Finance and Economics Discussion Series
Divisions of Research & Statistics and Monetary Affairs
Federal Reserve Board, Washington, D.C.

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2017-023

Please cite this paper as:
Swem, Nathan (2017). "Information in Financial Markets: Who Gets It First?," Finance and Economics Discussion Series 2017-023. Washington: Board of Governors of the Federal Reserve System, https://doi.org/10.17016/FEDS.2017.023.

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Information in Financial Markets: Who Gets It First?

Nathan Swem*

February 2017

Abstract

I compare the timing of information acquisition among institutional investors and sell-side analysts, and I show that hedge fund trades predict the direction of subsequent analyst ratings change reports while other investors' trades do not. In addition, hedge funds reverse trades after analyst reports, while other investors follow the analysts. Finally, I show that hedge funds perform best among stocks with high analyst coverage. These results suggest that hedge funds have superior information acquisition skills, and that analysts assist hedge funds in exploiting information acquisition advantages. These dynamics illustrate how hedge funds play an important role in information generation.

JEL classification: G10, G11, G12, G14, G20, G24

*Board of Governors of the Federal Reserve System. I thank Aydoğan Altı, Michael Clement, Anastassia Fedyk, Nicholas Hirschey, Travis Johnson, Gonzalo Maturna, Taylor Nadauld, Alessio Saretto, Clemens Sialm, Laura Starks, Sheridan Titman, Parth Venkat, Adam Winegar and seminar participants at The Federal Reserve Board and the University of Texas at Austin, as well as attendees of the Trans-Atlantic Doctoral Conference, for helpful comments. This article represents the views of the author, and should not be interpreted as reflecting the views of the Board of Governors of the Federal Reserve System or other members of its staff. Please send questions or comments to: nathan.f.swem@frb.gov.

1. Introduction

Portfolio managers at investment firms and sell-side research analysts at brokerage firms play prominent roles in incorporating information into stock prices. In addition to commissioning sell-side analyst information with brokerage fees, most investment firms also maintain internal staffs of buy-side research analysts to generate private information. While publicly available sell-side information has been extensively studied, information generated privately by buy-side analysts is harder to examine. Investment firms outnumber sell-side analyst brokerage firms by more than 8-to-1, which suggests that buy-side research analysts, while less well understood, may also play a significant role in incorporating information into prices.

In this paper, I compare buy-side and sell-side information by relating the direction of investor trades to the direction of sell-side upgrade and downgrade reports. I first address the simple question: who gets information first, sell-side or buy-side? In subsequent tests I examine the private communications between buy-side and sell-side researchers as they gather, vet, and process information. With these tests I investigate whether information flows from the sell-side to the buy-side, as generally assumed, or vice-versa. My results show that certain investors acquire information before sell-side analysts, and that sell-side analysts assist early informed investors by making their private information more broadly known. My results also suggest that investors strategically communicate their private information to sell-side analysts to accelerate the incorporation of their information into prices.

I begin by comparing the trades made by hedge funds, mutual funds, broker-dealer asset managers, and pension funds to upgrade and downgrade reports published by sell-side analysts in the following quarter. I find that the direction of hedge fund trades positively correlates with the direction of subsequently published sell-side upgrade and downgrade reports.

Abnormal announcement returns [-1,+1] average 3-4% for my sample of sell-side analyst reports, which is consistent with Irvine (2003) and others. These market reactions suggest that the reports contain new fundamental information, as in Loh and Stulz (2011), and/or that analysts publish reports when fundamental information is disclosed, as in Altınkılıç and Hansen (2009). In either case, my results indicate that hedge fund trades begin incorporating important fundamental information before the information becomes more broadly known.

I then compare sell-side reports to investor trades in the following quarter, to determine how investors incorporate sell-side information into their trading decisions. I find that hedge funds are unique: they trade in the opposite direction as the sell-side reports recommend. For example, after sell-side analysts publish upgrade reports I find that hedge funds sell. These patterns suggest that hedge funds anticipate sell-side reports, and then reverse their trades after market prices have adjusted to the information contained in, or coinciding with, the analyst reports. These patterns are consistent with the profit-taking trades of the early-informed investors in Hirshleifer, Subrahmanyam, and Titman (1994) (hereafter *HST*).

To best exploit their skills in acquiring information, the early-informed investors in HST prefer ex-ante to *fish in crowded pools*, i.e. investigate more well-known stocks. Among crowded pools, a greater number of later-informed investors provides liquidity and enables the early-informed to eventually unwind trades. I investigate whether sell-side analysts assist hedge funds, in the way that later informed investors assist the early informed in HST, in order to better understand where hedge funds most profitably exploit their information acquisition efforts. I find that, despite defying sell-side analyst recommendations, hedge funds generate higher risk-adjusted returns among stocks with higher sell-side analyst coverage. While my results do not cleanly identify a causal link between analyst coverage and hedge fund performance, they are consistent with *crowded pools*. Helping investors who are faster to acquire information represents a previously un-explored benefit of sell-side research.

My results relate to a number of papers examining private communications between analysts and investors. For example, Irvine, Lipson, and Puckett (2007) shows that sell-side analysts privately communicate information to important investor clients before publishing reports. In addition, Klein, Saunders, and Wong (2014) finds that hedge funds are particularly likely to receive tips from sell-side analysts. The practice of sell side analyst privately tipping hedge funds, as outlined in these papers, provides an entirely plausible explanation for my findings that hedge fund trades predict the direction of subsequent analyst reports. I investigate analyst tipping in order to determine if hedge fund trades anticipate sell-side reports due to tips, or because hedge funds acquire information faster than sell-side analysts.

I first examine sell-side analyst tipping by grouping the sell-side analyst reports according to the specific day, within each quarter, that the reports are published. I then measure the extent to which hedge fund trades predict the reports published on each day of the following quarter. The above papers on tipping, as well as Kadan, Michaely, and Moulton (2014), show that sell-side analyst tips occur 1-5 days before reports are published. Consistent with tipping, I find that hedge fund trades predict analyst reports published in each of the first five trading days of the following quarter. However, I also find that hedge fund trades predict analyst reports made 10, 20, even 30+ trading days into the following quarter. These results suggest that analyst tipping may be occurring, but also indicate that tipping cannot completely explain the degree to which hedge fund trades anticipate sell-side analyst reports.

To extend the above I also examine sell-side reports with differing levels of information content. Specifically, I define sell-side analyst reports not published on quarterly earnings release dates, but that move stock prices significantly, as high-information content *influential* reports, following Loh and Stulz (2011). I define reports published on (or shortly after) earnings release dates as low-information *earnings season* reports, following Ivković and Jegadeesh (2004) and Altınkılıç and Hansen (2009). I find that hedge fund trades anticipate both earnings season reports and influential reports. The former result suggests that hedge funds acquire company-specific information faster than sell-side analysts. The latter result suggests that hedge funds anticipate analyst-specific information, which is more indicative of private communications between hedge funds and sell-side analysts.

I show that, in addition to tipping, private communications often involve investors disclosing important information to sell-side analysts. In Brown et al. (2016) private communications between investors and sell-side analysts appear common, and Brown et al. (2015) suggests that sell-side analysts catering to hedge funds tend to have superior information. Large hedge fund managers often disclose privately generated research in public forums, such as the annual Ira Sohn Conference.[1] Other hedge funds, such those examined in Ljungqvist and Qian (2016), publish their research analysis directly. In both instances hedge fund disclosures accelerate the incorporation of their private information into prices. Communicating information to sell-side analysts, in order to influence the content of subsequent sell-side reports, is an additional mechanism by which a hedge fund, or any institutional investor, can accelerate the incorporation of their private information into prices.

I examine hedge funds' strategic information disclosures to sell-side analysts by grouping hedge funds and analysts according to size. Larger investors generate more brokerage commissions, as shown in Goldstein et al. (2009), which suggests that larger hedge funds should have greater access to analysts. Reports published by larger brokerage firm sell-side analysts cause larger stock price reactions, as shown by Stickel (1995). Therefore, the largest hedge funds have motivation, and the best ability, to privately communicate information to the

[1] Notable examples include David Einhorn of Greenlight Capital discussing The St. Joe Company (JOE) in 2010, and William Ackman of Pershing Square Capital discussing Herbalife (HLF) in 2012.

analysts at the largest brokerage firms. Consistent with strategic information disclosures, I find that the trades of the largest hedge funds most strongly predict the *influential* reports of sell-side analysts employed by the largest brokerage firms. My tests cannot rule out alternative explanations, such as correlated information generation processes. However, my results raise the possibility that an as-yet unexplored mechanism exists, strategic information disclosures to analysts, by which hedge funds incorporate their information into prices.

My results support recent research investigating techniques by which hedge funds acquire private information. For example, Jeng et al. (2013) examines expert networks, which are patronized with particular vigor by hedge funds. In addition, Solomon and Soltes (2015) finds that hedge funds are best at extracting information from private meetings with corporate management teams, and Gargano, Rossi, and Wermers (2016) shows that hedge funds most aggressively file Freedom of Information Act (FOIA) requests to obtain information from regulators. Finally, Agarwal et al. (2013) shows that hedge funds most aggressively lobby the SEC to exempt portfolio positions from 13-F disclosures in order to prevent piggy-backing off of their information acquisition efforts. My results suggest that sell-side analysts assist hedge funds in profitably exploiting their information acquisition efforts, which suggests an indirect mechanism by which analyst coverage contributes to robust information environments.

I also examine the trades of mutual funds, broker-dealer asset managers, and pension funds and I find that, in contrast to hedge funds, their trades do not anticipate sell-side reports. Also in contrast to hedge funds, these investors trade in the direction recommended by the sell-side reports. These results suggest that these types of institutional investors rely heavily on the information published by sell-side analysts, as examined in Kacperczyk and Seru (2007). Taken together my samples of mutual funds, broker dealers, and pension funds accounts for $4.3 trillion in equities positions indicating sell-side analysts are an important source of information for a very large segment of institutional equities portfolio management.

My final results document a shift in the composition of institutional investors, which has implications for information generation. Over my sample period (2004-2014) the share of mutual funds, broker dealers, and pension funds has fallen dramatically, from 46% of all institutional equities holdings in 2004 to 29% in 2014, due to the decline of active mutual funds. Over this period only 49 new active mutual funds opened, while 777 closed.[2] By contrast, hedge funds' share of institutional investor equity holdings grew from 3% to 8% over this period as 931 new hedge funds opened and only 555 closed. The number of sell-side analysts increased by 15% as 4,190 new publishing analysts were hired, while 3,783 departed. My results suggest that a large but shrinking share of investors use sell-side information to inform trades, while a growing share of investors are either agnostic to sell-side information (ETFs) or use sell-side information to exit previously initiated positions (hedge funds).

2. Data

I hand-collect samples of institutional investors from the 13-F holdings data using techniques drawn the empirical literature that examines investor information and investment processes by inferring trades from holdings disclosures, beginning with Grinblatt and Titman (1989), and including Daniel et al. (1997), Kacperczyk, Sialm, and Zheng (2008), and Cremers and Petajisto (2009), for mutual funds, and Brunnermeier and Nagel (2004), Griffin and Xu (2009), and Ben-David, Franzoni, and Moussawi (2012) for other institutional investors.

[2] Over this period a very substantial 1,639 new ETFs opened, while only 350 closed. Ben-David, Franzoni, and Moussawi (2017) examines other implications of the rise of ETFs.

2.1. Institutional Investor Samples and Variables

I identify 1,356 hedge funds, 113 brokerage firms, and 38 pension funds from 2004-2014 by hand-matching names of institutional asset managers from the Thomson Reuters Institutional Holdings (13F) Database from Wharton Research Data Services (WRDS) with names of asset managers from the Factset LionsShares holdings data. I perform this hand-matching because Factset LionShares classifies institutional investors according to their style. I use the holdings data from Thomson Reuters following Ben-David, Franzoni, and Moussawi (2012) and others who show that Thomson Reuters (and subsumed companies such as CDA/Spectrum) has the most comprehensive historical 13-F holdings data.[3]

I also assemble a sample of 2,394 actively managed mutual funds using the Thompson Reuters S12 file from WRDS. While mutual fund management companies (e.g. Fidelity Management and Research), file aggregated holdings on form 13-F, the SEC also requires holdings disclosures for individual mutual funds (e.g. Fidelity Contrafund, Fidelity Magellan, etc).[4] I begin the sample period in 2004 as that year the SEC required that individual mutual funds file quarterly holdings disclosures on forms N-30D, N-Q, and N-CSR (instead of its previous policy of requiring bi-annual filings). I select actively managed mutual funds in a similar manner as Kacperczyk, Sialm, and Zheng (2008): I exclude all funds with Investment Objective Codes (IOCs) corresponding to international funds (IOC code 1), fixed-income funds (IOC codes 5 and 6), as well as unclassified (IOC code 9) and missing. I summarize the samples of mutual funds, and the other types of investors outlined above, in Appendix A: Tables 1 and 2.

