Trading in the Presence of Short-Lived Private Information:

Evidence from Analyst Recommendation Changes

Ohad Kadan

Roni Michaely

Pamela C. Moulton*

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Abstract

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* Kadan is at the Olin Business School, Washington University in St. Louis (kadan@wustl.edu); Michaely is at Johnson@Cornell Tech, SC Johnson College of Business, Cornell University (rm34@cornell.edu); and Moulton is at the School of Hotel Administration, SC Johnson College of Business, Cornell University (pmoulton@cornell.edu).
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Abstract

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JEL classification: G14, G18, G23, G24

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1. Introduction

In today's financial markets, active portfolio managers continuously pursue informational advantages. Much of the asset management industry is focused on generating proprietary informational signals and then quickly exploiting these signals through trade. In this competitive and fast-paced environment, even a short-lived informational advantage may constitute a meaningful edge. How do informed traders benefit from such short-lived private information? A Wall Street adage suggests that professional investors often follow a "buy the rumor and sell the news" strategy.[1] That is, if an investor possesses a private, short-lived positive informational signal about an asset, she will buy the asset when the information is private and then sell it when the signal is revealed publically, reaping short-term profits.

While there is some anecdotal evidence supporting this "buy the rumor and sell the news" strategy, it is not clear, a priori, whether some investors are able to obtain this type of informational advantage or whether such a strategy would necessarily be optimal. There is virtually no formal evidence on the extent to which this strategy is used and by whom. While buying early on an informative signal is obvious, the strategy for taking profits and benefiting from the information rents is not entirely clear. Perhaps a trader should take profits immediately upon the broad release of information, or perhaps the signal has long-term implications (i.e., prices do not fully reflect the information immediately), inducing early-informed traders to hold on to the asset, benefitting from the long-term drift. Different types of early-informed traders may take profits at different times depending on the speed with which information is incorporated into prices, the trader's investment horizon, the nature of the information she holds, and her attitude toward risk. Some of these factors are considered theoretically in Hirshleifer, Subrahmanyam, and Titman (1994) and Brunnermeier

[1] The term "rumor" is interpreted broadly to include any information obtained before it is publicly announced, including very accurate information.

(2005). Also intriguing is the fact that if some traders are following the "buy the rumor, sell the news" strategy to profit from their private signals, then other traders must be following a mirror-image strategy, suffering losses during informational events due to adverse selection. Who are these traders?

In this paper we exploit the unusual richness of a proprietary database to reveal the inner workings of trading in the face of short-lived private information, exploiting a unique setting in which short-lived differences in information are plausible. Consistent with Hirshleifer et al. (1994) and Brunnermeier (2005), we first show that, on average, investors who are likely to possess short-lived private information indeed buy the rumor and sell the news. Interestingly, when we go beyond existing theory to document the trading strategies of different classes of informed traders, we find that they differ in their profit-taking patterns, reflecting variations in their trading horizons and motives. While "buying the rumor" is pervasive among early-informed traders, the "selling the news" portion of the strategy is used by only a subset of early-informed traders. We are able to characterize the type of traders that are more likely to both "buy the rumor" and "sell the news" and those that only "buy the rumor." We also study the trading strategies of uninformed traders and investigate how the market is cleared, shedding new light on liquidity provision and the inevitable adverse selection associated with information differences. Finally, our setting allows us to quantify the informational rents by estimating the monetary value of a short-lived informational advantage.

To examine short-lived differences in information, we focus on sell-side analyst recommendation changes as times when information varies across investor classes because either (i) brokerages share information about their analysts' recommendations early with their institutional clients;[2] or (ii) institutional investors do their own research and reach similar conclusions before analysts release their recommendations. Thus, the few days before analyst recommendation changes serve as a period during which institutions that are attentive to firm-specific news have an informational advantage compared to other traders. We use this setting to study how the trading patterns of different players vary with their information.

Our analysis is made possible by a proprietary dataset that identifies daily buy and sell volumes of all institutions, individuals, and market makers on the New York Stock Exchange (NYSE), including several useful sub-categories. Within institutional trades, the dataset separately identifies program trades, which are orders to trade baskets of multiple stocks. Program trading is not motivated by news about one particular stock, and we use this feature to separate program institutional trades from the "news-driven" institutional trading that is more likely to have private information in advance of analyst recommendation changes. Within news-driven institutional trades the dataset further identifies proprietary trades, in which NYSE member firms trade for their own account, and agency trades, in which member firms enter orders for their customers.[3] Within program institutional trades the dataset identifies trades as either index-arbitrage or non-index-arbitrage. Because the dataset includes the trades of *all* participants on the NYSE and there is a natural "adding-up constraint" (i.e., there is a buyer for every seller), we can also determine who loses when some traders profit.

[2] Papers documenting evidence consistent with early information leakage around analyst recommendations include Irvine, Lipson, and Puckett (2007), Goldstein, Irvine, Kandel, and Wiener (2009), Juergens and Lindsey (2009), Christophe, Ferri, and Hsieh (2010), and Busse, Green, and Jegadeesh (2012). The practice of brokerages providing early information about their recommendations to their clients does not appear to be illegal during our sample period. See Section 2.2 for a detailed discussion.
[3] The NYSE designates as "proprietary" all trades made by member firms for their own account, and it designates as "agency" all trades for member firms' customers, which would include those customers' own proprietary trades. Consequently, any differences we find between the trades of proprietary and agency trades are, in fact, a lower bound on the actual differences. See Section 2.1 for more details.

The Hirshleifer et al. (1994) and Brunnermeier (2005) models provide useful guidance for our empirical analysis. They predict that early-informed investors will buy stocks prior to positive information releases and reverse their positions when the information is released publicly. Hirshleifer et al. (1994) also predict that late-informed investors will trade in the direction of the information when it is released more broadly, but not before. Both models predict that early-informed investors' trading will be greater for information events with larger price changes on the day the information is made public. While our results are generally supportive of these predictions, the richness of our dataset allows us to go beyond the level of detail in the theories.

We find that news-driven institutions (the early-informed group) buy into a stock before it is upgraded, reflecting a "buy the rumor" strategy. This behavior applies to both agency and proprietary trades, showing that both types of news-driven institutional traders possess an informational edge. Moreover, as predicted by the theories, during the days preceding analyst upgrades these institutions buy more of stocks that subsequently have bigger announcement-day price increases. But we observe a striking difference between proprietary and agency traders' profit-taking practices. Proprietary traders sell more than 50% of their initial stake immediately upon an upgrade announcement (and reverse more than 80% of their positions on downgrade announcements), whereas agency traders defer their profit-taking. Thus, while "buying the rumor" applies to all news-driven institutions, the "sell the news" phenomenon is attributable solely to proprietary trades. This behavior serves as a strong indication of divergence in trading motives and horizons among institutions. Proprietary trades appear to be more speculative and short-term oriented, reflected in institutions' realizing short-term profits by reversing their initial positions swiftly. In contrast, agency trades appear to have a longer horizon, as we do not observe short-term reversals in these trades. These findings are particularly relevant in light of the Volcker Rule (introduced in 2010 and implemented in 2014), which restricts the ability of banks to engage in speculative short-term proprietary trades. Our results provide the first formal academic evidence on the speculative nature of proprietary trades and how they deviate from more traditional investment activities.

The economic magnitude of the trading profits associated with information asymmetries is large. During our 1999-2010 sample period, we estimate that the average return earned by proprietary traders from buying the rumor four days before an analyst upgrade and selling the news on the upgrade day, and executing the mirror-image strategy around analyst downgrades, is 1.71% per event. For proprietary traders who use leverage, the effective returns would be even larger.

Examining the behavior of individual investors (the late-informed group), we find no abnormal buying prior to upgrades (nor selling prior to downgrades), in line with the theoretical predictions. Furthermore, we find significant net buying by individuals on the day of the upgrades, consistent with the theoretical predictions. We do not find significant individual selling on the day of downgrades. This behavior is consistent with Barber and Odean (2008), who argue that individuals tend to buy (but not sell) attention-grabbing stocks.

In terms of market clearing, two groups of traders can potentially serve the role of providing liquidity to the early-informed news-driven institutions: market makers and program traders (non-news-driven institutions).[4] While market makers have the formal role of providing liquidity, program institutional traders are also in a natural position to serve this role since they trade large baskets of securities and are not attentive to firm-specific news, leaving their orders susceptible to being adversely selected by executing against informed orders.[5] Empirically, we find that program

[4] Individuals could also provide liquidity, but during our study period individuals represent less than 2% of total trading volume and thus cannot realistically provide enough liquidity to meet the demands of news-driven institutions, who represent over 60% of trading volume.
[5] Such a "winner's curse" scenario resembles Rock (1986), in which uninformed orders to buy initial public offering (IPO) shares are more likely to get executed when informed traders withdraw from the market, implying that the IPO is a "lemon."

traders, but not market makers, are on the other side of the news-driven institutional trades at the daily level.[6] Thus, program traders (more specifically, those that are not engaged in index arbitrage) emerge as de-facto liquidity providers to news-driven institutional investors.

To verify that our results are indeed driven by some market participants having information before others, and not more general trading patterns unrelated to early information acquisition, we conduct three placebo tests. Analyses of analyst reiterations of previous recommendations (which prior evidence suggests do not carry much information), earnings announcements (when firms are prohibited from sharing information early), and days with similar-magnitude returns but no recommendation changes (to capture other price-moving events that are less likely to involve information leakage) all reveal trading patterns that differ dramatically from those in our main tests, supporting the interpretation that short-lived informational advantages drive our main results.

Our findings offer an inside look at how different types of investors trade in the face of asymmetric information. The rich dataset and the setting around analyst recommendation changes allow us to document the behavior of all the players, including informed traders, uninformed traders, and liquidity providers. We provide the first formal piece of empirical evidence confirming the considerable anecdotal evidence of "buy the rumor, sell the news" trading strategies. We also provide the first empirical evidence on the divergence in horizons and motives between institutional proprietary and agency trades. Our analysis further reveals a previously unexplored feature of program trades, who turn out to be the "victims" of adverse selection due to their lack of attention to firm-specific news.

The remainder of the paper is organized as follows. In Section 2 we discuss the different types of traders in detail, review the theoretical background, and develop our empirical predictions.

[6] It may be that market makers provide liquidity intraday but then reduce their positions by the end of the day to manage their overnight inventory risk; our daily-level dataset does not allow us to observe such intraday dynamics.

Section 3 describes our sample and data. Section 4 presents our main results. Section 5 presents the results of placebo tests. Section 6 details robustness checks, and Section 7 concludes.

2. Empirical Strategy and Predictions

Our goal is to study how different types of investors trade when facing short-term information asymmetry. Our empirical strategy is guided by considering the institutional features of different types of traders in our dataset. For some of the analysis we can invoke existing theoretical models of investor behavior with short-lived informational differences. We next discuss the types of traders considered in our analysis and review the relevant theoretical background. We then combine these discussions into workable predictions for our empirical analysis.

2.1. Trader Types and Features

At the highest level, the NYSE dataset identifies trading by institutions, individuals, and market makers. Since the dataset is comprehensive, the daily buy-sell trade imbalances of these three groups always add up to zero, a property which we refer to as the adding-up constraint. Institutional trading includes both news-driven institutions (such as actively managed mutual funds and hedge funds) and non-news-driven institutions in the form of program traders. News-driven institutional trades are further divided into proprietary and agency trades, and program institutional trades are further divided into index-arbitrage and non-index-arbitrage trades. The distinctions between these different types of institutional trades play an important role in our analysis, and we next elaborate on the key aspects of each of the categories.

2.1.1. News-driven institutional: proprietary and agency. The NYSE dataset divides news-driven institutional trades between proprietary trades (for a member firm's own account) and agency trades (on behalf of a member firm's clients).[7] During our sample period (1999-2010), many investment banks employed traders who were solely dedicated to proprietary trading in an attempt to boost the banks' profits. These proprietary desks functioned like internal hedge funds, operating as separate entities within the bank. Their trades were known to be speculative in nature and often accounted for significant portions of investment banks' profits and losses during our study period.[8] The Volcker rule, proposed in 2010 as an addition to the Dodd-Frank Act and implemented in 2014, was an explicit attempt to curb financial institutions' speculative proprietary trading. Of specific interest to the regulator was the short-term horizon of proprietary trading, which was viewed as an activity that may destabilize depository institutions. Indeed, the rule views proprietary trading in the context of trading accounts defined as *"[…] any account used for acquiring or taking positions in the securities and instruments […] for the purpose of selling in the near term (or otherwise with the intent to resell in order to profit from short-term price movements) […]"* (Dodd-Frank Wall Street Reform and Consumer Protection Act, Section 619). In contrast, agency trades include trades for clients with typically long-term investment horizons, so agency trades in aggregate are less likely to reflect short-term speculative strategies. Thus, while both proprietary and agency traders may have similar sources of information, the trading motives and horizons of these two types of traders differ. We are not aware of prior academic research documenting the differences between agency and proprietary trades, likely due to the lack of appropriate data.

2.1.2. Program institutional trades: index-arbitrage and non-index-arbitrage. The NYSE defines program trades as baskets of at least 15 securities valued at $1 million or more. Program

[7] Member firms owned seats on the NYSE until the NYSE went public in 2006, after which seats were replaced by trading licenses.

[8] See for example "Investment Banks' Superstar Proprietary Traders: Where Are They Now?" by Julia La Roche, Business Insider, August 19, 2011.

trades are used to efficiently execute trades in multiple securities at once and are generally not driven by news about a specific security. The NYSE database further categorizes program trades as index-arbitrage or non-index-arbitrage. Index arbitrage traders take offsetting positions in index stocks and futures to profit from small mis-pricings between the cash and futures markets. Non-index-arbitrage program trades are often used by asset managers such as Exchange Traded Funds (ETFs), who view program trades as a way to increase efficiency and reduce costs.[9] By trading baskets of stocks irrespective of firm-specific news, program traders expose themselves to being adversely selected by being on the "wrong side" in situations where other traders possess superior information about a firm. In fact, Hendershott and Seasholes (2009) find that non-index-arbitrage program traders lose money in aggregate.

2.1.3. Individuals. All non-institutional trades are in this category. Individuals are unlikely to be directly in touch with sell-side analysts, and they typically rely on public sources of information. The trading patterns of individuals have been studied in papers such as Barber and Odean (2008), Odean (1998), and Kaniel, Saar, and Titman (2008). Nevertheless, we are not aware of prior studies documenting individual behavior around events associated with early information acquisition.

2.1.4. Market makers. The market maker category includes NYSE specialists (pre-2007), designated market makers (post-2007), and other market makers (entire period).[10] While all of these market makers provide liquidity as their main business, other types of traders may also emerge as de-facto liquidity providers at any time.

[9] For example, Michael Sobel, head of equity trading at Barclays Global Investors (currently BlackRock), the world's largest manager of ETFs, states that program trading "allows you to do cash and sector balancing… But if you had to boil it down as to why we use it, it's because it increases efficiency and reduces costs" (Ortega, 2005).
[10] During our sample period, Supplemental Liquidity Providers (SLPs, introduced in 2008) were categorized the same way as other proprietary institutional traders in our dataset. SLP Market Makers (SLMMs) were not introduced on the NYSE until 2012 and so are not present in our sample.

