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Informational environments and the relative information content of analyst recommendations and insider trades

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A B S T R A C T

Analysts and insiders increase price informativeness by revealing new information to financial markets, and prior work has shown that these parties hold both firm-specific and aggregate information. This study examines how the level of informational efficiency with respect to a stock price's firm and industry-level information environment can differently mediate the information content of analyst recommendations and insider trades. I find that (1) the decrease in information revealed by insider trades is larger than that from analyst recommendations when a stock's price is more efficient with respect to firm-specific information, while (2) the increase in information revealed by analyst recommendations is larger than that from insider trades when a stock's price is less efficient with respect to industry-level information. Taken together, my results indicate that analysts (insiders) may have relative informational expertise with regards to industry (firm) information, and that both appear to rely on their specific expertise when informing prices.

1. Introduction

Sell-side analysts and corporate insiders act as information intermediaries to financial markets by disclosing information through their actions, thereby assisting the price discovery process. The purpose of this study is to examine the association between the informational environment and the information content revealed by a key signal from analysts and insiders, i.e. analyst stock recommendations and insider trades.

The comparison of these two groups is interesting because although both analyst and insiders are informed capital market participants, they serve different roles which can lead to relative differences in firm vs industry expertise. Ultimately, this could lead to each group being more reliant on a specific information channel when informing prices. Given that prices will only react to unanticipated information that has not already been previously impounded by the market, differences in informational efficiency with respect to firm and industry information may differently impact the information content from each group's signal. For example, if analysts have more industry expertise than firm-specific expertise, and insiders have more firm-specific expertise than industry expertise, I would expect the informativeness of analyst recommendations to be more dependent than insider trades on the amount of industry information that has already been impounded into prices. Thus, when comparing a price with an efficient environment with respect to industry information to a price with a less efficient industry information environment, I would expect the average increase in information revealed by analyst recommendations to be greater than that of insider trades.

While these two parties often disclose other information regarding a firm's valuation inputs (e.g. sales revenue, capital expenditures, and long-term growth forecasts), I choose to specifically compare analyst recommendations and insider trades because the information content from these two signals should be most directly related to each party's opinion regarding the market value of the firm. That is, I argue that analysts and insiders should aggregate the information from sales revenue, capital expenditures, long-term growth forecasts and any other relevant information to the stock's value when making a stock recommendation or deciding whether to purchase equity.

I compare the relative changes in magnitude of information revealed to markets by analyst recommendations and insider trades under various conditions of the firm's information environment. I use the firm's probability of informed trade, PIN, (Easley, Kiefer and O'Hara, 1997), and future earnings response coefficient,

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FERC (Collins, Kothari, Shanken, & Sloan, 1994), as proxies for the firm-specific information environment, and use a measure of slow industry information diffusion, IDELAY (Engelberg Ozoguz and Wang, 2018; Hou, 2007) as a proxy for the industry-level information environment. Finally, for further robustness, I also make relative comparisons of each signal using synchronicity as an alternative moderator of information content for these signals, as well as using a structural break around the passing of Regulation Fair Disclosure, where the information environments of both common and firm-specific information change after the passing of this rule.

I find that when PIN is low or FERC is high, i.e. when prices are more efficient with regards to firm-specific information, the amount of information content is more attenuated for insider trades versus analyst recommendations. Analyst recommendations, however, are generally unaffected by both of these proxies for the firm-specific informational environment. On the other hand, when industry-specific information is not well-reflected by prices, i.e. when IDELAY is high, the increase in the magnitude of information revealed by analyst recommendations is significantly larger than that from insider trades. The impact of IDELAY as a moderator of information content for insider trades is insignificant, implying that they do not reveal any additional information when markets are slow in responding to industry-level information. Collectively, these results imply that insider trades rely more heavily on firm-specific information than analyst recommendations, and analyst recommendations rely more heavily on industry information when informing prices. Further comparisons of these two signals using synchronicity and Reg-FD confirm the results in the main analyses.

This paper contributes to research involving information intermediaries and price discovery by documenting that proxies for a particular type of informational efficiency can have differential effects on the amount of information revealed to prices by analyst recommendations and insider trades. While prior literature has documented that analysts and insiders possess both types of information, my results imply a relative informational advantage that each party's signal relies upon when informing prices. While the focus of this paper centers around the information revelation activities of these two groups and not around implications of arbitrage opportunities,[2] my results imply that market participants who utilize these signals for investment decisions may wish to make their decisions conditional on the current information environment for firm and industry information.

The remainder of the paper is structured as follows: Section 2 presents a brief overview of prior literature regarding analysts and insiders as information intermediaries. Section 3 details the research design. Section 4 discusses the data sources and reports univariate statistics. Section 5 tabulates and discusses multivariate analyses. Section 6 reexamines the analysts' and insiders' signals with alternative specifications for robustness. Section 7 concludes and gives suggestions for future work.

2. Related literature and predictions

Analysts collect raw data from sources such as management forecasts, conference calls, and macro-level forecasts, and then process such data to create information in the form of stock recommendations that are disclosed to financial markets. Because the information acquisition and processing is not costless (Bloomfield, 2002), analysts are often assigned to cover multiple firms that have similar business operations, e.g. those within the same industry or sector. This allows information acquired by an analyst about one firm to then be applied to other firms covered by the same analyst, thereby decreasing the average cost of information and processing (Ramnath, 2002; Veldkamp, 2006; Engelberg, Ozoguz, & Wang, 2018). Because analysts are assigned to similar firms, this allows analysts to develop industry expertise with regards to (1) estimating the valuation inputs for their assigned firms or (2) ranking the investment quality of firms within a given industry (Boni & Womack, 2006; Kadan, Madureira, Wang, & Zach, 2009).

The fact that analysts may develop industry expertise does not preclude them from also possessing firm-specific information. Mikhail, Walther, and Willis (1997) show that analyst outputs contain idiosyncratic information by documenting that an analyst's firm-specific experience for issuing earnings forecasts and stock recommendations is correlated with greater accuracy for earnings forecasts. Liu (2011) finds that analysts produce more firm-specific information for firms with higher idiosyncratic return volatilities, but finds that analysts produce more industry information when the absolute value of the stock's industry beta is high. Soltes (2014) documents that analysts acquire firm-specific information through private communications with management, and find that these communications often occur around the time in which analysts publish their reports. Brown, Call, Clement, and Sharp (2015) survey sell-side equity analysts and also find private communication with management to be the second most important factor, behind industry information, in forming stock recommendations. Collectively, the literature suggests that analysts are likely to possess both industry and firm-specific information.

While analysts gather and process information from external sources to create private information, insiders are involved with the firm's internal activities which can result in them having an informational advantage when estimating their own firm's intrinsic value (Piotroski & Roulstone, 2005). Insiders can reveal information to markets through their trades by buying when they believe that the price of the firm is too low relative to its intrinsic value, and selling when they believe that price is too high. Regarding evidence of insiders revealing firm-specific information to the market, Aboody and Lev (2000) find that insider trades are most profitable at R&D intensive firms, consistent with insiders taking advantage of firm-level information asymmetries. Similarly, Hutton, Lee, and Shu (2012) provide evidence of insiders revealing firm-specific information through management forecasts of annual EPS, finding that they are most accurate when earnings are strongly tied to firm-specific factors such as a firm's abnormal inventory, or excess plant capacity.

On the other hand, evidence suggests that insiders also acquire non-idiosyncratic information. Foucault and Fresard (2013) provide evidence that managers acquire information from their industry peers, and use it to make corporate investment decisions. Anilowski, Feng, and Skinner (2007) and Bonsall, Bozanic, and Fischer (2013) find that management guidance is correlated with contemporaneous aggregate equity returns around the disclosure window. Seyhun (1988) finds that a signal created by aggregating the cross-section of insider trades appears to predict 2-month ahead future aggregate equity returns. Overall evidence suggests that, in addition to firm-specific information, insiders also possess information that is common to multiple firms.

While the literature suggests that analysts and insiders possess both industry-level and firm-specific information, I argue that

[2] Because my paper focuses on the relative information content from these two groups' signals, the framework on which my analyses are based do not explicitly take into account the impact of information processing and transaction costs. Therefore, following Bloomfield's (2016) definitions of price efficiency, while my results show a correlation between future stock returns and the signals from analyst recommendations and insider trades, I can only argue that prices may fail to reflect “right-price efficiency”, i.e. that prices reflect all available information, and not that prices violate “no-profit efficiency”, i.e. the existence of arbitrage opportunities after accounting for all trading costs.

these two groups will have relatively different levels of informational expertise with regards to industry and firm information, and thus the information revealed by each group's signal will reflect their relative expertise. When informing prices, I expect that (1) insider trades will rely more on firm-specific information than analyst recommendations because insiders operate from within the firm and can thereby take advantage of firm-specific information asymmetries, and (2) analyst recommendations will rely more on industry-level information than insider trades because analysts have an incentive to collect information common to multiple firms to reduce the costs of information acquisition.