[3]The SEC requires institutional investment managers with more than $100 million in exchange-traded or NASDAQ-quoted equity securities to file 13-F reports within 45 days of the end of each calendar quarter for all equity positions greater than 10,000 shares or $200,000 in market value.

[4]The holdings of several brokerage firms identified in the 13-F sample include holdings related to mutual funds, which are included in the mutual fund sample. The is the only potential overlap between my samples.

I aggregate the holdings data at the stock level to summarize information arrival for each of my samples of institutional investors. There are many ways to summarize the holdings data, but I follow Sias, Starks, and Titman (2006) and Chen, Hong, and Stein (2002) who show that the *number* of institutional investors buying (selling) best summarizes the aggregate positive (negative) views of the investors. Therefore, for each stock i and quarter t I calculate the following to summarize the positive (buys) and negative (sells) information for each sample of investors:

$$Buys_{i,t} = \sum_{j \in Investor sample} \mathbb{1}_{shares_{j,i,t} - shares_{j,i,t-1} > 0},$$

$$Sells_{i,t} = \sum_{j \in Investor sample} \mathbb{1}_{shares_{j,i,t} - shares_{j,i,t-1} < 0},$$

In the equations above, $shares_{j,i,t}$ represents the number of shares of company i held by each of the investors in each investor sample (indexed by j), at the end of quarter t.[5] In addition, I calculate $NetBuys_{i,t}$ by taking the *number* of investors buying stock i and subtracting the *number* of investors selling stock i during quarter t:

$$NetBuys_{i,t} = Buys_{i,t} - Sells_{i,t}.$$

I also calculate $Holders_{i,t}$: the number of investors in each sample that hold stock i as of the end of quarter t. I calculate the above variables for my samples of hedge funds, mutual funds, broker-dealers, pension funds and for all institutions in the 13-F holdings data. I summarize these variables in Table 1.

[5]These measures do not capture short selling or short covering.

2.2. *Sell-Side Analyst Sample and Variables*

I follow Ivković and Jegadeesh (2004), and others, in focusing on the sell-side analyst reports that involve a change in the analyst's company-specific buy/sell/hold investment recommendation, which I identify using the Institutional Brokers' Estimate System (IBES) recommendations detail file from WRDS. These data contain the recommendations for 8,531 unique analysts working at 646 unique brokerage firms, which I summarize in Appendix A: Tables 1 and 3. I define $Upgrades_{i,t}$ as the number of upgrade reports published by all covering analysts for company i during quarter t. I define $Downgrades_{i,t}$ as the number of downgrade reports published for company i during quarter t. I define $NetUpgrades_{i,t}$ as the difference: $Upgrades_{i,t}$ minus $Downgrades_{i,t}$.

I also separate analyst reports according to their information content. Specifically, I define *earnings season* reports as those which are published within 3 days including and following company earnings reports. As discussed in Altınkılıç and Hansen (2009), the information in these reports is generally highly correlated with the information in the company's earnings release.[6] In addition, I follow Loh and Stulz (2011) and define high-information *influential* reports. These reports are not published around company earnings, but cause significant relative stock price reactions.[7] In order to exclude information disclosures not related to earnings, for *influential* reports I exclude reports in which more than one analyst publishes on the same day. Finally, I define *non-influential reports* as those with minimal or opposite stock price reaction (relative to the market) as the report recommends.

I calculate $Rating_{i,t}$ to summarize the average buy/sell/hold recommendation for all covering analysts. I assign a value of -1 to the lowest within–brokerage firm analyst rating

[6]The *earnings season* reports comprise roughly 41,000 (24%) of the 167,000 sell-side analyst reports in my sample, which is similar to 21% of the sample used in Altınkılıç and Hansen (2009).

[7]I find that 14% of the reports in my sample are *influential*, versus 12% in Loh and Stulz (2011).

and a value of +1 to the highest rating. I assign a zero for ratings of *hold*, *equal-weight*, *neutral*, etc. For each stock, $Rating_{i,t}$ averages the [-1,0,+1] ratings for all covering analysts for stock i as of quarter-end t. I also calculate the number of analysts covering: $Analysts_{i,t}$. I summarize these variables in Table 1.

2.3. Overall Sample and Controls Variables

I calculate controls variables including: $Return_{i,t}$ which is the 1-quarter total return from the Center for Research in Security Prices (CRSP) 1925 US Stock Database from WRDS, and $Turnover_{i,t}$ which is total quarterly volume divided by prior-quarter shares outstanding from CRSP. I winsorize each variable at 1% and 99%, but all results are robust to including outliers. I perform regressions using the quarterly panel which comprises of all stocks in CRSP with share codes 10 and 11 (common equity) and 31 (American Depository Receipts). I exclude stocks covered by fewer than two sell-side analysts, and with prices below $1. The time-series of my panel spans the 44 quarters from 2004-2014. The resulting panel contains roughly 95,000 stock/quarter observations which I summarize in Table 1.[8]

3. Results

My first empirical tests compare investors to sell-side analysts to determine who gets information first. I then examine how different types of investors react after sell-side analysts publish reports. My next tests explore private communications between investors and analysts. Finally, I relate examine hedge fund performance to sell-analyst coverage to determine how analysts help hedge funds exploit information acquisition speed advantages.

[8] In many regressions I de-mean and scale the above variables by standard-deviation within-stock. I also make abbreviations, "Upgr" for upgrades, etc. in the tables for formatting purposes.

3.1. Who Gets Information First?

In Tables 2-4 I present regressions in which I compare the information acquisition speed of sell-side analysts to that of various types of investors: hedge funds, mutual funds, broker dealers, pension funds and all 13-F filers aggregated. Equation (1) outlines my first set of regressions, which I present in Table 2, which relate the net direction of sell-side analyst reports to the net direction of investor trades in the prior quarter:

$$NetUpgrades_{i,t+1} = \beta_1\, NetBuys_{i,t} + \beta_2\, Return_{i,t} + \delta_t + \epsilon_{i,t}. \tag{1}$$

The positive coefficient for $NetBuys$ (β_1) in Column 1 of Table 2 indicates that the direction of hedge fund trades positively correlates with the direction of subsequently published sell-side analyst reports.[9] These results indicate that hedge funds get information before sell-side analysts publish their market-moving upgrade and downgrade reports.[10]

In contrast to Column 1, the coefficients for $NetBuys$ in Columns 2-4 of Table 2 are not statistically different from zero. This indicates that mutual funds, broker dealers, and pension funds do not get information before analysts. In addition, Column 5 indicates that, when aggregated together, the net direction of the trades of all institutional investors does not predict subsequent sell-side analyst information. I include $Return_{i,t}$ in each regression in Table 2 to proxy for (and control for) fundamental information revealed during quarter t.[11] The negative coefficient for $Return_{i,t}$ (β_2) suggests that sell-side analysts tend to upgrade recently well performing stocks and/or downgrade recently poorly performing stocks.

[9] The t-statistic for β_1 is robust to error clustering by firm, date, different SIC codes, and industry×SIC. Clustering errors by 2-digit SIC, which I show throughout, yields the lowest t-statistics.

[10] I include date fixed-effects throughout to control for market-wide shocks. However, my results are generally robust to firm, industry, and date×industry fixed-effects (see Appendix B), which indicates the effects shown exist in the time series and within various industry groupings.

[11] The results in Table 2 are robust to excluding $Return_{i,t}$.

In Tables 3 and 4 I present regressions that jointly relate both positive (buys) and negative (sells) investor information to subsequent sell-side analyst reports. These regressions provide robustness checks for the results in Table 2, and reveal additional information. First, these regressions allow for economic interpretation of the coefficients. Secondly, by separately examining buys and sells, and upgrades and downgrades, I can more precisely examine the information of sell-side analysts and investors. For example, the *net* variables in Equation (1) imply that an observation in which which ten hedge funds buy and ten hedge funds sell is indistinguishable from an observation in which no hedge funds buy or sell. Finally, fitting separate regressions for upgrades and downgrades allows me to include controls for the level of sell-side analyst information generation (such as the number of analysts covering: $Analysts_{i,t}$) which results in better-fitted regressions.

In Equation (2) I outline the regressions, which I present in Table 3, which jointly relate positive analyst information (upgrades) to prior investors buys and sells:

$$Upgrades_{i,t+1} = \beta_1 Buys_{i,t} + \beta_2 Sells_{i,t} + \beta_3 X_{i,t} + \delta_t + \epsilon_{i,t}. \tag{2}$$

The coefficient for $Buys$ (β_1) in Column 1 of Table 3 indicates that a one standard deviation increase in the number of hedge funds buying increases sell-side analyst upgrades in the following quarter by 0.0118, or by 2.4% relative to the sample average of 0.5.[12] The coefficient for $Sells$ (β_2) indicates that, holding the number of hedge funds buying constant, a one standard deviation increase in the number of hedge funds selling decreases the number of subsequent analyst upgrade reports by 0.0286, or 5.6%. I show that these results are robust to different controls, fixed-effects, and count regressions models in Appendix B: Table 1.

The positive coefficient for $Buys_{i,t}$ in Column 2 of Table 3 indicates that mutual fund

[12] I scale LHS variables by 100 in all regressions for readability in the tables.

buying predicts subsequent analyst upgrades. However, in the following table I show that mutual fund buying also predicts subsequent analyst downgrades. Similarly, the negative coefficients for $Sells_{i,t}$ in both Columns 3 and 4 indicate that selling by broker dealers and pension funds predicts fewer subsequent analyst upgrades. However, these effects are offset by the results in the following table which show that pension fund and broker dealer buying predicts sell-side downgrade reports. In summary, when combined with Table 4, my results suggest that mutual funds, pension funds, and broker dealers do not predict subsequent sell-side information.

The positive coefficients for $Analysts_{i,t}$ across the columns of Table 3 reflects the somewhat mechanical link between the number of sell-side analyst reports published and the number sell-side analysts covering. Similarly, the large negative coefficients for $Rating_{i,t}$ are due to the fact that analysts with *buy* ratings cannot upgrade. Therefore, stocks with higher $Rating_{i,t}$ are mechanically less likely to be upgraded in the subsequent quarter relative to stocks with lower $Rating_{i,t}$. The positive coefficients for $Turnover_{i,t}$ indicate that sell-side analyst upgrade reports are more frequent for stocks with higher turnover. Excluding these controls variables decreases the R^2 for these regressions by roughly 15 percentage points.

In Equation (3) I outline the regression that I present in Table 4, which jointly relate positive analyst information (downgrades) to prior investor buying and selling:

$$Downgrades_{i,t+1} = \beta_1 Buys_{i,t} + \beta_2 Sells_{i,t} + \beta_3 X_{i,t} + \delta_t + \epsilon_{i,t}. \tag{3}$$

The coefficients for $Buys$ (β_1) and $Sells$ (β_2) in Column 1 of Table 4 have opposite signs (but similar magnitudes) as the corresponding coefficients in Column 1 of Table 3.[13] These results show that the statistical and economic correlation between hedge fund trades and

[13] I show additional robustness tests in Appendix B: Table 2

subsequent analyst information, as shown in Table 2, is robust to separately examining upgrades, downgrades, buying and selling separately.

In contrast, the coefficients for both $Buys_{i,t}$ and $Sells_{i,t}$ in Columns 2-4 in Table 3 are positive. This indicates that for mutual funds, pension funds, and broker dealers both buying and selling predict sell-side analyst downgrades. This affirms the results presented in Table 2, and indicates that broker dealers, pension funds, and all 13-F filers aggregated together do not get information before sell-side analysts.

Consistent with Table 3, the coefficients for the information generation controls variables $Analysts_{i,t}$ and $Turnover_{i,t}$ are positive across the columns of Table 4. The positive coefficients for $Rating_{i,t}$ reflects the fact that stocks with higher $Rating_{i,t}$ are mechanically more likely to be downgraded in the subsequent quarter relative to stocks with lower $Rating_{i,t}$. The positive coefficients for $Return_{i,t}$ indicates that sell-side analyst downgrade reports are more frequent for stocks that have performed well in recent quarters.