2.2. Theoretical Motivation

In this section we discuss the theoretical underpinnings of trading in the face of short-lived information asymmetries. This discussion helps us link the different types of traders in our database to workable empirical predictions.

Consider a trader who obtains advance information about a pending positive news event related to a particular stock. It is clear that the trader will buy the stock prior to the broader release of information. A more subtle question is when this trader will sell the stock and realize the rents from her superior information. Should it be immediately upon the broad release of information, or should she wait a while until "the uninformed crowd" buys into the stock and then take profit? The answer to this question depends on several potential frictions. Two notable theories provide frameworks for answering these questions, highlighting different frictions and the way they affect informed and uninformed trading in the presence of short-lived private information.[11]

First is Hirshleifer et al. (1994), in which the main driving friction is risk aversion. They offer a two-stage rational expectations model with risk-averse investors of two types: "early-informed" and "late-informed." Early-informed investors learn information about a traded asset before other investors, and they can trade on their information at date 1. At date 2, the rest of the investors learn the information and can trade on it. Noisy liquidity demand in the model ensures that prices are not completely revealing, and the market is cleared by risk-neutral market makers. As expected, it is optimal for the early-informed investors to trade in the direction of their information when this information becomes available to them. When the information becomes available to the late-informed investors, risk aversion induces the early-informed to partially reverse their position by trading against their early information. Combining the two predictions

[11] Holden and Subrahmanyam (1996) show that short-term information becomes dominant in the presence of risk aversion.

produces "buy the rumor, sell the news" behavior for positive signals, with a mirror image of this strategy when the signal is negative.

Hirshleifer et al. (1994) also show that the amount of trading by the early-informed investors before the information is released more broadly is larger for more favorable information.[12] As for the late-informed investors, they do not trade early, but instead trade in the direction of the signal when it becomes available to them.

The second model motivating our analysis is Brunnermeier (2005), which highlights the importance of the short-term focus of speculators in driving the "sell the news" behavior. A main friction in this model is the disparity of trading horizons between traders, as reflected in their focus on short- versus long-term signals. Unlike in Hirshleifer et al. (1994), all agents in Brunnermeier's model are risk-neutral. The value of the firm has short-term and long-term components. Some investors are informed about the long-term component, while an early-informed speculator gets a noisy signal about the short-term component, inducing her to trade in the direction of the signal. Importantly, even after the signal is revealed to the public, the early-informed speculator possesses an informational advantage compared to the market maker because of her ability to disentangle the actual signal from the noise in her own early trading. The market maker mistakenly attributes some of the early noise to long-term value, causing the price to overshoot on average in the direction of the signal. This makes it optimal for the early-informed speculator to trade against the signal when it becomes public by reversing a fraction of her initial position.

[12] Another prediction of Hirshleifer et al. (1994) is that there is a negative correlation between the price change on the day of the announcement and the trading on that day by the early-informed investors. This prediction, however, is directly attributable to the simplifying assumption in their model (made for tractability) that "informed traders are individually infinitesimal and fall on a continuum, so that no informed trader can affect the price" (page 1669). We do not pursue this prediction because news-driven institutional investors (the early-informed investors in our setting) are not infinitesimal. On the contrary, institutional trading would put upward (downward) pressure on prices when institutions buy (sell), which is likely to induce a positive correlation between institutional trade imbalance and contemporaneous stock prices.

2.2. Empirical Predictions

The institutional features of different types of traders identified in our data in combination with the adding-up constraint and the theoretical models allow us to develop predictions regarding trading behavior around analyst recommendation changes.

2.2.1 Early-informed traders. We identify the early-informed traders in the models as news-driven institutional investors.[13] One way that news-driven institutional investors may be informed early is that they receive information about stock recommendations from analysts (or salespeople who work at the analyst's brokerage house) a few days before the analyst recommendation becomes public, a practice known as "tipping" (e.g., Irvine et al., 2007).[14] Such early information leakage is not seen as illegal during our sample period (1999-2010). In an article about analysts sharing recommendations early, the Wall Street Journal notes that *"securities laws require firms like Goldman to engage in 'fair dealing with clients,' and prohibit analysts from issuing opinions that are at odds with their true beliefs about a stock,"* but do not explicitly prohibit sharing recommendations early with select clients (Craig, 2009). In contrast, securities laws such as Regulation Fair Disclosure (Reg FD) do bar selective disclosure by companies to analysts or investors, but *"no law prevents investors from trading on non-public information they have legally purchased from other private entities,"* according to securities lawyers (Mullins, Rothfeld, McGinty, and Strassburg, 2013).[15]

[13] Clearly even news-driven institutions are a noisy proxy for early-informed investors, as not all news-driven institutions possess early information before every analyst recommendation change. The presence of institutions that are not early-informed in the news-driven institutional category will add noise to our tests and would bias them against finding any differences between the group with early information (news-driven institutions) and the group without it (individuals).

[14] Information about future recommendation changes may also be communicated through responses to analyst surveys conducted by institutional investors (e.g., Morgenson, 2014).

[15] Although analysts' tipping of their clients apparently is not itself illegal, it may not be allowed by brokerage firms and can be subject to regulatory action if it involves a breach of trust (insider trading) or lack of internal controls (which are unfortunately not well-defined). The regulators' approach to tipping may have changed following the end of our sample period. In 2012 the Securities and Exchange Commission (SEC) fined Goldman Sachs for not having adequate policies and procedures in place to address the "risk that the firm's analysts could share material, nonpublic information about upcoming research changes" in their internal meetings, the contents of which are subsequently communicated to select clients (SEC, 2012).

Our empirical design also works if news-driven institutional investors are not actually informed early about sell-side analysts' views per se, but rather do their own research and reach similar conclusions about stocks in the few days before analysts announce recommendation changes, inspiring them to trade as if they had been tipped. Such an alternative would also lead to institutional investors being early-informed and would be consistent with other evidence of institutions trading as if they are informed before news is released (e.g., Campbell, Ramadorai, and Schwartz, 2009; Hendershott, Livdan, and Schürhoff, 2015).

Within news-driven institutional trades, the two theoretical models are mute about the differences between proprietary and agency trading patterns in the face of information asymmetry. Such a comparison is valuable given the interest of both policymakers and market participants in the trading practices of proprietary traders and the risks they impose on their institutions. Both types of news-driven institutions are likely exposed to advantageous information prior to analyst recommendation changes, giving rise to the "buy the rumor" strategy. However, the speculative nature of proprietary trading and proprietary traders' focus on short-term profits (as discussed in Section 2.1) suggest that they should be more inclined to use quick profit-taking strategies such as "selling the news" to partially reverse their initial position. In contrast, agency trades are likely reflective of longer-term investment horizons, implying deferred profit-taking.

In terms of trading magnitudes, both theoretical models predict that the amount of trading by early-informed investors prior to the day of the information release is larger for more favorable information and thus should be correlated with the price change upon the information release. This pattern likely applies to both proprietary and agency trades. The following empirical prediction summarizes this discussion.

Prediction 1 (trading by news-driven institutional investors):

- Both proprietary and agency institutional investors will exhibit abnormal trading in the direction of an analyst recommendation change in the few days preceding the recommendation change ("buy the rumor"). The magnitude of trade will be positively correlated with the price change on the day of the recommendation announcement.
- Proprietary traders are more likely to exhibit short-term profit-taking reflected in abnormal trading against the recommendation change when it is publicly announced ("sell the news"), partially reversing their initial position.

2.2.2. Late-informed traders. We identify the models' late-informed traders as individual investors in the data. These investors are not known to acquire information early and thus learn about an analyst recommendation change only when the analyst's report is published. We thus have the following prediction.

Prediction 2 (trading by individuals): Individual investors will not exhibit abnormal trading before the recommendation change is announced and will exhibit abnormal trading in the direction of the recommendation change when it is announced.[16]

2.2.3. Market clearing and liquidity provision. The adding-up constraint raises the question of how the market is cleared around analyst recommendation changes. Either a single trader or traders in aggregate who provide liquidity around these information events are expected to follow the

[16] This prediction comes from Hirshleifer et al. (1994) only; in Brunnermeier (2005) long-term traders (corresponding to individuals in our setting) do not trade based on the private signal when it becomes public. The reason is that, unlike in the Hirshleifer et al. model, the market maker learns the signal as well. Since the market maker is risk-neutral, she fully absorbs any risk and all the information related to the signal is correctly reflected in the price. This risk neutrality, however, is assumed for tractability only. If the market maker in Brunnermeier's model were risk averse, then the picture would change and the long-term traders would trade in the direction of the signal when it is publically revealed, in line with the Hirshleifer et al. (1994) prediction. We thank Markus Brunnermeier for clarifying this point for us.

losing strategy of "selling the rumor and buying the news" around analyst upgrades, allowing the early-informed traders to exploit their private information.

A priori it is not clear whether market makers or non-news-driven institutions (program traders) will take opposite positions to the news-driven institutions. On one hand, market makers have the formal role of liquidity provision. On the other hand, program traders are not attentive to news related to a particular stock, exposing them to a "winner's curse" problem in the spirit of Rock (1986). To see this, note that program traders submit orders for a basket of 15 or more stocks for reasons unrelated to the news of any particular stock. The order for each individual stock in the basket may be executed in part or in full, or it may not be executed at all; only the executed portion appears in our dataset. The execution of the order for a given stock depends on the extent of competition program traders face from news-driven institutions. Consider, for example, an upcoming upgrade of a particular stock. When news-driven institutions are "buying the rumor" for that stock, any sell orders of program traders (submitted for whatever basket rebalancing reasons) on that same stock are more likely to be executed simply because news-driven institutions are not competing with them on the sell side of the market. Similarly, when news-driven institutions are "selling the news," any buy orders of program traders are more likely to be executed. Thus, the orders of program traders that happen to be in the opposite direction of orders submitted by news-driven institutions are more likely to be adversely selected and therefore to be executed precisely when news-driven institutions are on the other side of the trade. Symmetrically, any orders of program traders that happen to be in the same direction of orders of news-driven institutions are less likely to be executed. Overall, program traders will have an abnormal share of their orders executed against the orders of news-driven institutions, making them de-facto liquidity providers through adverse selection.

Prediction 3 (liquidity provision): Market makers and/or program traders are expected to trade in the opposite direction of news-driven institutions. They will exhibit abnormal trading against the direction of the analyst recommendation change in the few days preceding the recommendation change and will exhibit abnormal trading in the direction of the recommendation change when it is publicly announced.

2.2.4. Other information events. Analyst recommendations are unusual in that different investors may be informed about an analyst's views at different points in time. This practice does not appear to be illegal, as discussed above. In contrast, for many other firm-related news releases (such as earning announcements) differential information release is illegal, especially since the enactment of Reg FD in August 2000. Our next prediction concerns such placebo information events, which are plausibly not associated with early release of information.

Prediction 4 (placebo information events): For informational events that are not associated with short-term informational advantages, news-driven institutions (both proprietary and agency) will not exhibit either "buy the rumor" or "sell the news" trading activity.

3. Data, Methodology, and Descriptive Statistics

Our analysis uses analyst stock recommendation data from the Thomson Financial Institutional Brokers Estimate (I/B/E/S) U.S. Detail File,[17] data on daily buy and sell transaction volume by trader type from the NYSE Consolidated Equity Audit Trail Data (CAUD) database, stock data from the Center for Research in Securities Prices (CRSP) database, and institutional holdings data from the Thomson Financial 13F quarterly holdings database. We also use information from the annual Institutional Investor All-Star Analyst rankings. Our sample period is

[17] The data we use were pulled in early 2012 and so reflect the corrections Thomson made in 2007 in response to the findings of Ljungqvist, Malloy, and Marston (2009) that previous versions of the I/B/E/S database had been altered.

1999 to mid-2010, and our sample includes all NYSE-listed domestic common stocks for which there are valid analyst recommendation changes in I/B/E/S, as defined in the next subsection.

3.1. Analyst recommendation changes

We define analyst recommendation changes based on the three-tier scale of buy, hold, and sell. We convert recommendations from the less common five-tier scale (e.g., strong buy, buy, hold, sell, strong sell) to the three-tier scale before identifying recommendation changes, so that our assessment of recommendation changes is not contaminated by the widespread change from five-tier to three-tier rating scales in 2002 prompted by the Global Analyst Research Settlement (Kadan, Madureira, Wang, and Zach, 2009). We define recommendation changes as upgrades or downgrades within the three-tier scale for which the previous recommendation was issued by the same brokerage firm within the past year, to minimize the possibility of stale forecasts. We use the date and time stamps in I/B/E/S to identify the exact day of the recommendation change (the event day). To ensure that the recommendation date we consider is the relevant one in terms of the trading activity surrounding it, if a recommendation is released after 4:00 p.m. we designate the next trading day as the recommendation change day.

To separate the effect of analyst recommendation changes from firm-specific news (Altinkilic and Hansen, 2009; Kim and Song, 2015), we apply two screens similar to Loh and Stulz (2011). First, we remove recommendation changes that occur on the same day as or the day following earnings announcements. Second, we remove recommendation changes on days when multiple analysts issue recommendations for the same firm, as clustering in recommendations may reflect the release of firm-specific news (Bradley, Jordan, and Ritter, 2008).[18] These filters remove

[18] This filter does not work for stocks covered by only one analyst, since clustering requires more than one analyst. In our sample, only about 0.6% of the recommendation changes occur in stocks covered by only one analyst, and excluding those recommendation changes does not affect our results.

about 28% of the recommendation changes in our sample period. As robustness checks, we also exclude recommendation changes when a stock has other recommendation changes in the prior four days, when recommendations are clustered in three-day periods, and on dividend announcement days.

3.2. The NYSE data and main variables of interest

We use proprietary data from the NYSE that allow us to precisely identify the trading activity of news-driven institutional investors (and proprietary versus agency separately), program institutions (and index-arbitrage versus non-index-arbitrage separately), individuals, and market makers, as discussed in Section 2.1. The dataset is constructed from the NYSE's CAUD files, which are the result of matching trade reports to the underlying order data. CAUD contains information on all orders that execute on the NYSE, including both trades that are executed electronically and those that are executed manually (by floor brokers). For each trade, CAUD shows the executed portion of the underlying buy and sell orders along with an account-type variable. Because CAUD reports the buyer and seller for each trade based on actual order data, the classification of buy and sell volume in our data set is exact, and thus we do not have to rely on trade classification algorithms. Providing the account-type classification is mandatory for brokers, although it is not audited by the NYSE on an order-by-order basis.[19] The CAUD database contains information at the stock/trade level; our dataset is derived from CAUD and contains total share volume and dollar volume bought and sold by each trader type for each stock/day.

Our CAUD-based dataset has two main advantages. First is its coverage. CAUD covers a large portion of trading in NYSE stocks and is therefore likely to provide a representative picture

[19] Kaniel et al. (2008) point out that any abnormal use of the individual investor designation by brokers in hopes of gaining advantages is likely to draw attention, preventing abuse of the system.

of trading.[20] Second is the separate identification of different trader types. CAUD is one of the few databases that identify individual, institutional, and market maker trading, as well as key subsets within institutional trades.