Following such logic, I argue that the magnitude of information revealed by analyst recommendations and insider trades will be differentially affected by firm-specific and industry-level proxies for the firm's information environment. When stock prices reflect a higher quantity of firm-specific information, the decrease in information revealed to financial markets by insider trades will be greater than the decrease in information revealed by analyst recommendations. Conversely, because I conjecture that the analysts' signal will rely more on industry information than the insider signal, I argue that the increase in the amount of information revealed to financial markets by the analyst signal will be greater than that from the insider signal if stock prices are less reflective of industry-level information.

3. Research design

3.1. Analyst recommendation and insider trading signals

The following section describes how analysts' and insiders' signals are created by aggregating their recommendations and trades. The analysts' signal, ANA henceforth, is constructed on a quarterly basis following Jegadeesh, Kim, Krische, and Lee (2004), who find the quarterly change in consensus recommendations to be more informative than the level of the consensus recommendation. I reverse code the variable from each recommendation by subtracting the level of the recommendation from 5, such that a strong buy is now coded as 4, a buy is coded as 3, a hold as 2, a sell as 1, and a strong sell is coded as 0. The quarterly consensus change is taken as the difference between the mean recommendations (RECLEVEL) of the current and prior quarters, and is shown algebraically in Equation (1).

$$ANA_t = \frac{1}{n_t}\left[\sum_{i=1}^{n} RECLEVEL_t\right] - \frac{1}{n_{t-1}}\left[\sum_{i=1}^{n} RECLEVEL_{t-1}\right] \quad (1)$$

Firms that do not have analyst coverage for consecutive quarters are removed from the sample. In order to account for the right skewness of these recommendations (Piotroski & Roulstone, 2004) and to also facilitate the comparison of information revelation by the two signals, I create non-parametric decile-ranked signals with double-sorts that are first based on analysts' consensus change, followed by the level of the consensus recommendation. Thus, in the event that two firms have the same magnitude of consensus change in recommendation, the firm's signal is considered to be stronger if its current level of consensus has a higher rank.[3]

The corporate insider signal, CI, is derived from Lakonishok and Lee (2001) as the difference between the number of open market purchases and the number of open market sales for all insiders reporting transaction information to the SEC database, divided by the total number of trades for each reporting period where there is at least one insider trade.[4]

$$CI_t = \frac{\text{Insider Buy Transactions}_{t-1}^{t} - \text{Insider Sell Transactions}_{t-1}^{t}}{\text{Insider Buy Transactions}_{t-1}^{t} + \text{Insider Sell Transactions}_{t-1}^{t}} \quad (2)$$

Similar to the construction of ANA, each signal is converted into a nonparametric variable by double sorting the variable into decile ranks over the entire sample period. The rank order of CI is determined by first sorting on the net purchase ratio, as described in Equation (2), then by the dollar magnitude of the signal. For example, if two firms each have signals where 100% of insider trades are purchasers, the firm with the higher magnitude, calculated as the total dollar amount traded scaled by the total market value of equity, would be assigned a higher rank.

3.2. Firm and industry informational environments

3.2.1. Firm-specific information efficiency

In order to measure the impact of the firm-specific information environment on the information content revealed by the analyst and insider signals, I use two previously established proxies, the Probability of Informed Trade (PIN) and Future Earnings Response Coefficient (FERC).

The PIN variable was developed by Easley, Kiefer, and O'Hara (EKO, 1997) within a microstructure trade model to measure the probability that a given trade is driven by firm-specific, private information. PIN is calculated as follows: $PIN = \alpha\mu/(\alpha\mu + \varepsilon_s + \varepsilon_b)$, where α is the probability of a private information event at the start of the trading day, μ is the arrival rate of orders motivated by private information, and ε_s and ε_b are the arrival rates of orders from uninformed sellers and buyers, respectively. Thus, the numerator equals the number of trades based on private information, while the denominator proxies for the total number of trades from both informed and uninformed investors. Intuitively, the ratio calculates the probability that the trade is based on new private information, and has successfully been used in other studies as a proxy for information asymmetry (Brown, Hillegeist, & Lo, 2004; Brown & Hillegeist, 2007). Since higher information asymmetries occur when prices do not fully reflect all private information, this implies that the magnitude of information revealed by insider trades signal will be more significantly reduced when PIN is low, relative to the analysts' signal.

I use quarterly estimated PIN data from the EKO model from 1994 to 2006. These estimations cover stocks in the NYSE, AMEX, and NASDAQ markets, and require a minimum number of 30 active trading days within a given quarter to provide a reliable estimate. I remove all corner solutions inherent in the computation of PIN from my sample, as these estimates are likely to be unreliable results from the optimization process. To maintain consistency across multiple information proxies, I create binary variables for each specification. Thus, for PIN, I use data from the prior quarter of each firm, assigning the subset of firms with the lowest levels of PIN a

[3] While prior papers have noted that the distribution of consensus analysts' recommendations may be truncated, which could potentially reduce the signal power in the extreme deciles, it is unlikely that such a distribution could affect the observed results. For this to occur, the nature of the information conveyed within the extreme deciles of the analyst signal would have to significantly differ from those of deciles 2–9, i.e. deciles 1 and 10 of the analyst signal would have to contain significantly more firm-specific information than deciles 2 and 9.

[4] Purchases of shares through the exercise/conversion of options, warrants or convertible bonds are not included in the calculation of CI. Yermack (1995) notes that option exercises are often a result of executive compensation schemes in an attempt to align the interests of shareholders with executives, thus making them unlikely to reflect insiders' sentiment about the firm.

value of one, and a value of zero to the remainder of the firm-years.[5] I expect that when PIN is low, the interaction coefficient on CI and PIN will be more negative than the interaction coefficient on ANA and PIN.

FERC is a measure of stock price informativeness developed by Collins et al. (1994). This approach measures the amount of future earnings information that has already been impounded into current stock prices by examining the degree to which future earnings load on regressions of yearly stock returns, after controlling for the firm's past and present levels of earnings, and the firm's future returns. If the coefficient on future earnings is high, then prices are more informative of future earnings.

The structural models used in computing FERC follow Lundholm and Myers (2002), who modify the original specification from Collins et al. (1994) by aggregating future earnings to create a more powerful test, as presented in Equation (3):

$$R_{it} = a + b_0X_{it-1} + b_1X_{it} + b_2(X_{it+1} + X_{it+2} + X_{it+3}) + b_3R_{it+3} + \varepsilon_{it} \tag{3}$$

X_{it+k} is the annual earnings per share, while R_{it} is a firm's annual return beginning at time t, and R_{it+3} is a three-year future return for the firm. R_{it+3} is used to control for an errors-in-variables problem involved in using realized earnings as expected earnings. b_2 is the future earnings response coefficient. If b_2 is high, then stock returns are more strongly informative of future earnings.

FERC has been used in a number of disclosure papers as a proxy for stock price informativeness of future earnings. In general, the literature (Gelb & Zarowin, 2002; Lundholm & Myers, 2002; Orpurt & Zang, 2009; Tucker & Zarowin, 2006) shows that firms with higher quality or more frequent disclosures have informational environments that are more revealing of firm-specific information, thereby resulting in higher FERC values. My use of the future earnings response coefficient differs from that of previous literature. While prior research measures changes in FERC as the dependent variable, I use FERC as an independent variable to proxy for the firm-specific informational environment and then measure the differences in the information content from the revelation of the two informed parties' signals.

I estimate FERC with yearly Compustat and CRSP monthly stock files. Following Tucker and Zarowin (2006), I scale all EPS variables by the stock price at the beginning of the fiscal year, and truncate the highest and lowest 1% of the distribution across the entire domain of independent variables. I then run rolling panel regressions for the trailing 36-months[6] of data across each industry, as specified by two-digit SIC industry code.[7] Similar to PIN, I then create a binary variable equal to one for the top quintile of industry-years for b_2 (the future-earnings response coefficient), and equal to zero for the remaining firms. I expect that when FERC is high, the interaction coefficient on CI and PIN will be more negative than the interaction coefficient on ANA and PIN.

[5] I also estimate PIN using an average of each firm's PIN in the trailing 12 months. These results do not lead to any major changes in statistical inference, and are available upon request.

[6] In sensitivity tests, I run the FERC analysis using rolling regressions of the prior 48 and 60 months, while changing the number of years of aggregated future earnings to 4 and 5 years. Results of such analyses are statistically similar, and hence, unreported.

[7] FERC can also be estimated on a firm-by-firm basis. While these results (not reported) have similar inferences, estimating FERC by SIC code allows me to retain a larger number of firm-quarters, thereby increasing the statistical power of the analyses.

3.2.2. Industry level information efficiency

In order to investigate the relative information content from analysts and insiders conditional on industry-level informational efficiency, I create an industry delay variable (IDELAY) that proxies for the speed of industry information transfer into prices. Hou (2007) examines industry information transfer rates amongst firms, and finds that firms with higher-levels of delay tend to be characterized as smaller firms with higher levels of analyst dispersion, lower levels of trading volume, and lower levels of market share within their given industry,[8] while Engelberg et al. (2018) find that industries that are less geographically concentrated also experience higher levels of industry delay. I proxy for the degree to which prices reflect industry-level information in a manner similar to Hou (2007) and Engelberg et al. (2018) by using the following specification:

$$FirmRET_{it} = a + b_1MktRET_{jt} + b_2MktRET_{jt-1} + b_3MktRET_{jt-2} + b_4IndRET_{kt} + b_5IndRET_{kt-1} + b_6IndRET_{kt-2} + \varepsilon_{it} \tag{4}$$

FirmRET is the monthly raw return of the firm, while MktRET is the value-weighted market adjusted return from the CRSP monthly stock file. IndRET is the industry return, and is calculated as the value-weighted monthly average for all the firms within a given two-digit SIC code.