3.2. How Do Investors React to Sell-side Information?

In Tables 5-7 I present results in which I show how investors react to sell-side analyst information. In Equation (4) I outline regressions in which the dependent variables are the net buying of investors, and the independent variables are the net direction of sell-side analyst reports published in the prior quarter:

$$NetBuys_{i,t+1} = \beta_1 \, NetUpgrades_{i,t} + \beta_2 \, Return_{i,t} + \delta_t + \epsilon_{i,t} \tag{4}$$

The negative coefficient for $NetUpgrades$ (β_1) in Column 1 of Table 5 indicates that hedge funds trade in the opposite direction as sell-side analyst reports published in the prior quarter recommend. When combined with the results above, these patterns suggest that hedge funds resemble the early informed investors in HST: they reverse their trades, taking profits, once their information becomes more widely known.

In stark contrast to hedge funds, the positive coefficients for $NetUpgrades$ in Columns 2-5 of Table 5 indicate that mutual funds, broker dealers, pension funds, and all 13-F filers trade in a manner consistent with the sell-side analyst reports published in the prior quarter. This suggests that for these investors, the information contained in sell-side analyst reports informs trades, and with a significant lag. These results are consistent with Kacperczyk and Seru (2007). The positive coefficients for $Return_{i,t}$ across the columns arises because every type of institutional investor tends to both buy recently well performing stocks and/or sell recently poorly performing stocks.

In Table 6 I present regressions that jointly relate both positive (upgrades) and negative (downgrades) sell-side analyst information to subsequent investor buying. These regressions, outlined in Equation (5), provide a robustness check for the results in Table 5, and provide a more precise examination of how investors react to sell-side analyst information:

$$Buys_{i,t+1} = \beta_1 Upgrades_{i,t} + \beta_2 Downgrades_{i,t} + \beta_3 X_{i,t} + \delta_t + \epsilon_{i,t}. \tag{5}$$

The coefficient for $Upgrades$ (β_1) in Column 1 of Table 6 is not statistically different from zero, which indicates that sell-side analyst upgrade reports have no bearing on subsequent hedge fund buying. This suggests that hedge funds do not follow the direction of the sell-side analyst upgrade reports published in the prior quarter. However, the negative coefficient for $Downgrades$ (β_2) indicates that after sell-side analyst downgrades *fewer* hedge funds buy. Broker dealers, shown in Column 3, are similar to hedge funds. This suggests one aspect in which hedge funds, and broker dealers, react in manner somewhat consistent with the information contained in sell-side analyst downgrade reports.

The positive coefficients for *Upgrades* in Columns 2 and 4 of Table 6 indicates that mutual funds and pension funds buy after sell-side analysts publish upgrade reports. In addition, the negative coefficients for *Downgrades* (β_2) in Columns 2 and 4 indicates that fewer mutual funds and pension funds buy after sell-side analysts publish downgrade reports. The results in Column 5 indicate that, when aggregated, all 13-F filers follow the direction of the sell-side analyst upgrade and downgrade reports published in the prior quarter. This suggests that sell-side analyst information is widely used by institutional investors.

The positive coefficients for $Return_{i,t}$ across the columns of Table 6 suggest a momentum pattern in which investors are more likely to buy recently well-performing stocks. In addition, the positive coefficients for $Turnover_{i,t}$ indicate that investors tend to buy stocks with higher turnover. Finally, positive coefficients for the number of holders for each type of investor reflects a somewhat mechanical correlation: stocks with a greater number of institutional investor holders are more likely to be bought in subsequent quarters.

In Table 7 I present regressions that jointly relate both positive (upgrades) and negative (downgrades) sell-side analyst information to subsequent negative (sell) investor information:

$$Sells_{i,t+1} = \beta_1 Upgrades_{i,t} + \beta_2 Downgrades_{i,t} + \beta_3 X_{i,t} + \delta_t + \epsilon_{i,t}. \tag{6}$$

The positive coefficient for *Upgrades* (β_1) in Column 1 of Table 7 indicates that hedge sell after sell-side analysts publish upgrade reports. In addition, the positive coefficient for *Downgrades* (β_2) in Column 1 indicates that after sell-side analysts publish downgrade reports fewer hedge funds sell. Both of these results are consistent with Table 5, and suggest that hedge funds trade in the opposite direction as sell-side analysts recommend.

In contrast, the coefficients for *Upgrades* (β_1) in Columns 2, 3, and 4 of Table 7 are positive. This indicates that fewer mutual funds, broker dealers, and pension funds sell after sell-side analysts publish upgrade reports. In addition, the coefficients for *Downgrades* (β_2) in Columns 3, 4, and 5 of are positive, which indicates that broker dealers, pension funds, and all 13-F filers when aggregated sell after sell-side analysts publish downgrade reports. Taken together, these results also support Table 5 and suggest that mutual funds, broker dealers, pension funds, and all 13-F filers tend to trade in the direction that sell-side analysts recommend, even one quarter after the analyst reports are published.

3.3. Are Sell-side Analysts Tipping the Hedge Funds?

Do hedge fund trades anticipate subsequent sell-side analyst reports because hedge funds independently acquire similar information faster than analysts? Or do hedge funds anticipate sell-side analyst reports as a result of private communications, such as those examined in Irvine, Lipson, and Puckett (2007)?

I first examine tipping by grouping sell-side analyst reports according to the specific day, within each quarter, that the reports are published. I then measure the extent to which hedge fund trades predict the reports published on each day of the following quarter. In Figure 1 I show the frequency of reports according to each intra-quarter trading day. I define reports published on (or within two days following) earnings release dates as *earnings season* reports, following Ivković and Jegadeesh (2004) and Altınkılıç and Hansen (2009). Earnings season reports are most frequent twenty trading days into each quarter, and non-earnings related sell-side analyst reports are published with relatively uniform intra-quarter frequency.

In the first panel of Figure 2 I present the β_1 coefficients from regressions similar to Equation (1), but with the analyst reports published only on the indicated intra-quarter trading day. The β_1 coefficients for the first several trading days of the quarter are positive and statistically significant, which is consistent with a pattern in which hedge funds predict analyst reports as a result of tipping. However, Figure 2 also shows that the β_1 coefficients are positive and statistically significant for the analyst reports published later into the quarter. This indicates that hedge fund trades predict analyst reports made 10, 20, even 30+ trading days into the following quarter, which is unlikely due to tipping. Taken together, these results suggest that analyst tipping may be occurring, but that tipping cannot entirely explain the degree to which hedge fund trades anticipate sell-side analyst reports.

To provide additional insight into tipping, I divide sell-side analyst reports by information content. The information in sell-side analyst *earnings season* reports generally overlaps with the information in company earnings releases, as discussed in Altınkılıç and Hansen (2009). In Column 2 of Table 8 I present the result of regressions similar to Equation (1) but in which I include only sell-side analyst *earnings season* reports when calculating $NetUpgrades_{i,t+1}$. The results indicate that hedge fund trades predict the direction of sell-side analyst *earnings season* reports, which suggests that hedge funds acquire company-specific information, related to quarterly earnings, faster than sell-side analysts.

I designate sell-side analyst reports not published on quarterly earnings release dates, but that move stock prices significantly, as *influential* reports, following Loh and Stulz (2011). In Column 4 of Table 8 I show that hedge fund trades also predict the direction of *influential* reports. In fact, as I show in Columns 3 and 5, hedge funds more strongly predict influential reports relative to other non-earnings season reports.[14] The fact that hedge funds anticipate *influential* suggests private communications of information between hedge funds and specific analysts. Finally, in Figure 2 I show that hedge funds predict *influential* analyst

[14] I use seemingly unrelated regressions to jointly estimate the results shown in Columns 3 and 4 of Table 8. This allows for comparison of the coefficients across the regressions, which I show in Column 5. As I cannot use fixed-effects in these regressions, I exclude data fixed effects from each regression in Table 8.

reports published after the first several trading days of the following quarter. This suggests private communications between hedge funds and sell-side analysts, but not tipping. Perhaps investors are the source of the information in *influential* analyst reports. I examine private communications involving information flows from investors to analysts in more detail below.

3.4. Do Hedge Funds Strategically Disclose Information to Sell-side Analysts?

In addition to private communications in which sell-side analysts privately communicate important information to investors, such as in Irvine, Lipson, and Puckett (2007), I investigate the extent to which investors privately communicate important information to analysts. The largest hedge funds pay the highest brokerage commissions, as shown in Goldstein et al. (2009). Therefore, I hypothesize that private communications from investors to sell-side analysts should result in larger hedge funds more strongly predicting sell-side analysts at larger brokerage firms, and smaller hedge funds more strongly predicting sell-side analysts at smaller brokerage firms. By contrast, if no private communications occur, size should have no relation to the extent to which hedge fund trades predict sell-side analyst reports.

Table 9 shows the results of the regressions outlined in Equations (7)-(9) which relate the direction of the trades of different sized hedge funds, with the direction of subsequent reports published by sell-side analysts employed by different sized brokerage firms. In order to rule-out sell-side analyst tipping and focus on high-information content analyst reports, I include only *influential* analyst reports published after the first 10 trading days of every quarter in the following regressions:

$$\text{Small } NetUpgr_{i,t+1} = \beta_1 \text{ Small } NetBuy_{i,t} + \beta_2 \text{ Med } NetBuy_{i,t} + \beta_3 \text{ Large } NetBuy_{i,t} + \epsilon_{i,t}, \quad (7)$$

$$\text{Med } NetUpgr_{i,t+1} = \beta_1 \text{ Small } NetBuy_{i,t} + \beta_2 \text{ Med } NetBuy_{i,t} + \beta_3 \text{ Large } NetBuy_{i,t} + \epsilon_{i,t}, \quad (8)$$

$$\text{Large } NetUpgr_{i,t+1} = \beta_1 \text{ Small } NetBuy_{i,t} + \beta_2 \text{ Med } NetBuy_{i,t} + \beta_3 \text{ Large } NetBuy_{i,t} + \epsilon_{i,t}. \quad (9)$$

Columns 1-3 of Table 9 show the results of estimating Equations (7)-(9) jointly using seemingly unrelated regression (SUR). This allows me to compare coefficients across the regressions: i.e. compare β_1 from Equation (7) with β_1 from Equation (9).[15] My tests comparing coefficients across regressions, shown in Column 4 of Table 9, compare similar-sized hedge funds to different-sized brokerage firm analysts. Consistent with strategic information disclosures, I find that the trades of large hedge funds more strongly correlate with large brokerage firm analysts (the β_3 coefficient of 1.82 in Column 3) relative to small brokerage firm analysts (the β_3 coefficient of 1.23 in Column 1). By contrast, the trades of small hedge funds correlate more strongly with small brokerage analysts (the β_1 coefficient of 2.32 Column 1) relative to large brokerage firm analysts (the β_1 coefficient of 0.52 Column 3).

In addition, I compare β_3 with β_1 coefficients within each regression outlined in Equations (7)-(9).[16] My tests comparing coefficients within each regression, shown in the last row of Table 9, compare different sized hedge funds with similar-sized brokerage firm analysts. In Column 5 of I show that overall, large hedge funds are no different from small hedge funds in predicting all sell-side analyst reports. However, I find that large hedge funds more strongly predict large brokerage firm analysts (the β_3 coefficient of 1.83 in Column 3) than do small hedge funds (the β_1 coefficient of 0.52 in Column 3). In addition, small hedge funds more strongly predict small brokerage firm analysts (the β_1 coefficient of 2.32 in Column 1) than do large hedge funds (the β_3 coefficient of 1.23 in Column 1).

Taken together, these results suggest a pattern consistent with my brokerage-commissions related private communications hypothesis. However, private information disclosures are challenging to empirically identify, and my tests cannot rule out alternative explanations. For example, my analysis cannot not rule out a pattern in which similarly sized hedge

[15]I compare coefficients using Chi-square tests: $\beta_{1,Large} - \beta_{1,Small} = 0$.

[16]I use F-tests to examine the difference of the two coefficients within the same regression: $\beta_3 - \beta_1 = 0$.

funds and brokerage firm analysts have correlated information acquisition processes. Such a phenomenon would probably manifest in similar results as I show in Table 9.

