Institutional Trading in Firms Rumored to be Takeover Targets

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Abstract

In this paper we examine institutional trading in proximity to takeover rumors by combining the ANcerno dataset of transaction-level institutional trades with a unique sample of takeover rumor 'scoops'. We find that institutions are net buyers in firms which subsequently become subject to takeover speculation and that institutional trading predicts which rumored firms will eventually receive takeover bids. Segregating funds according to their propensity to trade, we show that those less likely to purchase rumored targets by chance over the pre-rumor period are more likely to identify firms which will receive bid proposals and that they trade more profitably over both the pre- and post-rumor periods. We test for the presence of informed trading in a variety of ways and conclude that institutional investors appear to trade on material private information which identifies the firms soon to be the target of takeover speculation.

Keywords: Institutional trading, Takeover rumors, Rumored targets, Takeover announcements, Mergers and acquisitions

JEL Classification: G14, G23, G30, G34

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1. Introduction

The literature is divided regarding the ability of institutional investors to earn abnormal returns. While many authors[1] report evidence of such competence, some contend otherwise (e.g., Jensen, 1968; Carhart, 1997; Fama and French, 2010) or note that such profitability is short lived (Edelen et al., 2016). Furthermore, it remains unclear whether any observed capabilities result from superior analysis of public information, as claimed by Dechow et al. (2001), Engelberg et al. (2012), and Akbas et al. (2015), or from the ability to gather and interpret private information as argued by Christophe et al. (2004, 2010) and Irvine et al. (2007). Given this debate and the growing interest in the roles of institutions surrounding corporate events (Chemmanur et al., 2018), we seek to determine whether and how institutional investors take advantage of the well-documented abnormal returns around the takeover rumor date of potential target firms (Ahern and Sosyura, 2015; Betton et al., 2018).

Using a proprietary database of transaction-level institutional trading activity from ANcerno together with a hand-collected dataset of initial takeover rumors provided by Betton et al. (2018), we address the following specific research questions. First, do institutional investors profit by trading in firms before and/or after the initial publication of a takeover rumor? Second, do institutional investors behave as if they possess private information about those firms which will soon be rumored targets? Third, are results representative of all institutions or instead driven by a select group of funds? Finally, does the informational content of the rumor relate to the institutional ability to discover or discern its impact?

To answer these questions, we analyze daily institutional trading patterns over the (-30, +30) rumor date period, considering both the type of institutional investor as well as the content of the

[1] See, for example, Coval and Moskowitz (2001), Irvine et al. (2007), Boehmer et al. (2008), Kacperczyk et al. (2005, 2006), Diether et al. (2009), and Puckett and Yan (2011).

rumor article. We also examine the predictive power of institutional trading as well as the profitability of round-trip trades (a purchase followed by a sale, or vice-versa). Furthermore, we distinguish between "*smart*" funds and "*lucky*" funds according to their propensity to trade (as derived from a bootstrap procedure conditioned on the number of trades executed within the year). For robustness, we construct momentum quintiles to show that our main results are not driven by momentum trading as documented in Griffin et al. (2003). Finally, we perform a number of tests to provide evidence as to whether institutions are acting on public or private information.

Previewing our results, we find the following. First, institutional investors in aggregate trade in a profitable manner in the pre-rumor period, yet not in the post-rumor period. Second, publicly available information related to takeover propensity does not enable institutions to replicate this performance. Moreover, an analysis of intraday trading patterns, bid-ask spreads, and short utilization ratios confirms the presence of informed trading, and we thus infer that institutions trade on private information. Third, we find that smart funds are responsible for 71% of the abnormal net-buying observed over the (-10, -1) period, and 83.8% of post-commission profits over the (-30, +30) period, as compared to lucky funds. Finally, institutional trading over the pre-rumor period is related to information subsequently provided within the published rumor article; specifically, abnormal net-buying is higher when rumors present specific and multiple avenues by which private information may have been leaked.

Our study contributes to the literature on institutional trading around corporate events. Institutions have been shown to utilize private information to their advantage prior to seasoned equity offerings (Chemmanur et al., 2009), initial public offerings (Chemmanur et al., 2010), takeover announcements (Jegadeesh and Tang, 2010; Fich et al., 2020), earnings announcements (Berkman and McKenzie, 2012), stock split announcements (Chemmanur et al., 2015), open market share repurchases (Chemmanur et al., 2016), CEO turnovers (Chemmanur et al., 2018), and dividend reduction announcements (Henry et al., 2017). However, the literature is silent on institutional trading prior to takeover rumors, despite enticing returns: two-day rumor date CAARs have been shown to average 3.81%, with select categories of rumors demonstrating CAARs averaging up to 10% (Betton et al., 2018).

Our paper also contributes to the current debate on whether and how institutional investors profit prior to takeover announcements. Griffin et al. (2012), Jedadeesh and Tang (2010), and Fich et al. (2020) are among those contending that, at best, only subsets of institutions outperform prior to merger announcements. However, these papers do not examine the performance stemming from news announcements over the pre-bid period. We demonstrate that institutions benefit from impending takeover rumors, and we provide evidence supporting the presence of informed trading. Furthermore, we link our results to specific rumor article content to provide insight into the source of pre-rumor information that funds seem to obtain. Taken together, this information attests to the sophisticated nature of institutional trading within the context of mergers and acquisitions, most particularly for smart funds.

The remainder of this paper is organized as follows. Section 2 briefly summarizes the existing empirical evidence on institutional trading. Section 3 describes our data, while Section 4 presents our results Finally, Section 5 provides a summary and conclusion of our work.

2. Literature Review

A number of studies investigate the pre- and post-event trading patterns of institutional investors to infer whether they are in possession of material private information. Ali et al. (2004) and Battalio and Mendenhall (2005) determine that institutions trade based on private information about future earnings announcements. Irvine et al. (2007) find that some institutions significantly increase their purchases in firms soon to receive an analyst's initial buy recommendation. Campbell et al. (2009)

find that institutional trading significantly predicts firms' earnings surprises. Hendershott et al. (2015) show that lagged institutional order flow computed prior to Reuters' news announcements predicts the sentiment of the news, the stock market reaction on the news announcement day, the stock market reaction on crisis news days, and earning announcement surprises.

Using ANcerno data on institutional trade transactions from 1999 to 2005, Chemmanur et al. (2009) report that institutions possess private information about seasoned equity offerings (SEOs). Other studies offering evidence that institutions trade based on their private information include investigations of corporate spin-offs (Chemmanur and Hu, 2016), credit rating changes (Jain and Wang, 2013), dividend cuts (Henry et al., 2017), ex-dividend returns (Henry and Koski, 2017), IPOs (Chemmanur et al., 2010), and option backdating scandals (Bernile et al., 2015).

Within the context of mergers and acquisitions, Ashraf and Jayaraman (2014) examine changes in quarterly institutional ownership in response to takeover announcements. They find that 'active' institutions (investment companies and independent investment advisors) have superior skill in identifying mergers with higher wealth implications. They conclude that such institutions are better informed as to the likelihood of merger success. Using quarterly 13F filings, Bodnaruk et al. (2009) argue that funds affiliated with the advisors of bidders take positions in target firms before a takeover announcement.

Griffin et al. (2012) conclude that institutional investors do not possess private information related to takeover and earning announcements, as pre-announcement trades are not profitable and are not predictive of takeover outcomes. Jegadeesh and Tang (2010) use monthly data to study the pattern and profitability of institutional trades around takeover announcements between 1998 and 2005. Concurring with Griffin et al. (2012), they report that institutions, as a group, do not buy target stocks prior to bid announcements, and their pre-bid trades do not generate abnormal returns.

However, they identify two subsets of funds that demonstrate superior pre-trading skills: funds whose main broker is also the main broker for the investment bank advising the target firm, and funds previously displaying a greater than average chance of buying target stocks prior to announcements ("smart" funds).

Fich et al. (2020) study the trading strategies of hedge funds and mutual funds in a sample of 7,184 M&A announcements between 1990 and 2015. They find that hedge funds (mutual funds) increase (reduce) their holdings in takeover candidates starting in the most recent quarter prior to the bid announcement. These changes in ownership are both statistically significant and economically important and can predict future bid announcements. Moreover, these trading patterns accelerate during the announcement quarter, consistent with hedge funds executing merger arbitrage strategies and subsequently prompting an equilibrium response from mutual funds. This evidence leads the authors to conclude that hedge funds enjoy superior access to private information or have superior skill in processing public information.

In this research paper we also find that certain funds outperform others; however, in contrast to many of the above authors, we find evidence that institutions, as a group, are net buyers of target firms in the pre-event period, and that this aggregate activity is profitable and predictive of forthcoming bids. One likely explanation for this discrepancy is that our event of interest is the rumor date rather than the bid announcement used in prior studies. Only 21% of our sample rumors lead to a bid announcement, and these occur on average 116 days prior to the public bid announcement. In addition, we analyze trading on a daily basis as opposed to using monthly or quarterly data.

Employing data from ANcerno and using a sample of 501 takeover rumors from 2000 to 2011, Ahern and Sosyura (2015) present evidence of institutional trading in proximity to the rumor date. As institutional trading is not the primary focus of their paper, they refrain from analyzing the statistical significance of their results. However, they show that the institutional buy-sell imbalance is somewhat positive over the (-20, +1) rumor date period (Figure 4, p. 2083). They also note that institutional investors are net sellers of rumored targets in the 30 days following the rumor's publication, regardless of whether the rumor eventuates. Moreover, they demonstrate that as a fraction of total CRSP volume, institutional investors buy substantially fewer shares in rumored firms during the post-rumor period. They thus contend that stock returns of rumored target firms are driven by the overreaction of unsophisticated retail traders.

Our paper corroborates many of their findings while adding rigor by providing the associated statistical tests for significance. In addition, we expand on their analysis by providing daily institutional trading measures (broken down by rumor type and fund type), controlling for institutional momentum buying, examining the predictive power of institutional trades, calculating the profitability of such trades, and determining whether the trades are likely to occur by chance. While we concur that retail investors may be responsible for driving post-rumor target stock returns, we find evidence that short-sellers and market makers also play a role. Additionally, we show that target returns are driven by a subset of funds investing as if they possess private information.

3. Data

We employ the dataset first used by Betton et al. (2018) as our base sample of target firm takeover rumors, consisting of 2,074 observations between January 2002 and December 2011. These rumors are based on articles retrieved from Capital IQ, Factiva, ProQuest, Standard & Poor's Takeover Talk, and Zephyr, retaining only those for which there was no preceding instance of the same rumor for a period of at least 180 days. The content of each rumor article has been coded according to the justification provided for the speculated takeover bid. In order to preserve a clear distinction between rumors and takeover announcements, the authors exclude rumors in which either the rumored bidder or the target confirms that negotiations are underway. In addition, official announcement dates are verified using Factiva and Google to correct for Securities Data Corporation (SDC) announcement date errors and omissions, as SDC accuracy has been criticized in several studies (Bharadwaj and Shivdasani, 2003; Faccio and Masulis, 2005; Barnes et al., 2014; Mulherin and Simsir, 2015).

Institutional trading data are obtained from ANcerno (also known as the Abel/Noser Corporation), a New York based brokerage firm. ANcerno collects trade information directly from institutional clients, providing exclusive analysis regarding execution costs. Puckett and Yan (2011) investigate this dataset for survivorship and selection biases. They conclude that the former is not a concern and that the latter is likely minor. Specifically, they note that clients are required to submit all of their trades to ANcerno to receive an optimal consultation on execution costs, and as full confidentiality is provided, it is unclear why they would instead submit a non-random portion thereof. Moreover, Hu et al. (2018) note that any sample selection biases within ANcerno are not obvious, while Puckett and Yan (2011), Anand et al. (2012), and Jame (2018) show that ANcerno institutions on average do not differ from 13F institutions in return characteristics, stock holdings, or stock trades.[2] While these authors do find that ANcerno institutions are larger than the typical 13F institution, they note that many studies find evidence of a negative relation between fund size and performance (e.g., Yan, 2008; Lewellen, 2011), with ANcerno institutions therefore *less* likely to yield evidence of positive returns.

Institutional coverage within the ANcerno database is quite broad, and utilizing this dataset allows us to observe daily trades made by investment managers and plan sponsors. According to Hu et al. (2018), the data account for $37 trillion worth of trades and cover about 15% (12%) of the Center for Research in Security Prices (CRSP) volume over the period 1999 – 2005 (1999 – 2011).

[2] However, it remains unknown whether selection biases exist related to geographic location or investor aptitude.

Previous academic studies that use ANcerno data include Bethel et al. (2009), Chemmanur et al. (2009), Goldstein et al. (2009), Henry and Koski (2017), and Hu et al. (2014, 2018), among more than 50 others.[3]

The ANcerno data contains different variables for identifying the client, manager, broker, and stock related to each transaction. The *clientcode* is a unique identifier for each of ANcerno's institutional clients while *clienttypecode* classifies the type of institution: plan sponsors (*clienttypecode*=1), investment managers (*clienttypecode*=2), and brokers (*clienttypecode*=3). In our study, we only include transactions of plan sponsors and money managers (consistent with Pucket and Yan, 2011, and Chemmanur et al., 2018) as ANcerno data do not contain many broker clients. The *clientmgrcode* refers to the fund within each institution that is responsible for the trade. Further, the data identify whether the recorded transaction was initiated as a purchase or sale and also include the *Ticker* and *CUSIP* of the traded stock, the number of shares traded (*volume*), the execution price (*price*), and the commission paid for the transaction (*commission*).

ANcerno removed *clientcodes* in the data after September 2011 which was a key variable that separately identified trades from different institutions. This makes us unable to include 107 firms with takeover rumors after September 2011 as we examine daily institutional trading over the (-30, +30) day period relative to each rumor. We require daily CRSP files to get information on share prices, the number of shares outstanding, share volume, and returns; therefore, we delete firms with incomplete CRSP coverage (96 firms). We merge institutional trading data from ANcerno with the rumor sample and exclude 182 firms without any trades during a period of (-90, -1) days relative to the rumor, with our final sample including 1,689 takeover-rumored firms.[4]

[3] Hu et al. (2018) provides further commentary as well as an extensive list of publications which use ANcerno data.
[4] Using *lognumber*, a unique code assigned to each batch of trading data sent to ANcerno by a client, we also remove data repetitions related to corrections as per Anad et al. (2011) and Hu et al. (2018).

As shown in Panel A of Table 1, the number of rumors per year increases during the sample period and reaches a peak of 382 in 2011 despite excluding rumors after September 2011. Panel B reports the sample distribution according to the Fama-French 17 industry classification and shows that our sample includes firms from a wide range of industries. Panel C presents attributes of the rumor sample which have previously been used as determinants of takeover predictability, with definitions provided in Appendix A.

Insert Table 1 about here

Panel D reports summary statistics of institutional trading attributes within rumored targets. Results are given for executed transactions that occurred over the (-60, +20) day period relative to the rumor date. Overall, the number of transactions, the number of shares traded, and the dollar value of shares traded trend upward over time, as the final years of the study period have more rumors and greater ANcerno coverage of institutions.

Finally, Panel E presents the cumulative average abnormal returns (CAARs) of rumored firms around the rumor date. Rumors are labelled as "*accurate*" if the rumored firm in question is indeed the target of a formal takeover bid within 365 calendar days after the initial scoop article, and otherwise "*inaccurate*".[5] In addition, two mutually exclusive rumor categories are created based on the degree to which the rumor article content justifies a connection to future takeover prospects. "*Speculative*" rumors are based on either takeover chatter or an increase in option activity in the target firm, without any further explanation provided in the article. "*Informative*" rumors are based on at least three rumor justifications, excluding those comprising speculative rumors. Appendix A reports the individual rationales (e.g., M&A advisor hired, synergies cited, analyst reported) considered as justification for the rumor article's publication.

[5] We explore alternative definitions of rumor accuracy, with results presented in the Internet Appendix (Section A.III).

We find that takeover rumors yield significantly positive CAARs of 4.11% over the rumor date period, while accurate and inaccurate rumors result in significantly positive CAARs of 8.63% and 2.90%, respectively. Qualitatively similar results are also found over the longer (-20, +20) rumor date window. These findings are in line with prior research (e.g., Ahern & Sosyura, 2015; Betton et al., 2018) and demonstrate that net-buying shares in firms that will subsequently become the subject of a publicly announced takeover rumor can be reasonably presumed to be profitable. In addition, post-rumor we observe a strong market reversal for speculative rumors, with CAARs of -1.26% over the (+2, +20) period. Figure 1 plots these share price reactions around the rumor date.

Insert Figure 1 about here

4. Results

4.1 Institutional trading patterns over the rumor period

We begin by examining the trading activity of ANcerno institutions in rumored targets.[6] For each day *t*, we separately aggregate the dollar value of all institutional buy and sell transactions for every rumored firm *i*. To prevent institutional trading in large firms from dominating our results, we normalize institutional trades by each firm's market capitalization (MC), lagged by one year:

$$IBuys_{i,t} = \frac{\sum_{n=1}^{Number\ of\ Buys_{i,t}} (Dollar\ value\ of\ buys_{i,t}^{n})}{MC_{i,t-250}} \tag{1}$$

$$ISales_{i,t} = \frac{\sum_{n=1}^{Number\ of\ Sales_{i,t}} (Dollar\ value\ of\ sales_{i,t}^{n})}{MC_{i,t-250}} \tag{2}$$

We define institutional order flow (IOF) and institutional order volume (IOV) as follows:

$$\mathrm{IOF}_{i,t} = IBuys_{i,t} - ISales_{i,t} \tag{3}$$

[6] Hereafter, we use "institutions" to refer to ANcerno institutions unless indicated otherwise.

$$\mathrm{IOV}_{i,t} = IBuys_{i,t} + ISales_{i,t} \tag{4}$$

Our institutional trading measures are similar to those of Campbell et al. (2009) and Hendershott et al. (2015), and we winsorize trades at the top and bottom 1% to diminish the effect of outliers. As a basis for statistical tests, we use the (-90, -31) day window prior to the rumor announcement date (day 0) as our benchmark. Similar to Corwin et al. (2004) and Irvine et al. (2007), we employ a series of *t*-tests to evaluate the significance of any single day's average trading level as compared to benchmark levels.

Table 2 provides tabulated means of these institutional trading variables over the (-20, +20) time period relative to the initial rumor publication date, while Figure 2 plots institutional trading activity for each type of institution. As we see from Panels B and C of the graph, although there are fewer investment managers than pension plan sponsors in ANcerno, they account for most of the institutional trading activity we uncover. This is consistent with the findings of Hu et al. (2018) who find that the quantity and the size of investment managers' trades tend to be larger than those of pension plan sponsors.

Insert Table 2 about here

Insert Figure 2 about here

Institutional trading activity prior to takeover rumors is quite different from that which occurs in the post-rumor period. As shown in Column 3, IOF is significantly positive in the week prior to the rumor's release (driven by increased purchases), but significantly negative on the rumor date and thereafter.

As indicated in Column 5, the number of institutions engaging in trades significantly increases over the days shortly before the rumor. The small magnitude of this increase suggests that aggregate trading activity is mainly a consequence of increased trading intensity rather than additional entrants.