I run firm-by-firm rolling regressions for Equation (4) over the prior 36 months for each company's monthly raw return on the CRSP value-weighted return, the SIC two-digit industry-return, and two monthly lags for both the market and industry returns. Given that markets can be viewed as less reflective of information when lagged returns are predictive of future returns, I use market returns to parse out the effect of macro-level information, leaving the lags on the past industry returns as proxies for sluggish industry information transfer. I calculate the level of industry delay for each firm as the sum of $b_5 + b_6$, the two lagged industry coefficients, and assign a one to firms in the highest quintile of the delay measure and a zero to the remaining firms. Because IDELAY identifies firms whose stock prices have slower absorption rates when responding to new industry information, when IDELAY is high, the magnitude of information content from analyst recommendations should be increased by a greater amount than the magnitude of information content from insider trades.

3.3. Structural model

In order to analyze the effects of the firm and industry-level information environments as moderators of the information revealed by analysts and insiders, I use stock returns to measure the information content of each party's signal. I run a series of regressions of stock returns on interactions between the analyst and insider signals and proxies for firm and industry-level price efficiency with a vector of controls for long-horizon returns which have been established by prior research, as shown in equation (5).

$$SAR_{itn} = a + b_1ANA_{it} + b_2ANA_{it} \cdot INFO_{it} + b_3CI_{it} + b_4CI_{it} \cdot INFO_{it} + b_5INFO_{it} + b_6BEME_{it} + b_7SIZE_{it} + b_8MOM6RET_{it} + b_9MOM7RET12_{it} + b_{10}TURN_{it} + b_{11}BETA_{it} + \varepsilon_{it} \tag{5}$$

[8] Hou (2007) notes that slow information transfer could be caused by a firm's neglected information environment, as well as short-selling constraints, microstructure frictions, and other institutional constraints.

SAR_{itn} is future size-adjusted returns, where n = {3, 6, 12} denotes a 3, 6, 12 month time horizon. The use of varying return horizons to examine total information revelation reflects prior literature that correlates abnormal stock returns with analyst recommendations and insider trades over differing horizons. Lakonishok and Lee (2001) document that the information revealed by insider trades appears to be correlated with future stock-returns over horizons as large as 12 months, while Jegadeesh et al. (2004) find analyst recommendations to be associated with future returns over shorter horizons of 6 months or less. For ease of interpretation, I scale the decile rank of ANA and CI by 9, such that each signal ranges between 0 and 1. The coefficient of ANA and CI now represents the magnitude of information revealed in percentage terms. Because PIN, FERC and IDELAY are also binary variables, the interaction coefficients, b_2 and b_4, represent how the moderators affect the amounts of incremental information revealed by ANA and CI. Finally, to test how these proxies differentially moderate the information revealed by ANA and CI, I calculate the difference between b_2 and b_4 and use linear restriction tests to measure statistical significance.

Because prior literature has documented information revelation over longer horizons, the control vector includes variables used in prior research that are correlated with future expected returns (Daniel & Titman, 1997), as well as determinants of analysts' and insiders' actions (Jegadeesh et al., 2004; Rozeff & Zaman, 1998). I calculate size (SIZE) as log (Market Value of Equity) and book-to-market (BEME) as log (Book Value of Equity/Market Value of Equity) at the start of each quarter. I compute momentum (MOM6-RET) as a prior 6-month raw return, and MOM7RET12 as the prior raw return from months 7 through 12. Turnover (TURN) is calculated as aggregate trading volume over the trailing 6 months scaled by total shares outstanding at the beginning of the period. CAPM beta (BETA), is calculated over a 36-month rolling window using the Capital Asset Pricing Model.

4. Data sources, sample characteristics, and determinants of analyst and insider signals

4.1. Data sources

To examine the relative behavior of these two groups, I use quarterly data, spanning 1994–2006, from insider trade filings (SEC Forms 3, 4, 5) and the Institutional Brokers Estimate System (IBES) database. Forms 3, 4 and 5 are obtained from the Securities and Exchange Commission (SEC) Ownership Reporting System data file. This database contains transactions by all insiders who are subject to disclosure as mandated by the Securities Exchange Act of 1934 §16(a), which requires the reporting of all trades by any person who is either directly or indirectly the owner of more than 10 percent of any specific equity security by the tenth day of the calendar month after the trading month. The IBES stock recommendations database dates back to 1994 and includes the stock recommendations of financial analysts, as self-reported by over thousands of brokerages from the largest global houses to smaller regional and local shops.

My analyses require Compustat quarterly data and Center for Research in Security Prices (CRSP) monthly files for each firm. Analyses are restricted to U.S. firms listed on the NYSE, AMEX, or NASDAQ stock exchanges. In addition, to mitigate the potential effects of noise trading and poor liquidity on prices, I restrict the sample to those stocks with share prices of at least $3 (Conrad & Kaul, 1993), that also have at least one institutional investor holding, as reported in SEC Form 13F,[9] leaving the panel with 197,247 firm-quarter observations. A quarterly disclosure for each party is required to make relative comparisons between ANA and CI. After calculating the ANA signal from the IBES database and merging it with the current file, I am left with 100,564 firm-quarters. Finally, after merging the calculated CI signal from the insider trade database my sample set consists of 59,008 firm-quarter observations.

4.2. Sample characteristics

Table 1 shows univariate statistics from the data sample. On average, insiders are net sellers of stock. This is consistent with past research, and is likely because the disclosed data only reflects shares transacted on the open market, which excludes shares gifted to insiders as part of their compensation plans. Consistent with prior literature, analysts tend to be optimistic; the analysts' consensus recommendation throughout the entire panel is a "buy" rating. Conversely, the change in consensus recommendation is nearly zero, with the exception of the year 2002, where the average change in consensus decreases by 0.10. It is also interesting to note, when comparing the analysts' dispersion in recommendation for the 5 years before and after Reg-FD, passed at the end of 2000, that dispersion increased by 16.4% following the year in which Reg-FD was passed. This increase is consistent with insiders disclosing less selective information, and analysts being forced to perform their analyses with less available information, thereby resulting in higher magnitudes of disagreement. Finally, the sample prerequisites result in the average firm being large. In each year, the average market value of equity for firms in the sample falls around the 80^{th} percentile via NYSE breakpoints.

4.3. Univariate statistics

In Tables 2 and I partition firm-based characteristics by the strength of insiders' net trading activity and analysts' net changes in consensus recommendations. The high (low) partition represents firm-quarters where the signal is in the top (bottom) tercile of the sample. All other firms fall into the medium partition. Generally speaking, the univariate characteristics from Table 2 appear to be in accordance with prior literature which portrays insiders as contrarian investors and analysts as glamour-chasers (Jegadeesh et al., 2004; Piotroski & Roulstone, 2005). Regarding stock return momentum, analysts' signals are correlated with positive prior returns, while insiders appear to shun these firms. Book-to-market, a proxy for value (high B/M) and glamour (low B/M) shows that insiders exhibit the strongest buying preferences for firms with the highest levels of book to market, while analysts tend to issue buy recommendations to glamour firms. Relative to analysts, insiders also prefer smaller firms, with lower levels of turnover and analyst following, and firms with higher bid-ask spreads.

Regarding future profitability, it is interesting to note that at Q_{t+4}, high insider signals tend to have the lowest levels of EPS, but the largest positive changes in EPS when compared to medium/low partitions, while at Q_{t+1} the insider signal is associated with the most negative change in future EPS. These statistics are consistent with insiders' desires to avoid litigation risk by purchasing their own stock when near-term news will continue to be poor, but when a turnaround is expected in the future (Ke, Huddart, & Petroni, 2003). Conversely, analysts' favorable signals are associated with the strongest levels of changes in EPS at Q_{t+1}, consistent with their economic incentives to produce new and accurate near-term information about future profitability in an effort to generate additional trading volume (Irvine, 2000).

[9] Form 13F reports all institutions with more than $100 million of total holdings, or with common-stock positions within a specific firm of more than 10,000 shares or $200,000.

Table 1
Summary statistics from financial analysts and corporate insiders from 1994 to 2006.