3.5. Do Hedge Funds Prefer to Fish in the Crowded Pools?

The early-informed investors in Hirshleifer, Subrahmanyam, and Titman (1994) prefer to *fish in crowded pools*, i.e. ex-ante prefer to investigate more well-known stocks. I establish above that hedge funds tend to get information faster than sell-side analysts, which suggests that in my setting sell-side analyst coverage may perform a similar function as the later informed investors in HST. Therefore, I investigate the extent to which hedge funds prefer high sell-side analyst coverage *crowded pools* by calculating hedge funds' risk-adjusted returns among stocks sorted intro tercile bins according to sell-side analyst coverage and size, in a manner similar to Hong, Lim, and Stein (2000).

In Table 4 of Appendix A I show a 3x3 matrix of stocks, sorted by size and (within size bins) by analyst coverage, in which each tercile bin contains roughly 300 stocks. For example, the smallest/lowest analyst coverage bin includes 297 stocks which average $200 million in market capitalization and 3 analysts covering. The stocks in the smallest/highest analyst coverage bin are one-third larger ($300 million) but have triple the number of analysts covering (9). I calculate risk-adjusted returns using the four factor model from Carhart (1997) for the weighted hedge fund performance for the stocks in each of these 9 bins. I also calculate risk adjusted hedge fund performance among small/median/large size bins, low/median/high analyst coverage bins, and for all stocks.

In Table 10 I show the risk-adjusted hedge fund performance among the bins that correspond to the stocks summarized in Table 4 of Appendix A. I find that overall, hedge funds generate risk adjusted returns averaging 10 basis points (0.10%) per month, which is consistent with Griffin and Xu (2009). More importantly, I find that hedge fund risk-adjusted performance increases with analyst coverage, but not with size. Risk-adjusted performance increases from left-to-right across the first three columns of Table 10, which correspond to (within size) number of analysts covering tercile bins. In Column 4 of Table 10 I show that hedge fund risk-adjusted performance is significantly higher among stocks with high analyst coverage (Column 3) than among stocks with low analyst coverage (Column 1).[17] Interestingly, hedge fund performance does not vary significantly according to size (moving from top-to-bottom in Table 10).

The positive relation between hedge fund performance and analyst coverage that I show in Table 10 does not in itself establish a causal relation between sell-side analyst coverage and hedge fund performance. However, I believe the fact that hedge funds generate better returns among more well-known *crowded pools* is quite surprising considering the results I show in Table 2 which indicate that hedge funds trade in the opposite direction as the analysts recommend. In conjunction with my findings that hedge funds tend to get information before sell-side analysts, I believe the positive relation between hedge fund performance and sell-side analyst coverage provides strong evidence that sell-side analysts assist hedge funds by making their information more widely known.

3.6. Trends in Active Investors, ETFs, and Sell-side Analysts

My final results document a shift in the composition of institutional investors, which has implications for analysts and overall information generation. In Figure A1 of Appendix A I show that over my sample period (2004-2014) the market share of mutual funds, broker dealers, and pension funds holdings has fallen dramatically: from 46% of all institutional equities holdings in 2004 to 29% in 2014. This is due to two factors: Barclays sale of iShares

[17] In order to compare factor model alpha coefficients I run the factor models jointly using seemingly unrelated regression and then compare using Chi-square tests: $\alpha_{large,lowcovg} - \alpha_{large,highcovg} = 0$, etc.

to Blackrock in 2009 (roughly 5 percentage points), and the decline of active mutual funds (roughly 10 percentage points). In Table 11 I examine the latter, and show that only 49 new active mutual funds opened during the 11 years from 2004-2014, while 777 closed. During this period ETFs grew in size and number as 1,639 new ETFs opened, while only 350 closed.

Given my findings that mutual funds rely heavily on sell-side analysts for information, while ETFs generally do not, I was surprised to find that sell-side analysts have flourished over this period. Specifically, as I show in Table 12, the number of sell-side analysts grew by 15% as 4,190 new publishing analysts were hired, while only 3,783 departed. Along with analysts and ETFs, hedge funds have grown in size and number from 2004-2014. The share of institutional investor equity holdings held by hedge funds grew from 3% to 8% over this period as 931 new hedge funds opened and only 555 closed. Taken together, these trends suggest that a large but shrinking share of investors use sell-side information to inform trades, while a small but growing share of investors are either agnostic to sell-side information (ETFs) or use sell-side information to exit previously initiated positions (hedge funds). These trends suggest that rather than generate information, analyst increasingly pass information between different groups of investors.

4. Conclusion

My results illustrate previously unexamined ways by which investors and sell-side analysts interact and incorporate information into stock prices. Specifically, I show that hedge funds anticipate sell-side analyst reports, which indicates that hedge fund trades incorporate new fundamental information into stock prices before the information is more broadly known. By contrast, and consistent with prior research including Kacperczyk and Seru (2007), I find that mutual funds, broker dealers, and pension funds do not anticipate sell-side analysts and rely heavily on the information contained in sell-side reports.

I also find that hedge funds anticipate high information content analyst reports, such as those examined in Loh and Stulz (2011), which are published after the first week of the following quarter. In addition, hedge funds most strongly predict reports published by analysts at similarly sized sell-side largest brokerage firms. These results are consistent with a pattern in which hedge funds strategically disclose their private information to sell-side analysts, in a similar manner as examined in Ljungqvist and Qian (2016), in order to speed the incorporation of private information into stock prices. These strategic information disclosures suggest an additional mechanism by which hedge funds, or any early informed investor, incorporate information into prices.

Finally, my results suggest that, despite trading in the opposite direction as sell-side analyst reports recommend, hedge funds generate higher risk adjusted returns among stocks with higher sell-side analyst coverage. These results are consistent with Hirshleifer, Subrahmanyam, and Titman (1994), which illustrates that early-informed investors have the greatest advantages when the trading in *crowded pools*. Helping early informed investors profitably exploit information acquisition efforts suggests an alternative mechanism by which sell-side analysts contribute to a robust information environment.

Appendix A: Supporting Data

In this Appendix I present additional detail regarding institutional investors of different types, sell-side analyst brokerage firms, and individual sell-side analysts.

Figure A1 shows the progression of the market value of the aggregated holdings of my samples of hedge funds, mutual funds, broker/dealer asset managers, and pension funds from 2004-2014. The holdings of my samples of institutional investors account for roughly 28% of aggregate value of equity market capitalization over this period.

Table 1 shows summary statistics for my samples of hedge funds, mutual funds, broker/dealer asset managers, pension funds, and all 13-F filers aggregated. These data include only positions in common equity securities traded on public exchanges as reported by quarterly holdings disclosures.

Table 2 shows the largest individual institutional investor firms within each of my samples. The individual firms are ranked by the average value of their holdings from 2004-2014.

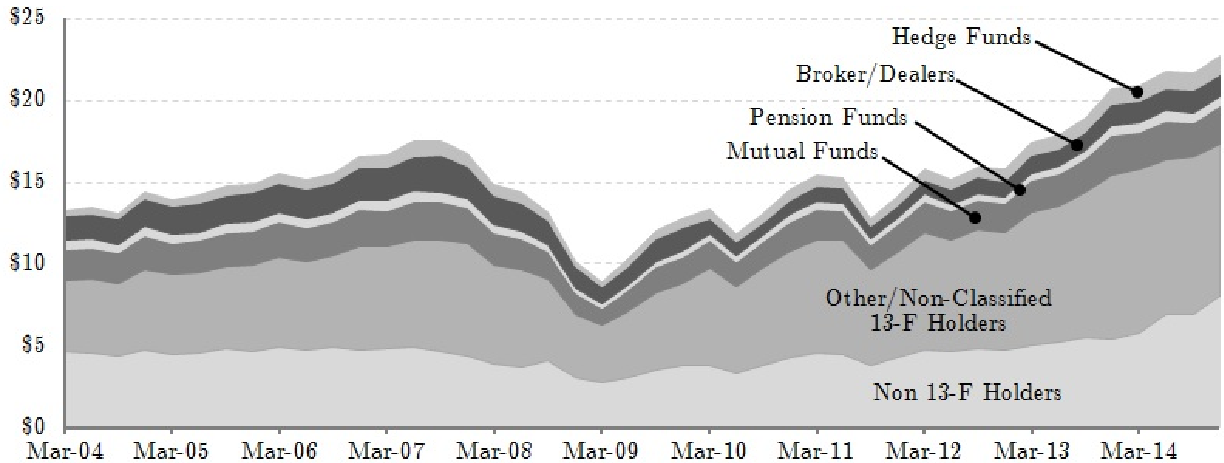
Table 3 shows the largest 25 individual sell-side brokerage firms according to the number of sell-side analysts in my sample. Data for no longer independent brokerage firms such as Merrill Lynch, Lehman, and Bear Stearns represent average number of analysts employed by these firms during the periods from 2004-2014 during which they were independent.

Table 4 shows the average size, number of analysts covering, and number of stocks for each of the tercile bins underlying the analysis presented in Table 10.

Figure A1: Trends in the Value of Institutional Asset Manager Holdings

In this figure I show the value, and relative share, of the aggregated holdings for my samples of hedge funds, mutual funds, broker/dealers, and pension funds. The Other/Non-Classified category represents the holdings of the 13-F filings not included in the above samples. The Non 13-F Holders category represents the value left over after deducting all 13-F holdings from total shares outstanding from each company. The holdings data are from quarterly mutual fund and 13-F holdings filings, and the shares outstanding data are from CRSP from 2004-2014. The share of institutional holdings panel excludes Non 13-F holders.

Value ($ trillion)



Share of Institutional Holdings

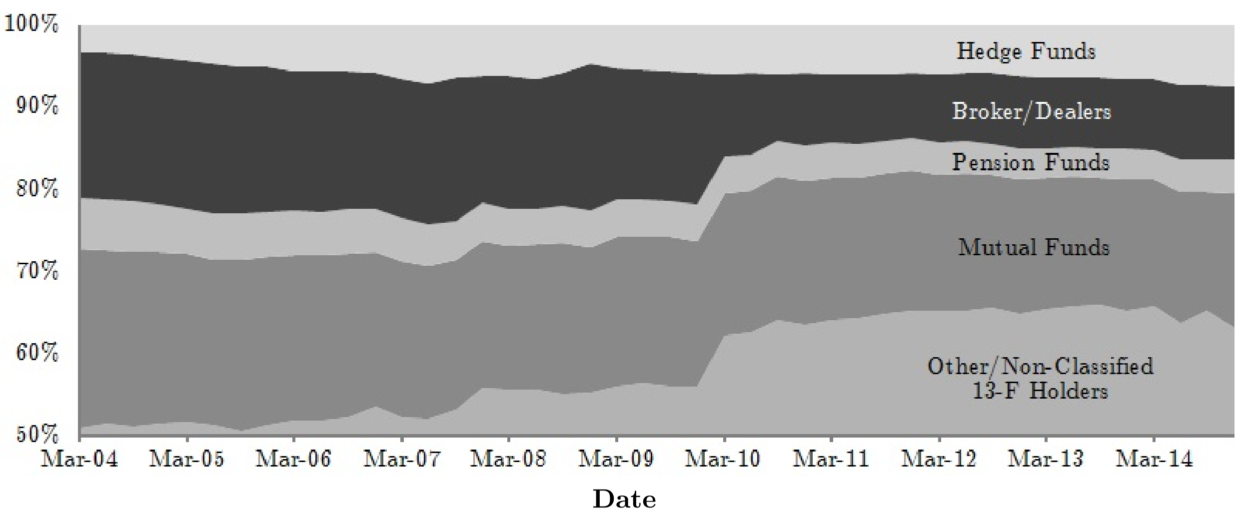


Table 1: Institutional Investor and Brokerage Firm Summary Statistics

In this table I present summary statistics for my samples of hedge funds, mutual funds, broker dealer asset managers, pension funds, all 13-F filers, and sell-side analyst brokerage firms. I describe the construction of the investor samples in Section 2.1 and sell-side analyst samples in Section 2.2. The summary statistics presented below reflect averages for each institutional investor and analyst brokerage firm over the quarters from 2004-2014.

