch	4	4	50.0
Doris Frankel	Reuters	4	4	0.0
772 Others		1710	420	36.4
Total		2214	603	37.6

Internet Appendix Table 4
Rumor Accuracy and Stock Returns: Journalist Fixed Effects

This table presents results of the relationship between journalist fixed effects and 1) the likelihood that a rumor comes true and 2) the target stock returns following the publication of the rumor. Columns 1 and 2 present fixed effect logit regression coefficients in which the dependent variable is a dummy variable equal to one if a merger rumor came true within one year of the first rumor date. Columns 3 and 4 present OLS regression coefficients. The dependent variable in column 3 is the rumor target's abnormal stock return on the date the first rumor article is published. The dependent variable in column 4 is the cumulative abnormal return over the days +1 to +10, relative to the rumor date. Abnormal returns are calculated as the target returns minus the CRSP value-weighted index return. Variables are defined in the appendix. Industry fixed effects include Fama-French 17 industry codes. Standard errors are clustered at the industry level and p-values are reported in parentheses. Significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *.

Dependent variable:	Rumor Comes True		Return Day 0	Returns $(+1, +10)$
	(1)	(2)	(3)	(4)
Day 0 Return		4.112***		
		(< 0.001)		
Dennis K. Berman	1.325**	1.311**	0.011	0.023
	(0.024)	(0.026)	(0.511)	(0.463)
Andrew Ross Sorkin	1.290***	0.910**	0.099	0.083
	(0.006)	(0.044)	(0.105)	(0.184)
Nikhil Deogun	−0.171	−0.190	−0.008	0.079
	(0.822)	(0.809)	(0.419)	(0.379)
Robert Frank	−15.860***	−14.720***	−0.054**	0.034**
	(< 0.001)	(< 0.001)	(0.045)	(0.014)
Robin Sidel	2.266***	2.194***	0.035	−0.152
	(0.006)	(< 0.001)	(0.571)	(0.176)
Anupreeta Das	0.571	0.665*	−0.009	0.025
	(0.145)	(0.073)	(0.593)	(0.335)
Michael J. De La Merced	−17.440***	−15.970***	−0.125	−0.109**
	(< 0.001)	(< 0.001)	(0.141)	(0.039)
Jeffrey Mccracken	−16.560***	−15.020***	−0.225***	0.203***
	(< 0.001)	(< 0.001)	(0.003)	(< 0.001)
Anita Raghavan	−0.361	−0.702	0.068	−0.065***
	(0.589)	(0.177)	(0.134)	(0.005)
Suzanne Kapner	1.747	1.943	−0.041**	−0.016

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Internet Appendix Table 4 - *Continued*

Dependent variable:	Rumor Comes True		Return Day 0	Returns $(+1, +10)$
	(1)	(2)	(3)	(4)
	(0.277)	(0.290)	(0.029)	(0.486)
Sarah Ellison	−0.621	−0.860	0.048	0.023
	(0.730)	(0.661)	(0.446)	(0.760)
Erica Copulsky	−0.466	−0.608	0.019	0.009
	(0.529)	(0.403)	(0.390)	(0.542)
Gina Chon	1.166	0.996	0.032	0.044
	(0.341)	(0.379)	(0.325)	(0.576)
Peter Lattman	−0.603	−1.158	0.115***	−0.296*
	(0.674)	(0.524)	(< 0.001)	(0.076)
David Enrich	−0.053	0.115	−0.035***	0.026
	(0.831)	(0.658)	(0.006)	(0.252)
Tennille Tracy	−16.920***	−15.580***	−0.067	−0.002
	(< 0.001)	(< 0.001)	(0.165)	(0.926)
John Carreyrou	−16.220***	−15.050***	0.006	0.017
	(< 0.001)	(< 0.001)	(0.812)	(0.120)
Leslie P. Norton	−0.388	−0.168	−0.041**	0.120***
	(0.653)	(0.854)	(0.011)	(< 0.001)
$\text{Returns}_{(-5,-1)}$	−0.684	0.892	−0.350**	0.117*
	(0.478)	(0.503)	(0.021)	(0.074)
Log(Target book assets)	−0.316***	−0.299***	−0.006**	−0.008***
	(< 0.001)	(0.001)	(0.045)	(0.002)
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	304	304	304	304
Pseudo/Adjusted R^2	0.202	0.226	0.188	0.173

Internet Appendix Table 5
Media Sources' Accuracy Rates
This table presents publishing activity for all media sources in the sample from 2000-2011. Scoop articles are the first reporting of the merger rumor. Accuracy rate is the fraction of scoop articles published by a newspaper in which a formal takeover bid is made for the target firm within one year.