In Column 6 (7), we report the ratio of the dollar trading volume of ANcerno buy (sell) transactions to the daily trading volume reported by CRSP for each day over the (-30, +30) rumor date period, where CRSP volume is calculated as the product of the CRSP daily closing price and the number of shares traded.[7] The ratio of ANcerno buy transactions to CRSP dollar volume significantly increases shortly prior to the rumor, albeit only at the 10% significance level on day (-1).[8] This implies that over the pre-rumor period, institutions purchase rumored firm shares more actively than does the broader cross-section of investors which includes retail investors. Given the significantly positive abnormal returns we find for rumored target firms on the rumor date (Table 1, Panel E), our findings are thus consistent with institutions acting on their private information concerning forthcoming rumor announcements and takeover possibilities.

Switching our focus to the post-rumor period, we see that institutions are net sellers of rumored targets, with ISales (IOF) significantly positive (negative) almost every day over the (0, +14) period as shown in Column 2 (3) of Table 2. Furthermore, the ratio of ANcerno sales to CRSP dollar volume over this timeframe is significantly above the benchmark level, highlighting the increased selling activity of institutions relative to a broader composition of investors. Such institutional selling may be expected, even in the absence of private information, as it is well-known that most rumors do not lead to a bid and thus rumored firm share prices tend to decline over time.

The pre-rumor/post-rumor change in IOF we uncover is compatible with the theoretical frameworks of Hirshleifer et al. (1994) and Brunnermeier (2005), who argue that "early-informed" investors are expected to at least partially sell their related holdings once information leakage occurs

[7] In order to identify trades solely between ANcerno clients, we follow Hu et al. (2018) and round transaction prices to the penny, and then impose the condition that the rounded transaction price should be equal for the same stock on the same day between buy and sell trades. If these conditions apply, we recognize the trades as double-sided and only include the maximum of the buy and sell volumes in our calculations for Column 6. We estimate an ANcerno to CRSP dollar volume of 9.3% during the benchmark period, which is between the 8% reported in Puckett and Yan (2011) and the 12% found in Hu et al. (2018). We adjust NASDAQ volumes according to Gao and Ritter (2010).
[8] This may be an indication that private information is leaking to other traders at this time.

and an informational advantage (i.e., that related to rumor prospects) is lost. However, it is not yet clear if institutional investors retain an informational advantage about future bid prospects once the rumor is published. In addition, it is unclear whether the content of the rumor article has any bearing on institutional trading activity.

We investigate these issues further, with Table 3 and Figure 3 presenting IOF and IOV trading measures according to the nature and accuracy of the rumor article.

Insert Table 3 about here

Insert Figure 3 about here

We find pre-rumor institutional order flow to be significant on multiple days for both accurate and inaccurate rumors, with the magnitude significantly larger for the former. On the rumor day, IOV peaks[9] while IOF drops significantly for rumored firms regardless of accuracy. IOF remains significantly negative for almost every day of the (+1, +20) rumor date period for accurately rumored firms. This is an interesting result, as these are the firms that will experience the well-documented share price increase on the impending takeover announcement date. This evidence supports the contention that institutions no longer possess private information regarding takeover prospects and lack the skill to utilize public knowledge to their advantage at this time. This evidence also supports the findings of Griffin et al. (2012) and Jegadeesh and Tang (2010) who contend that institutional investors do not trade as if they are informed prior to bid announcements.

Institutional trading activity also differs according to the nature of the rumor article's content (Table 3, Columns 5 – 8). Beginning on day (-7), we find IOF to be significantly higher for informative rumors than for speculative rumors in the pre-rumor period. This corroborates the notion

[9] It should be noted that some rumors in our sample are released after the market is closed. Consistent with this, we observe that a significant fraction of trades is recorded as occurring at the opening of trading on the day after the rumor.

that existing sources of reliable information not yet made public drive the trading activity of institutions during the pre-rumor period.[10] Post-rumor, we do not find much evidence of abnormal trading in firms with speculative rumors after day (+1), while we find significantly negative IOF (increased selling) in firms with informative rumors for most of the post-rumor period analyzed.

Our evidence thus suggests that in aggregate, institutional investors possess private information during the pre-rumor period related to takeover prospects, yet we find no such evidence during the post-rumor period. We infer that these investors are informed based upon the abnormally high levels of IOF in firms soon to be subject to takeover speculation. However, our findings raise an obvious question: who stands on the other side of pre-rumor and post-rumor trades? We discuss this issue in the following section.

4.2 Counterparties to institutional trades

While our findings suggest that institutions engage in abnormal trading of potential target firms, buying pre-rumor and selling post-rumor, it is important to consider who might be the counterparty to their trades. We offer a number of alternative explanations which are not mutually exclusive.

First, we recall from Table 2 that the ratio of ANcerno buy/sell trading volume to CRSP trading volume is significantly positive over the pre-rumor/post-rumor period. As ANcerno funds are representative of institutions (Puckett and Yan, 2011), the typical counterparty to ANcerno trades as captured by the CRSP dataset is not likely to be institutions. Rather, retail investors would appear to be the likely liquidity provider, as Ahern and Sosyura (2015) similarly deduce.

[10] In Table A4, we also examine institutional trading according to a variety of non-mutually exclusive takeover rationales as listed in Appendix A. Arguably, the rationales found to have significant IOF over the (-10, -1) period are those providing many opportunities for information leakage: *AdvisorHired*, *BlockPurchase*, *InsiderCited*, *PEFundInvolved*, and *SynergyCited*.

In support of this view, we show in Panel E of Table 1 that there is an incentive for retail investors to sell during the pre-rumor period. Specifically, over the (-20, -1) period we find a positive price runup of 1.7% for all rumors (significant at the 10% level), and 2.39% for accurate rumors (significant at the 1% level). Even without a price runup, the existence of heterogeneous beliefs may lead to heavy trading (Kandel and Pearson 1995; Kim and Verrecchia, 1994, 1997). Moreover, purchasing a rumored firm's stock post-rumor may be considered enticing for those believing rumors to be true, despite most rumors being false, and therefore a sign of non-sophisticated trading typically associated with retail investors. Furthermore, Barber and Odean (2008) show that retail investors face a costly search problem and solve this by purchasing those stocks that have recently caught their attention.

Retail investors are not necessarily the only counterparty, and further investigation reveals the trading activities of market makers as well. Market makers have an obligation to keep a fair and orderly market with reasonable liquidity for buyers and sellers (Lee et al., 1993) and may handle trades for clients or buy for their own accounts. In addition, according to the information asymmetry model (e.g., Copeland and Galai, 1983; Glosten and Milgrom, 1985; Kyle, 1985), market makers are able to identify changes in adverse selection and adjust bid-ask spreads accordingly. Examining changes in the bid-ask spread within our sample, we find significant increases shortly before the rumor, consistent with market makers acting as liquidity providers and receiving compensation through larger bid-ask spreads (see Figure A1 of the Internet Appendix). However, within our dataset we are unable to determine who the market makers are buying for, nor which side of the trade they are taking.

Finally, we also find evidence of short-selling activity over both the pre-rumor and post-rumor periods, as shown in Figure A2 of the Internet Appendix. Such trades may offset informed trades, as "falsely informed traders" (Cornell and Sirri, 1992) may fail to accurately recognize the extent of the inside information reflected in the stock prices and incorrectly believe they have superior information.

In line with our contentions, Hendershott et al. (2015) use Consolidated Equity Audit Trail Data (CAUD) files that contain detailed information on all orders executed on the NYSE and find that around news announcements, institutional trading volume is roughly half that of CRSP trading volume while retailers and market makers represents the other half. Similarly, Griffin et al. (2003) find that institutional trading represents about 45% of total trading volume on the NASDAQ while market makers and retail investors account for the rest. Ultimately, however, we are not able to provide definitive evidence as to the identity of those acting as liquidity providers for ANcerno funds.

4.3 Robustness tests

To test whether our results are driven by institutional momentum buying (also known as *trend-chasing* or *positive feedback trading*) as found in earlier studies (Lakonishok et al., 1992; Grinblatt et al., 1995; Badrinath and Wahal, 2002; Griffin et al., 2003), in Table 4 we partition our sample of rumored takeover firms into quintiles based on CAARs over the (-30, -10) window prior to the rumor. We then examine each quintile separately, with AARs and IOF displayed for each day. Rumored targets with the lowest CAR (-30, -10) are assigned to Quintile 1, while those with the highest CAR over the same period are assigned to Quintile 5. Our results show a similar pattern across quintiles: significant buying activity within one week prior to the rumor date contrasting with significant selling during the post-rumor period. Regardless of prior returns, institutions appear to identify potential takeover targets prior to the rumor date.

An alternative explanation could be that changes in institutional trading volume might increase return volatility, prompting news agencies to generate the rumor articles comprising our sample (Hendershott et al., 2015). To test this alternative hypothesis, for each day surrounding the rumor period we plot the return volatility and absolute value of stock returns (|AAR|) in Panels A and B of Figure 4. We find that both return volatility and the absolute value of stock returns increase significantly one day before the rumor while institutional order measures begin to rise eight days before the rumor (Table 2). This suggests that this alternative explanation is unlikely.[11] Furthermore, we note that the justifications which ostensibly provide the basis for the rumor's creation (e.g., *BlockPurchase*, *IndustryActivity*, *OptionsIncreased*, *TargetInitiated*, and *UnusualActivity*) limit the ability of news agencies to delay reporting until after high volatility in trading is observed.

Insert Table 4 about here

Insert Figure 4 about here

While we assert that institutions trade prior to rumors based on private information they possess on rumor and/or bid probability, it is plausible that institutions instead invest based on public information. If true, then within a sample of firms matched on takeover likelihood factors we should detect abnormal institutional trading. We provide results of the analysis of this alternative hypothesis in Table A1 of the Internet Appendix. We do not find any significant abnormal trading in the control sample, while the difference in IOF (rumored firms minus control firms) remains significantly positive in the pre-rumor period and significantly negative in the post-rumor period. This supports our prior findings and provides additional support for the notion that institutions trade as a result of being informed about rumor prospects.

4.4 The predictive power of institutional trading

4.4.1 Predicting rumor accuracy

[11] Unlike the end-date return volatility, intraday volatility is not easily observable by investors without access to the order book.

We further examine whether abnormal institutional trading prior to rumors can predict rumor accuracy (i.e., rumors resulting in a takeover announcement). We fit a logit regression where the dependent variable equals one if the rumored firm becomes subject to a takeover announcement within the following 365 days.[12] The main independent variable of interest is the buy-and-hold cumulative abnormal institutional order flow defined as follows:

$$BHAIOF_i(t_0, t_1) = \sum_{t_0}^{t_1}(IOF_i - IOF_{i,Benchmark})_t \tag{5}$$

where IOF_i is the institutional order flow of firm *i* and $IOF_{i,Benchmark}$ is the average daily institutional order flow calculated over the (-90, -31) window prior to the rumor date for firm i. We extensively control for other determinants of takeover candidacy by including multiple proxies for managerial motivation to pursue a deal, target newsworthiness, abnormal returns surrounding the rumor date, as well as year and industry fixed effects (Cornett et al., 2011; Ahern and Sosyura, 2015; Betton et al., 2018). Table 5 shows the results for a series of logistic regressions focusing on different time periods in proximity to the rumor date, while Appendix A provides variable definitions.

Insert Table 5 about here

The estimated logit regressions exhibit significant and positive coefficients for abnormal buy-and-hold IOF prior to accurate rumors. This finding provides multivariate support for our central premise that institutions privately gather and process information before material information (the rumor's release) is available for public consumption. This informational advantage is substantial, as takeover rumors in general and accurate rumors in particular are found to result in significant positive short-term abnormal returns for target firms on the rumor day. Establishing a stock position in such firms in advance of the rumor not only allows institutions to capture these abnormal returns, but also

[12] For robustness, we provide results according to various definitions of accuracy in the Internet Appendix.

makes such trades more innocuous than if target firm shares were purchased shortly before a forthcoming takeover announcement. In support of this view, Ke et al. (2003) note that with respect to illegal insider-trading prosecution, "risks are smaller the further removed the trades are from the principal informational event".

In Columns 3 and 4 of Table 5 we examine whether institutional trading is informative in predicting rumor accuracy after takeover rumors are made public. Contrary to our results in the first two columns, we find significant and negative coefficients for abnormal buy-and-hold institutional order flow (BHAIOF) over the post-rumor periods. In addition, the results in Columns 5 and 6 show significant and negative coefficients for BHAIOF(-5, +5) and BHAIOF(-10, +10). This indicates that institutions are significant sellers of rumored firms which eventually receive takeover bids, and thereby forego significantly positive returns upon the official takeover announcement.

We offer a number of non-mutually exclusive potential explanations for this behavior. First, such actions are consistent with the information acquisition model of Hirshleifer et al. (1994) in which institutions are expected to reverse their positions based on short-lived private information after realizing returns. Said differently, rumor publication reduces information asymmetry and this reduces the value of private information for informed institutions (Tetlock, 2010), encouraging institutions to reverse their positions and lock in their gains. Second, takeover negotiations are highly uncertain and time consuming (Gao and Oler, 2012), involving many different decision makers (e.g., target managers, bidder managers, target advisors, and bidder advisors) and subject to changing business conditions. Under such circumstances, institutional investors may lack confidence in their ability to predict the takeover announcement, preferring instead to ensure they avoid a potential price reversal for falsely rumored firms (Ahern and Sosyura, 2015; Betton et al., 2018). Third, expected future benefits are uncertain: takeover announcement date returns are significantly smaller for firms that have been rumored to be potential targets in the past (Ahern and Sosyura, 2015; Betton et al., 2018) while rumors reduce the likelihood of deal completion by about 40% (Alperovych et al., 2016). This may encourage institutional investors to pursue alternative uses of their funds (Wermers, 2003). Finally, the significant selling activity in accurately rumored firms shortly after the rumor date may reflect portfolio rebalancing requirements, as accurate rumors have the largest market reaction on the rumor day (Figure 1), yet institutional investors do not typically over-weight individual stocks in their portfolio for long (Alexander et al., 2007).

4.4.2 Predicting the stock market reaction to takeover rumors

We proceed to investigate the informativeness of institutional trading in a multivariate setting. In particular, we examine whether lagged abnormal institutional trading predicts abnormal returns around the rumor date while providing controls as motivated by the literature (e.g., Cornett et al. (2011), Ahern and Sosyura (2015), and Betton et al. (2018)). If institutions possess material private information regarding takeover rumors, they are likely to increase their net purchases in advance of those rumors which yield high rumor date returns. In this case, we expect positive coefficients for institutional buying measures in the regression models. Table 6 shows the results of the regressions.

Insert Table 6 about here

We first note that in line with the findings of Betton et al. (2018) and Ahern and Sosyura (2015), the independent variables *CAR(-5, -1)*, *informative* rumors, and *speculative* rumors each have significant coefficients. Of particular interest in this paper are the coefficients of our buy-and-hold cumulative abnormal institutional order flow (BHAIOF) measures as explanatory variables. The positively significant coefficients of *BHAIOF(-10, -1)* and *BHAIOF(-5, -1)* in the first two columns show that trades of institutions during the pre-rumor period have power in predicting rumor announcement returns. In Columns 3 to 7, we calculate individual institutional trading measures for every rumored firm on day (-1) relative to the rumor. Our results in Columns 3 to 5 suggest significantly positive predictive power for IOF, IOV, and IBuys. Offering further support, we see in Column 6 that institutional sales are negatively related to rumor date abnormal returns. However, this statistical significance is lost when we include institutional purchases in the same model (Column 7). Overall, our results in Table 6 show that institutional buying positively predicts rumor date returns, supporting the hypothesis that institutions possess private information related to takeover rumors over the pre-rumor period.

4.5 Private information or luck?

We now investigate whether the abnormal institutional trading we observe is driven by a subset of funds investing wisely. We first note that there are two ways that trades are reported by ANcerno. First, the investment manager may invest on behalf of a pension plan sponsor who subscribes to ANcerno; in this case we observe the investment manager trading for the specific plan sponsor. Second, the investment manager may directly report trades to ANcerno; in this case all trades are reported on behalf of the investment manager. Therefore, we follow Jame (2018) and refer to a client-manager pair as a fund, where the client could be either an investment manager or a plan sponsor. This identification also accounts for the possible hierarchical structure of funds and their management companies as documented in the literature (e.g., Sensoy et al., 2014; Korteweg and Sorensen, 2017).

We classify funds as "*smart*" and "*lucky*" funds based on their net positions in rumored firms and on the total number of securities they trade every year. Specifically, we aggregate all ANcerno transactions into a fund-firm level and calculate the buy-and-hold cumulative abnormal institutional order flow (BHAIOF) over the 30-day window prior to the rumor. As some funds might purchase rumored firms only by chance, we use a bootstrap procedure similar to that used by Jegadeesh and Tang (2010) to determine the probability that a fund buys rumored targets conditioned on the number of trades it executes within that year.[13] For each year-fund observation, we identify the pool of unique stocks traded by the fund during that year. In addition, for every fund, we replace each stock it trades with a random stock from the pool of traded stocks (without replacement) and compute the number of times each fund is a net-buyer of a rumored target within the month prior to the rumor. Using a bootstrap simulation (N=10,000), we estimate the probability distribution of the number of rumored targets that each fund purchases by chance.

Given the discrete nature of the outcome variable and the fact that rumors are independently scattered during any particular year, the number of times a fund purchases a rumored target by chance during the year, conditional on the total number of trades it executes, follows a Poisson distribution ($p_i \sim Po(\lambda)$). Using the probability function of the Poisson distribution (for each fund-year observation) we compute the probability of hitting 'r' targets by chance as:

$$P(X = r_{it}) = \frac{e^{-\lambda_{it}} * \lambda_{it}^{r_{it}}}{r_{it}!} \tag{6}$$

where r_{it} is the observed number of positive net-purchases within rumored targets by fund *i* within the month prior to the rumor during year *t*, and λ_{it} is the Poisson distribution parameter for fund *i* during year *t* which is estimated using the bootstrap simulation. For each calendar year, we label a fund as smart if both of the following two conditions are satisfied. First, the probability of hitting the rumored firms by chance is less than 5% (computed using Equation 6). Second, the observed number of hits on rumored firms is larger than the average number of hits ($r_{it} > \lambda_{it}$). If either condition is violated, we label the fund as lucky. To illustrate, Figure 5 presents the probability distribution of hitting rumored targets by chance for two anonymous funds during the year 2009.

Insert Figure 5 about here

[13] We refer the reader to Jegadeesh and Tang (2010, p.19) for an extended discussion.

We note that institutional trading desks usually divide trade orders into several trades or among several brokers, while in ANcerno the allocation to each broker is defined as a "ticket" and each ticket may lead to several different trade executions. Therefore, similar to Anand et al. (2012) and Busse et al. (2019) we perform the bootstrap methodology at the ticket level so that the trade execution by brokers does not affect our results.

We report results in Table 7, presenting the sample size and the number of funds that are classified as smart and lucky each year in Panel A. Overall, we classify 9% of net-buying funds as smart. In Panel B, we report whether the probability distribution representing the number of times a fund purchases rumored targets in one year is statistically different from the distribution in the following year. We observe that in all years the chi-squared statistic is significant at the 1% level which implies that smart funds persistently outperform lucky funds within a short horizon prior to takeover rumors.