	Mean	Median	Std Dev	Min	Max	n
Hedge Funds						
Portfolio Size	$756	$210	$2,019	$0.1	$31,494	1,356
Number of Pos	87	33	202	1	2,617	1,356
Turnover	24%	23%	14%	0%	76%	1,356
Mutual Funds						
Portfolio Size	$1,015	$182	$3,962	$0.0	$102,252	2,394
Number of Pos	94	59	154	1	2,486	2,394
Turnover	12%	11%	9%	0%	65%	2,394
Broker Dealers						
Portfolio Size	$16,000	$559	$46,857	$3.0	$341,393	113
Number of Pos	852	383	1,200	1	5,038	113
Turnover	17%	11%	14%	0%	55%	113
Pension Funds						
Portfolio Size	$18,191	$10,037	$23,293	$115.3	$116,367	38
Number of Pos	1,327	1,181	932	27	3,970	38
Turnover	7%	6%	9%	1%	48%	38
All 13-F Filers						
Portfolio Size	$1,779	$235	$8,855	$0.1	$341,393	5,541
Number of Pos	182	66	392	1	5,038	5,541
Turnover	13%	9%	13%	0%	83%	5,541
Sell-side Analyst Firms						
Analysts Employed	8	2	19	1	214	646
Companies Covered	72	12	177	1	1,337	646

Table 2: Summary of Individual Institutional Investors

In this table I show summary data for the five largest individual investors in each of my samples of hedge funds, mutual funds, broker/dealer asset managers, and pension funds based on quarterly equity holdings reported on 13-F forms, and mutual fund holdings disclosures, from 2004-2014. I describe the construction of each investor sample in Section 2.1.

Fund Name	Size $bn	# Positions	Turnover
Hedge Funds			
D. E. SHAW & CO., L.P.	$31,494	2,031	22%
RENAISSANCE TECHNOLOGIES LLC	$31,465	2,617	34%
CITADEL LLC	$23,844	2,289	35%
ADAGE CAPITAL MANAGEMENT, L.P.	$21,441	609	17%
AQR CAPITAL MANAGEMENT, LLC	$15,515	1,638	16%
Mutual Funds			
GROWTH FUND OF AMERICA	$102,252	221	6%
FIDELITY CONTRAFUND	$63,523	322	11%
WASHINGTON MUTUAL INVEST	$61,783	123	5%
INVESTMENT COMPANY OF AM	$53,174	131	5%
DODGE & COX STOCK FUND	$44,959	77	4%
Broker/Dealers			
BARCLAYS BANK PLC	$341,393	3,799	7%
JPMORGAN CHASE & COMPANY	$194,828	2,904	9%
MSDW & COMPANY	$179,452	4,156	8%
GOLDMAN SACHS & COMPANY	$156,732	3,653	12%
BANK OF AMERICA CORPORATION	$141,633	3,999	7%
Pension Funds			
COLLEGE RETIRE EQUITIES (TIAA-CREF)	$116,367	3,094	6%
NEW YORK STATE COMMON RET SYS	$54,861	2,023	3%
CALIFORNIA PUBLIC EMP' RET SYS	$53,505	3,970	3%
NEW YORK STATE TEACH' RET SYS	$40,355	1,589	2%
CALIFORNIA STATE TEACH RET SYS	$33,115	2,132	2%
All 13-F Filers			
VANGUARD GROUP, INC.	$639,629	3,896	1%
STATE STR CORPORATION	$579,727	3,623	2%
FIDELITY MGMT & RESEARCH CO	$551,468	2,725	9%
CAPITAL RESEARCH & MGMT CO	$472,615	749	4%
BARCLAYS BANK PLC	$341,393	3,799	7%

Table 3: Summary of Individual Sell-side Analyst Brokerage Firms

In this table I present the names of largest individual brokerage firms in my sample as ranked by the number of sell-side analysts employed on average from 2004-2014. I describe the sell-side analyst data in Section 2.2.

Brokerage Firm Name	Average Analysts	Average Covered Companies	Total Upgrade Reports	Total Downgrade Reports
MERRILL LYNCH	214	1,337	3,520	4,069
J.P. MORGAN	158	1,293	2,499	2,724
UBS	118	913	2,258	2,400
CITIGROUP	117	1,052	2,579	2,535
BEAR STEARNS	112	857	752	720
CREDIT SUISSE	110	990	1,735	1,953
GOLDMAN SACHS	110	1,054	2,517	2,856
DEUTSCHE BANK	107	897	1,632	1,904
LEHMAN	104	1,113	731	717
RAYMOND JAMES	104	856	2,345	2,758
MORGAN STANLEY	102	901	1,594	1,803
RBC	88	804	1,403	1,611
BARCLAYS	76	1,031	784	943
JEFFERIES	73	739	1,644	1,634
MORNINGSTAR	70	795	1,928	1,896
EDWARDS	69	662	355	508
STIFEL NICOLAUS	68	838	1,621	1,863
BANK OF AMERICA	67	833	660	735
WACHOVIA	63	807	1,552	1,806
SIDOTI	54	530	1,411	1,614
ROBERT W. BAIRD	50	591	1,367	1,551
OPPENHEIMER	45	516	797	1,032
BMO NESBITT BURNS	45	464	1,144	1,270
LEGG MASON WOOD WALKER	45	447	202	217
WILLIAM BLAIR & CO	43	438	425	622

Table 4: Analyst Coverage and Size Tercile Bins

In this table I present summary data for tercile sorts of stocks sorted by size and (within size bins) by analyst coverage, as described in Section 3.5. These data relate to the analysis of hedge fund performance presented in Table 10. Specifically, I show the average size ($ billions), average number of analysts covering, and the average number of stocks in each tercile bin between 2004-2014.

	Number of Analysts Covering Terciles:				
	1 Low Analysts Covering	2 Median Analysts Covering	3 High Analysts Covering	3-1	All Analysts Covering
1) Small					
Size	$0.2	$0.3	$0.3	$0.1	$0.3
Analysts	3	5	9	6	6
# stocks	297	297	297		891
2) Median					
Size	$1.1	$1.2	$1.3	$0.3	$1.2
Analysts	5	8	15	10	9
# stocks	297	297	297		891
3) Large					
Size	$6.0	$11.7	$31.3	$25.3	$16.3
Analysts	8	16	26	17	16
# stocks	297	297	296		890
3-1					
Size	$5.8	$11.5	$31.0		$16.1
Analysts	5	11	17		11
All Sizes					
Size	$2.4	$4.4	$11.0	$8.6	$5.9
Analysts	5	9	16	11	10
# stocks	892	891	890		2,672

Appendix B: Robustness Tests

In this section I present robustness tests which extend and support the analysis I present in Tables 3 and 4 which I discuss in Section 3.1. Specifically, I show that the statistical relation between the direction of hedge fund trades and the direction of subsequent sell-side analyst reports is robust to different controls, different fixed-effects, and count data regression specifications.

In Table 1 I show regressions assessing the relation between hedge fund buying and selling, and subsequent sell-side analyst upgrades which follow the structure of Equation (2) of Section 3.1. The positive coefficients for $HFbuys$ indicate hedge fund buying positively correlates with subsequent analyst upgrades. The negative coefficients for $HFsells$ indicate hedge fund selling negatively correlates with subsequent analyst upgrades, when controlling for hedge fund buying. Column 3 of Table 1 is identical to Column 1 of Table 3. The other columns of Table 1 indicate that the results presented in Table 3, for hedge funds, are robust to different controls, fixed effects, and count data regressions models.

In Table 2 I show regressions assessing the relation between hedge fund buying and selling, and subsequent sell-side analyst downgrades, which follow the structure of Equation (3) of Section 3.1. The negative coefficients for $HFbuys$ indicate hedge fund buying negatively correlates with subsequent analyst downgrades. The positive coefficients for $HFsells$ indicate hedge fund selling positively correlates with subsequent analyst upgrades, when controlling for hedge fund buying. Similar to the above, Column 3 of Table 2 is identical to Column 1 of Table 4. The other columns of Table 2 indicate that the results presented in Table 4, for hedge funds, are robust to different controls, fixed effects, and count data regressions models.

Table 1: Hedge Fund Trades and Sell-side Analyst Upgrade Reports

In this table I present OLS, Poisson, and negative binomial regressions assessing the relation between hedge fund buying and selling and subsequent sell-side analyst upgrade reports. The dependent variable is: $Upgr_{i,t+1}$ which is the number of sell-side analyst upgrade reports published. The independent variables of interest are: $Buys_{i,t}$ with is the number of hedge funds buying, and $Sells_{i,t}$ which is the number of hedge funds selling. All independent variables are de-meaned and scaled by standard deviation within firm. Controls include $Return_{i,t}$; 1-quarter return, $Analysts_{i,t}$; number of analysts covering, and $Turnover_{i,t}$; quarterly turnover. The data are stock (i) level at quarterly (t) frequency from 2004-2014. Standard errors are clustered by 2-digit SIC and T-stats are presented in parentheses: ***/**/* indicates significance at 1%/5%/10%.

	(1) $Upgr_{i,t+1}$	(2) $Upgr_{i,t+1}$	(3) $Upgr_{i,t+1}$	(4) $Upgr_{i,t+1}$	(5) $Upgr_{i,t+1}$	(6) $Upgr_{i,t+1}$	(7) $Upgr_{i,t+1}$
Hedge Funds:							
$Buys_{i,t}$	1.96***	0.18	1.18**	2.05***	1.15**	0.02*	0.02*
	(3.82)	(0.36)	(2.27)	(3.41)	(2.17)	(1.88)	(1.70)
$Sells_{i,t}$	-2.13***	-3.60***	-2.86***	-1.38***	-2.72***	-0.05***	-0.05***
	(-4.96)	(-9.25)	(-7.61)	(-2.92)	(-6.47)	(-5.59)	(-6.12)
$Return_{i,t}$		0.86*	0.10	0.54	-1.66***	0.01	0.01
		(1.82)	(0.22)	(1.12)	(-4.09)	(1.46)	(1.59)
$Analysts_{i,t}$		47.29***	48.08***	22.47***	48.47***	0.93***	0.93***
		(22.05)	(22.32)	(8.38)	(22.76)	(56.63)	(52.78)
$Rating_{i,t}$		-30.79***	-28.83***	-56.65***	-28.74***	-0.70***	-0.72***
		(-16.26)	(-15.90)	(-24.28)	(-22.01)	(-17.17)	(-17.11)
$Turnover_{i,t}$		9.03***	8.00***	4.62***	5.45***	0.08***	0.11***
		(5.62)	(5.96)	(3.74)	(4.82)	(7.40)	(5.56)
Intercept	54.45***	-42.78***	-44.65***	26.06***		-2.64***	-2.65***
	(25.98)	(-11.17)	(-11.78)	(4.57)		(-49.83)	(-51.79)
Model	OLS	OLS	OLS	OLS	OLS	Poisson	NegBin
Fixed-Effects	None	None	Date	Firm	Date×SIC	None	None
Observations	88,886	88,886	88,886	88,886	88,886	88,886	88,886
F-Statistic	35.20	236.9	236.8	172.9	250.5		
R^2	0.001	0.158	0.174	0.247	0.321		
χ^2						7988	7374