We construct daily measures of trading volume and trade imbalance for each trader type in each stock, and we standardize the measures by the rolling average daily volume over the prior year.[21] Specifically, we define Raw Trading Volume for stock *i*, investor type *x*, on day *t* as:[22]

$$Raw\ Trading\ Volume_{i,x,t} = \frac{\left(DollarVolumeBought_{i,x,t} + DollarVolumeSold_{i,x,t}\right)/2}{CRSPAvgDailyVolume_{i,y-1}} \quad (1)$$

where $DollarVolumeBought_{i,x,t}$ and $DollarVolumeSold_{i,x,t}$ are the dollar volume of shares of stock *i* bought and sold, respectively, by investor type *x* on day *t*, and $CRSPAvgDailyVolume_{i,y-1}$ is the CRSP average daily dollar volume of stock *i* in the year ending one week before the recommendation change, *y-1*. Similarly, we define Raw Trade Imbalance for stock *i*, investor type *x*, on day *t* as: [23]

$$Raw\ Trade\ Imbalance_{i,x,t} = \frac{DollarVolumeBought_{i,x,t} - DollarVolumeSold_{i,x,t}}{CRSPAvgDailyVolume_{i,y-1}} \quad (2)$$

To isolate the abnormal trading volume and abnormal trade imbalance surrounding analyst recommendation changes, we identify a benchmark period for each recommendation change. Our

[20] In the first half of our sample period, over 80% of trading in NYSE-listed stocks occurs on the NYSE and is therefore captured by CAUD. After the 2007 merger of NYSE with ARCA, our dataset includes trades on ARCA as well as on NYSE. We perform robustness checks for the early versus latter part of the sample period, when more trading occurs off the NYSE. Our results hold for both sub-periods.
[21] Standardizing by lagged average daily volume helps to make changes comparable across stocks, as in Kaniel et al. (2008). We replicate our tests with alternate variable scaling in our robustness checks.
[22] The numerator in equation (1) is divided by two because CAUD reports buys and sells separately; the sum of all buys plus all sells is equal to twice total volume. The actual trading volume for each trader type depends on the extent to which traders trade with their own type versus other types of traders, since each trade consists of a buy and a sell. If traders trade only with their own type, trader-type volume equals (trader-type buys + trader-type sells)/2, as we have defined it here; at the other extreme, if all traders trade only with other trader types, trader-type volume equals (trader-type buys + trader-type sells). Statistical inference is the same whichever volume approximation is used; we divide by two in keeping with the single-counting in the denominator.
[23] Trade imbalance is sometimes referred to in the literature as "order imbalance." We use the term trade imbalance because we observe only executed trades, not all orders submitted, in our dataset.

benchmark period is 45 to 11 days before and 11 to 45 days after the day of the analyst recommendation change. We calculate the Benchmark Trading Volume for stock i, investor type x, with analyst recommendation change on day t as the average Raw Trading Volume over days t-45 to t-11 and t+11 to t+45. Similarly, we calculate the Benchmark Trade Imbalance for stock i, investor type x, with analyst recommendation change on day t as the average Raw Trade Imbalance over days t-45 to t-11 and t+11 to t+45.

Our main variables of interest are the abnormal trading volume and abnormal trade imbalance for each investor type and recommendation change, defined as:

$$Abnormal\ Trading\ Volume_{i,x,t} = Raw\ Trading\ Volume_{i,x,t} - Benchmark\ Trading\ Volume_{i,x,t} \qquad (3)$$

and

$$Abnormal\ Trade\ Imbalance_{i,x,t} = Raw\ Trade\ Imbalance_{i,x,t} - Benchmark\ Trade\ Imbalance_{i,x,t} \qquad (4)$$

To calculate the benchmark period volume and imbalance, and thus the abnormal volume and imbalance for each recommendation change, we require at least 45 days of data before and after the recommendation change, reducing our sample from the eleven and a half years (January 1, 1999 to July 1, 2010) for which we have NYSE data to recommendation changes occurring between March 10, 1999 and April 22, 2010.

3.3. Descriptive statistics

Panel A of Table 1 presents descriptive statistics for the 2,122 stocks in our sample. Because our sample is restricted to firms with at least one analyst recommendation change, the stocks in our sample are generally large, with an average market capitalization \$6.490 billion. The average number of analysts covering a firm in our sample is seven (with a median of six), and the average institutional holdings is 66.6%.

Panel B shows how much trading is done by each trader type in our sample stocks. The total trading volume over the 1999 to mid-2010 period is over $97 trillion. News-driven institutional trades account for 67.7% of the total trading volume, and program institutional trades come in second at 22.2%. Market makers account for 8.4% of trading volume, while individuals represent 1.6%, which may appear small but nonetheless represents over $1.5 trillion of trading. The majority of news-driven institutional trades are agency trades: 58.7% of the total shares traded versus 9.1% that are proprietary trades. Within program institutional trades, non-index-arbitrage trades outweigh index-arbitrage trades by more than nine-to-one: 20.0% of total versus 2.2%.

Panel C summarizes the distribution of analyst recommendation changes by year. Overall, there are about five percent more downgrades than upgrades in our sample: 15,907 downgrades versus 15,101 upgrades. This ratio is consistent with prior literature (e.g., Kecskes et al., 2017). Both analyst upgrades and analyst downgrades are accompanied by large average abnormal returns on the day they are announced: Average one-day returns are 1.96% for upgrades and -1.83% for downgrades. The returns reported here and throughout this study are taken from CRSP and so do not take commissions into account. Using Ancerno data on institutional trades and commissions for a period that overlaps our study, Goldstein, Irvine, Kandel, and Weiner (2009) find that institutional commissions are generally between one and five cents per share, or five to 15 basis points as a percentage of share price, suggesting that the potential profit on analyst recommendation changes exceeds commission costs.

[Table 1 here]

4. Empirical evidence

We begin by providing preliminary evidence documenting the trading volume of each trader type around analyst recommendation changes in Section 4.1. In Section 4.2 we study the trade imbalances of each group, allowing us to test Predictions 1, 2, and 3. In Section 4.3 we estimate news-driven traders' profits around recommendation changes and examine how the magnitude of their imbalances is related to recommendation-day price changes. In Section 4.4 we investigate how institutional trading patterns differ across firm and analyst characteristics.

4.1. Preliminary results: Trading volume around recommendation changes

Figures 1 and 2 provide a first look at trading volume surrounding analyst recommendation changes. Figure 1-A (2-A) shows the average Raw Trading Volume for each of the main categories of traders over the period from 45 days before to 45 days after an upgrade (downgrade). Figure 1-B (2-B) shows the average Abnormal Trading Volume in the days immediately surrounding an analyst upgrade (downgrade).

[Figures 1 & 2 here]

All of the trader-type volumes appear to increase around analyst recommendation changes, with the largest spike occurring in the news-driven institutional category. Critically, in selecting these recommendation changes we have removed all earnings announcement dates and dates of clustered stock recommendations from multiple analysts. Thus the spike in volume around recommendation changes is likely associated with the recommendation change itself, not other news such as earnings announcements.

In Table 2 we test the statistical significance of the volume patterns displayed in Figures 1 and 2. We examine the cumulative abnormal volume for each trader type in the four days prior to the recommendation change (*Day -4 to -1*), on the recommendation-change day (*Day 0*), and in the four days following the recommendation change (*Day +1 to +4*). We choose a four-day pre-recommendation-change period based on the typical time between when analyst reports enter the internal review process and when the report is publicly released. Irvine et al. (2007) report that a four- to five-day lag is typical, and our discussions with equity analysts suggest that three to five days is typical during our sample period. To adjust for potential cross-sectional correlation and idiosyncratic time-series persistence, we report *t*-statistics that are based on standard errors double-clustered on stock and date in this and all subsequent analyses (Thompson, 2011).

[Table 2 here]

Table 2 presents the results separately for upgrades (Panel A) and downgrades (Panel B). The results show clearly that volume is significantly higher on the recommendation change day (day 0) for all trader types and for upgrades and downgrades. Note that the day-0 abnormal volumes for the news-driven institutional and individual categories differ by an order of magnitude. For example, for upgrades the day-0 news-driven institutional abnormal volume is 36.73%, nearly 30 times individual abnormal volume of 1.26%.

4.2. Direction and timing of trade around recommendation changes

Figures 3 and 4 present the average abnormal buy-sell trade imbalances surrounding analyst recommendation changes. These figures provide a graphical image of the adding-up constraint, and they offer a preliminary look at how Predictions 1 through 3 fare with the data. Panels A and B of Figure 3 show that all trader-type trade imbalances are quite flat until a few days before the upgrades. Just prior to the information release (days -4 to -1), we see a notable increase in positive imbalance by news-driven institutional traders, which reverses to a negative imbalance on the day the upgrade is announced; the build-up of imbalances and partial reversal are illustrated in Panel C. This pattern is consistent with "buy the rumor, sell the news" behavior.

The trade imbalances of individuals tell a very different story. The abnormal imbalances of individual investors appear roughly flat before upgrades and then slightly positive on the day the upgrade is announced. Figure 3 also reveals that market-maker imbalances are far less than required to offset the institutional imbalances. Instead, it is program institutional traders who emerge as the counterparties of the early-informed news-driven institutions, adversely selected to serve the role of de-facto liquidity providers around these events. The abnormal imbalance of program institutions forms nearly a mirror image to that of news-driven institutional investors before and on the day of upgrades.

Figure 4 suggests similar but less pronounced behavior for news-driven institutions around downgrades. Individual imbalances are more muted around downgrades than upgrades, and program institutions once again appear to absorb the trade imbalances of news-driven institutions.

[Figures 3 & 4 here]

In Table 3 we formally test Predictions 1 through 3 by considering the different sub-categories of trader types and testing the statistical significance of the imbalance patterns displayed in Figures 3 and 4. We examine the cumulative abnormal imbalance for each trader type in the four days prior to the recommendation change (*Day -4 to -1*), on the recommendation-change day (*Day 0*), and in the four days following the recommendation change (*Day +1 to +4*). A positive (negative) value corresponds to excess buying (selling) activity relative to the benchmark period.

[Table 3 here]

Table 3 presents the results separately for upgrades (Panel A) and downgrades (Panel B). Note that the sum of abnormal trade imbalances across all trader types for any given time period is always zero, reflecting the adding-up constraint. The table breaks down the trading by trader-type categories and sub-categories.

We consider the buying and selling pattern of the early-informed traders first. The results for news-driven institutional trades (the early-informed) show significant abnormal buying activity equal to 4.26% of average daily volume during the four days prior to an upgrade (Panel A of Table 3). On the day of the upgrade we observe abnormal selling activity by news-driven institutions equal to 1.43% of average daily volume. Thus, news-driven institutions appear to unload about a third of the amount they bought, taking profits immediately upon the information release. The analysis of the proprietary versus agency sub-categories shows that the "buying the rumor" activity applies to both types of traders, consistent with the idea that both proprietary and agency traders obtain information in advance of recommendation changes. In contrast, the two types of news-driven institutions exhibit different patterns of profit-taking. While proprietary traders exhibit significant abnormal selling on the day of the recommendation change, the trading of agency traders on that day is not statistically significant. Focusing on proprietary traders, we see that they buy 1.29% of average trading volume on the four days prior to the upgrade and then sell 0.70% of daily volume on the news-release date. Thus, proprietary traders take immediate profit for more than 50% of their initial buying activity, indicating that their trading horizon is quite short. The fact that agency trades do not exhibit a significant "sell the news" activity supports the view that their trading horizon is longer.[24]

The results in Panel B of Table 3 reveal that news-driven institutions also significantly sell before downgrades and buy on downgrade announcements, consistent with a "sell the rumor, buy the news" strategy. Echoing the results for upgrades, both proprietary and agency institutional traders appear to significantly sell before the downgrades, but only the proprietary traders

[24] Agency traders buy 2.97% of average trading volume prior to the recommendation change and sell a statistically insignificant amount of 0.73% of average trading volume on the day of the recommendation change. Ignoring the statistical insignificance of this estimate, we can infer that agency traders take profits on less than 25% of their trades immediately, which is less than a half of the percentage immediately unloaded by proprietary traders. This is another indication of the longer-term focus of agency traders compared to proprietary traders.

significantly buy on the announcement day (continuing into the following four days), consistent with reversing their positions to take short-term profits. Economically, the proprietary trader results for downgrades are even larger than for upgrades. Proprietary traders sell 1.7% of average trading volume prior to the downgrade and then buy 1.43% when the downgrade is announced. Thus, they immediately reverse 84% of their original trades, once again evidencing their short-term focus.

Overall, the results for news-driven institutional trades around both upgrades and downgrades are consistent with Prediction 1. We see that both types of news-driven institutions "buy the rumor" but only proprietary traders "sell the news," reversing 50%-84% of their initial position upon the information release.

Turning to individuals, the late-informed traders, Panels A and B of Table 3 mostly provide support for Prediction 2. First, individuals do not trade in the direction of information prior to recommendation changes (upgrades or downgrades). Second, the prediction that individuals should exhibit net buying on the day of upgrades is supported in Panel A (*t*-statistic of 1.9 corresponding to a p-value of 0.06). On the other hand, selling on the day of downgrades is insignificant in Panel B, likely because individuals do not tend to engage in short selling.[25] Individual investors can relatively easily respond to upgrades by buying the recommended stocks, but can trade on downgrades only if they already hold a particular stock or through a short sale.

To complete the picture we now consider how the market is cleared. Recall that either market makers or program traders may serve as liquidity providers (see Prediction 3). The results in both Panels A and B show that program traders take the lion's share of the opposite position to news-driven institutions both before and on the days of analyst recommendation changes. The

[25] In the U.S., short selling requires opening a margin account with a broker, making it less common among individuals.

abnormal trade imbalances of program traders for both upgrades and downgrades have the opposite sign to the imbalances of news-driven institutions, with a similar order of magnitude. In the sub-categories we see that non-index-arbitrage program traders play the dominant role in this trading activity. As discussed in Section 2, much of this trading activity reflects basket trading such as that of ETFs, which are not attentive to firm-specific news. As a result, program traders "win" more than their fair share of trades against the early-informed trades of news-driven institutions, rendering them de-facto liquidity providers. Meanwhile market-maker imbalances are not significant. One potential explanation is that market makers do supply liquidity at the time of the recommendation change but then unwind their positions over the rest of the day in order minimize their overnight inventory risk. This explanation is consistent with our observation in Table 2 that market maker volume is higher on recommendation change days, although their imbalances are not. A second potential explanation is that market makers have little need to step in when program traders are providing liquidity. In a robustness check, we examine the behavior of market makers before and after the NYSE's Hybrid market introduction, when specialists were replaced by designated market makers (Hendershott and Moulton, 2011). Market makers emerge as significant liquidity providers only in the four days before downgrades that occur post-Hybrid. Even at that time, program institutional traders still supply the bulk of liquidity to news-driven institutions.