Insert Table 7 about here

We next examine the trading patterns of smart and lucky funds around takeover rumors. Table 8 (9) presents the results for smart (lucky) funds, in aggregate and by rumor accuracy, with the results plotted in Panels A – C of Figure 6. In Columns 1, 3, and 5 of Table 8 we see that smart funds are significant net buyers of rumored target firms during the pre-rumor period, regardless of rumor accuracy, with IOF significantly positive throughout the entire (-8, -1) window relative to the rumor date. In contrast, we do not observe any abnormal IOF by lucky funds prior to rumors, as displayed in Table 9.

Insert Figure 6 about here

Insert Table 8 about here

Insert Table 9 about here

Upon rumor publication and afterwards, both smart and lucky funds engage in significant selling of rumored firm shares.[14] For smart funds, we observe significantly negative IOF in inaccurately rumored firms on eleven days over the (0, +20) period, whereas we observe such IOF on only 2 days in accurately rumored firms over this period. In contrast, we observe significantly negative IOF for lucky funds on every day of the (0, +20) period for accurately rumored firms, and on six days over this period for inaccurately rumored firms. Given that accurately rumored target firms will receive, on average, a premium upon bid announcement, the evidence presented in Tables 8 and 9 supports the proposition that smart funds are better informed than lucky funds over both the pre- and post-rumor periods.[15]

To further investigate whether trades of smart and/or lucky funds are informative and can predict rumor accuracy, we fit a logit regression where the dependent variable equals one if the rumored firm becomes subject to a takeover announcement within the following 365 days. We include measures of fund trading as explanatory variables along with other control measures, and present results in Table 10. Panel A presents the results using the buy-and-hold abnormal institutional order flow of smart funds as an independent variable. The positive and significant coefficients of $BHAIOF(-10, -1)_{smart}$ and $BHAIOF(-5, -1)_{smart}$ in the first two columns of Panel A show that trades of smart funds during the pre-rumor period have power in predicting rumor accuracy. The positive and statistically significant coefficients for $BHAIOF(+1, +5)_{smart}$ and $BHAIOF(+1, +10)_{smart}$ in Columns 3 and 4 indicate that smart fund trades during the post-rumor periods are informative in predicting rumor accuracy as well.

Insert Table 10 about here

[14] Since ANcerno does not provide reliable intraday time stamps and marks a significant fraction of trades as occurring at the opening of trading, we cannot examine whether transactions execute before or after the rumor is released to the market on day (0).

[15] Further evidence is provided in the Internet Appendix (Tables A3 and A4).

Finally, combining the pre- and post-rumor periods, the coefficients of $BHAIOF(-5, +5)_{smart}$ and $BHAIOF(-10, +10)_{smart}$ in Columns 5 and 6 remain positive and significant. Taken together, these results indicate that smart funds appear confident in not only identifying takeover targets prior to the rumor, but in predicting the existence and ultimate success of takeover negotiations. Such evidence is consistent with the accumulation of private information.

In Panel B of Table 10, we examine the predictive power of trades by lucky funds in a similar fashion to the above. Contrary to our prior results for smart funds, the pre-rumor trades of lucky funds do not predict rumor accuracy (Columns 1 and 2). When examining the post-rumor period as well as combined pre- and post-rumor windows, the BHAIOF of lucky funds is significant but *negatively* relates to rumor accuracy. This indicates that lucky funds are not able to predict rumor accuracy before or after the rumor's publication, and thus lucky funds do not appear to be informed.

4.6 The profitability of institutional trades around takeover rumors

In this section, we examine the profitability of institutional trading using actual execution prices and executed volume. We closely follow Pucket and Yan (2011) to calculate the holding-period profits of round-trip trades (trades in which funds purchase and sell or sell and repurchase the same stock) as the difference between the dollar values of consecutive sale and purchase transactions. We aggregate observations at the firm-fund levels and acknowledge any unrealized return as of the end of the trading period by marking the net positions to market at the end of each trading horizon (Irvine, 2007; Puckett and Yan, 2011; Chemmanur and He, 2016). We use volume-weighted average execution prices of purchases (sales) when funds execute multiple purchases (sales) as part of their round-trip transactions, and apply the DGTW benchmark (as per Daniel, Grinblatt, Titman, and Wermers, 1997) return over the holding periods to calculate abnormal profits.[16] Our measures of

[16] We refer the reader to Puckett and Yan (2011, pg. 609) for further details.

trading performance account for implicit trading costs (e.g., price impact) as we use actual prices of executed transactions in order to calculate the returns.

Results are presented in Table 11. Panel A shows the abnormal trading profits of smart and lucky funds for the whole sample while Panel B (C) presents their trading performance in accurately (inaccurately) rumored firms. The results demonstrate that smart funds outperform lucky funds, although both fund types earn significant abnormal returns through their trades over different horizons. This is consistent with previous studies that document the profitability of institutional trading around various events (e.g., Chemmanur et al., 2009; Busse et al., 2012; Bernile et al., 2015; Chemmanur and He, 2016; Chemmanur et al., 2018) and with studies demonstrating the superior performance of a subset of institutions (Ashraf and Jayarman, 2007; Bodnaruk et al., 2007; Jegadeesh and Tang, 2010; Griffin et al., 2012).[17]

Insert Table 11 about here

Our results in Table 11 indicate that traders informed about impending takeover rumors receive substantial profits. For example, we find that smart funds earn an average abnormal profit of about $365,900 per rumor over the (-5, +5) rumor date period. The economic magnitude of this trading activity is quite substantial and translates into gains of almost $28 million for smart funds within our sample. Additionally, establishing a stock position in such firms in advance of the rumor allows institutions to not only capture abnormal returns upon rumor publication but also to benefit further when the rumor is followed by a formal bid. This informed institutional trading pattern is thus consistent with illegal trading by insiders, calling into question the integrity of financial markets and meriting further regulatory attention.

[17] We perform a series of robustness tests in which we remove 79 observations for which the announcement is forthcoming within the next 30 days. All the results in Tables 1 to 11 remain qualitatively unchanged. The respective tables are unreported for brevity but are available from the authors upon request.

5. Conclusion

There is an ongoing debate about the nature of institutional trading surrounding corporate events and in particular whether institutional investors are informed (Bernile et al., 2015). In this paper, we combine two proprietary datasets, one consisting of transaction-level institutional trades and the other consisting of first-instance published takeover rumors, to answer the following questions: First, do institutions have private information about those firms which are subject to forthcoming takeover rumors? Second, do institutional investors appear to profit by trading in firms prior to the first publication of a takeover rumor? Third, are results representative of all institutions or instead driven by a select group of funds? Finally, does the type of takeover rumor matter? That is, does the informational content of the rumor relate to the institutional ability to discover or discern its impact?

We find institutional order flow to be significantly positive over the pre-rumor period, while significantly negative shortly thereafter, and this activity does not appear to be driven by institutional momentum buying. Our results hold after controlling for publicly available information, and when compared to a sample of firms matched according to takeover candidacy. The evidence is thus consistent with institutions utilizing private information when trading in rumored targets, as opposed to being skilled at gathering public information.

We examine profitability using actual execution prices and executed volume to establish that institutions on average do indeed trade profitably over the rumor date period on round-trip trades. To investigate further, we categorize institutions according to their propensity to trade. Specifically, we utilize a bootstrap procedure as per Jegadeesh and Tang (2010) to determine the probability that a fund buys rumored targets by chance conditional on the number of trades it executes within a given year. We define those funds less likely to purchase rumored targets by chance as ‘smart’ funds and those more likely to purchase rumored targets by chance as ‘lucky’ funds.

We find that smart funds represent 9% of our sample, and uncover a stark contrast in trading activity: smart funds drive pre-rumor purchases and display wisdom over the post-rumor period, relative to lucky funds, by refraining from significant sales of rumored firms which lead to actual bid proposals. The profitability of trading in rumored target firms is thus found to be significantly higher for smart funds than for lucky funds over both the pre- and post-rumor date periods, averaging 4.07% over the (-30, +30) rumor date period. Reduced selling of accurately rumored firms in the post-rumor period also allows smart funds to take advantage of a further price appreciation as the takeover announcement date approaches.[18] Money managers appear to engage more in such trading strategies than pension plan sponsors, but both are significant buyers of rumored firms throughout the seven-day pre-rumor period.

Regarding the informational content of the rumor, we find significantly increased IOF during the pre-rumor period when rumors are informative and/or justified by certain rationales such as *AdvisorHired*, *BlockPurchase*, *InsiderCited*, *PEFundInvolved*, and *SynergyCited*. These rumor types appear to offer institutions more opportunities to acquire private information. In contrast, other rumor types, such as those generated by takeover chatter or based solely on an increase in option activity in the target firm (speculative rumors) do not appear to generate any significant institutional trading activity. In general, corporate insiders, investment bankers, journalists, and lawyers (among others) may be informed of impending rumors and would have an incentive to leak this information (Van Bommel, 2003; Brunnermeier, 2005).

The evidence presented in this paper is thus consistent with institutions, and in particular smart funds, benefitting from short-lived private information by buying rumored firms in the pre-rumor

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[18] We do not report trade execution up until the announcement date of accurate rumors; however, in untabulated analysis we confirm that announcement date returns for rumored targets are significantly positive, as expected.

period and selling upon rumor publication or shortly thereafter (while selling less in accurately rumored firms).

Regulators have become more 'evidence based' in their approach to policy making concerning insider trading (Aspris et al., 2014). We propose that they incorporate our findings into their algorithms to help identify and limit the leakage of material private information related to takeover rumors and any subsequent bid announcements. This may serve to mitigate threats to the financial integrity of markets which have been associated with insider trading, such as increased price volatility (Leland, 1992), reduced liquidity (Agrawal and Cooper, 2015), increased legal risks (Haslem et al., 2017) and decreased investor confidence (Fishe and Robe, 2004) and a sense of moral injustice (Bris, 2005).

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Figure 1. Stock returns around takeover rumors

This figure plots the market price reaction around the rumor day based on bid occurrence (*Accurate* vs. *Inaccurate*) and two mutually exclusive rumor categories (*Speculative* vs. *Informative*). Our sample includes 1,689 takeover-rumored firms with available institutional trading data in ANcerno during the period January 2002 – September 2011. Rumors are labeled as accurate (*Accurate*) if the rumored firm in question is the target of a formal takeover bid within 365 calendar days after the initial scoop article, and inaccurate (*Inaccurate*) otherwise. Rumors labeled as speculative (*Speculative*) are based on either takeover chatter or an increase in option activity in the target firm, without any further justification of the rumor. Informative (*Informative*) rumors are based on at least three rumor justifications, excluding those labeled as speculative. CAARs are calculated using a standard market model (based on the CRSP value-weighted market index).

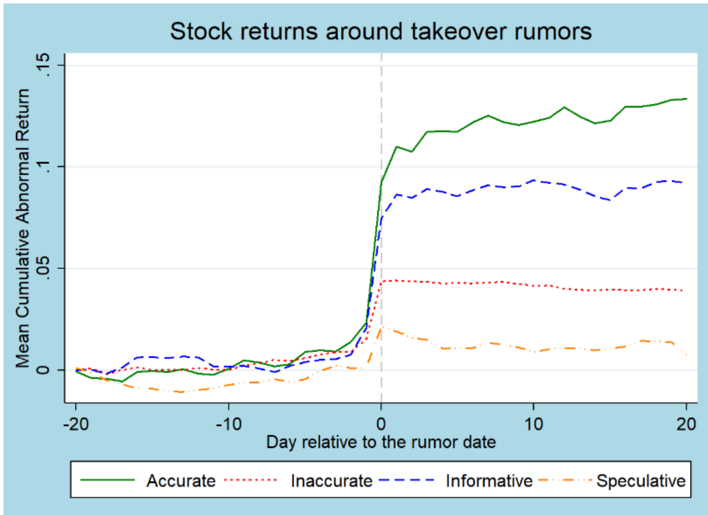
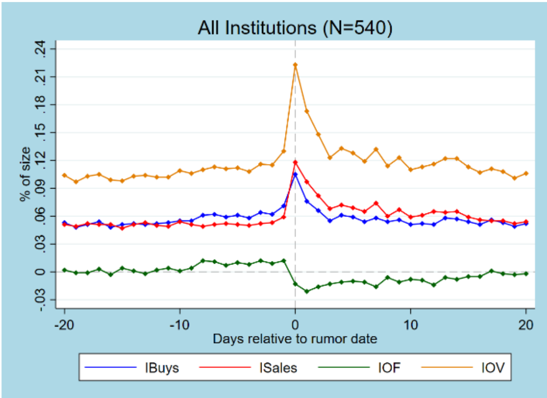


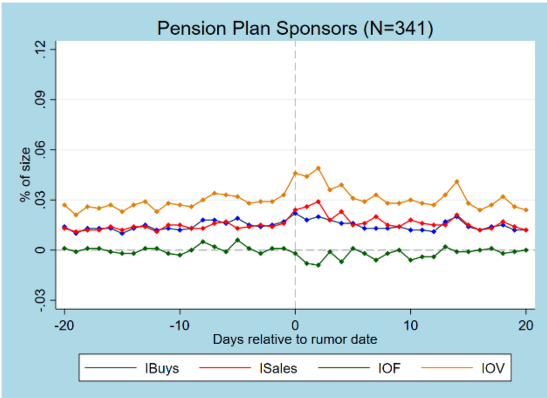
Figure 2. Institutional trading measures by type of institution

This figure depicts the daily means of four institutional trading measures by type of institution for each day over the period (-20, +20), where day 0 represents the initial rumor announcement date. The full sample includes 1,689 takeover-rumored firms from January 2002 to September 2011, with institutional trading data obtained from ANcerno. Panel A presents the results for all institutions while Panels B and C plot the results for pension plan sponsors and investment managers, respectively.

Panel A: All institutions



Panel B: Pension plan sponsors



Panel C: Investment managers

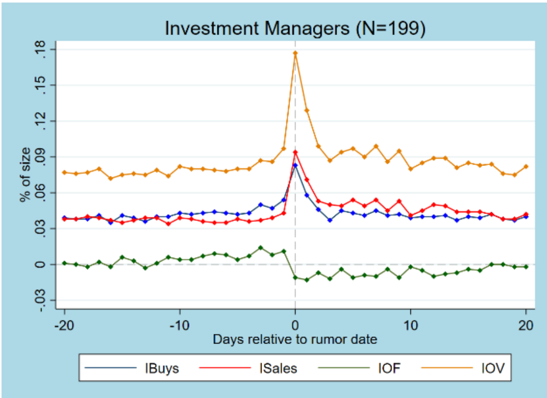


Figure 3. Institutional order flow by type of rumor

This figure plots the institutional order flow (IOF) for each day over the period (-10, +10), where day 0 represents the initial rumor announcement date. Panel A plots the IOF based on rumor accuracy (accurate vs. inaccurate). Rumors are labelled as accurate if the rumored firms in question indeed become the target of a formal takeover bid within 365 calendar days after the initial scoop article; otherwise, they are labelled as inaccurate. Panel B plots the IOF based on the rationales justifying the rumor article's publication. Speculative rumors are based on either takeover chatter or an increase in option activity in the target firm, without any further explanation provided in the article. Informative rumors are based on at least three rumor justifications, excluding those comprising speculative rumors.

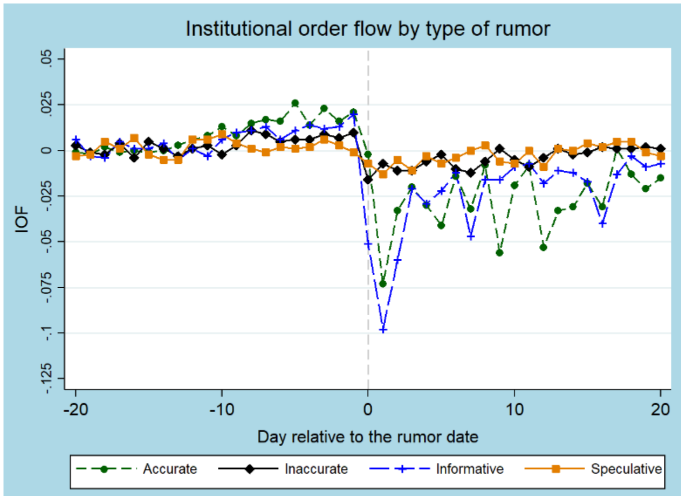
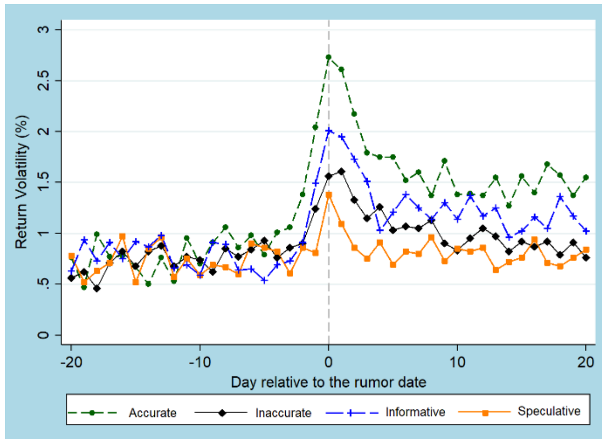


Figure 4. Price volatility around takeover rumors

Panel A plots the return volatility (i.e., the standard deviation of daily returns) of rumored firms around the takeover rumor date. The sample contains all 1,689 takeover-rumored firms from January 2002 to September 2011. Panel B plots market price reaction around the rumor day based on rumor accuracy (accurate vs. inaccurate) and two mutually exclusive rumor categories (speculative vs. informative). Appendix A provides variable definitions.

Panel A: Return volatility around the rumor date



Panel B: Stock price return around the rumor date

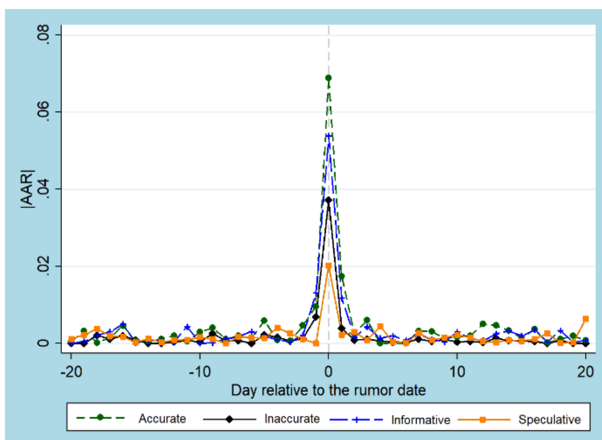
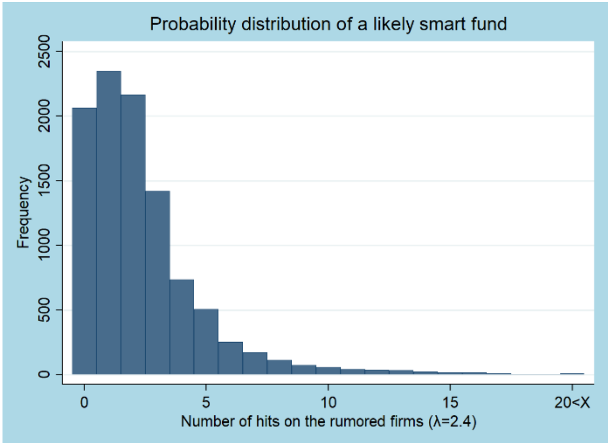


Figure 5. Probability distribution of buying rumored targets by chance

This figure presents the probability distribution of buying rumored targets by chance for two anonymous funds during the year 2009. The distribution is constructed using the bootstrap methodology discussed in Section 4.5. Both funds are net-buyers of six different rumored targets within the month prior to the rumor date ($r_{it} = 6$). Based on the probability distributions, the fund in Panel A is likely to be smart since there is only a 2.4% chance that it buys rumored firms by chance (see Equation 6; $r_{it} = 6$, $\lambda_{it} = 2.4$). The fund in Panel B is likely to be lucky since there is a 13.6% chance that it buys rumored firms by chance (see Equation 6; $r_{it} = 6$, $\lambda_{it} = 4.7$).