Table 2: Hedge Fund Trades and Sell-side Analyst Downgrade Reports

In this table I present OLS, Poisson, and negative binomial regressions assessing the relation between hedge fund buying and selling and subsequent sell-side analyst downgrade reports. The dependent variable is: $Dngr_{i,t+1}$ which is the number of sell-side analyst downgrade reports published. The independent variables of interest are: $Buys_{i,t}$ with is the number of hedge funds buying, and $Sells_{i,t}$ which is the number of hedge funds selling. All independent variables are de-meaned and scaled by standard deviation within firm. Controls include $Return_{i,t}$; 1-quarter return, $Analysts_{i,t}$; number of analysts covering, and $Turnover_{i,t}$; quarterly turnover. The data are stock (i) level at quarterly (t) frequency from 2004-2014. Standard errors are clustered by 2-digit SIC and T-stats are presented in parentheses: ***/**/* indicates significance at 1%/5%/10%.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$Dngr_{i,t+1}$	$Dngr_{i,t+1}$	$Dngr_{i,t+1}$	$Dngr_{i,t+1}$	$Dngr_{i,t+1}$	$Dngr_{i,t+1}$	$Dngr_{i,t+1}$
Hedge Funds:							
$Buys_{i,t}$	-1.47***	-5.11***	-2.57***	-6.51***	-2.07***	-0.07***	-0.08***
	(-2.85)	(-10.18)	(-5.26)	(-11.24)	(-3.98)	(-8.61)	(-8.75)
$Sells_{i,t}$	4.39***	0.49	2.05***	-0.90**	2.09***	0.01**	0.01
	(6.85)	(1.28)	(4.86)	(-2.11)	(5.37)	(2.09)	(0.86)
$Return_{i,t}$		-1.04	0.71	-1.54**	1.70***	-0.02**	-0.01
		(-1.59)	(1.26)	(-2.37)	(3.01)	(-2.01)	(-1.08)
$Analysts_{i,t}$		50.84***	51.72***	52.69***	52.22***	0.85***	0.84***
		(24.07)	(24.99)	(14.50)	(24.63)	(57.67)	(60.65)
$Rating_{i,t}$		23.53***	24.39***	63.24***	27.99***	0.40***	0.46***
		(10.66)	(11.66)	(32.56)	(12.47)	(9.16)	(10.63)
$Turnover_{i,t}$		11.75***	10.83***	10.91***	8.66***	0.08***	0.18***
		(5.58)	(5.74)	(4.95)	(5.55)	(5.79)	(6.79)
Intercept	62.24***	-68.05***	-69.75***	-88.55***		-2.74***	-2.83***
	(26.70)	(-15.86)	(-16.91)	(-11.44)		(-48.10)	(-56.43)
Model	OLS	OLS	OLS	OLS	OLS	Poisson	NegBin
Fixed-Effects	None	None	Date	Firm	Date×SIC	None	None
Observations	88,886	88,886	88,886	88,886	88,886	88,886	88,886
F-Statistic	35.12	205.2	235.7	268.4	210.4		
R^2	0.002	0.127	0.145	0.214	0.296		
χ^2						4002	5372

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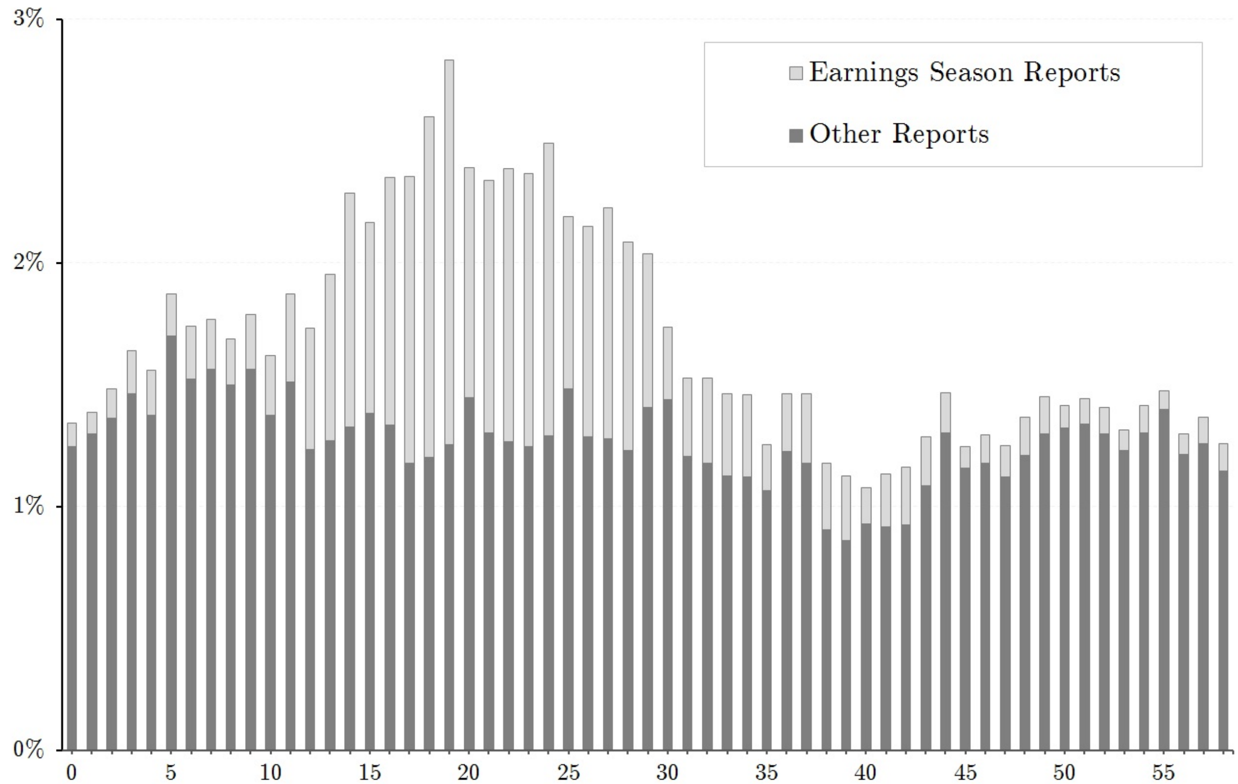
Figure 1: Intra-Quarter Sell-side Analyst Reports Frequency

In this figure I show the frequency of sell-side analyst upgrade and downgrade reports according to each within-quarter trading day. I define *earnings season* reports as reports published with the three days including and following company earnings announcements, as discussed in Sections 2.2 and 3.3. The data include quarters from 2004-2014.

Sell-side Reports Frequency



Trading Days From Start of Quarter

Figure 2: Intra-Quarter Sell-side Analyst Reports Correlations

In this figure I show the correlations between the direction of upgrade and downgrade reports published by sell-side analysts (published on each intra-quarter day) and the direction of hedge fund trades in the prior quarter. Each dot represents a β_1 coefficient from Equation (1) as discussed in Section 3.3, and each line represents a 95% confidence interval. *Earnings Season* reports are those published within 3 days including and following company earnings reports, and *Influential* reports are those with significant relative stock price reactions, as in Loh and Stulz (2011) and discussed in Section 2.2. The data include quarters from 2004-2014.

Correlation (β) With Prior Hedge Fund Trades

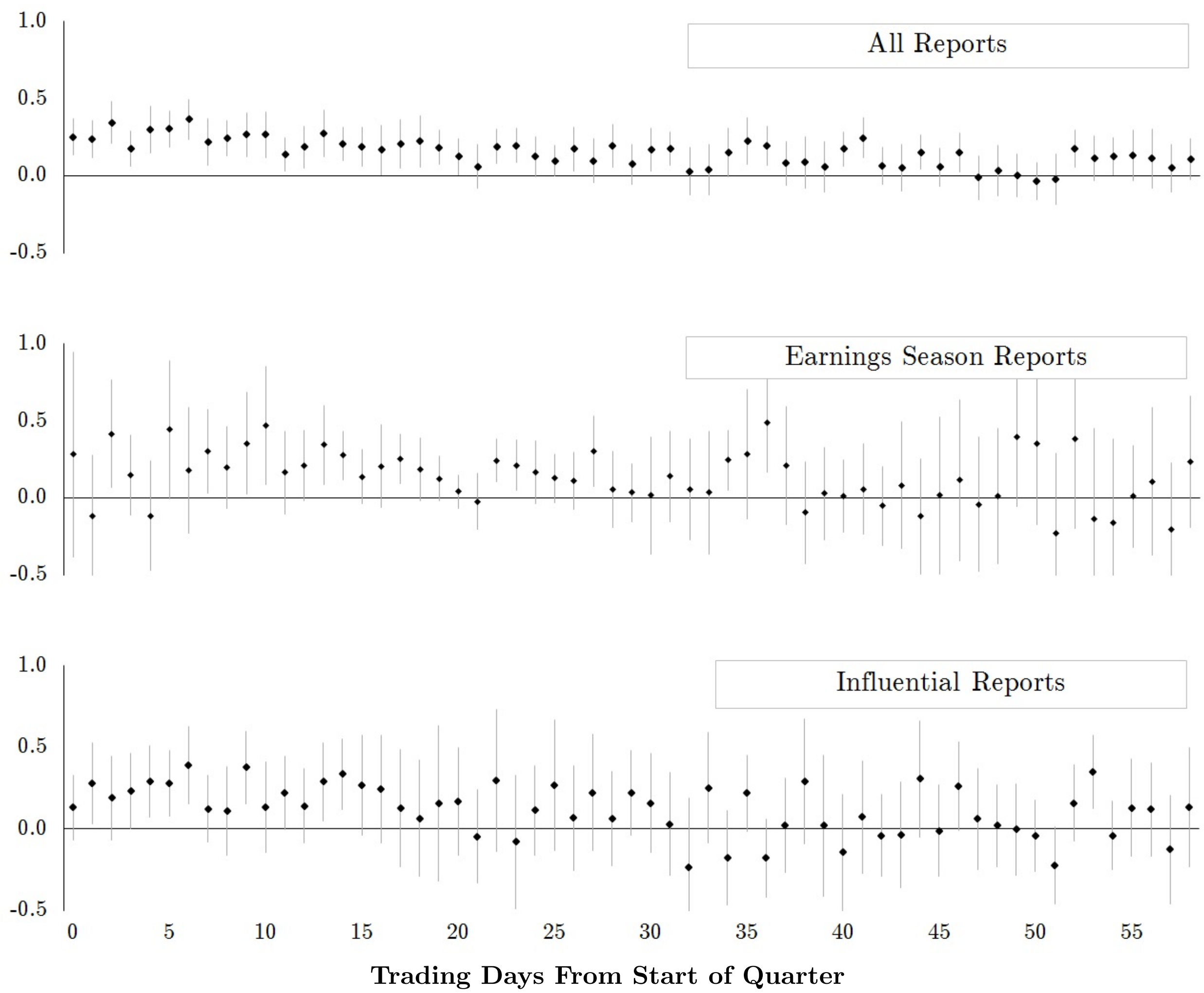


Table 1: Regressions Variables Summary Statistics

In this table I present summary statistics for my regressions variables, which I define in Sections 2.1 and 2.2, for the quarterly panel of stocks with at least two analysts covering between 2004-2014 as described in Section 2.3. I provide additional data in Table 1.

	Mean	Median	Std Dev	Min	Max	n
Hedge Funds						
$Buys_{i,t}$	12.6	10.0	10.5	0	187	94,174
$Sells_{i,t}$	12.7	10.0	10.7	0	152	94,174
$NetBuys_{i,t}$	(0.1)	0.0	7.0	(21)	20	94,174
$Holders_{i,t}$	21.5	17.0	17.9	0	240	94,174
Mutual Funds						
$Buys_{i,t}$	20.4	13.0	23.7	0	529	94,174
$Sells_{i,t}$	22.3	14.0	27.2	0	348	94,174
$NetBuys_{i,t}$	(2.1)	(1.0)	11.3	(45)	30	94,174
$Holders_{i,t}$	56.2	37.0	63.8	1	798	94,174
Broker Dealers						
$Buys_{i,t}$	9.0	8.0	5.1	0	58	94,174
$Sells_{i,t}$	8.5	8.0	4.9	0	43	94,174
$NetBuys_{i,t}$	0.5	0.0	4.8	(12)	14	94,174
$Holders_{i,t}$	18.0	16.0	9.0	0	62	94,174
Pension Funds						
$Buys_{i,t}$	4.3	4.0	3.3	0	31	94,174
$Sells_{i,t}$	4.9	4.0	4.1	0	28	94,174
$NetBuys_{i,t}$	(0.6)	0.0	3.9	(12)	10	94,174
$Holders_{i,t}$	11.3	11.0	6.8	0	31	94,174
All 13-F Filers						
$Buys_{i,t}$	96.7	70.0	93.8	0	2081	94,174
$Sells_{i,t}$	98.6	66.0	104.2	0	1060	94,174
$NetBuys_{i,t}$	(2.2)	1.0	31.8	(135)	100	94,174
$Holders_{i,t}$	212.3	143.0	219.6	1	2124	94,174
Analysts						
$Upgrades_{i,t}$	0.5	0.0	0.9	0	4	94,841
$Downgrades_{i,t}$	0.6	0.0	1.0	0	5	94,841
$NetUpgrades_{i,t}$	(0.1)	0.0	1.2	(4)	3	94,841
$Analysts_{i,t}$	10.9	9.0	7.6	2	61	94,841
$Rating_{i,t}$	0.4	0.5	0.3	(1.0)	1.0	94,841

Table 2: Investor Trades and Sell-side Analyst Reports

In this table I present OLS regressions assessing the relation between the direction of investor trades and the direction of subsequent sell-side analyst ratings change reports. The dependent variable is $NetUpgr_{i,t+1}$, which is the number of sell-side analyst upgrade reports minus the number of sell-side analyst downgrade reports published. The independent variables of interest are $NetBuys_{i,t}$ which is the number of investors buying minus the number selling. The columns correspond to the $NetBuys_{i,t}$ of hedge funds, mutual funds, broker/dealer asset managers, pension funds, and all 13-F filing institutions respectively. All independent variables are de-meaned and scaled by standard deviation within firm. The data are stock (i) level at quarterly (t) frequency from 2004-2014. Standard errors are clustered by 2-digit SIC and T-statistics presented in parentheses: ***/**/* indicates significance at 1%/5%/10%.