4.3. Economic magnitude of early-informed trading and profits

To assess the economic significance of the effect of information differences we now consider the magnitude of the profits associated with obtaining advance information. News-driven institutions' buying before analyst upgrades combined with the typical pattern of stock prices increasing on analyst upgrades gives rise to considerable short-term estimated profits.[26] During our 1999-2010 sample period, the average return from buying the rumor four days before an analyst upgrade and selling the news on the upgrade day, and executing the mirror-image strategy around analyst downgrades, is 1.71%. For proprietary traders who use leverage, the effective percentage returns would be even larger. We estimate aggregate news-driven institutional dollar profits based on the cumulative share imbalances acquired by news-driven institutions around analyst upgrades and the associated stock price changes by marking the aggregate cumulative position to market each day at the closing price. News-driven institutional profits from four days before to four days after an analyst recommendation change are approximately $61,000 per recommendation change, for a total of about $1.9 billion for the 31,008 recommendation changes in our sample. Given the aggregation in our dataset, these profit estimates are undoubtedly a lower bound, with the actual profits of the truly early-informed traders partially offset by uninformed trading within the news-driven institutional category.

An important determinant of the profits associated with information asymmetries is the quality of the signal. Recall that Prediction 1 states that the "buying the rumor" activity should be intensified for stronger signals, resulting in a positive correlation between trade imbalances before the recommendation changes and the price change on the day of the recommendation announcement. To evaluate this prediction we consider the following regression specification:

$$Imbalance_{i,t-4} = \alpha + \beta Return_{i,t} + \varepsilon_{i,t-4}\,, \qquad (5)$$

where $Imbalance_{i,t-4}$ cumulates news-driven institutional imbalances over the four days prior to the analyst recommendation change and $Return_{i,t}$ is the abnormal return for stock i on the day of the

[26] Because our dataset contains trading information aggregated by trader type, rather than trade by trade, we cannot assess the profitability of individual traders within each type. We also cannot observe trades in other markets that may be part of a larger strategy, such as hedged positions or multiple-security strategies.

analyst recommendation change, measured as the stock return minus the CRSP equal-weighted market return. Table 4 presents the results.

[Table 4 here]

Panel A of Table 4 presents the analysis for upgrades, for the entire news-driven institutional category in the first column and for the two sub-categories, proprietary and agency trades, in the remaining columns. For the entire news-driven institutional category (first column), the intercept is positive (3.25%) and significant (*t*-statistic of 4.1), indicating that news-driven institutions net buy stocks in the four days before they are upgraded even with no abnormal day-0 return. In addition, the coefficient on *Return* is significantly positive and economically meaningful, as an upgrade with the average 1.96% abnormal return would imply about a 1% higher imbalance (0.0196 x .51256) in the four days prior to the upgrade. Thus, news-driven institutions appear to buy more of the about-to-be-upgraded stocks whose prices rise more on the day of the upgrade. This is consistent with Prediction 1 that both the news-driven institutional buying and the subsequent change in price are driven by the same signal.[27] A similar picture emerges for downgrades, with the positive coefficient on *Return* indicating that news-driven institutions net sell more of the about-to-be-downgraded stocks that have the largest negative returns on the day the downgrades are announced. The coefficient estimates for returns lose significance in most of the proprietary and agency sub-category regressions (second and third columns of Panels A and B), though their intercepts remain significant, consistent with Table 3.

Prior literature has found that prices continue to drift in the same direction for up to several months following analyst recommendation changes (e.g., Womack 1996, Kecskes et al., 2017).

[27] We also separately examine the subset of analyst recommendation changes for which the abnormal return is in the opposite direction: negative returns on upgrade announcements and positive returns on downgrades. These opposite-reaction cases comprise 18.9% of the upgrades and 21.1% of the downgrades. We find that there is no significant imbalance for news-driven institutions prior to upgrades (downgrades) that have negative (positive) abnormal returns on the day they are announced.

Although it is not possible from our data to determine how long positions are held, it is nonetheless interesting to see whether news-driven institutions successfully identify analyst recommendation changes that will have not only the largest immediate price reactions (as shown in Table 4), but also the largest longer-term price movements. In Table 5 we present the average size-adjusted returns on the recommendation change day, the subsequent month, and the subsequent six months calculated on an unweighted basis and then calculated weighting each return by the abnormal trade imbalance of news-driven institutions in the four days prior to the recommendation change. Size-adjusted returns are calculated relative to CRSP market capitalization size decile returns, as in Womack (1996).

[Table 5 here]

Table 5 shows that the post-recommendation-change drift is greater for upgrades than downgrades in our sample. Interestingly, the longer holding period returns are higher overall when weighted by the institutional trade imbalances, with the one- and six-month post-upgrade returns showing the biggest gains from imbalance weighting. For example, while the six-month unweighted abnormal return is 6.55% for upgrades, when weighted by the institutional trade imbalances it is 9.39%. While we do not have information concerning the holding period of news-driven institutions, the superior weighted returns suggest that their buying decisions are effective for longer-term as well as short-term horizons.

4.4. Multivariate analysis of news-driven institutional trades

In line with the discussion in the previous section, we expect that across different recommendation changes, early-informed investors would trade more strongly on analyst recommendation changes that have higher information content. One such case is when the analyst issuing the recommendation is an "all-star" analyst. Additionally, it is likely that the signal is more informative for small stocks, which are covered by fewer analysts and are subject to greater information asymmetries. Furthermore, we would expect that news-driven institutions would be more inclined to trade on analyst recommendations for stocks they already own, namely when institutional ownership is high. In particular, we expect that institutions would be more inclined to trade prior to downgrades when they already own the stock and thus no short selling is required or when other institutions hold it and it is easier to borrow for a short sale. Pontiff (2006) predicts that traders engaged in risky arbitrage will take smaller speculative positions when idiosyncratic risk is large. His intuition is that such traders are not fully hedged and so large idiosyncratic movements in price deter them from taking large positions. Applying this intuition to our situation, institutions may be less likely to "buy the rumor and sell the news" in stocks with higher idiosyncratic risk, proxied by volatility. To investigate these cross-sectional implications, we run regressions of the following form:

$$\begin{aligned} Imbalance_{i,t+k} &= \alpha + \beta_1 AllStar_{i,t} + \beta_2 SmallFirm_{i,t} + \beta_3 LargeFirm_{i,t} + \beta_4 HighInst_{i,t} \\ &+ \beta_5 LowInst_{i,t} + \beta_6 HighVolat_{i,t} + \beta_7 LowVolat_{i,t} \\ &+ \varepsilon_{i,t+k}\,, \end{aligned} \tag{6}$$

where $Imbalance_{i,t+k}$ is the news-driven institutional abnormal trade imbalance in stock i with a recommendation change on day t. The variable k takes values in {-4, 0, 4}. When k = 0 we are focusing on the abnormal volume on the day of the recommendation change (day t); when k = -4 we are cumulating the abnormal imbalance over the four days prior to the recommendation change (days t-4 to t-1); and when k = 4 we are cumulating the abnormal imbalance over the four days following the recommendation change (days t+1 to t+4). $AllStar_{i,t}$ is an indicator variable that is equal to one if the analyst making the recommendation change is ranked as an all-star analyst by Institutional Investor in the prior year, else zero; $SmallFirm_{i,t}$ ($LargeFirm_{i,t}$) is an indicator variable that is equal to one if the firm is in the smallest (largest) firm-size quartile based on the firms in the recommendation-change sample, else zero; $HighInst_{i,t}$ ($LowInst_{i,t}$) is an indicator variable that is equal to one if the firm is in the highest (lowest) institutional ownership percentage quartile as of the previous quarter-end, else zero; and $HighVolat_{i,t}$ ($LowVolat_{i,t}$) is an indicator variable that is equal to one if the firm is in the highest (lowest) return volatility quartile as of the previous quarter-end, else zero.[28]

[Table 6 here]

The regression results in Panel A of Table 6 show that, all else equal, the "buy the rumor, sell the news" trading of news-driven institutions around analyst upgrades is stronger for small firms. This is consistent with news-driven institutions being more likely to possess advantageous information about smaller firms. A similar result holds for stocks with high institutional ownership, reflecting that these are the stocks in which news-driven institutions are more likely to be active (for a given level of firm size). The "buy the rumor, sell the news" trading activity is weaker for stocks with high volatility. Traders buy significantly less on the rumor and sell more on the news (negative coefficient on days -4 to -1 and positive coefficient on day 0 for high volatility stocks), supporting the Pontiff (2006) conjecture that speculators are less likely to engage in risky arbitrage in more volatile stocks. The results also suggest that news-driven institutions are more likely to "buy the rumor" when the analyst issuing the recommendation is an all-star analyst, but the statistical significance is weaker (t-statistic of 1.9).

Panel B shows that the corresponding "sell the rumor, buy the news" pattern of trading around analyst downgrades is larger for smaller stocks and those with the highest institutional ownership. The latter result is consistent with news-driven institutions finding it easier to trade on

[28] The results of similar regressions including additional cross-sectional explanatory variables are discussed in Section 6.

downgrades when they already hold the stock or when it is widely held by institutions, making it easier to borrow for a short sale. The Pontiff (2006) prediction is also supported in the case of downgrades, with high-volatility stocks showing a significant positive coefficient before and negative coefficient the day of downgrades, suggesting that the sell the rumor, buy the news trading pattern is indeed weaker for more volatile stocks.

5. Placebo tests: Information events without early information leakage

To strengthen the foundation of our tests, we also examine the counterfactual: What are the trading patterns around events that are *not* accompanied by early information acquisition by some investors? Our Prediction 4 states that those instances should not induce either the "buy the rumor" or the "sell the news" trading patterns. If such events do induce the buy/sell trading pattern, it would suggest that our main results may not be driven by trading on early information acquisition. For example, perhaps news-driven institutional investors always buy before and sell on days with large positive returns, and analyst upgrades are simply one cause of large positive returns. A related concern is that there may be omitted variables related to the behavior of different trader types, driving the differences in their trading behavior irrespective of whether they are early-informed or late-informed. To address these concerns, we conduct three placebo (falsification) tests to examine the trading behavior of different trader types around times when we do not expect some investors to be informed early: analyst reiterations of previously published recommendations (or "confirming" recommendations), earnings announcements, and days with large abnormal returns without recommendation or earnings announcements. In all three cases we do not expect that some traders are early informed, so we should not find "buy the rumor" and/or "sell the news" trading patterns.

Our first placebo test examines analyst reiterations of previously published recommendations: for example, when an analyst who has already rated a stock as a "buy" announces that she is maintaining her "buy" recommendation. There are 17,286 such analyst reiterations for NYSE stocks in our sample period, and they have an average abnormal one-day return of 0.0349% (p-value <0.001). Table 7 presents the mean abnormal trade imbalances for each trader type surrounding these reiterations.

[Table 7 here]

Consistent with Prediction 4, Panel A shows no evidence of news-driven institutional investors net buying or selling in the days before the reiteration is announced, nor do any of the trader types or sub-categories demonstrate significant imbalances on the day of the reiteration announcement. In the next two panels we focus on the subsamples of reiterations that are accompanied by the largest price moves (top-quartile abnormal returns, which average 3.752%, in Panel B and bottom-quartile abnormal returns, which average -3.202%, in Panel C). If the largest returns are a reaction to the reiterations (for example, when the market expects an analyst to downgrade a stock but the analyst maintains her recommendation), we could see imbalance patterns similar to those for analyst recommendation changes if news-driven institutional investors are informed early about the surprising reiteration. The results in Panels B and C do not show any "buy the rumor, sell the news" behavior. It is likely that gaining information that a reiteration will have a significant impact is harder than gaining information that a recommendation change will move a stock's price. The early-informed trader needs to correctly anticipate that the analyst will not change the recommendation *and* know that the market expects the analyst to change the recommendation.

Our second placebo test uses earnings announcements as placebo events. Earnings announcements generally lead to large returns, but early information leakage is unlikely. Insider trading laws and regulations (e.g., Reg FD) prevent companies from revealing material non-public information to analysts and investors prior to earnings announcements. We construct the earnings announcement sample as follows. For each analyst recommendation change in our sample, we identify a placebo event defined as the earnings announcement date for the same stock that has the closest abnormal return to that of the analyst recommendation change (day 0).[29,30] We exclude from consideration the nine-day periods (days *t-4* to *t+4*) surrounding all actual analyst recommendation change dates for that stock, to avoid overlap with analyst recommendation changes. Placebo events are chosen without replacement, so there are no duplicates in the placebo event set. Because of the limited number of earnings announcements for each stock, our placebo sample is somewhat smaller than the recommendation change sample (25,931 placebo events versus 31,008 recommendation changes). Table 8 presents the mean abnormal trade imbalances for each trader type surrounding earnings announcements with positive abnormal returns (Panel A) and negative abnormal returns (Panel B).

[Table 8 here]

The results in Table 8 support Prediction 4. Most importantly, for earnings announcement days with large abnormal returns, news-driven institutions do not exhibit the "buy the rumor, sell the news" behavior associated with early information acquisition. In contrast to the results in our analysis of analyst recommendation changes, news-driven institutions do not demonstrate

[29] We define "closest abnormal return" as the return that has the same sign as and minimum absolute distance from the day-0 abnormal return of the actual analyst recommendation change. The average abnormal return is 3.350% on the positive placebo dates and -3.271% on the negative placebo dates.
[30] In the presence of Reg FD, it is unlikely that there exist any informational differences among investors regarding the announced earnings. Large price changes and high volume following earnings announcements can be explained by differences in interpretation as in Harris and Raviv (1993).

significant buying prior to earnings announcements with positive abnormal returns (Panel A), nor do they exhibit significant net selling prior to earnings announcements with negative abnormal returns (Panel B). Furthermore, news-driven institutional investors are net buyers rather than sellers on the day of earnings announcements with positive abnormal returns, and they are net sellers rather than buyers on the day of earnings announcements with negative abnormal returns. Interestingly, individuals exhibit net abnormal selling on positive-return earnings announcements and in the following days, consistent with individuals providing liquidity to institutions.[31]

Market makers also emerge as significant liquidity providers on positive earnings announcement days, in contrast to their generally neutral net trading pattern on analyst recommendation change days. Why market makers are willing to provide liquidity (i.e., carry overnight inventory following earnings announcements) around scheduled earnings announcements but not around the unscheduled analyst recommendation changes is not obvious. One reason may be that trading volume is significantly higher around earnings announcements, making it easier for market makers to trade out of their positions if they want to reduce their risk. On average trading volume is 18% higher on earnings announcement days compared to recommendation change days. A countervailing effect comes from stock return volatility, which is 20% higher around earnings announcements than around recommendation changes, suggesting greater inventory risk. However, bid-ask spreads are also wider (by 11%), suggesting that market makers are compensated for taking additional risk around earnings announcements, which may explain their higher liquidity provision.