Panel A: Probability distribution of a likely smart fund



Panel B: Probability distribution of a likely lucky fund

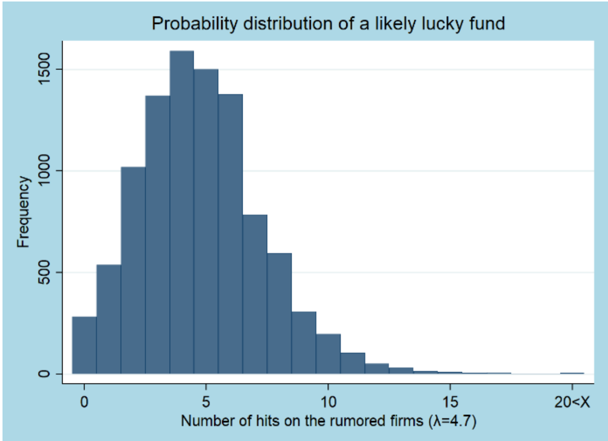


Figure 6. Institutional order flow by type of fund

This figure plots the institutional order flow (IOF) for each day over the period (-20, +20), where day 0 represents the initial rumor announcement date. Rumors are labelled as accurate if the rumored firms in question indeed become the target of a formal takeover bid within 365 calendar days after the initial scoop article; otherwise, they are labelled as inaccurate. The classification of funds as smart and lucky funds is described in detail in Section 4.5.

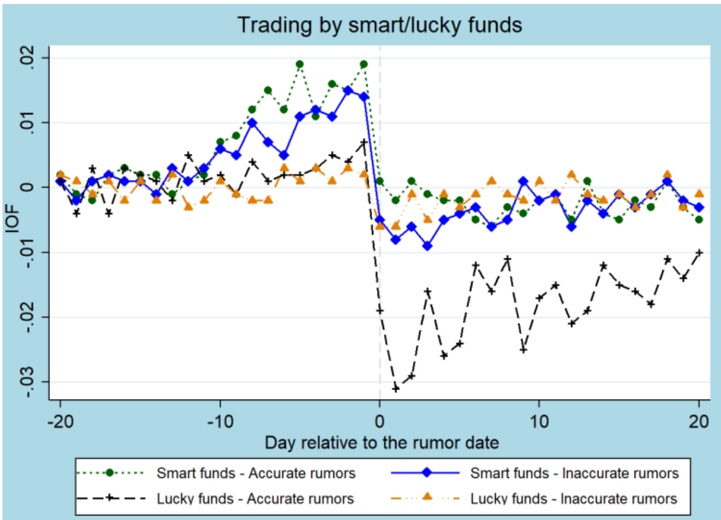


Table 1. Summary statistics of rumored target firms.

Panel A shows the time distribution of 1,689 takeover-rumored firms during the period from January 2002 to September 2011. Panel B reports the industry distribution of the sample based on the Fama-French 17 industry classification. For comparison purposes, the industry distribution of active CRSP firms as of December 31, 2011 is also reported. Panel C presents attributes of the rumor sample which have previously been used as determinants of takeover predictability, with definitions provided in Appendix A. Panel D presents summary statistics of the institutional trading attributes for rumored target firms. Panel E shows the CAARs of the rumored firms computed using a standard market model (based on the CRSP value-weighted market index). *P*-values are reported in parentheses and significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively. The institutional trading data are obtained from ANcerno Ltd. and cover all trades executed by ANcerno clients during the period (-60, +20) relative to the takeover rumor (day 0).

Panel A: Distribution by year of rumor

Year	Rumor count	% of total count
2002	31	1.84
2003	58	3.43
2004	84	4.97
2005	81	4.80
2006	151	8.94
2007	150	8.88
2008	140	8.29
2009	305	18.06
2010	307	18.18
2011	382	12.62
Total	1,689	100

Panel B: Industry distribution

Fama-French 17 Industry Classification	Rumor count	% of CRSP population	CRSP population
Food	59	46%	128
Mining and Minerals	25	17%	146
Oil and Petroleum Products	129	50%	258
Textiles, Apparel, and Footwear	34	61%	56
Consumer Durables	29	31%	93
Chemicals	22	29%	76
Drugs, Soap, Perfumes, Tobacco	171	72%	237
Construction and Construction Materials	34	31%	107
Steel Works	49	94%	52
Fabricated Products	2	7%	29
Machinery and Business Equipment	233	42%	557
Automobiles	23	30%	76
Transportation	49	28%	178
Utilities	6	4%	147
Retail Stores	109	51%	212
Banks, Insurance Companies, and Other Financials	8	0%	2,866
Other (Services, Wholesale, etc.)	707	44%	1,625
Total	1,689	25%	6,843

Panel C: Rumored target firm attributes

Variable	N	Mean	Median	SD	Min	Max
Cashratio	1,614	0.222	0.138	0.225	0.001	0.931
Changesize2y	1,567	0.307	0.131	0.675	-0.651	3.966
Concentration	1,620	0.562	0.535	0.203	0.252	0.986
Dormancy	1,687	2.135	0.1	9.321	0.033	65.533
Infoasymm	1,585	0.056	0	0.230	0	1
Prevmergers	1,689	1.036	1	1.653	0	13
Priorreturn2y	1,637	0.412	0.050	1.382	-0.940	8.010
Resmismatch	1,548	0.520	1	0.499	0	1
ROA	1,612	-0.001	0.009	0.064	-0.443	0.116
Salesgrowth2y	1,569	0.359	0.134	1.058	-0.932	8.231
Salesshock	1,618	0.112	0.078	0.120	0	0.660
SalesshockSq	1,618	0.027	0.006	0.063	0	0.436
Shareturnover	1,607	13.439	13.568	0.952	9.706	15.255
Size	1,614	7.531	7.633	1.696	2.540	10.853

Continued on the next page

Table 1 continued

Panel D: Institutional trading attributes for rumored target firms

Year	# of trades	# of shares traded (mill.)	$ value of shares traded (bill.)	Average share volume	Median share volume	Average dollar volume	Median dollar volume	# of investment managers	# of plan sponsors
2002	31,105	453	11.5	14,581	1,580	369,432	39,063	16	147
2003	27,050	308	6.9	11,406	1,600	249,457	31,040	14	110
2004	73,156	800	13.1	10,941	1,000	179,020	18,275	13	103
2005	57,723	857	21.2	14,846	990	368,320	29,025	13	73
2006	156,562	1,894	53.9	12,096	770	344,384	23,612	19	36
2007	170,790	1,521	53.7	8,908	600	314,972	22,879	14	32
2008	117,844	1,650	46.4	14,002	880	393,703	26,745	68	68
2009	1,226,490	8,034	159.2	6,550	300	129,804	7,227	148	174
2010	1,313,300	6,126	160.4	4,664	200	122,106	5,794	145	170
2011	1,541,392	6,377	163.3	4,136	181	105,942	5,511	127	171

Panel E: Abnormal event returns for rumored target firms

	N	CAAR(0, +1)	CAAR(-20, -1)	CAAR(+2, +20)	CAAR(-20, +20)
All rumors	1,689	4.11***	1.70*	0.03	5.93***
		(0.001)	(0.085)	(0.607)	(0.001)
Accurate	359	8.63***	2.39***	1.85**	13.36***
		(0.001)	(0.001)	(0.012)	(0.001)
Inaccurate	1,330	2.90***	1.53*	-0.50	3.94**
		(0.001)	(0.097)	(0.173)	(0.018)
Informative	435	6.56***	2.08**	0.32	9.23***
		(0.001)	(0.029)	(0.285)	(0.001)
Speculative	304	1.79***	0.12	-1.26***	0.76
		(0.001)	(0.471)	(0.008)	(0.152)

Table 2. Institutional trading activity

This table presents daily averages of the ANcerno-based institutional trading measures for all 1,689 takeover-rumored firms during the period (-30, +30), where day 0 represents the initial rumor announcement date. Tests of significance are based on t-tests of individual day observations relative to the (-90, -31) benchmark period distribution prior to the rumor. The significance of multiple day periods, i.e., (-30, -21) and (+21, +30), is evaluated by comparing the daily means across all days in the multiple day period to the daily means of all days in the benchmark period. IBuys (ISales) denote institutional purchases (sales) and are computed based on Equation 1 (2). IOF (IOV) is defined as the difference between (the sum of) the dollar value of institutional purchases and institutional sales. *#Institutions trading* denotes the daily average number of institutions trading per rumored firm. *ANcerno purchases (sales) to CRSP $ volume* is computed as the ratio of the dollar value of institutional purchases, divided by the dollar value of all trades (as reported by CRSP) over a given period. Our methodology matches that of Corwin et al. (2004) and Irvine et al. (2007). Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively. The bracketed signs in Columns 6 and 7 indicate whether the ANcerno purchases/sales to CRSP $ volume are larger (+) or smaller (-) than the respective benchmark values for the period (-90, -31) reported in the last row.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Relative day	IBuys (% of size)	ISales (% of size)	IOF (% of size)	IOV (% of size)	#Institutions trading	ANcerno purchases to CRSP $ volume	ANcerno sales to CRSP $ volume
-30 to -21	0.049	0.050	-0.001	0.099	5.104	0.045 (-)	0.046 (-)
-20	0.053	0.051	0.002	0.104	4.938	0.043 (-)	0.044 (-)
-19	0.048	0.049	-0.001	0.097	5.064	0.046 (-)	0.047 (+)
-18	0.051	0.052	-0.001	0.103	5.150	0.046 (+)	0.045 (-)
-17	0.054	0.051	0.003	0.105	5.129	0.044 (-)	0.044 (-)
-16	0.048	0.051	-0.003	0.099	5.040	0.046 (+)	0.046 (-)
-15	0.051	0.047	0.004	0.098	5.066	0.048 (+)	0.047 (+)
-14	0.052	0.051	0.001	0.103	5.151	0.043 (-)	0.044 (-)
-13	0.051	0.053	-0.002	0.104	5.112	0.046 (+)	0.047 (+)
-12	0.052	0.050	0.002	0.102	4.998	0.045 (-)	0.045 (-)
-11	0.053	0.049	0.004	0.102	5.023	0.043 (-)	0.044 (-)
-10	0.055	0.054	0.001	0.109	5.156	0.046 (+)	0.045 (-)
-9	0.055	0.051	0.004	0.106	5.160	0.045 (-)	0.046 (+)
-8	0.061**	0.049	0.012*	0.110	5.147	0.043 (-)	0.044 (-)
-7	0.062***	0.051	0.011*	0.113	5.250**	0.046 (-)	0.046 (-)
-6	0.059**	0.052	0.007	0.111	5.204	0.044 (-)	0.044 (-)
-5	0.061***	0.051	0.010***	0.112	5.282***	0.055** (+)	0.045 (-)
-4	0.058	0.05	0.008**	0.108	5.257***	0.058*** (+)	0.044 (-)
-3	0.064***	0.052	0.012***	0.116**	5.192***	0.056*** (+)	0.043 (-)
-2	0.062***	0.053	0.009***	0.115**	5.308***	0.065*** (+)	0.043 (-)
-1	0.071***	0.059	0.012***	0.130***	5.424***	0.048* (+)	0.040 (-)
0	0.105***	0.118***	-0.013***	0.223***	6.016***	0.037* (-)	0.048 (+)
+1	0.076***	0.097***	-0.021***	0.173***	5.523***	0.035** (-)	0.054** (+)
+2	0.066***	0.082***	-0.016***	0.148***	5.438***	0.036 (-)	0.053** (+)
+3	0.055	0.068***	-0.013***	0.123***	5.290**	0.031*** (-)	0.055*** (+)
+4	0.061***	0.072***	-0.011***	0.133***	5.461***	0.034** (-)	0.057*** (+)
+5	0.059**	0.069***	-0.010***	0.128***	5.278**	0.034** (-)	0.055*** (+)
+6	0.054	0.065***	-0.011***	0.119	5.295**	0.036 (-)	0.048 (+)
+7	0.058	0.074***	-0.016***	0.132***	5.092	0.033** (-)	0.051** (+)
+8	0.054	0.060**	-0.006***	0.114	5.115	0.031*** (-)	0.055*** (+)
+9	0.056	0.067***	-0.011***	0.123**	5.133	0.034** (-)	0.057*** (+)
+10	0.051	0.059**	-0.008***	0.110	5.198	0.038 (-)	0.050* (+)
+11	0.052	0.061***	-0.009***	0.113	5.156	0.041 (-)	0.053** (+)
+12	0.051	0.065***	-0.014***	0.116	5.047	0.035 (-)	0.049* (+)
+13	0.058	0.064***	-0.006	0.122	5.088	0.038 (-)	0.048 (+)
+14	0.057	0.065***	-0.008**	0.122	5.094	0.037 (-)	0.049 (+)
+15	0.054	0.059***	-0.005	0.113	5.118	0.040 (-)	0.046 (+)
+16	0.051	0.056	-0.005	0.107	5.062	0.048 (+)	0.046 (-)
+17	0.056	0.055	0.001	0.111	5.017	0.045 (-)	0.045 (-)
+18	0.053	0.055	-0.002	0.108	5.017	0.042 (-)	0.049* (+)
+19	0.049	0.052	-0.003	0.101	5.038	0.040 (-)	0.056*** (+)
+20	0.052	0.054	-0.002	0.106	4.995	0.040 (-)	0.048 (+)
+21 to +30	0.053	0.054	-0.001	0.107	5.116	0.041 (-)	0.049 (+)
Benchmark (-90 to -31)	0.051	0.052	-0.001	0.103	5.097	0.046	0.046

Table 3. Institutional trading activity by rumor type

This table presents daily averages of the ANcerno-based institutional trading measures for all 1,689 takeover-rumored firms during the period (-30, +30), according to the type of rumor. Rumors are labelled as accurate if the rumored firm in question indeed becomes the target of a formal takeover bid within 365 calendar days after the initial scoop article; otherwise, it is labelled as inaccurate. Speculative rumors are based on either takeover chatter or an increase in option activity in the target firm, without any further explanation provided in the article. Informative rumors are based on at least three rumor justifications, excluding those comprising speculative rumors. Tests of significance are based on t-tests of individual day observations relative to the (-90, -31) benchmark period distribution prior to the rumor. The significance of multiple day periods, i.e., (-30, -21) and (+21, +30), is evaluated by comparing the daily means across all days in the multiple day period to the daily means of all days in the benchmark period. IOF (IOV) is defined as the difference between (the sum of) the dollar value of institutional purchases and institutional sales. Our methodology is identical to Corwin et al. (2004) and Irvine et al. (2007). Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	Type of rumor							
Relative day	Accurate rumors		Inaccurate rumors		Informative rumors		Speculative rumors	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	IOF	IOV	IOF	IOV	IOF	IOV	IOF	IOV
-30 to -21	0.001	0.103	-0.001	0.098	0.001	0.090	-0.001	0.130
-20	-0.001	0.103	0.003	0.104	0.006	0.089	-0.003	0.129
-19	-0.002	0.108	-0.001	0.094	-0.003	0.096	-0.002	0.128
-18	0.002	0.106	-0.002	0.102	-0.004	0.095	0.005	0.134
-17	-0.001	0.107	0.004	0.104	0.005	0.099	0.001	0.124
-16	0.000	0.102	-0.004	0.098	0.001	0.098	0.007	0.125
-15	-0.001	0.099	0.005	0.098	0.001	0.087	-0.002	0.129
-14	0.000	0.104	0.001	0.103	0.004	0.084	-0.005	0.120
-13	0.003	0.105	-0.003	0.104	-0.005	0.097	-0.005	0.125
-12	0.006	0.102	0.001	0.102	0.001	0.085	0.006	0.119
-11	0.008	0.106	0.003	0.101	-0.003	0.089	0.006	0.126
-10	0.013	0.117**	-0.002	0.107	0.006	0.090	0.009	0.133
-9	0.008	0.112**	0.003	0.104	0.010	0.092	0.004	0.121
-8	0.015*	0.113***	0.011	0.109	0.011	0.094	0.001	0.118
-7	0.017**	0.121***	0.009	0.111	0.013**	0.106	-0.001	0.124
-6	0.016**	0.126***	0.005	0.107	0.006	0.089	0.002	0.134
-5	0.026***	0.128***	0.006**	0.108	0.011*	0.114*	0.001	0.132
-4	0.014**	0.116**	0.006*	0.106	0.014***	0.090	0.002	0.128
-3	0.023***	0.121***	0.009**	0.115	0.012**	0.104	0.006	0.142*
-2	0.016***	0.120***	0.007**	0.114	0.013**	0.093	0.003	0.143**
-1	0.021***	0.131***	0.010***	0.130***	0.020***	0.119***	-0.001	0.152***
0	-0.002	0.311***	-0.016***	0.199***	-0.051***	0.306***	-0.007*	0.163***
+1	-0.073***	0.290***	-0.007	0.142***	-0.098***	0.258***	-0.013**	0.165***
+2	-0.033***	0.144***	-0.011**	0.149***	-0.060***	0.163***	-0.005	0.160***
+3	-0.020***	0.128***	-0.011*	0.122*	-0.021***	0.131***	-0.011*	0.135
+4	-0.030***	0.151***	-0.006	0.128**	-0.029***	0.130***	-0.003	0.139
+5	-0.041***	0.143***	-0.002	0.124**	-0.022***	0.127***	-0.007	0.134
+6	-0.014***	0.129***	-0.010*	0.116	-0.012**	0.103	-0.004	0.130
+7	-0.032***	0.158***	-0.012**	0.125**	-0.047***	0.116**	0.000	0.124
+8	-0.008*	0.121***	-0.006	0.112	-0.016***	0.110**	0.003	0.118
+9	-0.056***	0.156***	0.001	0.114	-0.016***	0.126***	-0.006	0.138*
+10	-0.019***	0.130***	-0.005	0.105	-0.009**	0.106	-0.007	0.162***
+11	-0.008**	0.123***	-0.009*	0.110	-0.007**	0.131***	0.000	0.128
+12	-0.053***	0.154***	-0.004	0.106	-0.018***	0.132***	-0.009	0.157***
+13	-0.033***	0.149***	0.001	0.115	-0.011***	0.115**	0.001	0.141**
+14	-0.031***	0.152***	-0.002	0.114	-0.012***	0.124***	0.000	0.132
+15	-0.018***	0.130***	-0.001	0.108	-0.017***	0.105	0.004	0.139*
+16	-0.031***	0.128***	0.002	0.101	-0.040***	0.133***	0.002	0.133
+17	0.001	0.154***	0.001	0.099	-0.013***	0.099	0.005	0.121
+18	-0.013***	0.116	0.001	0.106	-0.003	0.094	0.005	0.122
+19	-0.021***	0.123**	0.002	0.095	-0.009**	0.093	-0.001	0.129
+20	-0.015***	0.121	0.001	0.102	-0.007*	0.098	-0.003	0.126
+21 to +30	-0.011*	0.115	0.002	0.104	-0.003	0.101	-0.001	0.119
Benchmark (-90 to -31)	0.001	0.105	-0.001	0.102	0.001	0.096	0.001	0.126