	(1) $NetUpgr_{i,t+1}$	(2) $NetUpgr_{i,t+1}$	(3) $NetUpgr_{i,t+1}$	(4) $NetUpgr_{i,t+1}$	(5) $NetUpgr_{i,t+1}$
Hedge Funds:					
$NetBuys_{i,t}$	5.14***				
	(9.23)				
Mutual Funds:					
$NetBuys_{i,t}$		0.10			
		(0.31)			
Broker/Dealers:					
$NetBuys_{i,t}$			-0.54		
			(-1.62)		
Pension Funds:					
$NetBuys_{i,t}$				0.46	
				(1.11)	
All 13-F Filers:					
$NetBuys_{i,t}$					0.14
					(0.31)
$Return_{i,t}$	-1.48**	-1.93***	-2.20***	-2.18***	-2.22***
	(-2.00)	(-2.71)	(-2.93)	(-2.94)	(-2.99)
Intercept	-0.82***	-0.84***	-0.81***	-0.81***	-0.81***
	(-4.87)	(-5.00)	(-4.95)	(-4.97)	(-4.96)
Fixed Effects	Date	Date	Date	Date	Date
Observations	88,886	88,886	88,886	88,886	88,886
F-Statistic	50.14	4.492	4.897	5.196	4.362
R^2	0.022	0.019	0.019	0.019	0.019

Table 3: Investor Trades and Sell-side Analyst Upgrade Reports

In this table I present OLS regressions assessing the relation between investor buying and selling and subsequent sell-side analyst upgrade reports. The dependent variable is: $Upgr_{i,t+1}$; the number of sell-side analyst upgrade reports published. The independent variables are: $Buys_{i,t}$; the number of investors buying, and $Sells_{i,t}$; the number of investors selling. The columns correspond to hedge funds, mutual funds, broker/dealer asset managers, pension funds, and all 13-F filing institutions respectively. All independent variables are de-meaned and scaled by standard deviation within firm. Controls include *Return*; 1-quarter return, $Analysts_{i,t}$; number of sell-side analysts covering, $Rating_{i,t}$; average sell-side analyst buy/sell/hold rating, and $Turnover_{i,t}$; quarterly turnover. Data are stock (i) level at quarterly (t) frequency from 2004-2014. I cluster standard errors by 2-digit SIC and present T-stats in parentheses: ***/**/* indicates significance at 1%/5%/10%.

	(1) $Upgr_{i,t+1}$	(2) $Upgr_{i,t+1}$	(3) $Upgr_{i,t+1}$	(4) $Upgr_{i,t+1}$	(5) $Upgr_{i,t+1}$
Hedge Funds:					
$Buys_{i,t}$	1.18**				
	(2.27)				
$Sells_{i,t}$	-2.86***				
	(-7.61)				
Mutual Funds:					
$Buys_{i,t}$		1.79***			
		(4.24)			
$Sells_{i,t}$		-0.46			
		(-1.09)			
Broker/Dealers:					
$Buys_{i,t}$			-0.59		
			(-1.18)		
$Sells_{i,t}$			-1.13**		
			(-2.18)		
Pension Funds:					
$Buys_{i,t}$				0.22	
				(0.59)	
$Sells_{i,t}$				-1.98***	
				(-5.40)	
All 13-F Filers:					
$Buys_{i,t}$					0.03
					(0.07)
$Sells_{i,t}$					-2.59***
					(-5.50)
$Return_{i,t}$	0.10	-0.06	-0.11	-0.17	-0.41
	(0.22)	(-0.12)	(-0.23)	(-0.34)	(-0.82)
$Analysts_{i,t}$	48.08***	47.89***	48.03***	48.11***	48.25***
	(22.32)	(22.51)	(22.43)	(22.55)	(22.75)
$Rating_{i,t}$	-28.83***	-30.13***	-29.16***	-29.54***	-28.94***
	(-15.90)	(-16.37)	(-15.84)	(-16.09)	(-16.48)
$Turnover_{i,t}$	8.00***	7.76***	8.01***	7.91***	8.14***
	(5.96)	(5.70)	(5.77)	(5.67)	(5.82)
Intercept	-44.65***	-43.50***	-44.37***	-44.35***	-45.05***
	(-11.78)	(-11.88)	(-11.83)	(-11.89)	(-12.39)
Fixed Effects	Date	Date	Date	Date	Date
Observations	88,886	88,886	88,886	88,886	88,886
R^2	0.174	0.174	0.173	0.174	0.174

Table 4: Investor Trades and Sell-side Analyst Downgrade Reports

In this table I present OLS regressions assessing the relation between investor buying and selling and subsequent sell-side analyst downgrade reports. The dependent variable is: $Dngr_{i,t}$; the number of sell-side analyst downgrade reports published for stock i during quarter t. The independent variables are: $Buys_{i,t}$; the number of investors buying, and $Sells_{i,t}$; the number of investors selling. The columns correspond to hedge funds, mutual funds, broker/dealer asset managers, pension funds, and all 13-F filing institutions respectively. All independent variables are de-meaned and scaled by standard deviation within firm. Controls include $Return_{i,t}$; 1-quarter return, $Analysts_{i,t}$; number of sell-side analysts covering, $Rating_{i,t}$; average analyst buy/sell/hold rating, and $Turnover_{i,t}$; quarterly turnover. Data are stock (i) level at quarterly (t) frequency from 2004-2014. I cluster standard errors by 2-digit SIC and present T-stats in parentheses: ***/**/* indicates significance at 1%/5%/10%.

	(1) $Dngr_{i,t+1}$	(2) $Dngr_{i,t+1}$	(3) $Dngr_{i,t+1}$	(4) $Dngr_{i,t+1}$	(5) $Dngr_{i,t+1}$
Hedge Funds:					
$Buys_{i,t}$	-2.57***				
	(-5.26)				
$Sells_{i,t}$	2.05***				
	(4.86)				
Mutual Funds:					
$Buys_{i,t}$		2.10***			
		(3.31)			
$Sells_{i,t}$		1.48***			
		(3.89)			
Broker/Dealers:					
$Buys_{i,t}$			3.27***		
			(5.10)		
$Sells_{i,t}$			3.07***		
			(7.58)		
Pension Funds:					
$Buys_{i,t}$				1.23*	
				(1.95)	
$Sells_{i,t}$				2.84***	
				(6.48)	
All 13-F Filers:					
$Buys_{i,t}$					2.68***
					(4.13)
$Sells_{i,t}$					4.15***
					(9.30)
$Return_{i,t}$	0.71	1.15**	1.10*	1.01*	1.35**
	(1.26)	(2.11)	(1.96)	(1.80)	(2.49)
$Analysts_{i,t}$	51.72***	51.50***	51.41***	51.47***	51.04***
	(24.99)	(25.50)	(25.24)	(25.08)	(25.47)
$Rating_{i,t}$	24.39***	22.81***	23.52***	24.37***	22.55***
	(11.66)	(11.04)	(11.12)	(11.63)	(10.94)
$Turnover_{i,t}$	10.83***	10.24***	10.21***	10.49***	9.87***
	(5.74)	(5.69)	(5.73)	(5.78)	(5.64)
Intercept	-69.75***	-68.27***	-68.40***	-68.95***	-66.90***
	(-16.91)	(-17.51)	(-16.95)	(-16.97)	(-17.39)
Observations	88,886	88,886	88,886	88,886	88,886
R^2	0.145	0.145	0.145	0.145	0.146

Table 5: Investor Reactions to Sell-side Analyst Reports

In this table I present OLS regressions assessing the relation between sell-side analyst upgrade and downgrade reports, and the direction of subsequent institutional investor's trades. The dependent variables are $NetBuys_{i,t+1}$, which is the number of buyers minus the number of sellers for hedge funds, mutual funds, broker/dealer asset managers, pension funds, and all 13-F filing institutions respectively. The independent variables are $NetUpgrades_{i,t}$ which is the number of sell-side analyst upgrade reports minus the number of analyst downgrade reports published. All independent variables are de-meaned and scaled by standard deviation within firm. The data are stock (i) level at quarterly (t) frequency from 2004-2014. Standard errors are clustered by 2-digit SIC and T-stats are presented in parentheses: ***/**/* indicates significance at 1%/5%/10%.

	(1) Hedge Funds $NetBuys_{i,t+1}$	(2) Mutual Funds $NetBuys_{i,t+1}$	(3) Broker Dealers $NetBuys_{i,t+1}$	(4) Pension Funds $NetBuys_{i,t+1}$	(5) All 13-F Filers $NetBuys_{i,t+1}$
$NetUpgrades_{i,t}$	-3.72***	7.40***	2.52***	3.38***	4.22***
	(-7.22)	(22.13)	(6.92)	(9.87)	(7.23)
$Return_{i,t}$	8.03***	8.45***	10.28***	7.30***	14.06***
	(13.21)	(10.59)	(15.32)	(12.23)	(17.55)
Intercept	-0.40***	-2.66***	-1.43***	-4.35***	-3.32***
	(-2.88)	(-10.57)	(-10.01)	(-7.91)	(-13.72)
Fixed Effects	Date	Date	Date	Date	Date
Observations	88,238	88,238	88,238	88,238	88,238
F-Statistic	90.32	296.6	148.8	123.7	158.5
R^2	0.039	0.035	0.082	0.110	0.070

Table 6: Investor Buying After Sell-side Analyst Reports

I this table I present OLS regressions assessing the relation between sell-side analyst upgrade and downgrade reports, and subsequent institutional investor buying. The dependent variables are $Buys_{i,t+1}$, which is the number of investors buying for hedge funds, mutual funds, broker/dealer asset managers, pension funds, and all 13-F filing institutions respectively. The independent variables of interest is $Upgrades_{i,t}$ which is the number of sell-side analyst upgrade reports and $Downgrades_{i,t}$ the number of sell-side analyst downgrade reports published. The dependent variables are de-meaned and scaled by standard deviation within firm. Controls include $Return_{i,t}$; the 1-quarter return, and $Holders_{i,t}$ the number of holders for each institutional investor type. The data are stock (i) level at quarterly (t) frequency from 2004-2014. Standard errors are clustered by 2-digit SIC and T-stats are presented in parentheses: ***/**/* indicates significance at 1%/5%/10%.

	(1) Hedge Funds $Buys_{i,t+1}$	(2) Mutual Funds $Buys_{i,t+1}$	(3) Broker Dealers $Buys_{i,t+1}$	(4) Pension Funds $Buys_{i,t+1}$	(5) All 13-F Filers $Buys_{i,t+1}$
$Upgrades_{i,t}$	-0.09	3.25***	0.21	2.14***	2.46***
	(-0.19)	(6.12)	(0.51)	(4.76)	(4.27)
$Downgrades_{i,t}$	-1.36***	-6.82***	-3.24***	-2.70***	-4.44***
	(-3.62)	(-15.79)	(-8.03)	(-7.57)	(-10.15)
$Holders_{i,t}$	0.56***	0.18***	0.80***	0.68***	0.04***
	(11.61)	(12.02)	(11.98)	(10.98)	(8.85)
$Return_{i,t}$	7.77***	6.84***	9.25***	8.78***	13.44***
	(9.66)	(11.04)	(16.30)	(19.47)	(18.14)
$Turnover_{i,t}$	3.47***	7.57***	2.38***	3.31***	5.18***
	(3.46)	(5.02)	(3.18)	(3.64)	(3.49)
Intercept	-10.23***	-15.06***	-14.02***	-11.94***	-9.77***
	(-6.85)	(-9.16)	(-8.50)	(-12.42)	(-5.59)
Fixed Effects	Date	Date	Date	Date	Date
Observations	88,241	88,241	88,241	88,241	88,241
R^2	0.076	0.093	0.129	0.106	0.076

Table 7: Investor Selling After Sell-side Analyst Reports

In this table I present OLS regressions assessing the relation between sell-side analyst upgrade and downgrade reports, and subsequent institutional investor selling. The dependent variables are $Sells_{i,t+1}$, which is the number of investors selling for hedge funds, mutual funds, broker/dealer asset managers, pension funds, and all 13-F filing institutions respectively. The independent variables are $Upgrades_{i,t}$ which is the number of sell-side analyst upgrade reports and $Downgrades_{i,t}$ the number of sell-side analyst downgrade reports published. The dependent variables are de-meaned and scaled by standard deviation within firm. Controls include $Return_{i,t}$; the 1-quarter return, and $Holders_{i,t}$ the number of holders for each institutional investor type. The data are stock (i) level at quarterly (t) frequency from 2004-2014. Standard errors are clustered by 2-digit SIC and T-stats are presented in parentheses: ***/**/* indicates significance at 1%/5%/10%.