Year	Number of Firms	Analysts' Consensus Recommendation	Analysts' Dispersion	Change in Analysts' Consensus Recommendations	Insiders' Net Trade Ratio (Trades)	Insiders' Net Trade Ratio (Dollars)	Insiders' Net Trade Ratio (Shares)	Market Value of Equity (in Millions)
1994	2880	2.87	0.679	−0.0184	−0.135	−0.193	−0.194	1884.90
1995	3523	2.85	0.641	−0.0364	−0.193	−0.256	−0.257	2055.50
1996	3894	2.86	0.636	−0.00723	−0.176	−0.248	−0.249	2311.61
1997	4232	2.96	0.607	−0.00871	−0.232	−0.311	−0.314	2744.71
1998	4599	2.97	0.596	−0.0229	−0.0369	−0.111	−0.115	3558.00
1999	4554	2.96	0.593	−0.0106	0.0289	−0.0265	−0.0295	4179.20
2000	4662	3.01	0.583	−0.0157	−0.115	−0.163	−0.167	5036.30
2001	4806	2.97	0.582	−0.0234	−0.325	−0.384	−0.387	4180.17
2002	4643	2.77	0.651	−0.102	−0.252	−0.318	−0.320	3767.22
2003	4781	2.53	0.702	−0.0256	−0.462	−0.514	−0.515	4042.63
2004	5257	2.61	0.712	−0.000330	−0.550	−0.609	−0.610	4858.49
2005	5437	2.68	0.717	0.00216	−0.516	−0.568	−0.570	5202.18
2006	5740	2.67	0.729	−0.0168	−0.526	−0.571	−0.572	5581.23

This table provides descriptive statistics at an annual level for the firms included in the sample. The total number of firm-quarters in the sample is 59,008. The sample consists of all firms listed on the NYSE, AMEX, or NASDAQ stock exchanges from 1994 to 2006, a total of 52 quarters, with data being taken from the filings of insider trades (SEC Forms 3, 4, 5), and the Institutional Brokers Estimate System (IBES) database. Change in analysts' consensus recommendation level is calculated as the change in the mean level of recommendation from the preceding to the current quarter as detailed in Section 3.2. Analysts' dispersion is calculated as the standard deviation of analysts' recommendations. The insider net trade ratios are calculated as the total number of purchases less the number of sells (in either trades, shares or dollars traded), divided by the sum of sells and purchases. Market value of equity is listed in millions.

Table 2
Summary statistics of firm characteristics by signal strength.

	Panel A: Corporate Insider Signal (CI)			Panel B: Financial Analyst Signal (ANA)		
	Low	Medium	High	Low	Medium	High
SIZE	6.51	7.12	5.87	6.75812	6.05	7.03
BEME	−1.13	−0.939	−0.609	−0.88868	−0.806	−1.02
MOM6RET	0.139	0.0430	−0.0644	−0.00343	0.0369	0.0854
TURN	9.81	6.75	5.40	8.36943	5.84	8.04
BETA	1.29	0.997	0.944	1.11083	0.991	1.13
PRICE	28.48	31.53	19.47	27.55	23.73	30.73
Analyst Following	7.27	9.10	5.72599	8.55	5.53	9.19
Chg in Inv. Attn	0.0864	0.0448	0.02426	0.0317	0.0535	0.0652
Chg in Sales at t+4	−0.00536	−0.00123	0.00194	−0.00127	−0.000690	−0.00269
Sales at t+4	0.225	0.182	0.17073	0.193	0.186	0.197
Chg in EPS at t+4	−0.00284	−0.00657	0.00778	0.00882	−0.00598	−0.00419
EPS at t+4	0.294	0.399	0.24580	0.324	0.293	0.354
Chg in Sales at t+1	−0.00290	−0.000860	−0.00028	−0.00373	0.000660	−0.00146
Sales at t+1	0.229	0.183	0.16929	0.193	0.187	0.199
Chg in EPS at t+1	0.0438	0.0247	−0.00500	0.00676	0.0154	0.0426
EPS at t+1	0.309	0.407	0.24723	0.328	0.303	0.365
% Spread	0.0104	0.0106	0.01868	0.0121	0.0161	0.0100
Volatility	0.0307	0.0242	0.02694	0.0272	0.0274	0.0264
FIRM-QTRS	17,675	23,505	17,828	17,702	23,602	17,704

This table provides descriptive firm characteristics, conditional on analyst and insider signal strength. Calculation of ANA and CI is discussed in Section 3.1. Firms fall into the high (low) partitions when their ranked signal strength for the given quarter is in the upper (lower) tercile of the sample. All other firms are placed in the medium partition. Size (SIZE) is taken as the log (Market Value of Equity) at the beginning of each quarter. Book-to-market (BEME) is calculated as the log (Book Value of Equity/Market Value of Equity) at the start of each quarter. Momentum is controlled for as a prior 6-month return (MOM6RET). Share turnover (TURN) is calculated as the sum of volume over the trailing 6 months divided by total shares outstanding at the beginning of the period. Beta is calculated using CAPM over a 36-month rolling window. PRICE is the average daily stock price over the given quarter. Change in investor attention is calculated as the change in the number of 13F filers from the beginning to the end of the quarter, divided by the number of 13F filers at the start of the quarter. Sales is calculated as Sales Revenue/Total Assets. EPS is earnings per share less extraordinary items. % Spread is the average daily spread over the given quarter, calculated as absolute value of (Ask − Bid)/Price. Volatility is calculated as the standard deviation of daily returns over the given quarter.

Overall, firms favored by insiders have increased market frictions, decreased levels of market attention from institutional investors, and poor prior performance, while conveying information about strong future performance (Q_{t+4}). On the other hand, firms favored by analysts tend to be more liquid, have increased attention from institutional investors, and forecast strong performance in the near future (Q_{t+1}). While a formal analysis of the horizons over which analyst and insider signals reveal information is not the main objective of this study, these described differences are likely to be at least partially responsible for the empirical findings from prior literature that document that information revealed by insider trades are generally more slowly absorbed by prices than information revealed by analyst recommendations.

Table 3 reports the means of size-adjusted,[10],[11] buy-and-hold abnormal returns over 3-, 6-, and 12-month time horizons within each decile of signal strength for both parties. In Fig. 1, I illustrate the information revealed by each signal over these varying horizons

[10] Size-adjusted buy-and-hold abnormal returns are created by calculating each firm's monthly abnormal return by subtracting the average return for firms in the same NYSE size decile, then compounding the corresponding abnormal returns over the specified horizon period. If a firm delists, CRSP delisting returns are used, which are calculated by comparing the value after delisting against the price on the security's last trading period.

[11] Similar inferences are obtained when reporting returns with market-adjusted and raw returns.

Table 3
Size-adjusted future returns by informed signal decile.

SIGNAL (Decile)	Panel A: Financial Analysts (ANA)			Panel B: Corporate Insiders (CI)		
	3 Month	6 Month	12 Month	3 Month	6 Month	12 Month
10	0.0140	0.0265	0.0486	0.0259	0.0461	0.110
9	0.00576	0.0132	0.0286	0.0159	0.0187	0.0576
8	0.00270	0.00520	0.0167	0.00619	0.0124	0.0342
7	0.00519	0.00810	0.0194	0.00901	0.0155	0.0301
6	0.0131	0.0214	0.0541	0.00207	0.000930	0.00534
5	0.0100	0.0139	0.0359	0.000916	0.00359	0.0217
4	0.00992	0.0201	0.0469	0.00280	0.00109	0.0123
3	0.000846	0.0000550	0.0117	−0.00136	0.00308	0.0122
2	−0.000892	−0.00325	0.00634	−0.00229	0.00751	0.0134
1	−0.00318	0.00219	0.0348	−0.00174	0.000130	0.00827

Panels A and B report average future size-adjusted returns calculated as described in Barber, Lyon, and Tsai (1999) for each ranked signal, sorted by decile over 3-, 6-, and 12-month time horizons. Construction of analysts' (ANA) and corporate insiders' (CI) signals is detailed in Section 3.1.

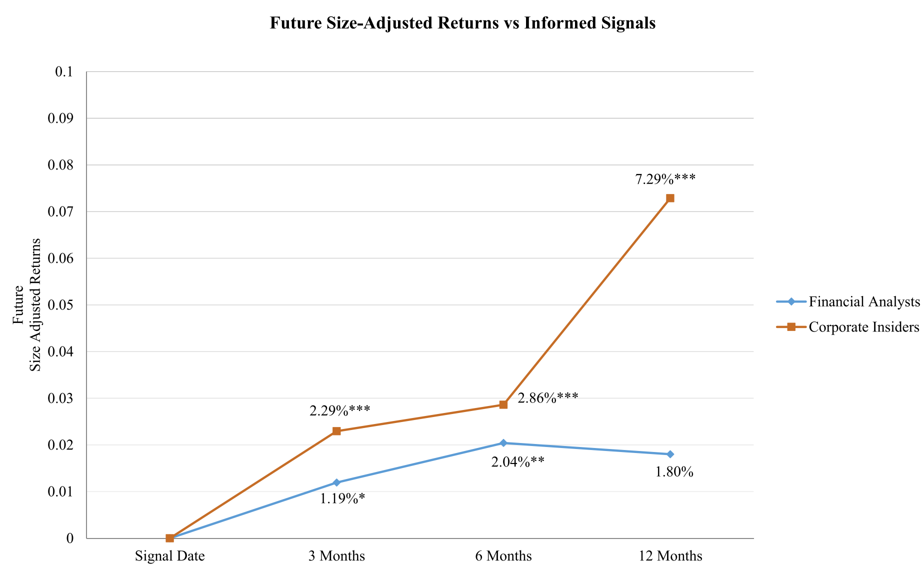

Fig. 1. Illustrates hedge returns calculated by subtracting the lowest(1–2) from the highest(9–10) deciles of signal strength for both analysts and insiders. The construction of analysts' (ANA) and corporate insiders' (CI) signals is detailed in Section 3.1. Average future buy and hold size-adjusted returns are calculated as described in Barber et al. (1999) for each ranked signal over 3-, 6-, and 12-month time horizons. Two-tailed statistical significance levels at 1%, 5%, and 10% are indicated as ***, **, and * respectively.

as calculated from a portfolio that is long in the top quintile and short in the bottom quintile of ANA and CI. Generally, these analyses indicate that the magnitude of information revealed by insider trades is larger than that which is revealed by analyst recommendations. In agreement with prior literature, the horizon over which prices absorb the information from these signals is longer for insiders than analysts. The portfolio return for the insider signal is correlated with stock returns of 2.86% over the first 6 months and 4.31% over the second 6 months of the twelve-month window, while the analogous return calculated from the analyst signal is correlated with stock returns of 2.04% at the 6-month horizon, with returns becoming insignificantly different from zero at the 12-month horizon.