Table 4. Institutional trading activity by momentum quintiles

This table presents abnormal returns and institutional order flow for our sample of 1,689 takeover-rumored firms by momentum quintiles. Firms are portioned into quintiles based on the cumulative abnormal return over the (-30, -10) window relative to the rumor announcement date (day 0). Tests of significance are based on t-tests of individual day observations relative to the (-90, -31) benchmark period distribution prior to the rumor. IOF is defined as the difference between the dollar value of institutional purchases and institutional sales. AAR denotes daily average abnormal returns computed using a standard market model (based on the CRSP value-weighted market index). Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Relative day	Quintile 1 (low returns)		Quintile 2		Quintile 3		Quintile 4		Quintile 5 (high returns)	
	AARs	IOF	AARs	IOF	AARs	IOF	AARs	IOF	AARs	IOF
-15	-1.14**	-0.009*	-0.27	-0.001	0.12	0.004	0.21	0.008	0.62	0.016***
-14	-0.84*	-0.008*	-0.09	0.001	0.04	-0.002	0.25	0.003	0.65	0.012**
-13	-0.75	-0.012**	-0.35	-0.006	-0.01	-0.002	0.38	0.001	0.81**	0.008
-12	-0.81	-0.013**	0.04	0.005	0.10	0.001	0.19	0.005	0.68*	0.011**
-11	-0.82*	-0.005	-0.43	-0.003	-0.22	0.008	0.36	0.005	0.64	0.015***
-10	-1.62***	-0.014***	-0.16	0.009	0.11	-0.001	0.44	0.008	1.43***	0.003
-9	0.96**	-0.007	0.16	0.009	-0.13	0.005	0.10	0.004	0.22	0.009
-8	-0.13	0.005	0.06	0.011	-0.02	0.006	0.19	0.009*	0.20	0.031***
-7	0.16	0.017***	0.12	0.014**	-0.12	0.004	-0.21	-0.001	0.41	0.019***
-6	0.35	0.011**	-0.35	-0.002	0.18	0.015**	-0.04	0.008	-0.12	0.005
-5	0.12	0.012**	0.23	0.004	0.29	0.003	0.09	0.017***	0.47	0.012**
-4	0.40	0.010**	-0.06	0.005	0.07	-0.004	0.45	0.012*	-0.03	0.016***
-3	-0.04	0.017***	-0.09	0.021***	0.02	0.005	0.05	0.012*	0.40	0.007
-2	-0.32	0.008	0.08	0.002	0.41	0.009	-0.03	0.011	0.48	0.015***
-1	0.74**	0.003	0.33	0.008*	0.70**	0.014***	0.88**	0.016***	0.78**	0.018***
0	3.89***	-0.015***	4.23***	-0.017***	2.84***	-0.008**	2.99***	-0.013***	4.64***	-0.011***
+1	0.14	-0.016***	0.07	-0.012***	0.65*	-0.025***	1.00***	-0.021***	0.12	-0.032***
+2	-0.52	-0.016***	0.06	-0.021***	-0.13	-0.003	0.14	-0.030***	0.01	-0.008
+3	-0.13	-0.008*	0.60	-0.019***	-0.16	-0.008**	-0.02	-0.004	0.24	-0.024***
+4	-0.83*	-0.013**	0.30	-0.011**	0.02	-0.019***	0.07	0.002	0.11	-0.015***
+5	-0.32	-0.010**	0.15	0.003	-0.04	-0.025***	0.00	-0.007	-0.01	-0.012***
+6	0.02	-0.014***	-0.02	0.001	-0.28	-0.023***	-0.01	-0.016***	0.16	-0.005
+7	0.38	-0.017***	0.24	-0.009*	0.07	-0.031***	-0.11	-0.029***	-0.02	0.008
+8	0.09	-0.005	0.07	-0.001	-0.13	-0.006	-0.04	-0.007	-0.28	-0.009*
+9	-0.11	-0.019***	-0.17	-0.013**	-0.12	0.003	-0.09	-0.014***	-0.07	-0.011*
+10	0.16	-0.015**	-0.26	-0.001	-0.21	-0.009	-0.17	-0.011*	0.30	-0.005
+11	0.30	0.005	0.33	-0.009	-0.24	-0.020***	0.17	-0.004	-0.31	-0.016***
+12	-0.22	-0.012*	0.10	-0.013*	-0.11	-0.018***	-0.04	-0.016***	0.44	-0.010
+13	-0.26	-0.002	-0.01	-0.008	-0.15	-0.012**	0.06	-0.016***	-0.37	0.008
+14	0.36	-0.014**	0.04	-0.007	-0.09	-0.015***	-0.03	-0.011**	-0.68	0.005
+15	-0.03	-0.012*	-0.04	0.005	-0.10	-0.019***	0.25	0.003	0.25	-0.002

Table 5. The predictive power of institutional trading

This table reports logit regression results in which the dependent variable is a dummy variable equal to one if the rumor leads to a takeover announcement wihin 365 days, and zero otherwise. The main independent variable of interest is the buy-and-hold cumulative abnormal institutional order flow defined as $BHAIOF_i(t_0, t_1) = \sum_{t_0}^{t_1}(IOF_i - IOF_{i,Benchmark})_t$, where IOF_i is the institutional order flow of firm *i* and $IOF_{i,Benchmark}$ is the average daily institutional order flow calculated over the (-90, -31) window prior to the rumor date for firm *i*. In Columns 1 and 2 (3 and 4), BHAIOF is computed using institutional trading data over the pre-rumor (post-rumor) periods. In Columns 5 and 6, BHAIOF is computed based on institutional trading pattern over the combined pre- and post-rumor period. The respective time periods are provided next to each variable name. Appendix A provides further variable definitions. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent: *Accurate*	Before rumor		After rumor		Around rumor	
BHAIOF(-10, -1)	0.139**					
	(0.025)					
BHAIOF(-5, -1)		0.220**				
		(0.032)				
BHAIOF(+1, +5)			-0.135***			
			(0.008)			
BHAIOF(+1, +10)				-0.068***		
				(0.002)		
BHAIOF(-5, +5)					-0.175***	
					(0.001)	
BHAIOF(-10, +10)						-0.296**
						(0.001)
Informative	0.975***	0.956***	0.965***	0.970***	0.973***	0.966***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Speculative	-0.571**	-0.550**	-0.555**	-0.554**	-0.544**	-0.540**
	(0.036)	(0.044)	(0.042)	(0.043)	(0.047)	(0.049)
Size	-0.252***	-0.251***	-0.255***	-0.254***	-0.258***	-0.256***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CAR(0, +1)	4.355***	4.438***	3.896**	4.004***	3.835***	3.918**
	(0.003)	(0.003)	(0.010)	(0.008)	(0.009)	(0.017)
CAR(-5, -1)	1.192	1.189	1.250	1.274	1.341	1.314
	(0.173)	(0.172)	(0.155)	(0.147)	(0.128)	(0.133)
CAR(-41, -1)	-0.062	-0.043	-0.043	-0.054	-0.082	-0.029
	(0.844)	(0.890)	(0.891)	(0.862)	(0.795)	(0.926)
ValuableBrand	-0.459**	-0.432*	-0.482**	-0.468**	-0.469**	-0.466**
	(0.040)	(0.054)	(0.031)	(0.036)	(0.036)	(0.037)
EstDealLikelihood	0.072	0.060	0.116	0.107	0.139	0.126
	(0.719)	(0.765)	(0.575)	(0.602)	(0.500)	(0.540)
Cashratio	-0.809*	-0.827**	-0.785*	-0.783*	-0.801*	-0.799*
	(0.053)	(0.048)	(0.060)	(0.060)	(0.055)	(0.056)
Changesize2y	0.105	0.109	0.101	0.105	0.095	0.101
	(0.422)	(0.403)	(0.440)	(0.420)	(0.471)	(0.440)
Concentration	-0.034	-0.027	-0.050	-0.061	-0.070	-0.071
	(0.931)	(0.944)	(0.898)	(0.875)	(0.857)	(0.854)
Dormancy	0.003	0.003	0.002	0.002	0.002	0.002
	(0.773)	(0.756)	(0.794)	(0.802)	(0.810)	(0.788)
Infoasymm	0.155	0.162	0.151	0.157	0.156	0.150
	(0.617)	(0.599)	(0.626)	(0.614)	(0.617)	(0.629)
Prevmergers	0.061	0.061	0.061	0.061	0.059	0.058
	(0.193)	(0.189)	(0.190)	(0.195)	(0.206)	(0.213)
Priorreturn2y	0.007	0.014	0.011	0.009	0.010	0.013
	(0.894)	(0.803)	(0.840)	(0.868)	(0.859)	(0.811)
Resmismatch	0.214	0.212	0.226	0.216	0.211	0.209
	(0.146)	(0.151)	(0.126)	(0.143)	(0.154)	(0.157)
ROA	-0.093	-0.209	-0.035	-0.014	-0.072	-0.041
	(0.943)	(0.872)	(0.978)	(0.991)	(0.956)	(0.975)

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Table 5 continued

Salesgrowth2y	0.001	0.001	0.005	0.004	0.005	0.005
	(0.986)	(0.991)	(0.954)	(0.961)	(0.952)	(0.953)
Salesshock	-4.596***	-4.569***	-4.653***	-4.696***	-4.668***	-4.799***
	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.005)
SalesshockSq	5.208	5.090	5.294*	5.368*	5.321*	5.583*
	(0.103)	(0.111)	(0.097)	(0.092)	(0.097)	(0.081)
Shareturnover	-0.180**	-0.181**	-0.189**	-0.185**	-0.186**	-0.188**
	(0.050)	(0.048)	(0.039)	(0.043)	(0.043)	(0.041)
Constant	2.507**	2.492**	2.646**	2.609**	2.648**	2.673**
	(0.042)	(0.043)	(0.032)	(0.034)	(0.031)	(0.030)
Industry / Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,459	1,459	1,459	1,459	1,459	1,459
Pseudo R^2	0.163	0.165	0.166	0.165	0.169	0.168

Table 6. Multivariate analysis of rumored target firm cumulative abnormal returns on the rumor date

This table reports coefficient estimates for a series of OLS regressions of target firm cumulative abnormal returns (CARs) on a number of explanatory variables. CARs are calculated as the sum of the value-weighted market-model abnormal returns for target firms over days (0, +1) relative to the initial rumor date (day 0). Of particular interest are the coefficients of the buy-and-hold cumulative abnormal institutional order flow defined as $BHAIOF_i(t_0,t_1) = \sum_{t_0}^{t_1}(IOF_i - IOF_{i,Benchmark})_t$, where IOF_i is the institutional order flow of firm *i* and $IOF_{i,Benchmark}$ is the average daily institutional order flow calculated over the (-90, -31) window prior to the rumor date for firm *i*. Other variable definitions are provided in Appendix A. Industry fixed effects are based on the Fama-French 17 industry classification. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Dependent: CAR(0, +1)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
BHAIOF(-10, -1)	0.003**						
	(0.019)						
BHAIOF(-5, -1)		0.022***					
		(0.000)					
IOF_{t-1}			0.090***				
			(0.000)				
IOV_{t-1}				0.082***			
				(0.000)			
$IBuys_{t-1}$					0.132***		0.131***
					(0.000)		(0.000)
$ISales_{t-1}$						-0.051**	-0.003
						(0.028)	(0.908)
Informative	0.035***	0.034***	0.035***	0.032***	0.033***	0.034***	0.033***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Speculative	-0.029***	-0.028***	-0.030***	-0.031***	-0.031***	-0.030***	-0.031***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)
Size	-0.003	-0.003	-0.001	-0.001	0.000	-0.002	0.000
	(0.552)	(0.524)	(0.868)	(0.830)	(0.996)	(0.579)	(0.998)
CAR(-5, -1)	-0.072*	-0.070*	-0.095**	-0.088**	-0.104***	-0.068*	-0.103***
	(0.069)	(0.078)	(0.017)	(0.024)	(0.008)	(0.087)	(0.009)
CAR(-41, -1)	0.008	0.009	0.006	0.013	0.011	0.009	0.011
	(0.545)	(0.486)	(0.673)	(0.323)	(0.401)	(0.501)	(0.398)
ValuableBrand	0.006	0.008	0.004	0.006	0.005	0.005	0.005
	(0.526)	(0.411)	(0.674)	(0.533)	(0.571)	(0.606)	(0.569)
EstAnnReturn	0.108	0.105	0.157	0.159	0.179	0.121	0.179
	(0.398)	(0.411)	(0.218)	(0.210)	(0.156)	(0.346)	(0.157)
Cashratio	-0.014	-0.015	-0.009	-0.012	-0.009	-0.015	-0.009
	(0.455)	(0.423)	(0.604)	(0.502)	(0.610)	(0.422)	(0.608)
Changesize2y	-0.009	-0.008	-0.009	-0.009	-0.009	-0.009*	-0.009
	(0.108)	(0.134)	(0.110)	(0.113)	(0.119)	(0.100)	(0.119)
Concentration	0.003	0.004	0.008	-0.000	0.005	-0.001	0.005
	(0.851)	(0.824)	(0.614)	(0.984)	(0.758)	(0.949)	(0.766)
Dormancy	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.254)	(0.255)	(0.298)	(0.335)	(0.352)	(0.271)	(0.353)
Infoasymm	-0.005	-0.004	-0.004	-0.003	-0.003	-0.003	-0.003
	(0.769)	(0.806)	(0.816)	(0.833)	(0.823)	(0.833)	(0.823)
Prevmergers	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.735)	(0.735)	(0.622)	(0.744)	(0.666)	(0.754)	(0.669)
Priorreturn2y	0.002	0.003	0.002	0.002	0.002	0.002	0.002
	(0.347)	(0.249)	(0.447)	(0.444)	(0.500)	(0.357)	(0.500)
Resmismatch	-0.002	-0.003	-0.002	-0.003	-0.003	-0.003	-0.003
	(0.716)	(0.678)	(0.707)	(0.638)	(0.647)	(0.693)	(0.646)
ROA	0.100*	0.095*	0.103*	0.090	0.090	0.104*	0.090
	(0.081)	(0.097)	(0.068)	(0.110)	(0.109)	(0.068)	(0.110)
Salesgrowth2y	0.006*	0.006	0.006	0.006	0.006	0.006*	0.006
	(0.087)	(0.100)	(0.100)	(0.120)	(0.120)	(0.100)	(0.120)
Salesshock	0.038	0.041	0.055	0.050	0.060	0.037	0.060
	(0.596)	(0.565)	(0.445)	(0.485)	(0.401)	(0.609)	(0.402)

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Table 6 continued

SalesshockSq	-0.061	-0.070	-0.094	-0.072	-0.096	-0.051	-0.096
	(0.653)	(0.605)	(0.487)	(0.589)	(0.471)	(0.706)	(0.473)
Shareturnover	0.002	0.002	0.001	-0.002	-0.002	0.001	-0.002
	(0.686)	(0.641)	(0.719)	(0.628)	(0.667)	(0.782)	(0.661)
Constant	0.060	0.058	0.035	0.083	0.064	0.068	0.065
	(0.397)	(0.412)	(0.617)	(0.238)	(0.358)	(0.343)	(0.355)
Industry / Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,459	1,459	1,459	1,459	1,459	1,459	1,459
Adjusted R^2	0.052	0.059	0.068	0.077	0.086	0.051	0.086

Table 7. Classification of smart and lucky funds

Panel A provides information on the number of funds with positive buy-and-hold cumulative abnormal institutional order flow (BHAIOF) over the 30-day window prior to the takeover rumor. These funds are classified into two groups, smart and lucky, based on the bootstrap methodology discussed in Section 4.5. In Panel B, we compute the aggregate chi-squared statistic as the sum of the chi-squared (χ^2) statistic for each year-fund observation with degrees of freedom equal to the sum of the degrees of freedoms (Adelson, 1966; Johnson, 2005; Ross, 2014). Individual chi-squared statistics are computed under the hypothesis that the probability distribution of the number of times a fund purchases rumored targets in one year is statistically different from the distribution in the following year.