Our third placebo test examines days on which stocks exhibit large abnormal returns but have neither analyst recommendation nor earnings announcements, capturing various other

[31] This result is consistent with Kaniel et al. (2008), who find patterns of individual trading consistent with risk-averse individuals providing liquidity to institutions.

substantial information events. We construct the placebo sample as follows. For each analyst recommendation change in our sample, we identify a placebo event defined as the stock-day on which the same stock has the closest abnormal return to that of the actual analyst recommendation change (day 0). We exclude from consideration earnings announcement days and the nine-day periods (days *t-4* to *t+4*) surrounding all actual analyst recommendation changes for that stock, to avoid overlap with analyst recommendation changes. Placebo events are chosen without replacement, so there are no duplicates in the placebo event set. The average absolute difference between actual and placebo day-0 abnormal returns is an insignificant 0.0013%, and there is no abnormal trading volume before the placebo dates. Table 9 presents the mean abnormal trade imbalances for each trader type surrounding the matching-return placebo dates.

[Table 9 here]

The results in Table 9 are consistent with Prediction 4. On the placebo large-return days, news-driven institutions simply trade in the direction of the price change on day zero, rather than exhibiting "buy the rumor, sell the news" behavior associated with early information acquisition. News-driven institutional investors are net buyers rather than sellers on the day of the placebo positive returns (Panel A), and they are net sellers rather than buyers on placebo negative-return days (Panel B). Furthermore, news-driven institutions do not demonstrate significant buying prior to the placebo positive-return days nor significant selling prior to the placebo negative-return days.

Overall, all three placebo tests show that news-driven institutions trade differently around information events when they do not possess short-lived private information. Most notably, the imbalance patterns show that both the "buy the rumor" and the "sell the news" patterns of news-driven institutions are related specifically to analyst recommendation changes, not events such as earnings announcements or other large-return days, where early private information is less likely, or reiterations, where information may be less valuable. Taken together, these results reinforce the conclusions of our main analysis, linking our findings more clearly to information differences between different groups of investors.

6. Robustness Checks

We conduct several additional tests to confirm the robustness of our results (results from robustness checks are in the internet appendix). First, excluding recommendation changes when the same stock has other recommendation changes in the prior four days yields identical inference; this filter addresses the concern that what looks like trading before one recommendation change could actually be motivated by another recommendation that precedes it. Second, eliminating all recommendation changes (for the same stock) that occur within a three-day period does not affect the results; this filter addresses the concern that such clustering may reflect news outside the recommendation changes themselves.[32] Third, excluding recommendation changes that occur on dividend announcement dates does not change our results. Fourth, excluding from our sample all recommendation changes announced after 4:00 p.m. does not alter our results. Firth, our results hold when our sample is divided into sub-periods for before versus after 2007, when Regulation National Market System (Reg NMS) and the NYSE's Hybrid market structure were implemented (Hendershott and Moulton, 2011; Chakrabarty and Moulton, 2012). Finally, results are qualitatively similar for three- and five-day periods surrounding analyst recommendation changes and for trade imbalances scaled by shares outstanding rather than prior-year average daily dollar volume.

[32] To illustrate the difference between the first two filters, suppose that three analysts all upgrade the same stock, one on each day, three days in a row; call them U1, U2, and U3. Under the first rule, we would exclude recommendation changes when the same stock has other recommendation changes in the prior four days: so U2 and U3 are dropped, but U1 remains in the sample. Under the second rule, we would exclude all recommendation changes that are clustered within a three-day period (i.e., that have other recommendation changes on the day before or day after): so U1, U2, and U3 are all dropped from the sample.

In multivariate regressions akin to those in Equation (6), we also test a number of other characteristics of recommendation changes, including the firm's book-to-market ratio, stock turnover, the number of analysts covering the firm, and whether the recommendation change is accompanied by an earnings forecast, issued by one of the 10 largest brokerages, issued by a brokerage firm that has an underwriting relationship with the firm, or occurs after the Global Settlement of 2002. None of these variables are found to be significantly related to the strength of the "buy the rumor, sell the news" trading activity of news-driven institutions.

In our study we focus on analyst recommendation changes and so exclude initiations of analyst coverage. Thus our results are not directly comparable to those of Irvine et al. (2007), who analyze analyst coverage initiations. To reconcile our results with theirs, we repeat our analysis for analyst coverage initiations. Using the methodology of Irvine et al., we identify 6,889 analyst coverage initiations for NYSE stocks during our sample period. We find that news-driven institutions are significant net buyers in the days prior to an analyst's initial positive recommendation, consistent with Irvine et al. and our findings for analyst recommendation changes. Also consistent with Irvine et al., but in contrast to our findings for analyst recommendation changes, we find no significant net selling by news-driven institutions on the day the initial recommendation is announced. Thus, while news-driven institutions appear to be contrarians when it comes to positive recommendation *changes*, this behavior is not observed for positive *initiations*. The differential response of institutions to the announcement of initial positive recommendations versus upgrades may be attributable to the magnitude of the price effects. Hirshleifer et al. (1994) predict that the magnitude of early-informed buying before and selling the day of the announcement are positively related to the strength of the signal, and in our samples the average abnormal return is significantly higher on analyst upgrades than on positive analyst initiations. Alternatively, news-driven institutions may not sell the news on positive analyst initiations because the initiation-related price increase is due to heightened investor recognition rather than new information.

7. Conclusion

In this paper we use an unusually comprehensive database to provide an inside look at trading in the face of short-lived private information. We examine analyst recommendation changes as times when information differences across different types of investors are likely. We document how informed investors trade on their short-lived information as well as how differences in their trading horizons and motives lead to different profit-taking strategies. We also study how uninformed investors trade around these events and how the market is cleared.

We find that news-driven institutions (who likely receive information early) are significant net buyers before analyst upgrades, and they buy more of stocks that ultimately have the biggest returns when analyst upgrades are announced. On the day of the upgrade, proprietary (but not agency) news-driven institutions trade in the opposite direction, selling upgraded stocks to complete the predicted "buy the rumor, sell the news" strategy. In contrast, individuals, who are unlikely to be informed early, do not exhibit abnormal trade imbalances before recommendation changes, and they buy when the upgrade is announced. Our placebo tests reveal that news-driven institutions do not "buy the rumor and sell the news" around events without early information acquisition. Finally, we find that program institutional traders are the de-facto liquidity providers to news-driven institutional investors, trading in a near mirror image to news-driven institutional investors around analyst recommendation changes as they are adversely selected in a winner's curse outcome. In aggregate, there appears to be a transfer of wealth among institutional traders, from program traders to news-driven institutions that are informed early.

The implications of our analysis are relevant to other situations where some investors have short-lived informational advantages. For example, until recently BlackRock regularly gathered nonpublic views from analysts through a survey to gain a short-term informational advantage. Because of public pressure, BlackRock agreed to stop gathering this information (Morgenson, 2014). There is also evidence of possible informed trading ahead of macroeconomic news announcements (Bernile, Hu, and Tang, 2015; Lucca and Moench, 2015). Recent press reports reveal that a number of high-speed traders pay for faster news feeds, giving them a few-second (or few-millisecond) advantage over investors who receive news releases through conventional media outlets (e.g., Hu, Pan, and Wang, 2014; Mullins et al., 2013; Patterson, 2014). Some news vendors have stopped selling direct access to high-speed traders, while regulators are investigating the practice and what it means for market fairness. Our findings may be relevant to these situations as well, where the timescale is smaller but the underlying principle of early- versus later-informed investors is the same.

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Table 1: Descriptive statistics

The sample consists of all domestic common stocks that were traded on the NYSE and had analyst recommendation changes between March 8, 1999 and April 22, 2010. Panel A presents descriptive statistics for the 2,122 stocks in the sample. *Market capitalization* is calculated annually from CRSP; Number of analysts covering (*# Analysts covering*) is calculated annually from I/B/E/S; *Institutional holdings* are calculated quarterly as the percentage of shares held by institutional owners from Thompson 13F database. All variables in Panel A are averaged for each stock over the sample period, and across-stock statistics are reported in Panel A. Panel B reports aggregate trading volumes by trader type for the sample stocks over the entire sample period, 1999-2010. Panel C reports separately for *Upgrades* and *Downgrades* number of analyst recommendation changes in the sample year-by-year and the average abnormal return on the recommendation-change day *(Avg Return)* , with Upgrades and Downgrades determined based on a three-tier scale (buy/hold/sell). The total number of recommendation changes in the sample is 31,008 (15,101 upgrades + 15,907 downgrades).

Panel A: Firms in sample

	Mean	Median	Std Dev
Market capitalization ($bn)	6.490	1.532	19.277
# Analysts covering	7.1	6.0	4.7
Institutional holdings (%)	66.6	69.4	22.6
Number of firms	2,122		

Panel B: Trading volumes by trader type

	Main Categories		Sub-Categories	
	Volume ($ billion)	% of Total	Volume ($ billion)	% of Total
News-driven Institutional	65,963	67.7%		
Proprietary			8,824	9.1%
Agency			57,139	58.7%
Program Institutional	21,644	22.2%		
Non-Index-Arb			19,461	20.0%
Index-Arb			2,183	2.2%
Individual	1,575	1.6%		
Market Maker	8,224	8.4%		
Total	97,406			

Panel C: Recommendation changes by year

	Upgrades		Downgrades	
Year	# Upgrades	Avg Return (%)	# Downgrades	Avg Return (%)
1999	1,151	1.33	1,106	-1.70
2000	386	1.39	598	-1.62
2001	795	1.25	1,050	-1.72
2002	1,194	1.48	2,124	-1.56
2003	1,667	1.99	1,871	-1.63
2004	1,414	1.73	1,437	-1.65
2005	1,328	1.92	1,077	-1.68
2006	1,157	1.96	1,189	-1.62
2007	1,774	2.02	1,476	-1.81
2008	2,016	2.42	1,981	-2.77
2009	1,735	2.72	1,607	-2.08
2010	484	2.00	391	-1.12
Total	15,101	1.96	15,907	-1.83

Table 2: Analysis of abnormal trading volumes surrounding analyst recommendation changes

This table presents mean abnormal trading volume percentages for each trader type in the days surrounding 15,101 analyst upgrades (Panel A) and 15,907 analyst downgrades (Panel B). Trading volume is defined as dollar volume of shares bought plus sold, scaled by prior year's average daily dollar volume. Abnormal trading volume is the trading volume minus average trading volume during the benchmark period (days *t-45* to *t-11* and days *t+11* to *t+45* relative to the day of the analyst recommendation change). *Day 0* is the day the analyst recommendation change is released if before 4:00 pm on a trading day, else the next trading day. *Day -4 to -1* (*Day +1 to +4*) reflects days -4 to -1 (+1 to +4), with abnormal volume calculated as the sum of the daily abnormal volumes over the four days. Means are reported in percentage points, and *t*-statistics (in parentheses below means) are based on standard errors that are double-clustered on stock and date.

Panel A: Mean abnormal trading volumes for analyst upgrades

	Main categories			Sub-categories		
	Day -4 to -1	Day 0	Day +1 to +4	Day -4 to -1	Day 0	Day +1 to +4
News-driven Institutional	38.74	36.73	29.04			
	(6.7)	*(19.4)*	*(5.2)*			
Proprietary				2.14	2.67	2.07
				(3.4)	*(14.7)*	*(3.8)*
Agency				36.59	34.06	26.97
				(6.9)	*(19.2)*	*(5.2)*
Program Institutional	6.68	8.71	10.76			
	(5.5)	*(20.4)*	*(9.3)*			
Non-Index-Arb				6.24	8.40	10.17
				(5.5)	*(20.8)*	*(9.5)*
Index-Arb				0.44	0.31	0.58
				(3.2)	*(7.1)*	*(4.2)*
Individual	1.29	1.26	1.16			
	(2.5)	*(8.2)*	*(2.0)*			
Market Maker	5.83	4.86	4.82			
	(6.5)	*(14.4)*	*(6.1)*			

Panel B: Mean abnormal trading volumes for analyst downgrades						
	Main categories			Sub-categories		
	Day -4 to -1	Day 0	Day +1 to +4	Day -4 to -1	Day 0	Day +1 to +4
News-driven Institutional	59.61	46.18	43.26			
	(11.5)	*(18.4)*	*(9.8)*			
Proprietary				4.90	3.42	3.89
				(7.8)	*(11.9)*	*(8.1)*
Agency				54.71	42.76	39.37
				(11.5)	*(18.7)*	*(9.6)*
Program Institutional	9.38	7.92	11.78			
	(8.1)	*(18.5)*	*(9.9)*			
Non-Index-Arb				8.85	7.61	11.31
				(8.3)	*(19.1)*	*(10.3)*
Index-Arb				0.53	0.31	0.47
				(3.2)	*(6.0)*	*(3.1)*
Individual	2.10	1.35	1.40			
	(5.9)	*(10.6)*	*(4.2)*			
Market Maker	7.53	5.88	5.22			
	(7.2)	*(13.7)*	*(5.6)*			

Table 3: Analysis of abnormal trade imbalances surrounding analyst recommendation changes

This table presents mean abnormal trade imbalance percentages for each trader type in the days surrounding 15,101 analyst upgrades (Panel A) and 15,907 analyst downgrades (Panel B). Trade imbalance is defined as dollar volume of shares bought minus sold, scaled by prior year's average daily dollar volume. Abnormal trade imbalance is the trade imbalance minus average trade imbalance during the benchmark period (days *t-45* to *t-11* and days *t+11* to *t+45* relative to the day of the analyst recommendation change). *Day 0* is the day the analyst recommendation change is released if before 4:00 pm on a trading day, else the next trading day. *Day -4 to -1* (*Day +1 to +4*) reflects days -4 to -1 (+1 to +4), with abnormal imbalance calculated as the sum of the daily abnormal imbalances over the four days. Means are reported in percentage points, and *t*-statistics (in parentheses below means) are based on standard errors that are double-clustered on stock and date.