5. Multivariate analyses

5.1. Unconditional analysis

As a baseline regression for the remainder of my analyses, I run equation (5) with the additional controls for long horizon returns, but without any of the interactions or main effects with the information environment proxies. Thus, after the inclusion of the vector of return determinants, my regression model in equation (6) unconditionally examines information revelation from ANA and CI.

$$SAR_{itn} = a + b_1 ANA_{it} + b_2 CI_{it} + b_3 BEME_{it} + b_4 SIZE_{it} + b_5 MOM6RET_{it} + MOM7RET12_{it} + b_7 TURN_{it} + b_8 BETA_{it} + \varepsilon_{it} \quad (6)$$

Results from these multivariate analyses are tabulated in Panels A, B and C of Table 4. After controlling for the aforementioned firm characteristics, conclusions remain similar to those of the univariate analyses in Table 3. The coefficient of CI is larger than that of ANA at all three horizons, consistent with Fig. 1 which indicates that the insider signal reveals more information than the analyst signal. The relative magnitudes of each signal's coefficient also confirm that the insider signal continues to persist across all three time horizons. For analysts, while the coefficient increases from the 3- to 6-month horizon, it becomes only marginally significant at the 10% confidence level over the 12-month period. The control variables also load in accordance with prior literature, with small size, lower B/M, and higher beta being positively correlated with future returns, while also showing evidence of short-term momentum (MOM6RET) and longer-term reversal (MOM7RET12), as consistent with Lee and Swaminathan (2000).

Table 4
Regressions of size-adjusted future returns on informed signals.

Parameter	Panel A: 3 Month Size-Adjusted Future returns		Panel B: 6 Month Size-Adjusted Future returns		Panel C: 12 Month Size-Adjusted Future returns	
	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
INTERCEPT	0.0136	0.00528**	0.0376	0.00947***	0.1049	0.0184***
ANA	0.0108	0.00318***	0.0155	0.00477***	0.0170	0.00923*
CI	0.0205	0.00382***	0.0264	0.00644***	0.0491	0.0123***
BEME	0.0121	0.00205***	0.0178	0.00370***	0.0210	0.00761***
SIZE	−0.00255	0.000650***	−0.00519	0.00121***	−0.0141	0.00262***
MOM6RET	0.0269	0.00445***	0.0570	0.00830***	0.0316	0.0131**
MOM7RET12	−0.00586	0.00362	−0.0177	0.00632**	−0.0324	0.00951***
TURN	−0.000250	0.000178	−0.000650	0.000279**	−0.00143	0.000478***
BETA	0.00365	0.00172**	0.00336	0.00285	0.0152	0.00643**

Construction of analysts' (ANA) and corporate insiders' (CI) signals is detailed in Section 3.1. Panels A–C regress the returns on control variables and the ANA/CI signals. Size, book-to-market, momentum, CAPM beta, and share turnover are used as controls for expected returns. Size is taken as the log (Market Value of Equity) at the beginning of each quarter. Book-to-market is calculated as the log (Book Value of Equity/Market Value of Equity) at the start of each quarter. Momentum is controlled for as a prior 6-month return (MOM6RET), as well as a prior return in months seven through twelve (MOM7RET12). Beta is calculated using CAPM over a 36-month rolling window, while share turnover is calculated as the sum of volume over the trailing 6 months divided by total shares outstanding at the beginning of the period. Two-tailed statistical significance levels at 1%, 5%, and 10% are indicated as ***, **, and * respectively, based on t-statistics calculated with Newey-West autocorrelation consistent standard errors. Directional comparisons of regression coefficients report Wald statistics from linear restriction tests, again with ***, **, * indicating significance at 1%, 5% and 10%, respectively.

5.2. Effects of informational environment on analyst and insider information content

5.2.1. Firm-specific informational efficiency

Tables 5 and 6 tabulate the effects of PIN and FERC as moderators of the information revealed by analyst recommendations and insider trades. Both sets of analyses confirm the differential effects of these proxies on the amount of information revealed to prices by ANA and CI. For firms with the lowest levels of PIN, the reduction in the magnitude of information revealed by insider trades is 2.2%, 2.9%, and 7.3% over 3, 6, and 12 month periods, and is significant at all time horizons. Conversely, analyst recommendations only show a significant decrease of 1.6% in information revelation when PIN is low at the 3-month horizon, with the ANA*PIN interaction being insignificant at 6 and 12 month periods. Comparing the magnitudes of the interaction coefficients across all three horizons reveals that the decrease in the amount of information revealed by insider trades is significantly larger than the decrease in the amount of information revealed by analyst recommendations when firms have low levels of PIN. Results are most significant at the 6-and 12-month windows, and are directionally correct at the 3-month window.

Results from the FERC analysis also reveal a significant decrease in the amount of information revealed by insider trades for firms with high FERC of 4.5%, 7.8%, and 9.0% for 3-, 6-, and 12-month horizons. On the other hand, the decrease in the amount of information revealed by analyst recommendations, as shown by the coefficient of ANA*FERC, is insignificant at all horizons. Consistent with the PIN analysis, linear restriction tests show that firm-specific informational efficiency attenuates the amount of information

Table 5
Regressions of size-adjusted future returns on informed signals and probability of informed trade (PIN).

Parameter	Expected Sign of Interaction	Panel A: 3 Month Size Adjusted Future Returns		Panel B: 6 Month Size Adjusted Future Returns		Panel C: 12 Month Size Adjusted Future Returns	
		Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
INTERCEPT		0.0108	0.00621*	0.0433	0.0110***	0.113	0.0208***
ANA		0.0165	0.00435***	0.0185	0.00659***	0.0128	0.0136
ANA*PIN		**−0.0160**	**0.00640****	**−0.00836**	**0.00968**	**0.00913**	**0.0178**
CI		0.0271	0.00465***	0.0353	0.00789***	0.0714	0.0152***
CI*PIN	(−)	**−0.0223**	**0.00765*****	**−0.0291**	**0.0121****	**−0.0725**	**0.0212*****
PIN		0.0239	0.00553***	0.0319	0.00843***	0.0524	0.0156***
SIZE		−0.00326	0.000825***	−0.00748	0.00153***	−0.0178	0.00326***
BEME		0.0124	0.00208***	0.0178	0.00378***	0.0216	0.00772***
MOM6RET		0.0284	0.00464***	0.0589	0.00872***	0.0363	0.0139***
MOM7RET12		−0.00490	0.00372	−0.0144	0.00670**	−0.0296	0.0100***
TURN		−0.000380	0.000192**	−0.000970	0.000295***	−0.00196	0.000514***
BETA		0.00437	0.00184**	0.00430	0.00305	0.0180	0.00690***
Expected comparison of interaction coefficients	CI*PIN - ANA*PIN > 0	Directionally Correct		Yes*		Yes***	

This table reports results of regressions of future size-adjusted buy-and-hold abnormal returns (SAR) on informed signals for analysts (ANA) and corporate insiders (CI) as developed in Section 3.1 and firm-specific probabilities of informed trade (PIN). Panels A, B, and C report future SAR's at the 3-, 6-, and 12-month horizons. PIN calculations, courtesy of Stephen Brown, are further detailed in Section 3.2.1 and calculated according to the methodology derived by Easley, Kiefer, and O'Hara (1997). PIN is then converted into a binary variable where firms in the lower quintile are assigned a value of one, while all remaining firms are assigned a value of zero. Size, book-to-market, momentum, CAPM beta, and share turnover are used as controls for expected returns. Size is taken as the log (Market Value of Equity) at the beginning of each quarter. Book-to-market is calculated as the log (Book Value of Equity/Market Value of Equity) at the start of each quarter. Momentum is controlled for as a prior 6-month return (MOM6RET), as well as a prior return in months seven through twelve (MOM7RET12). Beta is calculated using CAPM over a 36-month rolling window, while share turnover is calculated as the sum of volume over the trailing 6 months divided by total shares outstanding at the beginning of the period. Two-tailed statistical significance levels at 1%, 5%, and 10% are indicated as ***, **, and * respectively, based on t-statistics calculated with Newey-West autocorrelation consistent standard errors. Directional comparisons of regression coefficients report Wald statistics from linear restriction tests, again with ***, **, * indicating significance at 1%, 5% and 10%, respectively.