Panel A: Fund classification

Year	N	Smart	Lucky
2002	236	29	207
2003	305	37	268
2004	460	52	408
2005	594	76	518
2006	728	83	645
2007	861	105	756
2008	1,172	99	1,073
2009	1,258	107	1,151
2010	1,322	112	1,110
2011	896	85	811

Panel B: Transition between the smart and lucky categories (contingency table)

	Smart				Lucky			
Period	Persistent	Non-persistent	$\sum \chi^2$	P-value	Persistent	Non-persistent	$\sum \chi^2$	P-value
2002 – 2003	23	6	44.543	0.054	72	135	21.697	0.892
2003 – 2004	28	9	67.098	0.023	107	161	24.215	0.914
2004 – 2005	41	11	91.761	0.002	149	259	28.630	0.979
2005 – 2006	60	16	129.124	0.005	151	367	47.578	0.781
2006 – 2007	71	12	153.836	0.001	203	442	56.492	0.895
2007 – 2008	86	19	177.925	0.004	215	541	59.736	0.885
2008 – 2009	77	22	207.442	0.001	354	719	82.128	0.735
2009 – 2010	96	11	145.174	0.006	317	834	78.439	0.842
2010 – 2011	104	8	123.678	0.021	246	864	60.561	0.902

Table 8. Daily trading activity of smart funds

This table presents daily averages of smart fund trading measures for all 1,689 takeover-rumored firms during the period (-30, +30), where day 0 represents the initial rumor announcement date. IOF (IOV) is defined as the difference between (the sum of) the dollar value of institutional purchases and institutional sales. Tests of significance are based on t-tests of individual day observations relative to the (-90, -31) benchmark period distribution prior to the rumor. The significance of multiple day periods, i.e., (-30, -21) and (+21, +30), is evaluated by comparing the daily means across all days in the multiple day period to the daily means of all days in the benchmark period. Our methodology matches that of Corwin et al. (2004) and Irvine et al. (2007). Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	All rumors		*Accurate* rumors		*Inaccurate* rumors	
	(1)	(2)	(3)	(4)	(5)	(6)
Relative day	IOF	IOV	IOF	IOV	IOF	IOV
-30 to -21	0.002	0.014	0.002	0.016	0.001	0.014
-20	0.001	0.017	0.002	0.015	0.001	0.018
-19	-0.003	0.015	-0.001	0.016	-0.002	0.015
-18	0.001	0.016	-0.002	0.017	0.001	0.016
-17	0.002	0.018	0.002	0.014	0.002	0.019
-16	0.001	0.015	0.003	0.015	0.001	0.015
-15	0.002	0.019	0.002	0.015	0.001	0.020*
-14	0.001	0.016	0.002	0.016	-0.001	0.016
-13	0.002	0.013	-0.001	0.014	0.003	0.013
-12	0.001	0.012	0.001	0.017	0.001	0.011
-11	0.003	0.020*	0.002	0.018	0.003	0.020*
-10	0.006	0.021**	0.007*	0.024**	0.006	0.021**
-9	0.006	0.016	0.008**	0.019*	0.005	0.015
-8	0.010**	0.016	0.012**	0.022**	0.010**	0.015
-7	0.009**	0.020**	0.015***	0.029***	0.007**	0.017
-6	0.006**	0.021**	0.012***	0.034***	0.005*	0.018
-5	0.013***	0.027***	0.019***	0.032***	0.011**	0.026***
-4	0.012***	0.022***	0.011***	0.029***	0.012***	0.020***
-3	0.012***	0.027***	0.016***	0.024***	0.011***	0.028***
-2	0.015***	0.027***	0.015***	0.028***	0.015***	0.027***
-1	0.015***	0.033***	0.019***	0.031***	0.014***	0.033***
0	-0.004***	0.054***	0.001	0.052***	-0.005***	0.054***
+1	-0.007***	0.038***	-0.002	0.064***	-0.008***	0.031***
+2	-0.005***	0.022***	0.001	0.029***	-0.006***	0.020**
+3	-0.007***	0.022**	-0.001	0.017*	-0.009***	0.023***
+4	-0.004***	0.025***	-0.002	0.027***	-0.005***	0.024***
+5	-0.004***	0.022***	-0.002	0.024***	-0.004***	0.022***
+6	-0.003	0.020**	-0.005**	0.026***	-0.003**	0.018*
+7	-0.006***	0.027***	-0.006**	0.021**	-0.006***	0.028***
+8	-0.005**	0.021**	-0.003	0.016	-0.005***	0.022***
+9	0.001	0.021**	-0.004	0.018	0.001	0.022**
+10	-0.002	0.022**	-0.002	0.017	-0.002*	0.023***
+11	-0.001	0.020**	-0.001	0.019**	-0.001	0.020**
+12	-0.006**	0.017	-0.005*	0.014	-0.006***	0.018
+13	-0.001	0.019**	0.001	0.024***	-0.002	0.018*
+14	-0.004**	0.023**	-0.004*	0.025***	-0.004**	0.023**
+15	-0.002	0.019**	-0.005	0.019**	-0.001	0.019*
+16	-0.003	0.020**	-0.002	0.021**	-0.003*	0.020**
+17	-0.001	0.020**	-0.003	0.017	-0.001	0.021**
+18	0.001	0.021**	0.001	0.023**	0.001	0.021**
+19	-0.002	0.016	-0.003	0.019	-0.002	0.015
+20	-0.003	0.015	-0.005	0.015	-0.003	0.015
+21 to +30	-0.001	0.017	-0.002	0.019	-0.001	0.016
Benchmark (-90 to -31)	0.001	0.015	-0.001	0.017	0.001	0.015

Table 9. Daily trading activity of lucky funds

This table presents daily average trading measures of lucky funds for all 1,689 takeover-rumored firms during the period (-30, +30), where day 0 represents the initial rumor announcement date. IOF (IOV) is defined as the difference between (the sum of) the dollar value of institutional purchases and institutional sales. Tests of significance are based on t-tests of individual day observations relative to the (-90, -31) benchmark period distribution prior to the rumor. The significance of multiple day periods, i.e., (-30, -21) and (+21, +30), is evaluated by comparing the daily means across all days in the multiple day period to the daily means of all days in the benchmark period. Our methodology matches that of Corwin et al. (2004) and Irvine et al. (2007). Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	All rumors		*Accurate* rumors		*Inaccurate* rumors	
	(1)	(2)	(3)	(4)	(5)	(6)
Relative day	IOF	IOV	IOF	IOV	IOF	IOV
-30 to -21	0.001	0.047	0.002	0.048	0.001	0.047
-20	0.002	0.043	0.001	0.039	0.002	0.044
-19	0.001	0.042	-0.004	0.046	0.001	0.041
-18	0.001	0.048	0.003	0.041	-0.001	0.050*
-17	0.001	0.053**	-0.004	0.049*	0.001	0.054**
-16	-0.001	0.049	0.003	0.035	-0.002	0.054**
-15	0.001	0.039	0.002	0.037	0.001	0.040
-14	-0.001	0.044	0.001	0.039	-0.002	0.045
-13	0.001	0.053**	-0.002	0.045	0.002	0.055**
-12	-0.001	0.049*	0.005	0.038	-0.003	0.053*
-11	-0.001	0.046	0.001	0.044	-0.002	0.047
-10	0.001	0.050	0.002	0.045	0.001	0.051
-9	-0.001	0.046	-0.001	0.048	-0.001	0.045
-8	-0.001	0.039	0.004	0.047*	-0.002	0.037
-7	-0.001	0.048	0.001	0.043	-0.002	0.049
-6	0.003	0.045	0.002	0.039	0.003	0.047
-5	0.001	0.040	0.002	0.042	0.001	0.040
-4	0.003	0.048	0.003	0.036	0.003	0.051
-3	0.002	0.052*	0.005	0.039	0.001	0.056*
-2	0.003	0.047	0.004	0.035	0.003	0.050
-1	0.004*	0.057**	0.007*	0.048*	0.002	0.060**
0	-0.009***	0.113***	-0.019***	0.213***	-0.006***	0.086***
+1	-0.011***	0.078***	-0.031***	0.123***	-0.006***	0.066***
+2	-0.007***	0.075***	-0.029***	0.076***	-0.001	0.075***
+3	-0.007***	0.049**	-0.016***	0.055***	-0.005**	0.047*
+4	-0.006***	0.066***	-0.026***	0.072***	-0.001	0.065***
+5	-0.007***	0.057***	-0.024***	0.077***	-0.003**	0.052***
+6	-0.003**	0.050***	-0.012***	0.068***	-0.001	0.045
+7	-0.004**	0.055**	-0.016***	0.077***	0.001	0.049*
+8	-0.003*	0.049**	-0.011***	0.068***	-0.001	0.044
+9	-0.007***	0.053**	-0.025***	0.067***	-0.002**	0.049**
+10	-0.003*	0.046*	-0.017***	0.059***	0.001	0.043
+11	-0.005***	0.053**	-0.015***	0.065***	-0.002**	0.050**
+12	-0.003	0.049**	-0.021***	0.063***	0.002	0.045
+13	-0.005**	0.050**	-0.019***	0.067***	-0.001	0.046
+14	-0.004**	0.048**	-0.012***	0.059***	-0.002*	0.045
+15	-0.004**	0.052***	-0.015***	0.055***	-0.001*	0.051**
+16	-0.006***	0.045	-0.016***	0.062***	-0.003*	0.041
+17	-0.005	0.046	-0.018***	0.044**	-0.001	0.046
+18	-0.001	0.043	-0.011***	0.051**	0.002	0.041
+19	-0.005**	0.048*	-0.014***	0.055***	-0.003*	0.046
+20	-0.003*	0.047	-0.010***	0.055**	-0.001	0.045
+21 to +30	-0.003**	0.046	-0.009**	0.051**	-0.001	0.045
Benchmark (-90 to -31)	-0.001	0.044	0.001	0.042	-0.001	0.045

Table 10. The predictive power of trades by smart and lucky funds

This table reports logit regression results in which the dependent variable is a dummy variable equal to one if the rumor leads to a takeover announcement wihin 365 days. The main independent variable of interest is the buy-and-hold cumulative abnormal institutional order flow defined as $BHAIOF_i(t_0, t_1) = \sum_{t_0}^{t_1}(IOF_i - IOF_{i,Benchmark})_t$, where IOF_i is the institutional order flow of firm *i* and $IOF_{i,Benchmark}$ is the average daily institutional order flow calculated over the (-90, -31) window prior to the rumor date for firm *i*. Appendix A provides other variable definitions. Panel A shows regression estimates for smart funds while Panel B presents the results for lucky funds. Some controls are insignificant and untabulated for brevity. They include the following variables: *ValuableBrand*, *EstDealLikelihood*, *Cashratio*, *Changesize2y*, *Concentration*, *Dormancy*, *Infoasymm*, *Prevmergers*, *Priorreturn2y*, *Resmismatch*, *ROA*, *Salesgrowth2y*, *Salesshock*, *SalesshockSq*, and *Shareturnover*. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: The predictive power of *smart* fund trades						
Dependent: *Accurate*	(1)	(2)	(3)	(4)	(5)	(6)
BHAIOF(-10, -1) $_{smart}$	0.722**					
	(0.017)					
BHAIOF(-5, -1) $_{smart}$		1.041**				
		(0.035)				
BHAIOF(+1, +5) $_{smart}$			5.408**			
			(0.019)			
BHAIOF(+1, +10) $_{smart}$				3.296**		
				(0.013)		
BHAIOF(-5, +5) $_{smart}$					6.253***	
					(0.004)	
BHAIOF(-10, +10) $_{smart}$						3.812**
						(0.011)
Informative	0.935***	0.906***	0.973***	0.986***	0.924***	0.897***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Speculative	-0.586**	-0.612**	-0.575**	-0.569**	-0.598**	-0.598**
	(0.033)	(0.029)	(0.038)	(0.039)	(0.033)	(0.034)
Size	-0.252***	-0.243***	-0.267***	-0.252***	-0.241***	-0.239***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CAR(0, +1)	4.351***	4.377***	4.082***	4.149***	4.461***	4.454***
	(0.004)	(0.003)	(0.006)	(0.004)	(0.003)	(0.004)
CAR(-5, -1)	0.874	0.916	1.354	1.415	0.326	0.278
	(0.365)	(0.309)	(0.113)	(0.106)	(0.748)	(0.763)
CAR(-41, -1)	-0.027	-0.031	-0.094	-0.099	0.029	0.046
	(0.943)	(0.929)	(0.772)	(0.771)	(0.854)	(0.875)
Constant	2.742**	2.709**	1.991	2.027*	3.163**	3.215**
	(0.026)	(0.031)	(0.105)	(0.098)	(0.014)	(0.010)
Observations	1459	1459	1459	1459	1459	1459
Industry / Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.174	0.168	0.170	0.171	0.189	0.193
Panel B: The predictive power of *lucky* fund trades						
Dependent: *Accurate*	(1)	(2)	(3)	(4)	(5)	(6)
BHAIOF(-5, -1) $_{lucky}$	0.127					
	(0.483)					
BHAIOF(-10, -1) $_{lucky}$		0.072				
		(0.695)				
BHAIOF(+1, +5) $_{lucky}$			-0.163***			
			(0.002)			
BHAIOF(+1, +10) $_{lucky}$				-0.132***		
				(0.009)		
BHAIOF(-5, +5) $_{lucky}$					-0.472**	
					(0.018)	
BHAIOF(-10, +10) $_{lucky}$						-0.188**
						(0.041)

Continued on the next page

Table 10 continued

Informative	0.987***	0.986***	0.965***	0.961***	0.959***	0.964***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Speculative	-0.564**	-0.578**	-0.562**	-0.556**	-0.541**	-0.551**
	(0.039)	(0.035)	(0.040)	(0.043)	(0.048)	(0.045)
Size	-0.251***	-0.253***	-0.246***	-0.248***	-0.252***	-0.251***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CAR(0, +1)	4.229***	4.402***	3.934***	3.852**	3.452**	3.745**
	(0.004)	(0.003)	(0.009)	(0.011)	(0.022)	(0.013)
CAR(-5, -1)	1.229	1.202	1.292	1.290	1.356	1.324
	(0.162)	(0.171)	(0.147)	(0.142)	(0.123)	(0.131)
CAR(-41, -1)	-0.054	-0.065	-0.029	-0.038	-0.035	-0.029
	(0.879)	(0.842)	(0.918)	(0.905)	(0.917)	(0.922)
Constant	2.472**	2.213*	2.335*	2.508**	2.392**	2.256*
	(0.046)	(0.057)	(0.051)	(0.043)	(0.049)	(0.055)
Observations	1459	1459	1459	1459	1459	1459
Industry / Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.165	0.166	0.169	0.171	0.175	0.169

Table 11. The profitability of institutional trading

This table reports the abnormal profit (in thousands of dollars) of smart and lucky funds in rumored target firms over different trading horizons. Panel A shows the abnormal holding-period profit of smart and lucky funds for the whole sample while Panel B (C) presents the results for accurately (inaccurately) rumored firms. We use actual execution prices and executed volumes to calculate the raw profits and apply the DGTW benchmark (as per Daniel, Grinblatt, Titman, and Wermers, 1997) over the holding periods to calculate the abnormal profits. We use the volume-weighted average execution price of buys (sells) when funds execute multiple buy (sell) transactions and acknowledge any unrealized profit as of the end of the trading period by marking the net positions to market at the end of each trading horizon. P-values are in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	Before trading commissions			After trading commissions		
	(1)	(2)	(3)	(4)	(5)	(6)
Trade window	Smart	Lucky	Difference	Smart	Lucky	Difference
Panel A: All rumors						
[-30, +30]	417.0***	91.9*	325.2***	365.9***	70.7	295.1**
	(0.003)	(0.054)	(0.009)	(0.008)	(0.113)	(0.014)
[-20, +20]	342.9***	107.6**	237.5**	309.5***	70.1*	239.5**
	(0.001)	(0.031)	(0.015)	(0.006)	(0.096)	(0.011)
[-5, +5]	303.2***	120.8**	182.4**	267.5**	99.1**	168.4**
	(0.007)	(0.024)	(0.016)	(0.015)	(0.047)	(0.021)
Panel B: Accurate rumors						
[-30, +30]	707.0***	193.9**	513.0***	644.8***	156.6**	488.2**
	(0.001)	(0.016)	(0.003)	(0.005)	(0.035)	(0.010)
[-20, +20]	534.7***	157.1***	377.6***	478.0***	119.5 **	359.6***
	(0.001)	(0.008)	(0.002)	(0.004)	(0.017)	(0.007)
[-5, +5]	443.9***	135.5***	308.3***	417.5***	107.0**	310.4***
	(0.002)	(0.003)	(0.007)	(0.007)	(0.021)	(0.007)
Panel B: Inaccurate rumors						
[-30, +30]	338.7***	64.4	274.3**	290.6**	47.4	243.2**
	(0.008)	(0.127)	(0.019)	(0.012)	(0.269)	(0.023)
[-20, +20]	291.1***	91.4*	199.7**	263.8***	56.8*	207.0**
	(0.004)	(0.064)	(0.037)	(0.009)	(0.089)	(0.032)
[-5, +5]	265.2**	116.8**	148.4**	227.0**	96.9*	130.1*
	(0.012)	(0.039)	(0.040)	(0.026)	(0.061)	(0.053)

Appendix A. Variable definitions

Variable	**Definition**
Accurate	Dummy variable that equals one if the rumored target firm becomes subject to a formal takeover announcement within one calendar year after the initial rumor date; otherwise the variable equals zero (Ahern and Sosyura, 2015; Betton et al., 2018).
ANcerno purchases to CRSP $ volume	The ratio of the dollar value of institutional purchases, divided by the dollar value of all trades (as reported by CRSP) over a given period. Institutional purchases are computed based on the sample of institutions covered in the ANcerno database (Ahern and Sosyura, 2015).
ANcerno sales to CRSP $ volume	The ratio of the dollar value of institutional sales, divided by the dollar value of all trades (as reported by CRSP) over a given period. Institutional sales are computed based on the sample of institutions covered in the ANcerno database (Ahern and Sosyura, 2015).
BHAIOF(t_0,t_1)	Buy-and-hold cumulative abnormal institutional order flow, computed as the difference between the daily institutional order flow (IOF) and the benchmark level of IOF (measured as the daily average IOF over the period (-90, -31)), aggregated over the period (t_0,t_1): $BHAIOF_i(t_0, t_1) = \sum_{t_0}^{t_1}(IOF_i - IOF_{i,Benchmark})_t$ (Hendershott et al., 2015).
CAR	Cumulative abnormal return on the rumor date, computed using a standard market model based on the CRSP value-weighted market index (Campbell et al., 1997).
CashRatio	The ratio of cash and marketable securities to marketable assets (Cornett et al., 2011).
ChangeSize2Yrs	The percentage change in the firm's total assets over the previous two years (Cornett et al., 2011).
Concentration	The ratio of the sales of the largest four firms to the total three-digit SIC industry sales of the target firm (Cornett et al., 2011).
Dormancy	The number of months since the last merger in the same three-digit SIC industry as the target firm (Cornett et al., 2011).
EstAnnReturn	The expected announcement return of the target firm if a takeover announcement does come true, estimated from a linear regression of target announcement day returns on target size, industry, and year fixed effects in a sample of 2,342 official merger announcements of public targets over the period from 2002 to 2011 as provided by the SDC database (Ahern and Sosyura, 2015).
EstDealLikelihood	The rumor date target firm return divided by the EstAnnReturn (Ahern and Sosyura, 2015).
Infoasymm	An indicator variable equal to one if a firm's stock price is both overvalued (with a market-to-book value greater than the industry median) and opaque (the share turnover is lower than the industry median) (Cornett et al., 2011).
IBuys	The aggregated dollar value of institutional purchases normalized by the firm's market capitalization, lagged by one year (Hendershott et al., 2015).
ISales	The aggregated dollar value of institutional sales normalized by the firm's market capitalization, lagged by one year (Hendershott et al., 2015).
IOF	The difference between institutional purchases, IBuys, and institutional sales, ISales (Hendershott et al., 2015).
IOV	The sum of institutional purchases, IBuys, and institutional sales, ISales (Hendershott et al., 2015).
PrevMergers	Count variable of the number of times a firm proposes or receives a merger bid in the prior two years (Cornett et al., 2011).
PriorReturn2Yrs	The change in a firm's stock price in the two years prior to a given quarter (Cornett et al., 2011).
ResMismatch	Dummy variable that equals one if either i) a firm's sales growth in the last two years is less than the industry median and the long-term debt ratio is greater than the industry median, or ii) the firm's sales growth in the last two years is greater than the industry median and the long-term debt ratio is less than the industry median; otherwise the variable equals zero (Cornett et al., 2011).
ROA	Ratio of net income before extraordinary (or nonrecurring) items to total assets at the end of the fiscal year prior to the control or pre-rumor period (Cornett et al., 2011).
SalesGrowth2Yrs	The percentage change in the firm's sales over the previous two years (Cornett et al., 2011).
SalesShock	The absolute value of the difference between the two-year median industry sales growth rate and the two-year median sales growth rate of all sample target firms (Cornett et al., 2011).
SalesShockSq	The square of sales shock (Cornett et al., 2011).

ShareTurnover	The ratio of the number of the firm's shares of stock traded to total shares outstanding (Cornett et al., 2011).
ValuableBrand	An indicator variable representing target firm inclusion in a list of the top 100 brands from the marketing consultancy firms Interbrand and BrandZ at any time between 2002 and 2011 (Ahern and Sosyura, 2015).
#Institutions trading	The daily number of institutions trading in a firm (Irvine et al., 2007).