Panel A: Mean abnormal trade imbalances for analyst upgrades

	Main categories			Sub-categories		
	Day -4 to -1	Day 0	Day +1 to +4	Day -4 to -1	Day 0	Day +1 to +4
News-driven Institutional	4.26	-1.43	0.33			
	(4.6)	*(-3.8)*	*(0.3)*			
Proprietary				1.29	-0.70	0.67
				(2.5)	*(-2.7)*	*(1.1)*
Agency				2.97	-0.73	-0.34
				(2.1)	*(-1.3)*	*(-0.2)*
Program Institutional	-3.62	1.12	-1.55			
	(-5.5)	*(4.6)*	*(-2.5)*			
Non-Index-Arb				-3.31	1.31	-1.23
				(-5.5)	*(5.5)*	*(-2.1)*
Index-Arb				-0.32	-0.19	-0.31
				(-1.6)	*(-2.8)*	*(-1.6)*
Individual	-0.44	0.35	1.03			
	(-0.7)	*(1.9)*	*(1.4)*			
Market Maker	-0.20	-0.04	0.19			
	(-1.7)	*(-0.5)*	*(1.4)*			

Panel B: Mean abnormal trade imbalances for analyst downgrades

	Main categories			Sub-categories		
	Day -4 to -1	Day 0	Day +1 to +4	Day -4 to -1	Day 0	Day +1 to +4
News-driven Institutional	-4.37	0.80	0.59			
	(-4.5)	*(2.4)*	*(0.5)*			
Proprietary				-1.70	1.43	1.52
				(-2.6)	*(4.3)*	*(2.0)*
Agency				-2.67	-0.63	-0.92
				(-2.7)	*(-1.5)*	*(-1.0)*
Program Institutional	3.58	-0.64	-0.08			
	(4.4)	*(-2.5)*	*(-0.1)*			
Non-Index-Arb				3.72	-0.76	-0.46
				(4.8)	*(-3.1)*	*(-0.6)*
Index-Arb				-0.14	0.11	0.38
				(-0.7)	*(1.5)*	*(1.9)*
Individual	0.54	-0.10	-0.53			
	(1.4)	*(-0.7)*	*(-1.2)*			
Market Maker	0.24	-0.06	0.02			
	(0.9)	*(-0.7)*	*(0.1)*			

Table 4: Regressions of institutional abnormal trade imbalances on returns

This table presents regression analyses of abnormal trade imbalances in the days prior to analyst upgrades (Panel A) and downgrades (Panel B). The dependent variable is abnormal trade imbalance for *News-driven Institutional* traders and *Proprietary* and *Agency* subsets of news-driven institutional traders. Trade imbalance is defined as dollar volume of shares bought minus sold, scaled by prior year's average daily dollar volume. Abnormal trade imbalance is the trade imbalance minus average trade imbalance during the benchmark period (days *t-45* to *t-11* and days *t+11* to *t+45* relative to the day of the analyst recommendation change). *Day 0* is the day the analyst recommendation change is released if before 4:00 pm on a trading day, else the next trading day. *Day -4 to -1* reflects days -4 to -1, with abnormal imbalance calculated as the sum of the daily abnormal imbalances over the four days. *Return day 0* is the abnormal return for the stock on the day of the analyst recommendation change. Parameter estimates are reported in percentage points, and *t*-statistics (in parentheses below parameter estimates) are based on standard errors that are double-clustered on stock and date.

Panel A: Analyst upgrades

Dependent Variable	News-driven Institutional Trade Imbalance Day -4 to -1	Proprietary Trade Imbalance Day -4 to -1	Agency Trade Imbalance Day -4 to -1
Intercept	3.25	1.02	2.23
	(4.1)	*(2.5)*	*(1.9)*
Return day 0	51.26	13.61	37.86
	(2.2)	*(1.0)*	*(2.6)*
# Observations	15,101	15,101	15,101

Panel B: Analyst downgrades

Dependent Variable	News-driven Institutional Trade Imbalance Day -4 to -1	Proprietary Trade Imbalance Day -4 to -1	Agency Trade Imbalance Day -4 to -1
Intercept	-3.56	-1.38	-2.18
	(-3.3)	*(-2.2)*	*(-2.1)*
Return day 0	44.59	17.44	26.92
	(2.4)	*(1.8)*	*(1.1)*
# Observations	15,907	15,907	15,907

Table 5: Long-run returns after analyst recommendation changes

This table presents mean size-adjusted returns (as in Womack, 1996) for the day recommendation changes are announced and the following one- and six-month windows. Mean returns are calculated both unweighted and weighted by the abnormal trade imbalances of news-driven institutions in the four days prior to the analyst recommendation change announcement. Panel A presents results for the 15,101 analyst upgrades, and Panel B presents results for the 15,907 analyst downgrades.

Panel A: Analyst upgrades

	One-day Event Return	One-month Postevent return	Six-month Postevent return
Unweighted	1.87	3.34	6.55
Weighted by news-driven institutional abnormal trade imbalances	2.03	5.02	9.39

Panel B: Analyst downgrades

	One-day Event Return	One-month Postevent return	Six-month Postevent return
Unweighted	-1.68	-1.88	-1.75
Weighted by news-driven institutional abnormal trade imbalances	-2.04	-2.87	-2.47

Table 6: Regressions of institutional abnormal trade imbalances surrounding analyst recommendation changes

This table presents multivariate analyses of abnormal trade imbalances in the days surrounding analyst upgrades (Panel A) and downgrades (Panel B). The dependent variable is abnormal trade imbalance for news-driven institutional traders. Trade imbalance is defined as dollar volume of shares bought minus sold, scaled by prior year's average daily dollar volume. Abnormal trade imbalance is the trade imbalance minus average trade imbalance during the benchmark period (days *t-45* to *t-11* and days *t+11* to *t+45* relative to the day of the analyst recommendation change). *Day 0* is the day the analyst recommendation change is released if before 4:00 pm on a trading day, else the next trading day. *Day -4 to -1* (*Day +1 to +4*) reflects days -4 to -1 (+1 to +4), with abnormal imbalance calculated as the sum of the daily abnormal imbalances over the four days. *All-star analyst* is an indicator variable that is equal to one if the analyst making the recommendation change is ranked as an all-star analyst by Institutional Investor in the prior year, else zero; *Small firm (Large firm)* is an indicator variable that is equal to one if the firm is in the smallest (largest) firm-size quartile, else zero; *High institutional ownership (Low institutional ownership)* is an indicator variable that is equal to one if the firm is in the highest (lowest) insitutional ownership percentage quartile as of the previous quarter-end, else zero; and *High volatility* (*Low volatility*) is an indicator variable that is equal to one if the firm is in the highest (lowest) volatility quartile as of the previous quarter-end, else zero. Parameter estimates are reported in percentage points, and *t*-statistics (in parentheses below parameter estimates) are based on standard errors that are double-clustered on stock and date.

Panel A: Analyst upgrades

Dependent Variable	News-driven Institutional Trade Imbalance		
	Day -4 to -1	Day 0	Day +1 to +4
Intercept	1.44	-0.46	0.75
	(3.8)	*(-2.3)*	*(0.3)*
All-star analyst	2.58	0.25	2.18
	(1.9)	*(0.2)*	*(1.2)*
Small firm	3.09	-0.06	-1.07
	(2.1)	*(-2.8)*	*(-0.3)*
Large firm	-0.95	1.45	1.61
	(-2.4)	*(1.6)*	*(0.5)*
High institutional ownership	0.48	-1.18	1.15
	(2.9)	*(-2.4)*	*(0.4)*
Low institutional ownership	-4.61	-2.10	-5.60
	(-1.3)	*(-1.0)*	*(-1.6)*
High volatility	-0.99	0.48	0.96
	(-2.9)	*(2.0)*	*(0.3)*
Low volatility	-2.95	-0.02	-2.26
	(-0.8)	*(0.0)*	*(-0.7)*
# Observations	15,101	15,101	15,101

Panel B: Analyst downgrades			
Dependent Variable	News-driven Institutional Trade Imbalance		
	Day -4 to -1	Day 0	Day +1 to +4
Intercept	-5.01	0.34	0.36
	(-2.8)	*(1.8)*	*(1.5)*
All-star analyst	0.66	1.61	-0.28
	(0.3)	*(1.8)*	*(-0.1)*
Small firm	-1.93	1.32	0.95
	(-2.2)	*(2.8)*	*(0.3)*
Large firm	3.48	-0.57	0.14
	(1.7)	*(-0.7)*	*(0.1)*
High institutional ownership	-5.01	0.75	2.68
	(-3.4)	*(2.4)*	*(0.9)*
Low institutional ownership	5.53	1.83	6.15
	(1.5)	*(1.3)*	*(0.8)*
High volatility	1.92	-1.59	-2.90
	(2.0)	*(-3.3)*	*(-1.0)*
Low volatility	1.19	-0.15	5.25
	(0.5)	*(-0.2)*	*(1.7)*
# Observations	15,907	15,907	15,907

Table 7: Placebo tests of abnormal trade imbalances surrounding analyst recommendation reiterations

This table presents mean abnormal trade imbalance percentages for each trader type in the days surrounding 17,286 analyst recomendation reiterations (Panel A), 4,322 reiterations accompanied by top-quartile abnormal returns (Panel B), and 4,322 reiterations accompanied by bottom-quartile abnormal returns (Panel C). Trade imbalance is defined as dollar volume of shares bought minus sold, scaled by prior year's average daily dollar volume. Abnormal trade imbalance is the trade imbalance minus average trade imbalance during the benchmark period (days *t-45* to *t-11* and days *t+11* to *t+45* relative to the day of the analyst reiteration). *Day 0* is the day the analyst recommendation reiteration is released if before 4:00 pm on a trading day, else the next trading day. *Day -4 to -1* (*Day +1 to +4*) reflects days -4 to -1 (+1 to +4), with abnormal imbalance calculated as the sum of the daily abnormal imbalances over the four days. Means are reported in percentage points, and *t*-statistics (in parentheses below means) are based on standard errors that are double-clustered on stock and date.

Panel A: Mean abnormal trade imbalances for analyst reiterations

	Main categories			Sub-categories		
	Day -4 to -1	Day 0	Day +1 to +4	Day -4 to -1	Day 0	Day +1 to +4
News-driven Institutional	-0.20	0.03	-1.18			
	(-0.2)	*(0.1)*	*(-1.2)*			
Proprietary				-0.08	0.08	0.01
				(-0.2)	*(0.6)*	*(0.0)*
Agency				-0.12	-0.05	-1.19
				(-0.1)	*(-0.1)*	*(-1.2)*
Program Institutional	0.11	-0.02	-0.34			
	(0.1)	*(-0.1)*	*(-0.4)*			
Non-Index-Arb				0.62	0.14	-0.14
				(0.8)	*(0.7)*	*(-0.2)*
Index-Arb				-0.50	-0.16	-0.20
				(-1.6)	*(-1.4)*	*(-0.6)*
Individual	-0.10	-0.03	0.50			
	(-0.2)	*(-0.2)*	*(1.6)*			
Market Maker	0.19	0.02	1.03			
	(0.9)	*(0.2)*	*(1.9)*			

Panel B: Mean abnormal trade imbalances for analyst reiterations with large positive returns						
	Main categories			Sub-categories		
	Day -4 to -1	Day 0	Day +1 to +4	Day -4 to -1	Day 0	Day +1 to +4
News-driven Institutional	-0.14	-0.23	0.31			
	(-0.1)	*(-0.3)*	*(0.1)*			
Proprietary				0.03	0.00	-0.01
				(0.0)	*(0.0)*	*(0.0)*
Agency				-0.17	-0.23	0.32
				(-0.1)	*(-0.4)*	*(0.2)*
Program Institutional	-0.12	0.17	0.45			
	(-0.1)	*(0.4)*	*(0.3)*			
Non-Index-Arb				-0.07	0.14	0.43
				(-0.1)	*(0.3)*	*(0.3)*
Index-Arb				-0.05	0.03	0.02
				(-0.2)	*(0.4)*	*(0.1)*
Individual	0.13	0.13	0.17			
	(0.1)	*(0.3)*	*(0.2)*			
Market Maker	0.12	-0.07	-0.93			
	(0.3)	*(-0.3)*	*(-1.9)*			

Panel C: Mean abnormal trade imbalances for analyst reiterations with large negative returns						
	Main categories			Sub-categories		
	Day -4 to -1	Day 0	Day +1 to +4	Day -4 to -1	Day 0	Day +1 to +4
News-driven Institutional	0.00	-0.12	0.44			
	(0.0)	*(-0.2)*	*(0.2)*			
Proprietary				-1.26	0.33	-0.19
				(-1.3)	*(0.8)*	*(-0.2)*
Agency				1.26	-0.45	0.63
				(0.6)	*(-0.7)*	*(0.3)*
Program Institutional	0.08	0.20	-0.41			
	(0.1)	*(0.4)*	*(-0.3)*			
Non-Index-Arb				0.09	0.18	-0.38
				(0.1)	*(0.4)*	*(-0.3)*
Index-Arb				-0.01	0.02	-0.03
				(0.0)	*(0.2)*	*(-0.1)*
Individual	-0.09	-0.05	-0.03			
	(-0.2)	*(-0.2)*	*(-0.1)*			
Market Maker	0.00	-0.03	0.01			
	(0.0)	*(-0.2)*	*(0.0)*			

Table 8: Placebo tests of abnormal trade imbalances surrounding earnings announcement days

This table presents mean abnormal trade imbalance percentages for each trader type in the days surrounding earnings announcements with returns similar to upgrade days (Panel A) and downgrade days (Panel B). Trade imbalance is defined as dollar volume of shares bought minus sold, scaled by prior year's average daily dollar volume. Abnormal trade imbalance is the trade imbalance minus average trade imbalance during the benchmark period (days *t-45* to *t-11* and days *t+11* to *t+45* relative to the earnings announcement day). *Day 0* is the day the earnings announcement is released if the announcement is made before 4:00 pm on a trading day, else the next trading day. *Day -4 to -1* (*Day +1 to +4*) reflects days -4 to -1 (+1 to +4), with abnormal imbalance calculated as the sum of the daily abnormal imbalances over the four days. Means are reported in percentage points, and *t*-statistics (in parentheses below means) are based on standard errors that are double-clustered on stock and date.

Panel A: Mean abnormal trade imbalances for positive-return earnings announcements

	Main categories			Sub-categories		
	Day -4 to -1	Day 0	Day +1 to +4	Day -4 to -1	Day 0	Day +1 to +4
News-driven Institutional	-2.85	2.23	2.54			
	(-0.7)	*(2.4)*	*(1.3)*			
Proprietary				-1.21	-0.58	0.05
				(-1.3)	*(-1.5)*	*(0.0)*
Agency				-1.64	2.81	2.49
				(-0.5)	*(3.0)*	*(1.3)*
Program Institutional	6.66	2.17	2.92			
	(1.4)	*(2.8)*	*(1.7)*			
Non-Index-Arb				5.88	1.61	3.53
				(1.3)	*(2.2)*	*(2.1)*
Index-Arb				0.78	0.56	-0.61
				(1.3)	*(1.6)*	*(-0.9)*
Individual	0.21	-1.03	-1.91			
	(0.3)	*(-3.9)*	*(-2.2)*			
Market Maker	-4.03	-3.37	-3.54			
	(-1.9)	*(-4.4)*	*(-2.2)*			

Panel B: Mean abnormal trade imbalances for negative-return earnings announcements						
	Main categories			Sub-categories		
	Day -4 to -1	Day 0	Day +1 to +4	Day -4 to -1	Day 0	Day +1 to +4
News-driven Institutional	1.43	-2.46	1.82			
	(0.9)	*(-2.3)*	*(0.6)*			
Proprietary				-0.41	-0.83	0.96
				(-0.5)	*(-2.3)*	*(1.0)*
Agency				1.84	-1.62	0.86
				(1.0)	*(-1.7)*	*(0.3)*
Program Institutional	0.99	0.68	6.36			
	(0.7)	*(1.0)*	*(3.7)*			
Non-Index-Arb				0.29	1.23	7.87
				(0.2)	*(2.0)*	*(4.7)*
Index-Arb				0.70	-0.55	-1.51
				(1.6)	*(-2.9)*	*(-3.6)*
Individual	0.25	-0.42	-2.82			
	(0.2)	*(-1.9)*	*(-3.9)*			
Market Maker	-2.67	2.20	-5.35			
	(-1.4)	*(1.6)*	*(-1.5)*			

Table 9: Placebo tests of abnormal trade imbalances surrounding matching-return days

This table presents mean abnormal trade imbalance percentages for each trader type in the days surrounding 15,101 placebo positive-return days (Panel A) and 15,907 placebo negative-return days (Panel B). Trade imbalance is defined as dollar volume of shares bought minus sold, scaled by prior year's average daily dollar volume. Abnormal trade imbalance is the trade imbalance minus average trade imbalance during the benchmark period (days *t-45* to *t-11* and days *t+11* to *t+45* relative to the placebo day). *Day 0* is the placebo day. *Day -4 to -1* (*Day +1 to +4*) reflects days -4 to -1 (+1 to +4), with abnormal imbalance calculated as the sum of the daily abnormal imbalances over the four days. Means are reported in percentage points, and *t*-statistics (in parentheses below means) are based on standard errors that are double-clustered on stock and date.