	(1) Hedge Funds $Sells_{i,t+1}$	(2) Mutual Funds $Sells_{i,t+1}$	(3) Broker Dealers $Sells_{i,t+1}$	(4) Pension Funds $Sells_{i,t+1}$	(5) All 13-F Filers $Sells_{i,t+1}$
$Upgrades_{i,t}$	2.13**	-3.62***	-3.49***	-4.35***	-0.02
	(2.47)	(-5.66)	(-8.88)	(-7.64)	(-0.02)
$Downgrades_{i,t}$	-5.75***	0.82	1.78***	2.35***	2.81***
	(-6.92)	(1.32)	(3.40)	(4.32)	(4.18)
$Holders_{i,t}$	1.44***	0.26***	1.62***	2.32***	0.05***
	(14.23)	(13.88)	(13.44)	(21.40)	(9.35)
$Return_{i,t}$	-2.58***	-3.17***	-7.36***	-2.71***	-2.17***
	(-3.22)	(-4.83)	(-11.90)	(-4.55)	(-4.64)
$Turnover_{i,t}$	9.14***	8.74***	7.46***	2.97***	9.34***
	(4.27)	(4.48)	(4.79)	(3.18)	(4.43)
Intercept	-30.87***	-17.74***	-30.96***	-22.69***	-12.24***
	(-9.94)	(-8.61)	(-11.80)	(-12.34)	(-5.84)
Fixed Effects	Date	Date	Date	Date	Date
Observations	88,243	88,243	88,243	88,243	88,243
R^2	0.160	0.080	0.138	0.173	0.135

Table 8: Hedge Fund Trades and Different Types of Sell-Side Reports

I this table I present OLS and seemingly unrelated (SUR) regressions assessing the relation between the direction of the trades of hedge funds, and the direction of subsequent sell-side analyst ratings change reports of different types. The dependent variables are $NetUpgr_{i,t+1}$, which is the number of sell-side analyst upgrade reports minus the number of analyst downgrade reports. The different columns correspond to different types of reports: *Earnings Season* reports are those published within 3 days including and following company earnings reports, *Non-Influential Reports* are those with minimal or opposite stock price reaction (relative to the market) as the report recommends, and *Influential* reports are those with significant relative stock price reactions, as defined in Loh and Stulz (2011) and discussed in Section 2.2. The independent variables of interest are $NetBuys_{i,t}$, which is the number of hedge funds buying minus the number of hedge funds selling. All independent variables are de-meaned and scaled by standard deviation within firm. The data are stock (i) level at quarterly (t) frequency from 2004-2014. T-statistics (for regressions coefficients) and Chi-square statistics (for differences of coefficients tests) are presented in parentheses: *** indicates significance at 1% level, ** indicates 5%, and * indicates 10%.

	(1)	(2)	(3)	(4)	(4)-(3)
	All	Earnings Season	Non-Influential	Influential	
	$NetUpgr_{i,t+1}$	$NetUpgr_{i,t+1}$	$NetUpgr_{i,t+1}$	$NetUpgr_{i,t+1}$	
Hedge Funds:					
$NetBuys_{i,t}$	5.76***	3.01***	1.73***	2.79***	1.06**
	(9.67)	(6.68)	(5.37)	(8.62)	(5.56)
$Return_{i,t}$	0.58	0.35	0.12	-1.74***	
	(0.78)	(0.66)	(0.38)	(-5.44)	
Intercept	-0.83***	-0.69***	-0.42	0.15	
	(-4.84)	(-6.22)	(-1.33)	(0.49)	
Model	OLS	OLS	SUR	SUR	
Fixed Effects	None	None	None	None	
Observations	88,886	88,886	88,886	88,886	
R^2	0.003	0.001	0.000	0.001	

Table 9: Hedge Fund and Sell-side Analyst Broker Firm Breakdown by Size

I this table I present seemingly unrelated (SUR) and pooled OLS regressions assessing the relation between the direction of the trades of different size hedge funds, and the direction of subsequent sell-side analyst ratings change reports by sell-side analysts employed by different sized brokerage firms. The dependent variables are $NetUpgr_{i,t+1}$, which is the number of sell-side analyst upgrade reports minus the number of analyst downgrade reports. The independent variables of interest are $NetBuys_{i,t}$, which is the number of hedge funds buying minus the number of hedge funds selling. Hedge funds and sell-side analysts are grouped into tercile bins according the hedge fund portfolio size and sell-side analyst brokerage firm size (according the number of sell-side analysts). All independent variables are de-meaned and scaled by standard deviation within firm. The data are stock (i) level at quarterly (t) frequency from 2004-2014. T-statistics (for regressions coefficients) and Chi-square statistics (for differences of coefficients tests) are presented in parentheses: *** indicates significance at 1% level, ** indicates 5%, and * indicates 10%.

	Brokerage Firm Size Terciles:				
	1 Small Brokerage Firms $NetUpgr_{i,t+1}$	2 Median Brokerage Firms $NetUpgr_{i,t+1}$	3 Large Brokerage Firms $NetUpgr_{i,t+1}$	3-1	All Brokerage Firms $NetUpgr_{i,t+1}$
Small HFs:					
$NetBuys_{i,t}$	2.32***	-0.24	0.52	-1.78**	4.81***
	(3.78)	(-0.44)	(0.92)	(4.93)	(3.59)
Median HFs:					
$NetBuys_{i,t}$	1.14***	0.51	0.84**	-0.30	4.70***
	(2.74)	(1.37)	(2.21)	(0.31)	(4.83)
Large HFs:					
$NetBuys_{i,t}$	1.23***	0.94***	1.82***	0.62**	5.84***
	(6.22)	(5.24)	(10.02)	(4.94)	(8.88)
$Return_{i,t}$	0.23	-0.20	0.24*		0.54
	(1.41)	(-1.37)	(1.67)		(0.73)
Intercept	-2.84***	-1.21***	-0.60***		-1.10***
	(-17.72)	(-8.39)	(-4.11)		(-5.41)
Model	SUR	SUR	SUR		OLS
Fixed Effects	None	None	None		None
Observations	88,886	88,886	88,886		88,886
R^2	0.001	0.000	0.001		0.003
$\beta_{Large} - \beta_{Small}$	-1.09*	1.18**	1.30**		1.03
	(2.71)	(3.90)	(4.62)		(0.51)

Table 10: Hedge Fund Performance and Sell-side Analyst Coverage

In this table I present aggregated hedge fund performance, as measured by the alpha coefficients, using the 4-factor models from Carhart (1997). The different alphas indicate aggregated hedge fund performance among different groups of stocks over the months from 2004-2014. I form nine groups by sorting stocks into terciles by size, and then (within size terciles) by the number of sell-side analysts covering. I show the averages size, analyst coverage, and number of stocks in each bin in Table 4 of Appendix A. I also show alphas for stocks sorted into terciles by size only (first three rows of the final column), and for stocks sorted by the number of analysts covering only (first three columns of the final row). T-statistics (for alpha coefficients) and Chi-square statistics (for differences of alphas) are presented in parentheses: *** indicates significance at 1% level, ** indicates 5%, and * indicates 10%.

	Number of Analysts Covering Terciles:				
	1 Low Analysts Covering	2 Median Analysts Covering	3 High Analysts Covering	3-1	All Analysts Covering
Size Terciles:					
1) Small	-0.05%	0.09%	0.31%*	0.36%**	0.16%
	(0.28)	(0.51)	(1.70)	(4.29)	(1.08)
2) Median	-0.11%	0.12%	0.12%	0.23%*	0.06%
	(0.99)	(1.12)	(0.96)	(1.93)	(0.73)
3) Large	0.04%	0.08%	0.16%**	0.12%	0.12%*
	(0.37)	(0.90)	(2.58)	(1.31)	(1.81)
3-1	0.09%	-0.01%	-0.15%		-0.04%
	(0.24)	(0.00)	(0.69)		(0.08)
All Sizes	0.01%	0.08%	0.16%*	0.15%*	0.10%*
	(0.09)	(0.99)	(2.49)	(2.67)	(1.72)

Table 11: Trends in the Number of Institutional Investors

In this table I present the yearly progression in the number of unique individual hedge funds, mutual funds, broker/dealer asset managers, pension funds, and ETFs. I describe the selection of my samples of hedge funds, mutual funds, broker/dealers, and pension funds in Section 2.1. ETF data come from CRSP (all securities with Share Code 73).

	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Hedge Funds											
Year Start	410										
New Entrants	+102	+120	+128	+124	+57	+67	+82	+64	+68	+98	+21
Exits	-10	-10	-24	-37	-61	-93	-102	-55	-57	-62	-44
Year End	502	612	716	803	799	773	753	762	773	809	786
Mutual Funds											
Year Start	1,818										
New Entrants	+17	+11	+6	+4	+3	+2	+2	+4	+0	+0	+0
Exits	-99	-103	-107	-50	-85	-73	-66	-31	-55	-49	-59
Year End	1,736	1,644	1,543	1,497	1,415	1,344	1,280	1,253	1,198	1,149	1,090
Broker/Dealers											
Year Start	52										
New Entrants	+6	+3	+2	+9	+8	+6	+8	+3	+6	+6	+2
Exits	-1	-5	-1	-1	-2	-11	-3	-6	-6	-4	-3
Year End	57	55	56	64	70	65	70	67	67	69	68
Pension Funds											
Year Start	25										
New Entrants	+0	+0	+1	+1	+0	+2	+1	+0	+2	+4	+0
Exits	-1	-1	-1	-0	-0	-0	-0	-0	-0	-1	-0
Year End	24	23	23	24	24	26	27	27	29	32	32
ETFs											
Year Start	136										
New Entrants	+35	+52	+155	+269	+163	+123	+175	+216	+132	+135	+184
Exits	-2	-0	-1	-1	-40	-55	-35	-25	-56	-83	-52
Year End	169	221	375	643	766	834	974	1,165	1,241	1,293	1,425

Table 12: Trends in the Number of Sell-side Analysts

In this I present the yearly progression in the number of unique individual sell-side analysts, sell-side analyst reports, and stocks. I describe the sell-side analyst data in Section 2.2. The stock data come from CRSP: all securities with share codes 10, 11 and 31.

	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Analysts											
Year Start	2,729										
New Entrants	+599	+512	+451	+382	+356	+321	+428	+360	+290	+240	+251
Exits	-280	-318	-331	-368	-482	-334	-264	-315	-315	-429	-347
Year End	3,048	3,242	3,362	3,376	3,250	3,237	3,401	3,446	3,421	3,232	3,136
Analyst Reports											
Upgrades	6,199	6,314	5,700	6,356	6,638	6,471	5,419	5,888	4,645	3,815	4,078
Downgrades	7,201	6,621	7,128	6,821	8,033	6,401	5,515	6,211	6,659	5,255	4,208
All Reports	13,400	12,935	12,828	13,177	14,671	12,872	10,934	12,099	11,304	9,070	8,286
Stocks											
Year Start	5,182										
New Entrants	+279	+281	+287	+316	+114	+116	+169	+134	+158	+229	+301
Exits	-385	-364	-359	-417	-407	-379	-322	-318	-289	-253	-200
Year End	5,076	4,993	4,921	4,820	4,527	4,264	4,111	3,927	3,796	3,772	3,873
Analysts/Stock	5.4	5.7	5.9	5.8	5.8	6.3	7.0	7.5	7.7	7.7	7.6
Rpts/Stock/Yr	2.6	2.6	2.6	2.7	3.1	2.9	2.6	3.0	2.9	2.4	2.2