Rumor content characteristics (rationales)

Variable	**Definition**
AdvisorHired	Rumor indicates that the target firm has retained the services of an investment bank or financial advisor.
AnalystReport	Rumor is the result of one or more analysts reasoning that a takeover seems logical.
BidderDenied	Rumor indicates that a potential bidding firm denies that parties are in negotiations.
BidderMentioned	Rumor indicates the name of one or more potential bidders.
BlockPurchase	Rumor indicates that 5% or more of shares outstanding have recently been purchased by a single entity.
FinancingSource	Rumor provides substantial details as to how financing for the deal would occur.
IndustryActivity	Rumor indicates that either a competitor is being taken over or that the target industry appears ripe for takeovers.
Informative	Rumor based on at least three rumor justifications, excluding those labeled as speculative.
InsiderCited	Rumor predicated on an anonymous source.
MgmtConcerns	Rumor indicates concerns with the current management.
OptionsIncreased	Rumor specifically mentions that an increase in call options is indicative of an impending takeover.
PEFundInvolved	Rumor indicates that a private equity or hedge fund has expressed interest in a potential takeover deal.
Speculative	Rumor based solely on either takeover chatter or an increase in option activity in the target firm, with no further justification provided.
SynergyCited	Rumor indicates that the target firm has specific attributes that would provide unique synergies to an acquirer.
TakeoverChatter	Rumor provides very few details yet mentions that the target firm is subject to ongoing takeover chatter.
TargetDenied	Rumor indicates that the target firm denies that parties are in negotiations.
TargetDistress	Rumor indicates that the target firm has been experiencing substantial financial and/or operating distress.
TargetInitiated	Rumor is initiated by the target firm itself.
Undervalued	Rumor indicates that the target firm can be seen as undervalued, prompting takeover interest.
UnusualActivity	Rumor indicates that something unusual has occurred that has led to takeover speculation (e.g., two chief executive officers simultaneously absent from a conference or other changes in executive team schedules or habits).

Internet Appendix for

Institutional Trading in Firms Rumored to be Takeover Targets

Frederick Davis, Hamed Khadivar, Thomas J. Walker

This Internet Appendix has four parts. Section A-I presents the comparison of institutional order flow (IOF) within our sample to that of a control sample matched on proxies of takeover likelihood. Section A-II provides analysis of the bid-ask spread, the abnormal volume of transactions, and the activity of short-sellers to ensure evidence is consistent with the presence of informed trading around the rumor date. Section A-III supplements our main analysis of institutional order flow by ensuring that results are robust to various definitions of rumor accuracy. Finally, Section A-IV demonstrates the significance of institutional order flow according to the content of the rumor article.

A-I. Control Sample Formation Based on Takeover Likelihood

To examine whether the unusual institutional trading activity we document may be due to institutions analyzing publicly available information, we use propensity score matching to construct a control sample based on common proxies of takeover likelihood. Specifically, we match on firm leverage, firm size, the market-to-book ratio, the return on assets, the presence of a blockholder, and the presence of same-industry (at the three-digit SIC code level) bids within the prior year (Hasbrouck, 1985; Palepu, 1986; Ambrose and Megginson, 1992; Cremers et al. 2009; Cornett et al., 2011).[19] We choose that firm as the control firm which has the closest takeover propensity score (the smallest

[19] We define a blockholder as an institutional investor holding 5% or more of a firm's shares outstanding.

Mahalanobis distance) relative to the rumored firm at the end of the fiscal year prior to the takeover rumor.

As presented in Table A1, we note that our control firms show no signs of abnormal IOF (Column 3). Moreover, the difference in IOF (i.e., the rumored firms' IOF minus the control firms' IOF) is significantly positive shortly prior to the rumor, and significantly negative shortly thereafter (Column 5), supporting our prior findings.

Insert Table A1 about here

A-II. Intraday Analysis Around the Rumor Date

We perform additional analyses to provide insight into who is trading around the rumor date and whether such trading is informed. We begin by calculating abnormal daily bid-ask spreads prior to takeover rumors for rumored firms and their matched peers. We obtain the respective intraday information from Trade-and-Quote (TAQ) and follow the algorithm of Lee and Ready (1991) to distinguish between buyer-and seller-initiated transactions. We then follow Holden and Jacobsen (2014) and apply the filters and adjustments for withdrawn or canceled quotes and compute the effective bid-ask spread as the percentage increase in the ratio of the transaction price over the prevailing mid-quote prior to the transaction.[20] As per Peress and Schmidt (2020), for every firm in our sample we construct the abnormal spread measure by subtracting the average daily spread during the benchmark period (-90, -31) from its daily spread, scaled by the benchmark period average.

[20] The code for making these adjustments is available on Craig Holden's web page (http://kelley.iu.edu/cholden/). In addition, we find similar results when using share-weighted and dollar volume-weighted spread measures instead of the price spread.

In order to ensure that our intraday analyses are not driven by takeover time-series clustering and industry-level variation (Mitchell and Mulherin, 1996), we match every rumored firm with a control firm with the same three-digit SIC code and the smallest Mahalonobis distance calculated along three dimensions: the firms' market capitalization (natural logarithm), their market-to-book ratio, and their past stock return (the average daily stock return during the last six months prior to the rumor, adjusted using the CRSP equally-weighted market index). We follow Gao and Oler (2012) and define the universe of possible matching firms as all firms in the intersection of CRSP and Compustat that have financial statement data available as of the most recent month-end at least 30 days before the rumor date.

Insert Figure A1 about here

Our results are plotted in Figure A1 and show that, shortly prior to the rumor, the abnormal spread is positive for rumored firms, indicating that market makers recognize adverse selection in potential takeover targets (Song and Walking, 2000). In addition, we find that over the last four days prior to the rumor, the abnormal daily spread of rumored firms increases significantly and becomes statistically different from the daily spread of their matched peers. This implies that market makers are demanding a higher margin in the presence of trading which is likely to be informed.

Next, we examine intraday buying and selling trading patterns of investors since earlier studies (e.g., Cready and Hurtt, 2002; Easley et al., 2008; Kaul et al., 2008) argue that the number of transactions captures the probability of informed trading.[21] For each firm in our sample, we define abnormal active buying and selling separately as follows:

$$AAB_{i,t} = (Buyer_{i,t} - \overline{Buyer_i})/\overline{Buyer_i} \tag{1*}$$

[21] We find qualitatively similar results when using the number of shares or the dollar value of the transactions.

$$AAS_{i,t} = (Seller_{i,t} - \overline{Seller_i})/\overline{Seller_i} \tag{2*}$$

where $AAB_{i,t}$ ($AAS_{i,t}$) is the abnormal active-buying (active-selling) of firm i on day t, $Buyer_{i,t}$ ($Seller_{i,t}$) is the number of buyer-initiated (seller-initiated) transactions in the equity market for firm i on day t, and $\overline{Buyer_i}$ ($\overline{Seller_i}$) is the daily average number of buyer-initiated (seller-initiated) transactions of firm i during an estimation window of (-90, -31) relative to the rumor date. We then define the daily trade imbalance as follows:

$$Imbalance_{i,t} = AAB_{i,t} - AAS_{i,t} \tag{3*}$$

where $AAB_{i,t}$ and $AAS_{i,t}$ are computed based on Equations 1* and 2*. Table A2 presents the cross-sectional daily averages of abnormal purchases and sales for rumored firms and their matched peers. We observe a significant increase in both buyer- and seller-initiated transactions of rumored firms starting eight days prior to the rumor date while there is no unusual trading pattern in the control group. The number of buy-side transactions in rumored firms becomes significantly higher than that within control firms shortly prior to the rumor and is significantly lower throughout the entire post-rumor period. These findings are indicative of institutions engaging in informed trading over these periods.

Insert Table A2 about here

Finally, we examine whether there is unusual short-selling activity prior to takeover rumors. We use data from Markit which collects short-selling activity directly from security lending desks at financial institutions. The database provides both the number of shares lendable and the number of shares on loan.[22] As per Ahern and Sosyura (2015), we define the short utilization ratio as the number

[22] For a detailed description of the Markit database, see Saffi and Sigurdsson (2011) and Engelberg et al. (2013).

of shares on loan divided by the number of shares lendable. For each firm in our sample, we compute the abnormal short utilization as the difference between the daily short utilization and its average over the (-90, -31) period relative to the rumor date.[23] Figure A2 plots the abnormal short utilization for rumored firms and their corresponding matched firms around the rumor date. The short utilization of rumored firms increases significantly within the week prior to rumors and is statistically different from that of the matched peers. This suggests that short-sellers are acting as a counterparty to ANcerno fund trades, and are thus not similarly informed.

Insert Figure A2 about here

A-III. Institutional Order Flow According to Rumor Accuracy

In this section, we wish to examine whether the institutional order flow (IOF) we have observed for accurately rumored firms depends on our definition of accuracy. We thus present in Table A3 (and display in Figure A3) the IOF for both smart and lucky funds when firms receive a bid within a period of 30 days (Columns 1 and 2), 31 to 90 days (Columns 3 and 4), and 91 to 180 days (Columns 5 and 6) after the initial rumor date.

Insert Table A3 about here

Insert Figure A3 about here

Our results indicate that lucky funds do not engage in significant net-buying of accurately rumored firms over the pre-rumor period yet engage in significant net-selling over the post-rumor period, regardless of the definition of accuracy employed. This is consistent with our main results.

[23] To account for the delay in settlement and delivery in short sales, we record short-selling activity for day *t* using the data from Markit on day *t* + 3 (Geczy et al., 2002; Ahern and Sosyura, 2015).

Smart funds engage in significant net-buying of accurately rumored firms shortly prior to the rumor date, regardless of the definition of accuracy employed and this is also consistent with our main results.

The significant selling by smart funds over the post-rumor period predominately occurs when firms receive a bid within the next 30 days. This is likely due to the fact that institutions are known to sell shares in firms subject to takeover announcements (e.g., Bethel et al., 2009; Griffin et al., 2012).

Finally, we use different definitions of rumor accuracy and investigate whether the trades by smart and/or lucky funds are informative and robust to the definition of accuracy. Specifically, we fit different logit regressions where the dependent variables equal one if the rumored firm becomes subject to a takeover announcement within the following 30, 60, and 180 days. We include measures of fund trading as explanatory variables along with other control measures, and present results in Table A4. We find that, regardless of the definition of accuracy, trades of smart funds are a positively significant predictor of post-rumor bid announcements.

Insert Table A4 about here

A-IV. Institutional Order Flow Based on Rumor Content

We categorize rumors according to sixteen non-mutually exclusive takeover rationales as provided in the article text and separately examine institutional trading patterns in each category. We compute the buy-and-hold cumulative abnormal institutional order flow as follows:

$$BHAIOF_i(t_0, t_1) = \sum_{t_0}^{t_1}(IOF_i - IOF_{i,Benchmark})_t \quad (4^*)$$

where IOF_i is the institutional order flow of firm *i* and $IOF_{i,Benchmark}$ is the average daily institutional order flow calculated over the (-90, -31) window prior to the rumor date for firm *i*.

Table A5 presents the results for rumor categories with significant BHAIOF(-10, -1). We find a statistically significant buy-and-hold cumulative abnormal institutional order flow in five rumor categories including *AdvisorHired*, *BlockPurchase*, *InsiderCited*, *PEFundInvolved*, and *SynergyCited*. In general, these rumor types appear to offer institutions more opportunities to acquire private information, as the first four categories imply the existence of additional entities that are privy to bid prospects. In general, an increased number of individuals responsible for maintaining confidentiality increases the likelihood of leakage while reducing expectations of punishment as the source of leakage becomes more uncertain.

Insert Table A5 about here

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Figure A1. Bid-ask spread analysis

This figure depicts the abnormal effective bid-ask spread for rumored firms and their matched peers around the rumor date. Control firms operate in the same industry (based on three-digit SIC codes) and have the smallest Mahalonobis distance to the sample firms based on three dimensions: the firms' market capitalization, their market-to-book ratio, and their past stock return. We obtain intraday data from the TAQ database and use the algorithm of Lee and Ready (1991) to determine the initiating side of the transaction (buyer vs. seller). We construct the abnormal spread measure by subtracting the average daily spread during the benchmark period (-90, -31) from the daily spread, scaled by the benchmark period average. To reduce the influence of outliers, we winsorize the top and bottom 1% of daily observations. The squares on the rumored firm line indicate abnormal spreads that are significantly different between rumored firms and their matched peers at the 5% level.

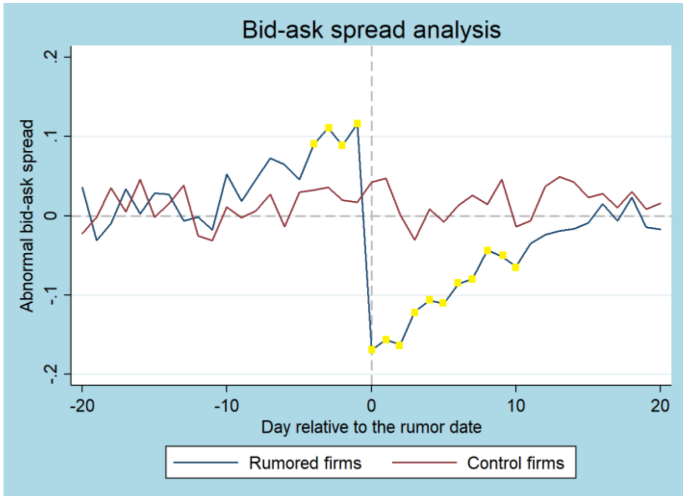
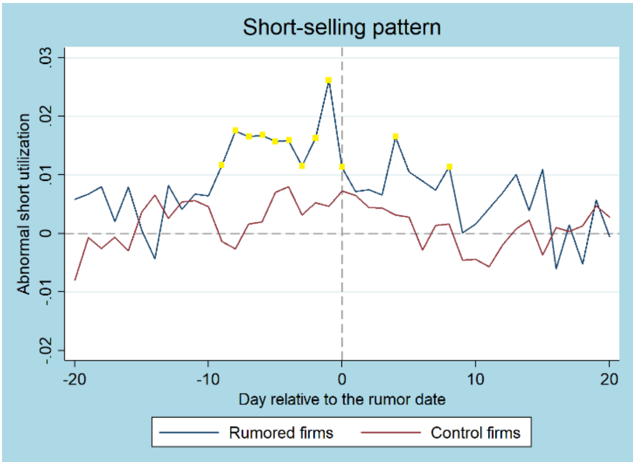


Figure A2. Abnormal short utilization

This figure depicts the abnormal short utilization for 1,317 firms that are rumored to be takeover targets, as well as for a corresponding sample of 1,317 matched firms, over the (-20, +20) period relative to the rumor date. Control firms operate in the same industry (based on three-digit SIC codes) and have the smallest Mahalonobis distance to the sample firms based on three dimensions: the firms' market capitalization, their market-to-book ratio, and their past stock return. We obtain short-selling data from Markit. Given that the earliest date available in Markit is July 2006, we lose 372 observations from the main sample. We define the short utilization ratio as the number of shares on loan divided by the number of shares lendable. For each firm in our sample, we compute the abnormal short utilization as the difference between the daily short utilization and its average over the (-90, -31) period relative to the rumor date. To reduce the influence of outliers, we winsorize the top and bottom 1% of daily observations. Panel A presents the results for all the rumored firms and their corresponding matched peers. The squares on the rumored firm line indicate abnormal short utilizations that are significantly different between rumored firms and their matched peers at the 5% level. Panel B presents the results based on rumor accuracy (accurate vs. inaccurate). Rumors are labelled as accurate if the rumored firms in question indeed become the target of a formal takeover bid within 365 calendar days after the initial scoop article; otherwise, they are labelled as inaccurate.

Panel A: Short-selling patterns for rumored firms and their matched peers



Panel B: Short-selling patterns for accurate and inaccurate rumors

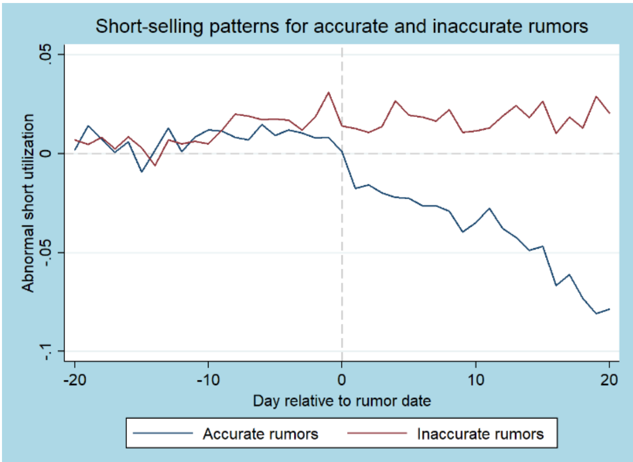
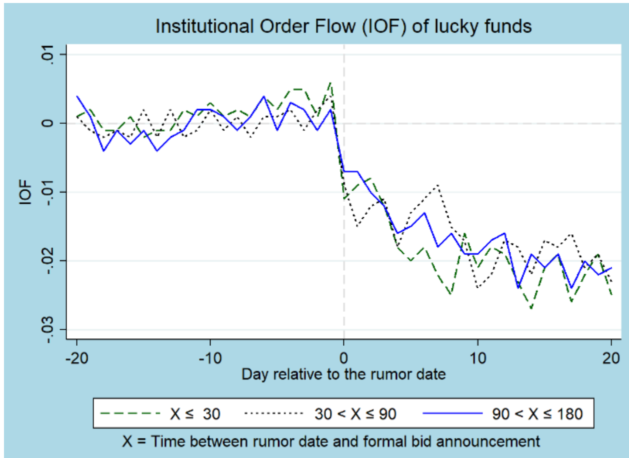


Figure A3. Institutional trading patterns based on the time to the formal bid announcement

This figure depicts the institutional order flow (IOF) around takeover rumors that are accurate (followed by a formal bid announcement). Precise quantities are reported in Table A3. Panel A presents the results for lucky funds and Panel B plots the results for smart funds, each defined in Section 4.5. Rumors are categorized into three groups according to the time between the takeover rumor and the formal bid announcement as indicated below by 'X'.