Media Source	All Articles	Percent of All Articles	Scoop Articles	Percent of Scoops	Accuracy Rate
Dow Jones News Service	625	29.2	67	13.4	38.8
Wall Street Journal	448	20.9	158	31.5	38.6
New York Times	219	10.2	38	7.6	28.9
New York Post	95	4.4	24	4.8	37.5
Reuters News	73	3.4	26	5.2	19.2
NYT Blogs	59	2.8	12	2.4	16.7
MarketWatch	57	2.7	3	0.6	33.3
St. Louis Post-Dispatch	46	2.1	1	0.2	0.0
Barron's	38	1.8	15	3.0	26.7
Boston Globe	38	1.8	8	1.6	25.0
Wall Street Journal Online	33	1.5	4	0.8	50.0
Washington Post	30	1.4	2	0.4	50.0
Pittsburgh Post-Gazette	30	1.4	5	1.0	20.0
USA Today	29	1.4	2	0.4	0.0
Associated Press Newswires	25	1.2	5	1.0	20.0
Denver Post	21	1.0	5	1.0	20.0
Atlanta Journal-Constitution	21	1.0	0	0.0	
News & Observer Raleigh	17	0.8	3	0.6	0.0
Bloomberg	16	0.7	10	2.0	80.0
Financial Times	15	0.7	8	1.6	62.5
New York Daily News	13	0.6	1	0.2	100.0
Los Angeles Times	7	0.3	6	1.2	16.7
Houston Chronicle	7	0.3	2	0.4	50.0
Philadelphia Inquirer	7	0.3	0	0.0	
St. Petersburg Times	7	0.3	0	0.0	
BusinessWeek	5	0.2	4	0.8	25.0
San Francisco Chronicle	5	0.2	3	0.6	0.0
Newsweek	1	0.0	0	0.0	
Star-Ledger	1	0.0	1	0.2	0.0
San Diego Union-Tribune	1	0.0	0	0.0	
75 Others	153	7.1	88	17.6	26.1
Total	2142	100.0	501	100.0	33.3

Internet Appendix Table 6
Rumor Accuracy and Stock Returns: Newspaper Fixed Effects
This table presents results of the relationship between newspaper fixed effects and 1) the likelihood that a rumor comes true and 2) the target stock returns following the publication of the rumor. Columns 1 and 2 present fixed effect logit regression coefficients in which the dependent variable is a dummy variable equal to one if a merger rumor came true within one year of the first rumor date. Columns 3 and 4 present OLS regression coefficients. The dependent variable in column 3 is the rumor target's abnormal stock return on the date the first rumor article is published. The dependent variable in column 4 is the cumulative abnormal return over the days +1 to +10, relative to the rumor date. Abnormal returns are calculated as the target returns minus the CRSP value-weighted index return. Variables are defined in the appendix. Industry fixed effects include Fama-French 17 industry codes. Standard errors are clustered at the industry level and p-values are reported in parentheses. Significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *.

Dependent variable:	Rumor Comes True		Return Day 0	Returns (+1, +10)
	(1)	(2)	(3)	(4)
Day 0 Return		4.702***		
		(< 0.001)		
The Wall Street Journal	0.521	0.688	−0.026	−0.011
	(0.521)	(0.411)	(0.144)	(0.592)
Dow Jones News Service	0.338	0.312	0.015	0.039*
	(0.594)	(0.623)	(0.358)	(0.067)
New York Times	0.633	0.600	0.008	0.010
	(0.395)	(0.427)	(0.757)	(0.623)
Reuters News	−0.678	−0.459	−0.045**	0.018
	(0.315)	(0.505)	(0.026)	(0.592)
New York Post	1.058	1.216	−0.017	0.051**
	(0.131)	(0.109)	(0.338)	(0.032)
Barron's	−0.720	−0.573	−0.052**	0.057
	(0.346)	(0.459)	(0.011)	(0.180)
NYT Blogs	−0.502	−0.548	−0.047	0.009
	(0.467)	(0.347)	(0.451)	(0.586)
Bloomberg	2.351***	2.327***	0.047	0.027
	(0.004)	(0.004)	(0.186)	(0.486)
The Boston Globe	0.557	1.046	−0.085	−0.022*
	(0.630)	(0.374)	(0.143)	(0.075)
Financial Times	2.466***	2.450***	0.011	0.007

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Internet Appendix Table 6 - *Continued*

Dependent variable:	Rumor Comes True		Return Day 0	Returns (+1, +10)
	(1)	(2)	(3)	(4)
	(< 0.001)	(< 0.001)	(0.818)	(0.821)
Los Angeles Times	1.167	1.673	−0.077***	0.061**
	(0.435)	(0.277)	(0.008)	(0.048)
Denver Post	−0.004	0.326	−0.061***	−0.013
	(0.997)	(0.785)	(< 0.001)	(0.799)
Associated Press Newswires	−14.670***	−15.630***	−0.005	0.014
	(< 0.001)	(< 0.001)	(0.719)	(0.523)
Pittsburgh Post-Gazette	−13.860***	−14.810***	−0.005	0.045**
	(< 0.001)	(< 0.001)	(0.825)	(0.022)
The Globe and Mail	1.292**	1.226*	0.022	0.043
	(0.012)	(0.052)	(0.566)	(0.107)
The Sunday Times	−13.560***	−14.360***	−0.079***	0.039
	(< 0.001)	(< 0.001)	(0.002)	(0.149)
Techcrunch	−14.540***	−15.320***	−0.058	0.108**
	(< 0.001)	(< 0.001)	(0.201)	(0.015)
$\text{Returns}_{(-5,-1)}$	−0.862	1.043	−0.379***	0.069
	(0.344)	(0.437)	(0.005)	(0.353)
Log(Target book assets)	−0.258***	−0.242**	−0.005**	−0.008***
	(0.004)	(0.015)	(0.047)	(0.003)
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	304	304	304	304
Pseudo/Adjusted R^2	0.184	0.217	0.157	0.029