Panel A: Mean abnormal trade imbalances for positive-return days						
	Main categories			Sub-categories		
	Day -4 to -1	Day 0	Day +1 to +4	Day -4 to -1	Day 0	Day +1 to +4
News-driven Institutional	1.00	0.84	0.21			
	(1.2)	*(2.8)*	*(0.2)*			
Proprietary				0.47	0.17	0.56
				(0.8)	*(1.1)*	*(1.0)*
Agency				0.53	0.67	-0.35
				(0.5)	*(2.1)*	*(-0.3)*
Program Institutional	-0.80	-0.37	-2.00			
	(-1.1)	*(-1.6)*	*(-2.7)*			
Non-Index-Arb				-0.81	-0.33	-2.01
				(-1.1)	*(-1.5)*	*(-2.8)*
Index-Arb				0.01	-0.04	0.01
				(0.0)	*(-0.7)*	*(0.0)*
Individual	0.65	-0.14	0.65			
	(1.5)	*(-1.2)*	*(1.2)*			
Market Maker	-0.86	-0.33	1.14			
	(-1.0)	*(-1.2)*	*(1.2)*			

Panel B: Mean abnormal trade imbalances for negative-return days

	Main categories			Sub-categories		
	Day -4 to -1	Day 0	Day +1 to +4	Day -4 to -1	Day 0	Day +1 to +4
News-driven Institutional	-1.58	-0.69	-0.80			
	(-1.0)	*(-2.6)*	*(-1.0)*			
Proprietary				-1.03	-0.29	-1.23
				(-0.9)	*(-0.9)*	*(-1.1)*
Agency				-0.55	-0.40	0.43
				(-0.4)	*(-1.0)*	*(0.3)*
Program Institutional	0.83	0.58	2.04			
	(1.3)	*(2.8)*	*(2.8)*			
Non-Index-Arb				0.81	0.53	2.04
				(1.3)	*(2.7)*	*(2.9)*
Index-Arb				0.02	0.06	0.00
				(0.1)	*(1.0)*	*(0.0)*
Individual	0.05	0.17	0.28			
	(0.1)	*(1.3)*	*(0.7)*			
Market Maker	0.71	-0.06	-1.52			
	(1.1)	*(-0.2)*	*(-1.9)*			

Figure 1: Volumes surrounding analyst upgrades

Daily *Raw Trading Volume* for each stock is defined as trader-type volume scaled by average daily total trading volume in prior year. Daily *Abnormal Trading Volume* for each stock is equal to Raw Trading Volume minus trader-type Benchmark Trading Volume, measured over the period from -45 to -11 and +11 to +45 days relative to each analyst recommendation change. Graphs depict averages across 15,101 analyst upgrades from March 10, 1999 to April 22, 2010.

Figure 1-A: Upgrades -45 days to +45 days

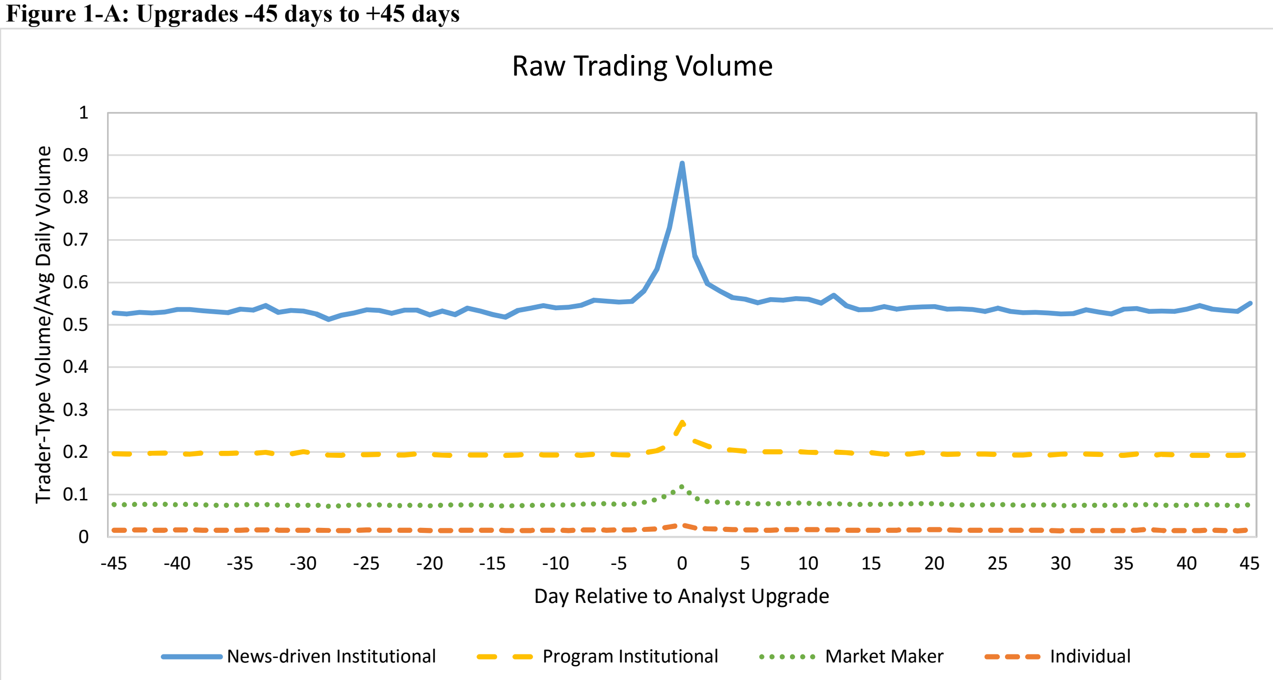

Figure 1-B: Upgrades -5 days to +5 days

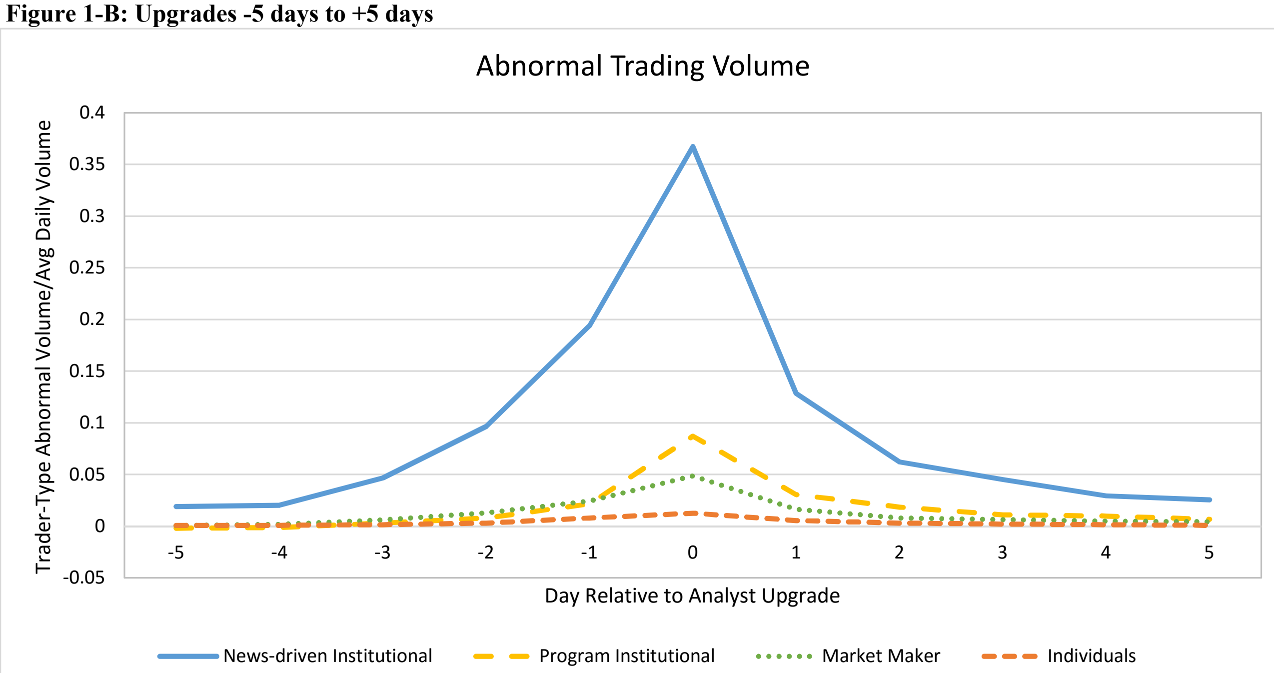

Figure 2: Volumes surrounding analyst downgrades

Daily *Raw Trading Volume* for each stock is defined as trader-type volume scaled by average daily total trading volume in prior year. Daily *Abnormal Trading Volume* for each stock is equal to Raw Trading Volume minus trader-type Benchmark Trading Volume, measured over the period from -45 to -11 and +11 to +45 days relative to each analyst recommendation change. Graphs depict averages across 15,907 analyst downgrades from March 10, 1999 to April 22, 2010.

Figure 2-A: Downgrades -45 days to +45 days

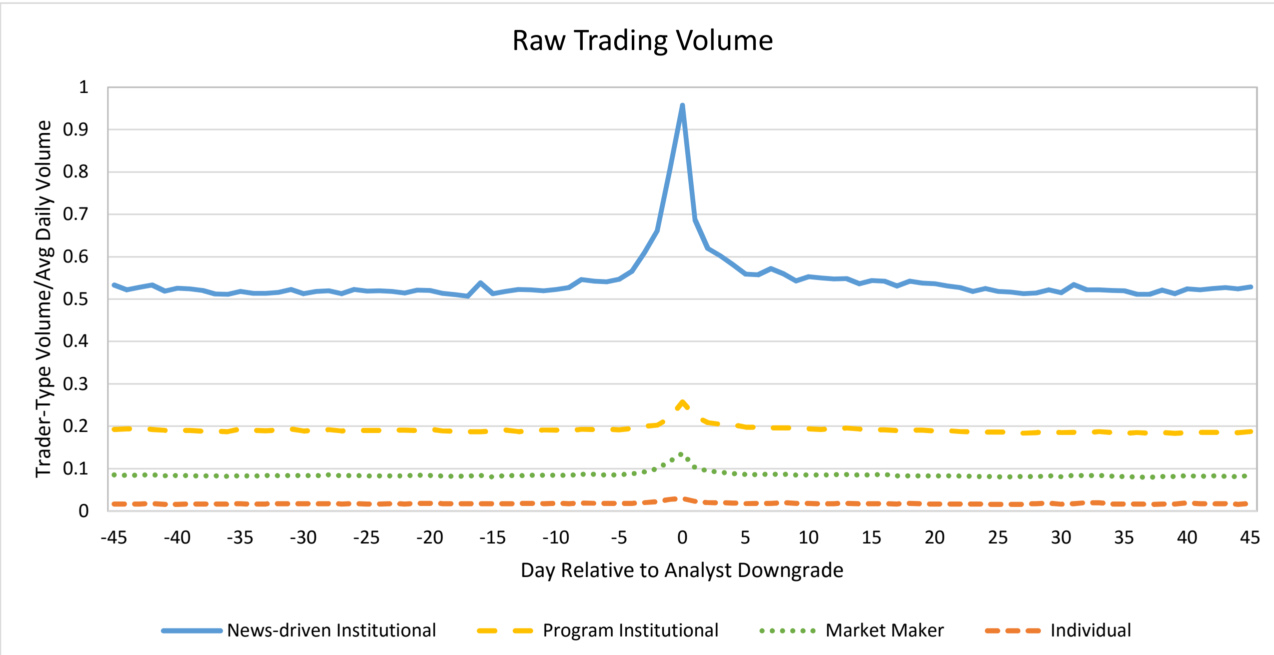

Figure 2-B: Downgrades -5 days to +5 days

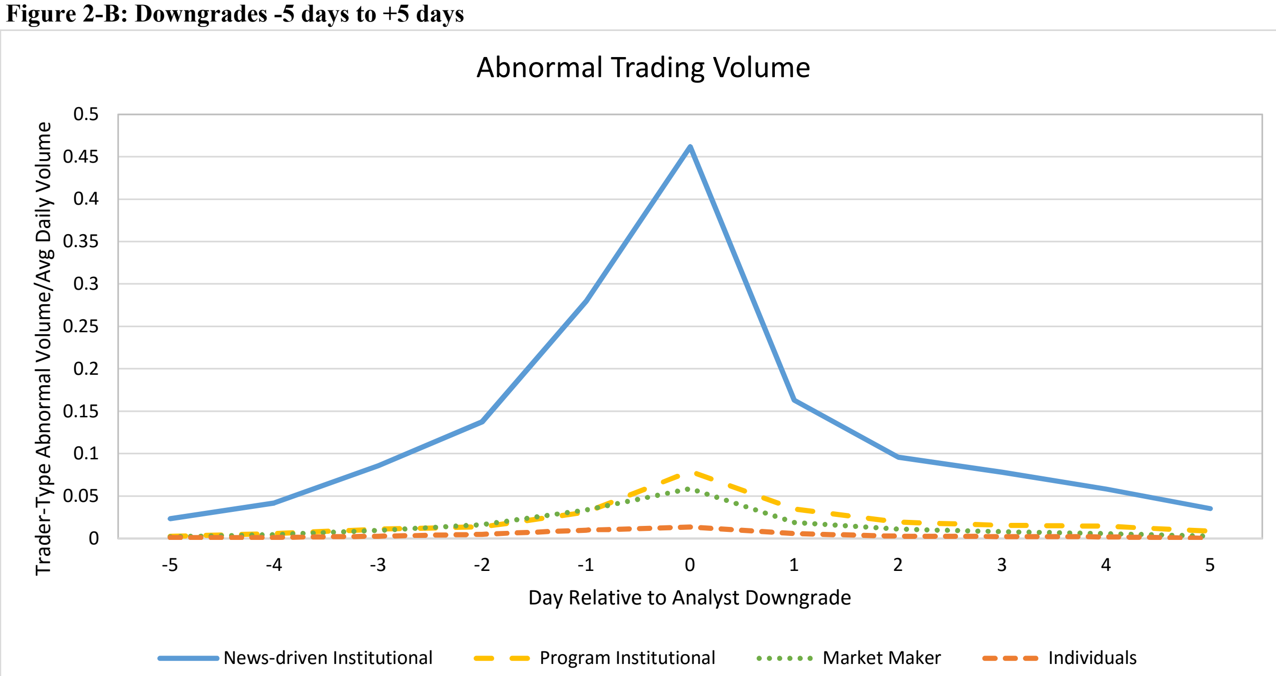

Figure 3: Imbalances surrounding analyst upgrades

Daily *Raw Trade Imbalance* for each stock is defined as trader-type imbalance scaled by average daily total trading volume in prior year. Daily *Abnormal Trade Imbalance* for each stock is equal to Raw Trade Imbalance minus trader-type Benchmark Trade Imbalance, measured over the period from -45 to -11 and +11 to +45 days relative to each analyst recommendation change. Graphs depict averages across 15,101 analyst upgrades from March 10, 1999 to April 22, 2010.