Panel A: Institutional order flow (IOF) of lucky funds



Panel B: Institutional order flow (IOF) of smart funds

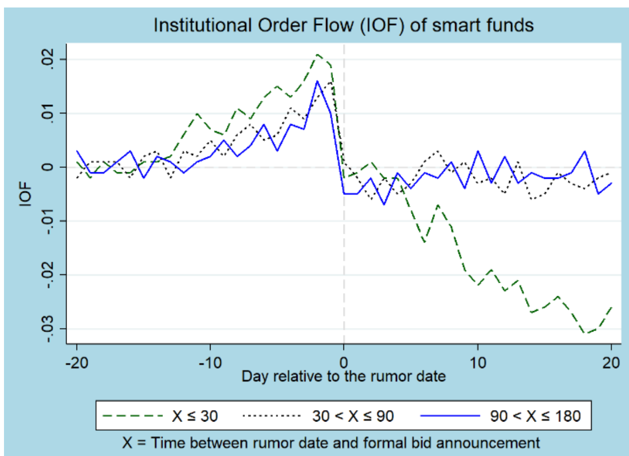


Table A1. Institutional trading activity in rumored firms and their matched peers

This table presents daily averages of the ANcerno-based institutional trading measures for 1,493 takeover-rumored firms and their matched peers. We lose 196 of our original 1,689 observations due to incomplete data availability from Compustat. The control sample is constructed based on propensity score matching along five dimensions: firm size, the market-to-book ratio, the return on assets, firm leverage, the presence of a blockholder, and the presence of same-industry (at the three-digit SIC code level) bids within the prior year. Tests of significance are based on t-tests of individual day observations relative to the (-90, -31) benchmark period distribution prior to the rumor. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Relative day	Rumored firms		Control firms		Difference	
	(1)	(2)	(3)	(4)	(1) - (3)	(2) - (4)
	IOF	IOV	IOF	IOV	IOF	IOV
-30 to -21	0.001	0.101	0.001	0.099	0.000	0.002
-20	0.001	0.105	0.001	0.102	0.000	0.003
-19	-0.002	0.104	0.002	0.099	-0.004	0.005
-18	0.001	0.099	0.001	0.105	0.000	-0.006
-17	-0.001	0.104	-0.001	0.102	0.000	0.002
-16	0.001	0.105	0.002	0.103	-0.001	0.002
-15	-0.002	0.101	0.002	0.101	-0.004	0.000
-14	0.002	0.106	-0.001	0.099	0.003	0.007
-13	-0.001	0.105	-0.002	0.103	0.001	0.002
-12	0.004	0.103	0.003	0.108	0.001	-0.005
-11	0.006	0.107	0.003	0.106	0.003	0.001
-10	0.009	0.115*	0.001	0.101	0.008	0.014*
-9	0.006	0.110	0.000	0.105	0.006	0.005
-8	0.018**	0.115***	-0.002	0.106	0.020**	0.009*
-7	0.018**	0.124***	-0.003	0.101	0.021***	0.023**
-6	0.017**	0.128***	-0.001	0.103	0.018**	0.025**
-5	0.023***	0.131***	0.001	0.098	0.022***	0.033***
-4	0.016**	0.120**	0.001	0.103	0.015**	0.017**
-3	0.021***	0.123***	0.005	0.103	0.016**	0.020***
-2	0.018***	0.125***	0.003	0.098	0.015***	0.027***
-1	0.025***	0.129***	0.001	0.103	0.024***	0.026***
0	0.001	0.297***	-0.002	0.104	0.003*	0.193***
+1	-0.069***	0.302***	0.001	0.102	-0.070***	0.200***
+2	-0.029***	0.141***	-0.001	0.100	-0.028***	0.041***
+3	-0.026***	0.129***	0.001	0.105	-0.027***	0.024***
+4	-0.031***	0.156***	-0.004	0.098	-0.027***	0.058***
+5	-0.037***	0.148***	-0.001	0.104	-0.036***	0.044***
+6	-0.018***	0.125***	-0.002	0.096	-0.016***	0.029***
+7	-0.034***	0.159***	0.004	0.105	-0.038***	0.054***
+8	-0.011**	0.122***	0.001	0.103	-0.012***	0.019***
+9	-0.051***	0.148***	0.001	0.101	-0.052***	0.047***
+10	-0.022***	0.135***	-0.002	0.101	-0.020***	0.034***
+11	-0.010**	0.127***	-0.002	0.098	-0.008**	0.029***
+12	-0.046***	0.151***	0.001	0.103	-0.047***	0.048***
+13	-0.032***	0.141***	0.002	0.104	-0.034***	0.037***
+14	-0.035***	0.158***	-0.001	0.101	-0.034***	0.057***
+15	-0.021***	0.128***	-0.002	0.104	-0.019***	0.024***
+16	-0.034***	0.126***	0.005	0.105	-0.039***	0.021***
+17	-0.005	0.142***	-0.002	0.101	-0.003*	0.041***
+18	-0.011***	0.118*	-0.001	0.103	-0.010**	0.015**
+19	-0.018***	0.121**	0.002	0.099	-0.020***	0.022**
+20	-0.014**	0.123	-0.001	0.100	-0.013**	0.023**
+21 to +30	-0.010	0.115	0.001	0.104	-0.011**	0.011*
Benchmark (-90, -31)	0.001	0.104	0.001	0.103	0.000	0.001

Table A2. Abnormal intraday trading

This table shows the daily active buy- and sell-side initiated transactions for rumored target firms around the rumor date. We obtain intraday data from the TAQ database and use the algorithm of Lee and Ready (1991) to determine the initiating side of the transaction (buyer or seller). Abnormal buying, abnormal selling, and trade imbalances are computed based on Equations 1* to 3*. To reduce the influence of outliers, we winsorize the top and bottom 1% of daily observations. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	Rumored firms			Control firms			Difference
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Relative day	Abnormal buying	Abnormal selling	Trade imbalance	Abnormal buying	Abnormal selling	Trade imbalance	(3) - (4)
-15	0.026	0.019	0.007	0.034	0.041	-0.007	0.014
-14	0.017	0.012	0.005	0.042	0.019	0.023	-0.018
-13	-0.012	0.005	-0.017	0.032	0.023	0.009	-0.026
-12	0.056	0.068^{*}	-0.012	0.029	0.034	-0.005	-0.007
-11	0.025	0.031	-0.006	-0.007	0.01	-0.017	0.011
-10	0.027	0.015	0.012	0.036	0.027	0.009	0.003
-9	0.051	0.056	-0.005	0.028	0.039	-0.011	0.006
-8	0.105^{**}	0.084^{*}	0.021	0.041	0.036	0.005	0.016
-7	0.135^{***}	0.108^{**}	0.027	0.046	0.024	0.022	0.005
-6	0.127^{***}	0.102^{***}	0.025	0.019	0.031	-0.012	0.037^{*}
-5	0.162^{***}	0.117^{***}	0.045^{*}	-0.008	-0.023	0.015	0.030
-4	0.155^{***}	0.129^{***}	0.026	-0.018	-0.033	0.015	0.011
-3	0.193^{***}	0.149^{***}	0.044^{**}	-0.011	-0.005	-0.006	0.050^{**}
-2	0.216^{***}	0.135^{***}	0.081^{***}	0.045	0.016	0.029	0.052^{***}
-1	0.459^{***}	0.172^{***}	0.287^{***}	0.047	0.021	0.026	0.261^{***}
0	0.617^{***}	0.396^{***}	0.221^{***}	0.039	0.028	0.011	0.210^{***}
+1	0.564^{***}	0.493^{***}	0.071^{***}	0.051	0.032	0.019	0.052^{***}
+2	0.516^{***}	0.543^{***}	-0.027^{*}	0.012	0.018	-0.006	-0.021^{***}
+3	0.349^{***}	0.481^{***}	-0.132^{***}	0.014	0.035	-0.021	-0.111^{***}
+4	0.383^{***}	0.493^{***}	-0.110^{***}	0.051	0.043	0.008	-0.118^{***}
+5	0.361^{***}	0.473^{***}	-0.112^{***}	0.023	0.034	-0.011	-0.101^{***}
+6	0.311^{***}	0.473^{***}	-0.162^{***}	0.048	0.048	0	-0.162^{***}
+7	0.276^{***}	0.379^{***}	-0.103^{***}	0.015	-0.009	0.024	-0.127^{***}
+8	0.215^{***}	0.361^{***}	-0.146^{***}	0.018	0.012	0.006	-0.152^{***}
+9	0.254^{***}	0.409^{***}	-0.155^{***}	0.038	0.036	0.002	-0.157^{***}
+10	0.222^{***}	0.392^{***}	-0.170^{***}	0.026	0.037	-0.011	-0.159^{***}
+11	0.176^{***}	0.351^{***}	-0.175^{***}	0.015	0.025	-0.01	-0.165^{***}
+12	0.183^{***}	0.372^{***}	-0.189^{***}	-0.013	-0.007	-0.006	-0.183^{***}
+13	0.149^{***}	0.354^{***}	-0.205^{***}	0.022	0.009	0.013	-0.218^{***}
+14	0.132^{***}	0.319^{***}	-0.187^{***}	0.047	0.031	0.016	-0.203^{***}
+15	0.101^{***}	0.348^{***}	-0.247^{***}	0.013	0.028	-0.015	-0.232^{***}

Table A3. Institutional trading activity based on the time to bid announcement

This table presents the institutional order flow (IOF) around takeover rumors that are followed by formal bid announcements. Results are segregated based on fund type (smart or lucky) as defined in Section 4.5. Rumors are categorized into three groups according to the time between the takeover rumor and the formal bid announcement as indicated below by 'X'. Tests of significance are based on t-tests of individual day observations relative to the (-90, -31) benchmark period distribution prior to the rumor. The significance of multiple-day periods, (-30, -21) and (+21, +30), is evaluated by comparing the daily means across all days in the multiple day period to the daily means of all days in the benchmark period. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Time to formal bid announcement: X	$X \leq 30$ days (N = 79)		$30 < X \leq 90$ days (N = 67)		$90 < X \leq 180$ days (N = 54)	
Relative day	Smart	Lucky	Smart	Lucky	Smart	Lucky
-30 to -21	0.002	-0.001	0.001	0.001	-0.001	0.002
-20	0.001	0.001	-0.002	0.001	0.003	0.004
-19	-0.002	0.002	0.001	-0.001	-0.001	0.001
-18	0.001	-0.001	0.001	-0.002	-0.001	-0.004
-17	-0.001	-0.001	0.001	-0.001	0.001	-0.001
-16	-0.001	0.001	-0.002	-0.002	0.003	-0.003
-15	0.001	-0.002	0.002	0.002	-0.002	-0.001
-14	0.001	-0.001	0.003	-0.002	0.002	-0.004
-13	0.002	-0.001	-0.002	0.002	0.001	-0.002
-12	0.006	0.002	0.003	-0.002	-0.001	-0.001
-11	0.010**	0.001	0.002	-0.001	0.001	0.002
-10	0.007**	0.003	0.005	0.002	0.002	0.002
-9	0.006*	0.001	0.002	-0.001	0.005**	0.001
-8	0.011***	0.002	0.006	0.001	0.002	-0.001
-7	0.009***	0.001	0.008*	-0.002	0.004*	0.001
-6	0.013***	0.004	0.005	0.001	0.008**	0.004
-5	0.015***	0.002	0.006	0.001	0.003	-0.001
-4	0.013***	0.005	0.011**	0.002	0.008***	0.003
-3	0.016***	0.005	0.009**	-0.001	0.007***	0.002
-2	0.021***	0.001	0.013***	0.002	0.016***	-0.001
-1	0.019***	0.006	0.016***	0.004	0.010***	0.002
0	-0.002	-0.011***	0.001	-0.009***	-0.005	-0.007***
+1	-0.001	-0.009***	-0.002	-0.015***	-0.005*	-0.007***
+2	0.001	-0.008***	-0.006**	-0.012***	-0.002	-0.010***
+3	-0.002	-0.012***	-0.002	-0.011***	-0.007*	-0.012***
+4	-0.002	-0.018***	-0.005**	-0.018***	-0.001	-0.016***
+5	-0.008**	-0.020***	-0.003	-0.013***	-0.004	-0.015***
+6	-0.014***	-0.018***	0.001	-0.011***	-0.001	-0.013***
+7	-0.007***	-0.022***	0.003	-0.009***	-0.002	-0.018***
+8	-0.011***	-0.025***	-0.001	-0.015***	0.001	-0.016***
+9	-0.019***	-0.016***	0.001	-0.017***	-0.004*	-0.019***
+10	-0.022***	-0.021***	-0.003**	-0.024***	0.003	-0.019***
+11	-0.019***	-0.018***	-0.002	-0.022***	-0.003	-0.017***
+12	-0.023***	-0.019***	-0.005**	-0.017**	0.002	-0.016***
+13	-0.021***	-0.023***	0.001	-0.018***	-0.003	-0.024***
+14	-0.027***	-0.027***	-0.006**	-0.022***	-0.001	-0.019***
+15	-0.026***	-0.021***	-0.005**	-0.017**	-0.002	-0.021***
+16	-0.024***	-0.019***	-0.001	-0.018***	-0.002	-0.019***
+17	-0.027***	-0.026***	-0.003	-0.016**	-0.001	-0.024***
+18	-0.031***	-0.022***	-0.004	-0.021***	0.003	-0.020***
+19	-0.030***	-0.019***	-0.002	-0.019**	-0.005**	-0.022***
+20	-0.026***	-0.025***	-0.001	-0.023***	-0.003	-0.021***
+21 to +30	-0.028***	-0.017***	-0.005	-0.014**	-0.003	-0.005*
Benchmark (-90, -31)	0.001	0.002	0.002	0.001	0.001	0.002

Table A4. The predictive power of institutional trading based on the time to bid announcement

This table reports results for a series of logit regressions in which the dependent variables (*Accurate30*, *Accurate60*, and *Accurate180*) are dummy variables that equal one if the rumor leads to a takeover announcement within 30, 60, or 180 days, respectively, following the initial rumor announcement. The main independent variable of interest is the buy-and-hold cumulative abnormal institutional order flow defined as $BHAIOF_i(t_0, t_1) = \sum_{t_0}^{t_1}(IOF_i - IOF_{i,Benchmark})_t$, where IOF_i is the institutional order flow of firm *i* and $IOF_{i,Benchmark}$ is the average daily institutional order flow calculated over the (-90, -31) window prior to the rumor date for firm *i*. Appendix A provides other variable definitions. Some controls are insignificant and untabulated for brevity. They include the following variables: *ValuableBrand, EstDealLikelihood, Cashratio, Changesize2y, Concentration, Dormancy, Infoasymm, Prevmergers, Priorreturn2y, Resmismatch, ROA, Salesgrowth2y, Salesshock, SalesshockSq,* and *Shareturnover*. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent:	*Accurate30*		*Accurate60*		*Accurate180*	
BHAIOF(-10, -1) $_{smart}$	4.315***					
	(0.001)					
BHAIOF(-10, -1) $_{lucky}$		2.483				
		(0.516)				
BHAIOF(+1, +10) $_{smart}$			3.784**			
			(0.032)			
BHAIOF(+1, +10) $_{lucky}$				-3.170		
				(0.296)		
BHAIOF(-10, +10) $_{smart}$					5.654**	
					(0.019)	
BHAIOF(-10, +10) $_{lucky}$						-1.052**
						(0.694)
Informative	1.156***	1.249***	0.792***	0.841***	0.756***	0.783***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Speculative	-0.791**	-0.736**	-0.608**	-0.593**	-0.581**	-0.556**
	(0.021)	(0.025)	(0.028)	(0.030)	(0.038)	(0.041)
Size	-0.261***	-0.256***	-0.242***	-0.249***	-0.248***	-0.239***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CAR(0, +1)	7.158***	7.254***	5.417***	5.764***	3.956**	4.041***
	(0.001)	(0.001)	(0.008)	(0.005)	(0.011)	(0.008)
CAR(-5,-1)	1.522*	1.372	0.962	0.986	0.508	0.563
	(0.086)	(0.126)	(0.315)	(0.295)	(0.676)	(0.644)
CAR(-41,-1)	0.328	0.261	-0.021	-0.039	0.081	0.089
	(0.541)	(0.685)	(0.692)	(0.803)	(0.635)	(0.620)
Constant	1.632*	1.786*	2.154**	2.013**	2.492**	2.635**
	(0.076)	(0.071)	(0.035)	(0.038)	(0.026)	(0.024)
Industry / Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,459	1,459	1,459	1,459	1,459	1,459
Pseudo R^2	0.174	0.161	0.143	0.136	0.181	0.177

Table A5. Institutional trading patterns based on the content of the rumor article

This table reports daily institutional order flow (IOF) for rumors with significant buy-and-hold cumulative abnormal IOF over the (-10, -1) period, relative to the rumor date (day 0). Buy-and-hold cumulative abnormal IOF is computed based on Equation 4*. Appendix A provides the definitions of individual rumor rationales. Tests of significance are based on t-tests of individual day observations relative to the (-90, -31) benchmark period distribution prior to the rumor. The significance of multiple day periods, i.e., (-30, -21) and (+21, +30), is evaluated by comparing the daily means across all days in the multiple day period to the daily means of all days in the benchmark period. Our methodology matches that of Corwin et al. (2004) and Irvine et al. (2007). Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Relative day	(1) *AdvisorHired* (N = 170)	(2) *BlockPurchase* (N = 65)	(3) *InsiderCited* (N = 236)	(4) *PEFundInvolved* (N = 202)	(5) *SynergyCited* (N = 77)
-30 to -21	0.002	-0.002	0.001	0.001	-0.002
-20	-0.003	0.002	0.002	-0.001	0.003
-19	-0.002	0.001	-0.002	0.001	-0.002
-18	0.003	-0.005	0.001	0.002	-0.001
-17	0.003	0.006	0.003	-0.001	0.004
-16	0.001	-0.001	0.001	0.006	0.000
-15	-0.001	0.001	-0.003	-0.001	0.002
-14	0.002	0.004	0.000	0.002	-0.001
-13	-0.001	-0.005	-0.004	0.003	-0.002
-12	0.001	-0.003	0.002	0.004	0.002
-11	0.005	-0.006	0.002	0.002	0.005
-10	0.006	0.004	0.003	0.009*	0.002
-9	0.007	0.010	0.015**	0.007	0.005
-8	0.011*	0.006	0.007	0.012**	0.006
-7	0.013**	0.015**	0.019***	0.018**	0.005
-6	0.007	0.012	0.008**	0.013***	-0.001
-5	0.015**	0.016**	0.009**	0.008	0.012**
-4	0.018***	0.012*	0.018***	0.017***	0.008*
-3	0.014**	0.008*	0.017***	0.014***	0.005
-2	0.020***	0.017***	0.016***	0.011**	0.018***
-1	0.023***	0.029***	0.021***	0.019***	0.013**
0	-0.033***	-0.021***	-0.047***	-0.029***	-0.024***
+1	-0.055***	-0.077***	-0.041***	-0.035***	-0.041***
+2	-0.041***	-0.057***	-0.069***	-0.072***	-0.056***
+3	-0.035***	-0.014*	-0.031***	-0.029***	-0.017***
+4	-0.035***	-0.026**	-0.038***	-0.027***	-0.032***
+5	-0.024***	-0.019**	-0.026***	-0.036***	-0.022***
+6	-0.020***	-0.023**	-0.020**	-0.023***	-0.021***
+7	-0.029***	-0.012	-0.017**	-0.011*	-0.025***
+8	-0.013**	-0.002	-0.009	-0.019***	-0.017***
+9	-0.006	-0.020**	-0.015**	-0.003	-0.014**
+10	-0.011	-0.013*	-0.003	-0.023***	-0.009
+11	-0.010	-0.018**	-0.007	-0.002	-0.011
+12	-0.015*	-0.009	-0.005	-0.016**	-0.007
+13	-0.014*	-0.004	-0.016**	-0.007	-0.010
+14	-0.017**	-0.011	-0.006	-0.004	-0.018***
+15	-0.015*	-0.001	-0.009	-0.008	-0.019***
+16	-0.019**	-0.007	-0.014*	-0.013**	-0.005
+17	-0.002	-0.004	-0.007	-0.009	-0.015**
+18	-0.005	-0.003	-0.003	-0.003	-0.009
+19	-0.001	-0.006	-0.005	-0.006	-0.007
+20	-0.011	-0.001	-0.006	-0.004	-0.006
+21 to +30	-0.004	-0.002	-0.005	-0.005	0.001
Benchmark (-90 to -31)	0.001	0.002	-0.002	0.002	0.001