Table 6
Regressions of size-adjusted future returns on informed signals and future earnings response coefficient (FERC).

Parameter	Expected Sign of Interaction	Panel A: 3 Month Size Adjusted Future Returns		Panel B: 6 Month Size Adjusted Future Returns		Panel C: 12 Month Size Adjusted Future Returns	
		Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
INTERCEPT		0.0180	0.00734**	0.0445	0.0126***	0.131	0.0245***
ANA		0.0110	0.00498**	0.0215	0.00758***	0.0108	0.0153
ANA*FERC		**−0.00190**	**0.0114**	**−0.0291**	**0.0178**	**−0.0446**	**0.0303**
CI		0.0297	0.00573***	0.0454	0.00941***	0.0793	0.0186***
CI*FERC	(−)	**−0.0447**	**0.0125*** **	**−0.0780**	**0.0207*** **	**−0.0896**	**0.0370** **
FERC		0.00663	0.00956	0.0185	0.0161	0.0151	0.0262
SIZE		−0.00317	0.000908***	−0.00670	0.00164***	−0.0193	0.00362***
BEME		0.0126	0.00289***	0.0171	0.00504***	0.0195	0.0104*
MOM6RET		0.0254	0.00512***	0.0536	0.00919***	0.0332	0.0159**
MOM7RET12		0.000782	0.00491	−0.00740	0.00855	−0.0239	0.0127*
TURN		−0.000360	0.000298	−0.000910	0.000483*	−0.00230	0.000849***
BETA		0.000866	0.00278	−0.00187	0.00443	0.0224	0.0104**
Expected comparison of interaction coefficients	CI*FERC - ANA*FERC < 0	Yes**		Yes*		Directionally Correct	

This table reports results of regressions of future size-adjusted buy-and-hold abnormal returns (SAR) on informed signals for analysts (ANA) and corporate insiders (CI) as developed in Section 3.1 and future earnings response coefficients (FERC). Panels A, B, and C report future SAR's at the 3-, 6-, and 12-month horizons. FERC, further detailed in Section 3.2.1, is calculated using a rolling regression over the past 36 months for each firm in a manner similar to that of Lundholm and Myers (2002). FERC is then converted into a binary variable where firms in the upper quintile are assigned a value of one, while all remaining firms are assigned a value of zero. Size is taken as the log (Market Value of Equity) at the beginning of each quarter. Book-to-market is calculated as the log (Book Value of Equity/Market Value of Equity) at the start of each quarter. Momentum is controlled for as a prior 6-month return (MOM6RET), as well as a prior return in months seven through twelve (MOM7RET12). Beta is calculated using CAPM over a 36-month rolling window, while share turnover is calculated as the sum of volume over the trailing 6 months divided by total shares outstanding at the beginning of the period. Two-tailed statistical significance levels at 1%, 5%, and 10% are indicated as ***, **, and * respectively, based on t-statistics calculated with Newey-West autocorrelation consistent standard errors. Directional comparisons of regression coefficients report Wald statistics from linear restriction tests, again with ***, **, * indicating significance at 1%, 5% and 10%, respectively.

revealed by the insiders' signal more than the analysts' signal—-with results indicating statistical significance at 3- and 6-month horizons.

Summing the coefficients on CI + CI*INFO for both FERC and PIN measures the total amount of information revealed by insider trades under a more efficient firm-specific environment. In five of six specifications, the summed coefficients are insignificantly different from zero, and are marginally negative in the sixth specification (untabulated). That is, insiders do not appear to reveal new information to prices when the information environment is already efficient with respect to firm-specific information.

Overall, using PIN and FERC as moderators of the information revealed by both signals provides evidence that insider trades depend more heavily on firm-specific information than analyst recommendations in terms of contributing to the price discovery process. Given that the coefficients on ANA*PIN and ANA*FERC are insignificant in five of six regressions, the information content revealed by analyst recommendations appears to be relatively unimpacted by the degree of informational efficiency for firm-specific information, and implies that the majority of their information content comes from non-idiosyncratic sources.

5.2.2. Industry-level informational efficiency

Table 7 presents analyses of IDELAY as a moderator of information revealed by analyst recommendations and insider trades. When IDELAY is not in the upper quintile, the magnitude of the ANA coefficient is economically small, 0.6%, 0.9%, and 0.8% over the 3-, 6-, and 12-month horizons, respectively. However, in the upper quintile of IDELAY, i.e. where the industry-level information environment is most inefficient, the information content from analyst recommendations, i.e. the coefficient on ANA*IDELAY, increases by 3.3%, 4.5%, and 6.1%, and is statistically significant at all of the tested horizons. These results, in combination with the findings from Section 5.2.1 imply that analyst recommendations rely more strongly on industry-level sources when informing prices.

Regarding the amount of information revealed by insider trades when IDELAY is not in the upper quintile, magnitudes are large and similar to those of the baseline regressions in Table 4, and are economically significant. When IDELAY is high, the coefficient of CI*IDELAY is insignificant at all three horizons, indicating that insider trades do not reveal significantly more information when markets are inefficient with respect to industry-level information. Overall, the relative comparisons of interaction coefficients ANA*IDELAY with CI*IDELAY reveal that the mechanism by which analyst recommendations inform prices is significantly more dependent on industry-level inefficiencies when compared to insider trades.

Fig. 2A, B, and 2C graphically compare interaction coefficients from Tables 5–7, respectively, and summarize the relative impact of differing firm and industry level informational environments via PIN, FERC, and IDELAY on the informed signals. Results can be summarized as follows: (1) when stock price informativeness is higher with respect to firm-specific information, the decrease in information content from insider trades is greater than the decrease in information content from analyst recommendations. In fact, while insider trades reveal the largest magnitudes of information in the unconditional analyses, the degree in attenuation is so large when prices are highly informative with respect to firm specific information that insider trades no longer appear to inform prices. Conversely, the information content of analyst recommendations remains unchanged with both proxies of firm-level informational efficiency, implying that the information content from analyst recommendations is unlikely to rely on firm-specific information. (2) When industry information is slowly absorbed by prices, the amount of new information revealed by analyst recommendations is significantly larger than the amount of new information revealed by insider trades. In fact, the amount of new information revealed by insider trades remains completely unchanged. To the extent that the size-adjusted returns and the vector of controls in the regression appropriately capture risk-related expected returns, and ANA and CI are not correlated with a missing control variable, these findings indicate that insider trades rely

Table 7
Regressions of size-adjusted future returns on informed signals and industry delay (IDELAY).

Parameter	Expected Sign of Interaction	Panel A: 3 Month Size Adjusted Future Returns		Panel B: 6 Month Size Adjusted Future Returns		Panel C: 12 Month Size Adjusted Future Returns	
		Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
INTERCEPT		0.0168	0.00545***	0.0400	0.00966***	0.107	0.0188***
ANA		0.00646	0.00330**	0.00905	0.00479*	0.00824	0.00964
ANA*IDELAY	(+)	**0.0333**	**0.0104*****	**0.0446**	**0.0175****	**0.0614**	**0.0300****
CI		0.0200	0.00401***	0.0254	0.00644***	0.0480	0.0121***
CI*IDELAY		**0.00666**	**0.0106**	**0.00394**	**0.0195**	**0.00503**	**0.0396**
IDELAY		−0.0220	0.00824***	−0.0180	0.0144	−0.0196	0.0244
SIZE		−0.00263	0.000662***	−0.00493	0.00122***	−0.0137	0.00265***
BEME		0.0123	0.00205***	0.0185	0.00368***	0.0217	0.00761***
MOM6RET		0.0264	0.00446***	0.0565	0.00836***	0.0309	0.0131**
MOM7RET12		−0.00594	0.00362	−0.0183	0.00632***	−0.0336	0.00949***
TURN		−0.000230	0.000180	−0.000650	0.000282**	−0.00147	0.000482***
BETA		0.00393	0.00176**	0.003102	0.00291	0.0148	0.00658**
Expected comparison of interaction coefficients	CI*IDELAY - ANA*IDELAY < 0	Yes**		Yes*		Directionally Correct	

This table reports results of regressions of future size-adjusted buy-and-hold abnormal returns (SAR) on informed signals for analysts (ANA) and corporate insiders (CI) as developed in Section 3.1 and industry delay (IDELAY). Panels A, B, and C report future SAR's at the 3-, 6-, and 12-month horizons. IDELAY, further detailed in Section 3.2.2, is calculated using a rolling regression over the past 36 months for each firm in a manner similar to that of Engelberg et al. (2018). IDELAY is then converted into a binary variable where firms in the upper quintile are assigned a value of one, while all remaining firms are assigned a value of zero. Size is taken as the log (Market Value of Equity) at the beginning of each quarter. Book-to-market is calculated as the log (Book Value of Equity/Market Value of Equity) at the start of each quarter. Momentum is controlled for as a prior 6-month return (MOM6RET), as well as a prior return in months seven through twelve (MOM7RET12). Beta is calculated using CAPM over a 36-month rolling window, while share turnover is calculated as the sum of volume over the trailing 6 months divided by total shares outstanding at the beginning of the period. Two-tailed statistical significance levels at 1%, 5%, and 10% are indicated as ***, **, and * respectively, based on t-statistics calculated with Newey-West autocorrelation consistent standard errors.