Figure 3-A: Upgrades -45 days to +45 days

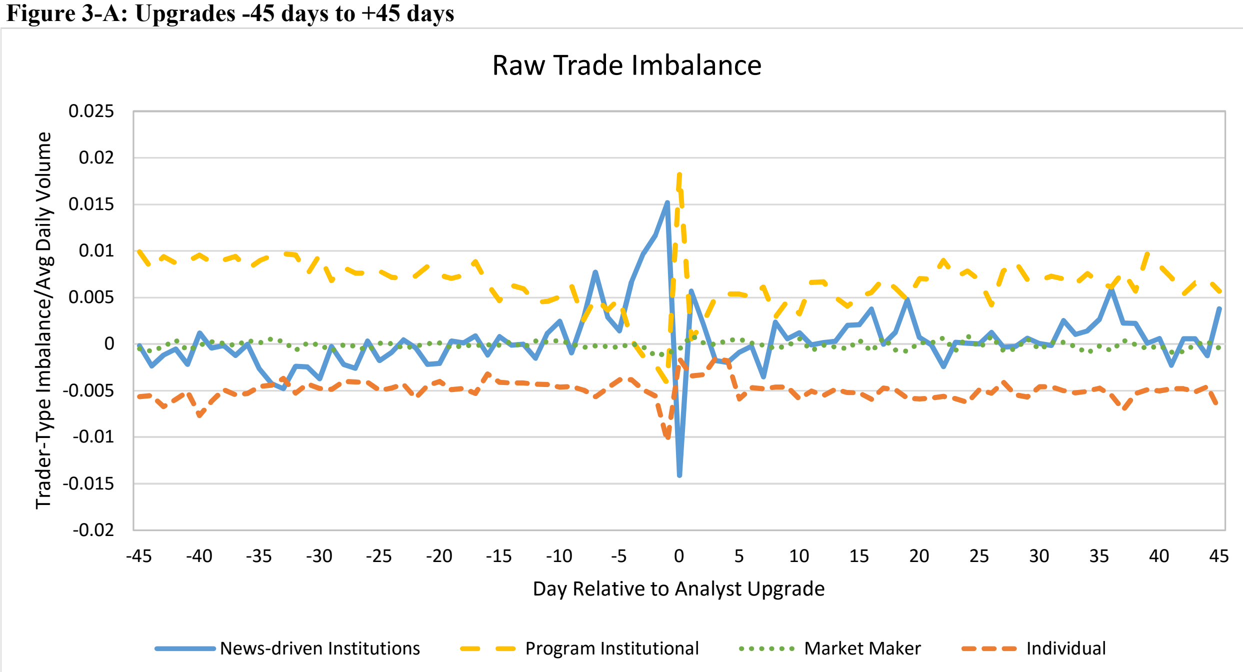

Figure 3-B: Upgrades -5 days to +5 days

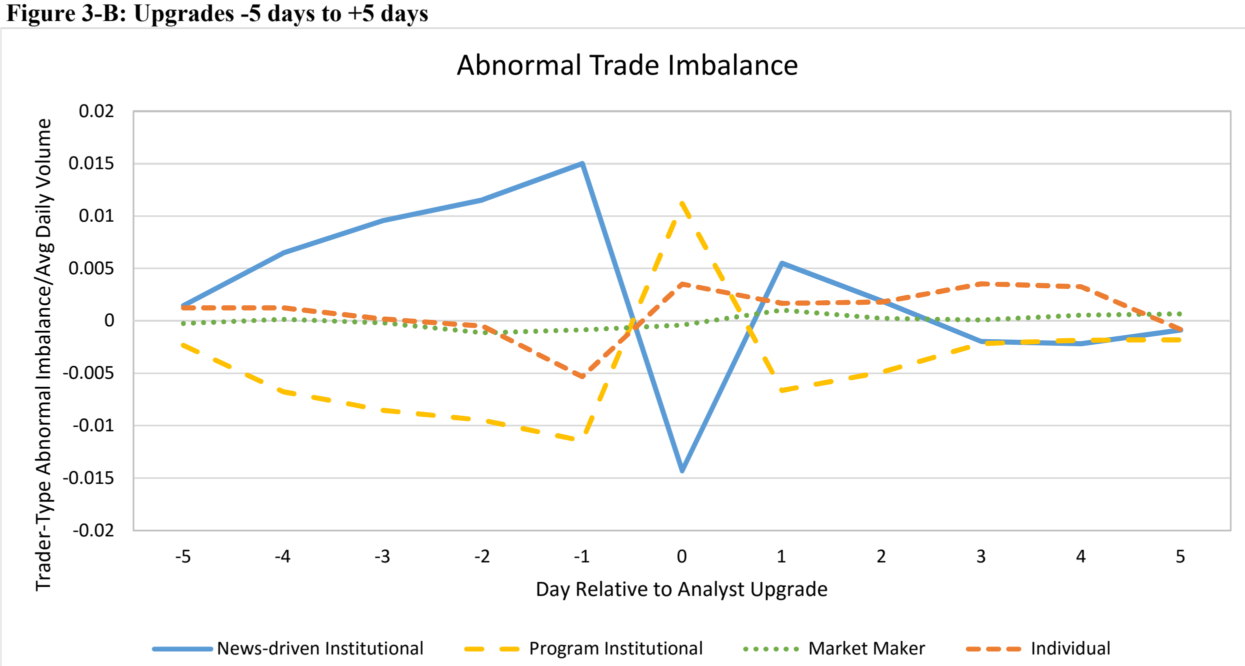

Figure 3-C: Upgrade -5 days to +5 days

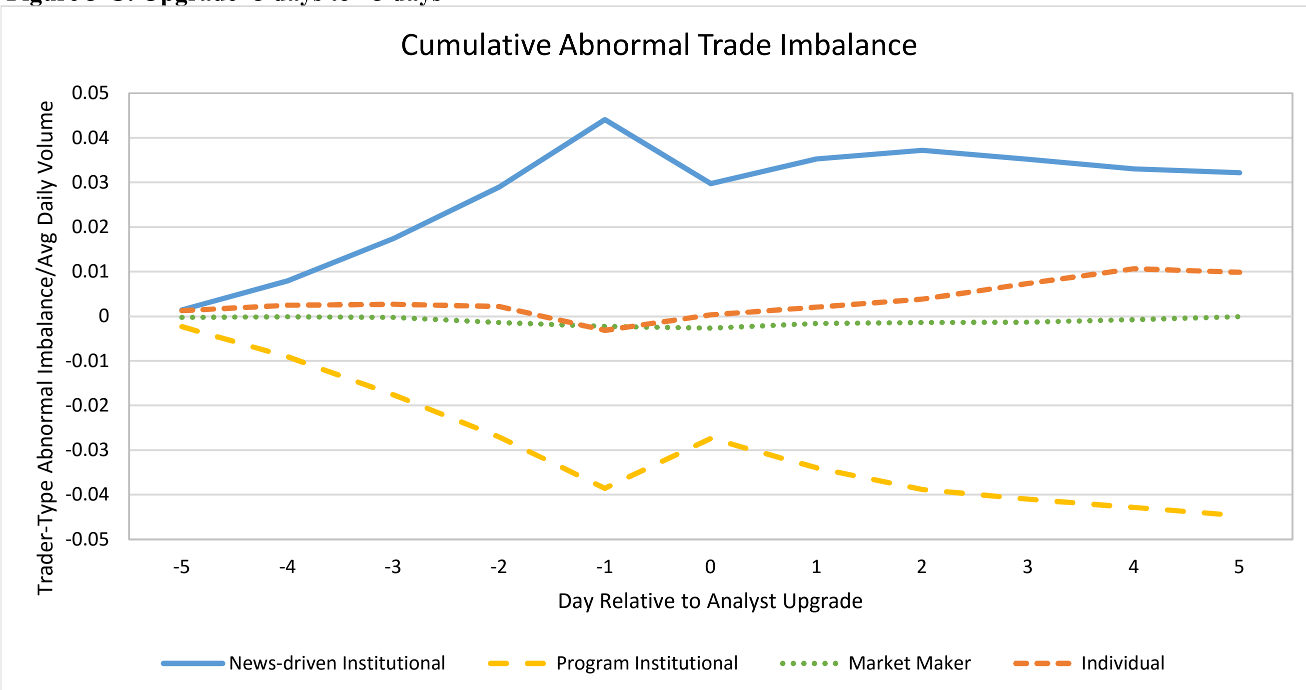

Figure 4: Imbalances surrounding analyst downgrades

Daily *Raw Trade Imbalance* for each stock is defined as trader-type imbalance scaled by average daily total trading volume in prior year. Daily *Abnormal Trade Imbalance* for each stock is equal to Raw Trade Imbalance minus trader-type Benchmark Trade Imbalance, measured over the period from -45 to -11 and +11 to +45 days relative to each analyst recommendation change. Graphs depict averages across 15,907 analyst downgrades from March 10, 1999 to April 22, 2010.

Figure 4-A: Downgrades -45 days to +45 days

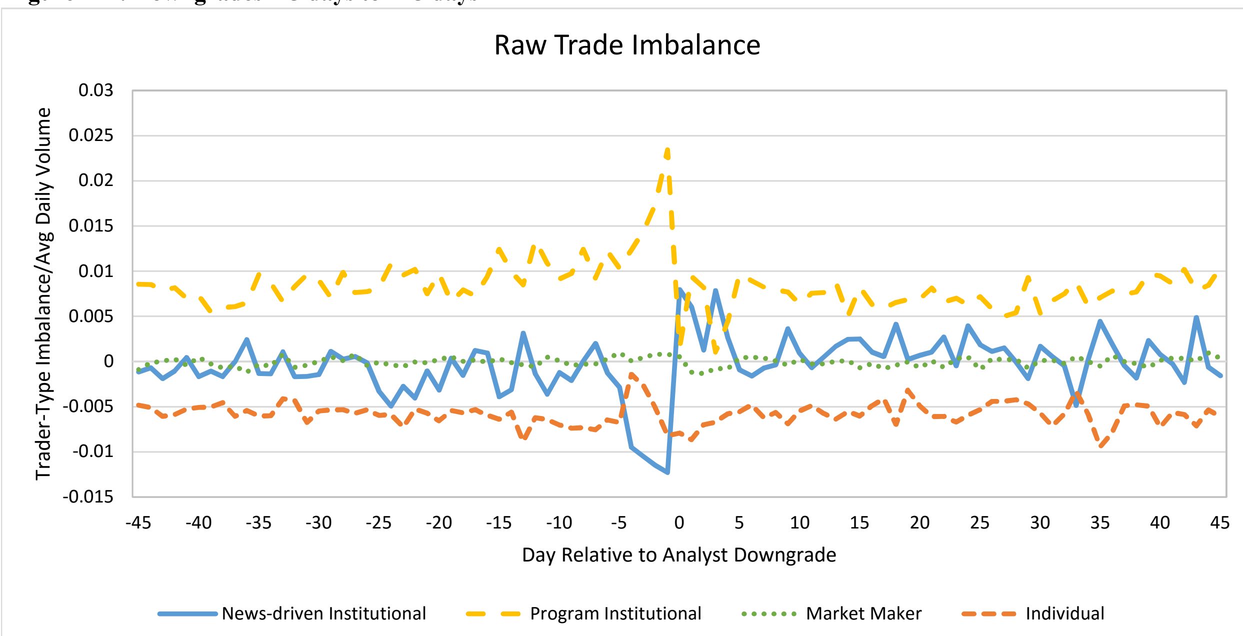

Figure 4-B: Downgrades -5 days to +5 days

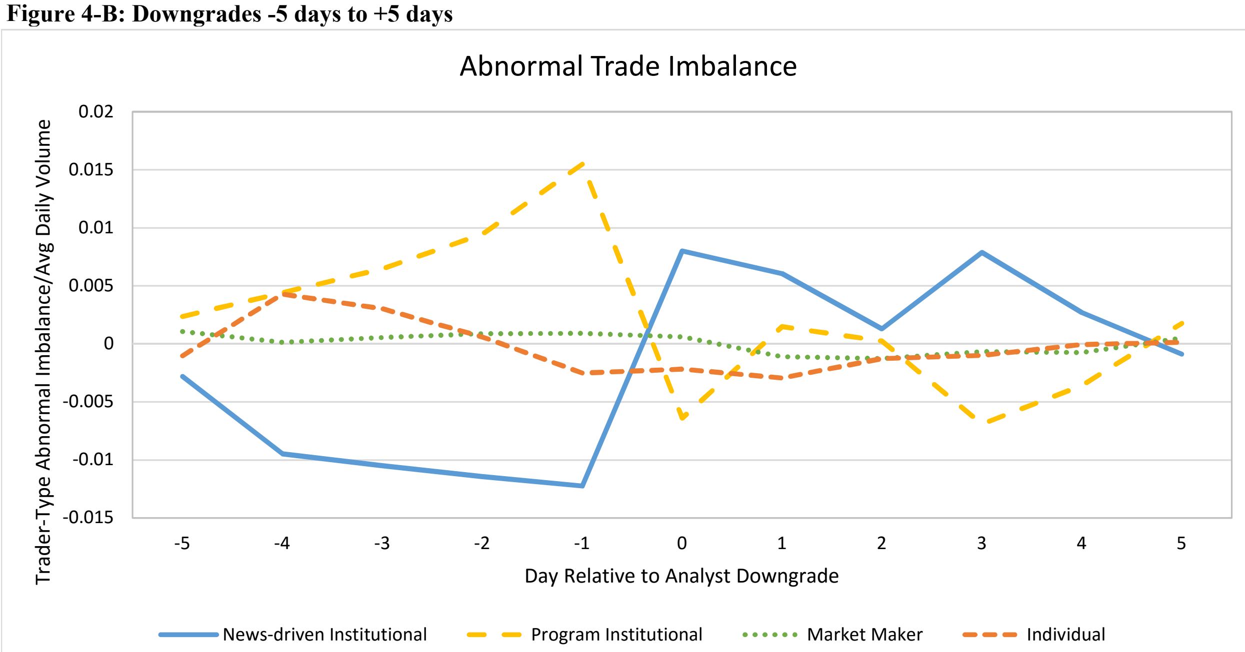

Figure 4-C: Downgrades -5 days to +5 days