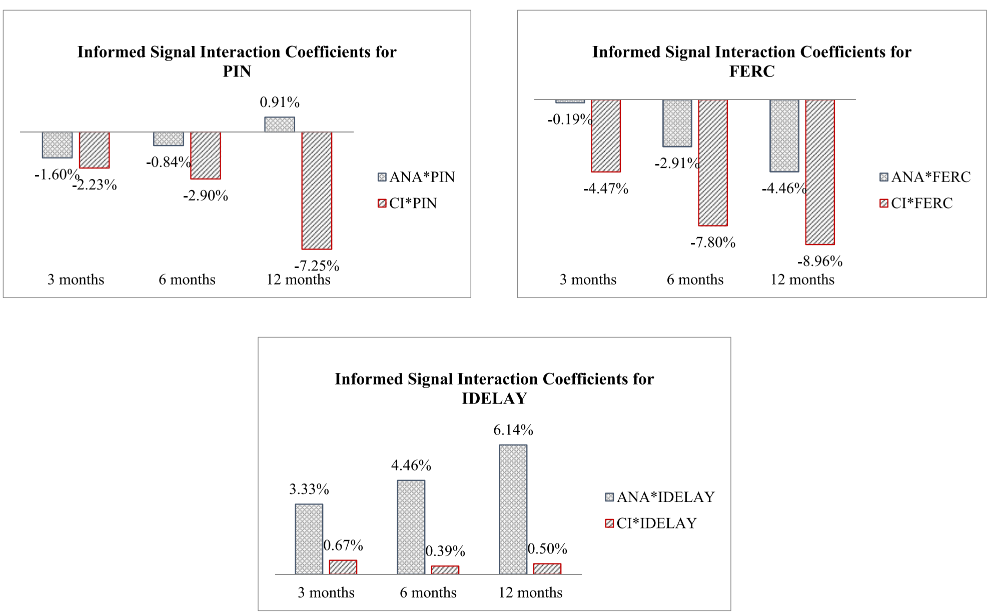

Fig. 2. Figures 2A, B, and 2C illustrate interaction coefficients from Tables 5–7 for the informed signal for analysts' (ANA) and corporate insiders' (CI), conditional on firms with low probability of informed trade (PIN), high future earnings response coefficients (FERC), and high industry delay (IDELAY), respectively. The construction of ANA and CI signals is detailed in Section 3.1. Calculations of PIN and FERC are detailed in Section 3.2.1, while calculations of IDELAY are detailed in Section 3.2.2.

more on firm-specific information than analyst recommendations when informing prices, while analyst recommendations depend more on industry-level information than insider trades.

6. Alternative specifications for informational environments

6.1. Return synchronicity

Analyses from Section 5 indicate that the information revealed via insider trades informs prices primarily by disseminating firm-specific information, while analyst recommendations primarily disseminate industry-specific information to prices. For further robustness, I test the relative magnitudes of information revelation from these signals conditional on two alternative specifications: (1) the synchronicity of a firm's stock prices, and (2) the structural break around the mandate of Regulation Fair Disclosure.

Synchronicity, calculated as the R-squared of market/industry model asset pricing regressions for a given firm, has been used as a measure of stock price efficiency with respect to firm-specific or market and industry information (Chan & Hameed, 2006; Durnev, Morck, Yeung, & Zarowin, 2003; Durnev, Merritt, Morck, & Yeung, 2004). In these papers, low R-squared values are indicative of a company where firm-specific information has been impounded more heavily into stock prices, whereas high R-square values are indicative of a firm where common information has been impounded more strongly into stock prices. While proxies used in prior tests in Section 5 only reflected the efficiency of one type of information, synchronicity captures relative levels of efficiency for firm-specific versus market and industry information, making it a unique tool to test the impact of the information environment on the relative differences in information content from analyst recommendations and insider trades.

When synchronicity is high, stock returns comove more strongly with industry and market returns, implying that the firm's information environment is less likely to already reflect firm-specific information, relative to industry and common information. Given that results in Section 5 indicate that insider trades appear to primarily inform prices by disseminating firm-specific information, the magnitude of information revealed by insider trades should become larger when synchronicity is high. In addition, since prices are more likely to already reflect common information, the magnitude of information revealed by analyst recommendations should decrease when synchronicity is high. Note that using SYNCH as a moderator of the two signals results in predictions of opposite signs on the interactions of ANA and CI with SYNCH, whereas results from other prior analyses, i.e. FERC, PIN, and IDELAY document significance in only one of the two tested interactions.

I calculate the relative amount of industry and macro-level versus firm-specific information already impounded in prices at any given point by measuring firm-level synchronicity over the preceding 36 months via firm-specific rolling regressions, following the methodology used by Piotroski and Roulstone (2004).[12] I calculate synchronicity using Equation (7):

$$FirmRET_{it} = a + b_1 MktRET_{jt} + b_2 MktRET_{jt-1} + b_3 IndRET_{kt} + b_4 IndRET_{kt-1} + \varepsilon_{it} \quad (7)$$

Synchronicity is measured as the R-squared of the regression. Remaining consistent with prior methodology, I rank the synchronicity scores into quintiles, and create a binary variable and assign a value of 1 to firms in the upper quintile, and a value of zero for all remaining firms. I then run the panel regressions using Equation (7), with SYNCH as the moderator variable.

Results in Table 8 indicate that synchronicity can impact the magnitude of information revelation from each group's signal in opposing directions. The interaction coefficient on CI*SYNCH is directionally positive at the 3- and 6-month horizons, and significantly positive at 12 months, while the interaction coefficient on ANA*SYNCH is significantly negative at the 3-month horizon, and directionally negative at 6 and 12 months. The relative differences between the coefficients on ANA and CI are significant at all three horizons, with the information revelation from insider trades increasing by a greater amount than that from analyst recommendations when synchronicity is high. Overall, results from the synchronicity analyses are consistent with inferences when PIN, FERC, and IDELAY are used as moderators of information content.

6.2. Regulation fair disclosure

Regulation Fair Disclosure (FD) was adopted by the SEC on October 23, 2000 in order to eliminate selective disclosure to analysts and institutional investors.[13] FD mandates that publicly traded companies disclose material information to all market participants simultaneously, in an attempt to reduce the informational advantages held by information intermediaries over individual investors. While Francis, Nanda, and Wang (2006) and Ke, Petroni, and Yu (2008) conclude that FD has succeeded in reducing information asymmetries between institutional investors and individual investors, they find evidence of a reduction in the magnitude and frequency of private disclosures from insiders to analysts and institutions, implying an increase in the informational advantages of insiders. Consistent with the aforementioned studies, Gomes, Gorton, and Madureira (2007) argues that FD resulted in unintended consequences, in that the cost of information acquisition increased for analysts, leading to firms having a higher cost of capital.

If FD reduces the selective transfer of information from insiders to analysts, then the post-FD information environment will be characterized by an increased level of private information held by insiders, and a decreased level of the aggregate amount of information available to analysts. Thus, the structural break around the passing of FD can be used as a moderator of information content for both signals. The magnitude of total information disclosed by insider trades (analyst recommendations) should become significantly larger (smaller) in the post-FD era. I assign a value of one to FD over the years 2001–2006, and zero for all prior years, and rerun the regression specification from equation (5). Findings from Table 9 show that the additional amount of information revealed by insider trades is positive and significant in the post-FD era relative to the pre-FD era across 3, 6, and 12-month horizons. Conversely, the analysts signal becomes significantly weaker at the 6 and 12 month horizons, to where the information content from ANA is neutralized at 6 and 12 month horizons following the passing of FD. Comparing the interaction coefficients shows that the information content of insider trades significantly increases compared to the information content of analyst recommendations across all three time windows in the post-FD era. These results highlight the causal impact of FD on the information content of analyst recommendations and insider trades, while also confirming the results from Tables 5 and 6, which documented that the insider signal reveals more information to prices when the information environment is less reflective of firm-specific information.

7. Conclusion and suggestions for future research

Analysts and insiders increase the informativeness of prices by collecting information from various sources, processing such information to determine its impact on the firm's equity value, then revealing their beliefs to financial markets in the form of analyst recommendations and insider trades. While prior literature has shown that both groups possess firm and industry information, I argue that analysts and insiders may be more advantaged in collecting and processing a particular type of information because of the roles that they play in relation to the firm, thereby leading to the informativeness of each group's signal being more reliant upon a particular information channel. Because prices move in response to unanticipated information, I test how the magnitude of information content from these disclosures by analysts and insiders may be differentially impacted by a stock price's level of informativeness with respect to firm and industry level information.

Using PIN and FERC as proxies for firm-specific informational efficiency, I demonstrate that the magnitude of information from insider trades is more significantly attenuated than the magnitude from analyst recommendations when prices are efficient with respect to firm-specific information. The decrease in insider trades' information content is economically and statistically significant

[12] Piotroski and Roulstone (2004) show that analysts (insiders) tend to impound more macro-level (firm-specific) information into prices. Other synchronicity determinants include the overall level of firm diversification, the level of intra-industry competition, and the volatility of the firm's earnings stream.

[13] http://www.sec.gov/news/headlines/gofd.htm.

Table 8
Regressions of size-adjusted future returns on informed signals and firm-level synchronicity (SYNCH).

Parameter	Expected Sign of Interaction	Panel A: 3 Month Size Adjusted Future Returns		Panel B: 6 Month Size Adjusted Future Returns		Panel C: 12 Month Size Adjusted Future Returns	
		Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
INTERCEPT		0.0119	0.00557**	0.0384	0.00983***	0.112	0.0192***
ANA		0.0171	0.00348***	0.0198	0.00536***	0.0273	0.0103***
ANA*SYNCH	(−)	**−0.0258**	**0.00796*****	**−0.0175**	**0.0115**	**−0.0425**	**0.0222***
CI		0.0182	0.00401***	0.0217	0.00700***	0.0325	0.0132**
CI*SYNCH	(+)	**0.0111**	**0.00937**	**0.0225**	**0.0149**	**0.0790**	**0.0325****
SYNCH		0.00856	0.00622	−0.0000600	0.00976	−0.00227	0.0177
SIZE		−0.00260	0.000686***	−0.00533	0.00126***	−0.0152	0.00270***
BEME		0.0121	0.00207***	0.0177	0.00373***	0.0203	0.00763***
MOM6RET		0.0271	0.00445***	0.0572	0.00832***	0.0325	0.0131**
MOM7RET12		−0.00568	0.00363	−0.0175	0.00634***	−0.0318	0.00955***
TURN		−0.000250	0.000179	−0.000640	0.000280**	−0.00139	0.000479***
BETA		0.00353	0.00179**	0.00315	0.00303	0.0132	0.00671**
Expected comparison of interaction coefficients	CI*SYNCH - ANA*SYNCH > 0	Yes***		Yes**		Yes***	

This table reports results of regressions of future size-adjusted buy-and-hold abnormal returns (SAR) on informed signals for analysts (ANA) and corporate insiders (CI) as developed in Section 3.1 and firm-level synchronicity. Panels A, B, and C report future SAR's at the 3-, 6-, and 12-month horizons. Synchronicity (SYNCH), detailed in Section 6.1, is calculated using a rolling regression over the past 36 months for each firm in a manner similar to that of Piotroski and Roulstone (2004). SYNCH is then converted into a binary variable where firms in the upper quintile are assigned a value of one, while all remaining firms are assigned a value of zero. Size is taken as the log (Market Value of Equity) at the beginning of each quarter. Book-to-market is calculated as the log (Book Value of Equity/Market Value of Equity) at the start of each quarter. Momentum is controlled for as a prior 6-month return (MOM6RET), as well as a prior return in months seven through twelve (MOM7RET12). Beta is calculated using CAPM over a 36-month rolling window, while share turnover is calculated as the sum of volume over the trailing 6 months divided by total shares outstanding at the beginning of the period. Two-tailed statistical significance levels at 1%, 5%, and 10% are indicated as ***, **, and * respectively, based on t-statistics calculated with Newey-West autocorrelation consistent standard errors. Directional comparisons of regression coefficients report Wald statistics from linear restriction tests, again with ***, **, * indicating significance at 1%, 5% and 10%, respectively.

Table 9
Regressions of size-adjusted future returns on informed signals and regulation fair-disclosure (FD).

Parameter	Expected Sign of Interaction	Panel A: 3 Month Size Adjusted Future Returns		Panel B: 6 Month Size Adjusted Future Returns		Panel C: 12 Month Size Adjusted Future Returns	
		Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
INTERCEPT		0.0118	0.00624*	0.0280	0.0102***	0.0961	0.0192***
ANA		0.0171	0.00505***	0.0370	0.00811***	0.0436	0.0143***
ANA*FD	(−)	**−0.00957**	**0.00648**	**−0.0371**	**0.00995*****	**−0.0460**	**0.0189****
CI		0.0127	0.00562**	0.0170	0.00942*	0.0305	0.0171*
CI*FD	(+)	**0.0220**	**0.00739***	**0.0275468**	**0.0117****	**0.0479**	**0.0226****
FD		0.00694	0.00538	0.0223	0.00838**	0.0209	0.0146
SIZE		−0.00309	0.000659***	−0.00593	0.00107***	−0.0150	0.00225***
BEME		0.0115	0.00205***	0.0171	0.00328***	0.0203	0.00630***
MOM6RET		0.0267	0.00430***	0.0566	0.00758***	0.0310	0.0118***
MOM7RET12		−0.00555	0.00371	−0.0172	0.00619***	−0.0320	0.00895***
TURN		−0.000330	0.000192*	−0.000750	0.000255***	−0.00155	0.000399***
BETA		0.00358	0.00186*	0.00327	0.00252	0.0150	0.00512***
Expected comparison of interaction coefficients	CI*FD - ANA*FD >0	Yes***		Yes***		Yes***	

This table reports results of regressions of future size-adjusted buy-and-hold abnormal returns (SAR) on informed signals for analysts (ANA) and corporate insiders (CI) as developed in Section 3.1 and Regulation Fair Disclosure (FD). Panels A, B, and C report future SAR's at the 3-, 6-, and 12-month horizons. FD is a binary variable where firms reporting after the passing of Regulation Fair Disclosure (October 23, 2000) are assigned a value of one, while firms reporting prior to Reg-FD are assigned a value of zero. Size is taken as the log (Market Value of Equity) at the beginning of each quarter. Book-to-market is calculated as the log (Book Value of Equity/Market Value of Equity) at the start of each quarter. Momentum is controlled for as a prior 6-month return (MOM6RET), as well as a prior return in months seven through twelve (MOM7RET12). Beta is calculated using CAPM over a 36-month rolling window, while share turnover is calculated as the sum of volume over the trailing 6 months divided by total shares outstanding at the beginning of the period. Two-tailed statistical significance levels at 1%, 5%, and 10% are indicated as ***, **, and * respectively, based on t-statistics calculated with Newey-West autocorrelation consistent standard errors. Directional comparisons of regression coefficients report Wald statistics from linear restriction tests, again with ***, **, * indicating significance at 1%, 5% and 10%, respectively.

under these conditions, while the decrease in information content of analyst recommendations is generally unimpacted. Conversely, when I use IDELAY to proxy for high levels of information inefficiency with respect to industry-wide information, I find that the amount of information revealed by analyst recommendations increases by a larger amount compared to the amount revealed by insider trades. Specifically, while the increase in the total amount of information disclosed by analysts is large and significant, I find no additional information content revealed by insider trades under this condition. Examining the relative information content of these two groups as moderated by SYNCH and Reg-FD, I find results that corroborate my main analyses—that insiders rely more heavily than analysts on firm-specific information and that analysts rely more heavily than insiders on industry information when informing prices.

While prior literature has documented that analysts and insiders have both firm-specific and industry-level information, the collective evidence from my analyses contributes to the literature on information intermediaries by documenting that insiders and analysts appear to have different advantages in obtaining or processing particular types of information, resulting in proxies for the firm and industry information environment having a differential impact on the information content of analyst recommendations and insider trades. While the purpose of this paper was not to directly test the applicability of trading strategies using analyst recommendations and insider trades, my results also imply that trading strategies based on analyst recommendations and insider trades should be conditional on the current firm and industry information environment.[14]

The fact that analysts and insiders differ across multiple dimensions provides additional suggestions for future research. For example, why are the horizons over which information from analyst and insider signals is impounded into prices so markedly different? Examining the relative affinity of money managers for each signal could provide additional insight into this question. If money managers are incentivized to "window-dress" their performance disclosures by holding firms with strong past performance in their portfolios, they may be more likely to follow analyst recommendations then insider trades, thereby resulting in the analyst signal being more rapidly impounded into prices, relative to the insider signal.

Additionally, it is noteworthy that the opposing preferences for firm characteristics such as past performance, and growth for analysts and insiders will give rise to a cross-section of firms where inter-group disagreement exists, i.e. analysts are issuing buy recommendations while insiders are selling shares. While the existing literature has assumed that arbitrageurs will always act in a coordinated manner to eliminate mispricing, disagreement in opinion from these two informed agents could impede the arbitrage mechanism. If news is released and these groups issue conflicting signals, prices may be slower in converging to fundamental value, thereby making market anomalies (e.g. momentum, post-earnings announcement drift, accrual fixation) more profitable and easily executable.

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[14] It is also worth noting that this study, which focuses on relative information content of analysts and insiders, requires the disclosure of both signals. Investors making trading decisions that require only one signal could examine the incremental information content from an analyst or insider signal that includes the absence of a signal in the given period. For example, McNichols and O'Brien (1998) provide evidence that dropped analyst coverage may signal negative future performance, while the omission of insider trading could also signal information to financial markets.