The Research of Analysts' Information Source: Empirical Evidence from A-Stock Market of China

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Abstract

This paper use stock returns around and after recommendation changes to measure the information produced by analysts, we find that analysts prefer to firm-specific information, analysts produce more firm-specific information than industry-level information. The amount of firm-specific information on stocks produced by analysts increases with the higher idiosyncratic return volatilities. The amount of industry information on stocks produced by analysts decreases with the stock's idiosyncratic return and increases with the absolute value of the stock's industry beta. At the last of paper, using the results of research, we show how investor may use analyst research more effectively and improve their investment performance.

Key words: Security Analyst, Information, Market Efficient

I. Introduction

With the development of Chinese economic, the number of financial analysts increases quickly, A number of studies document that financial analysts' research has investment value, Examples include Womack (1996), and Brav and Lehavy(2003),woo(2005),zhu(2007). The literature offers different views, however, on whether the information provided by analysts is mainly at the industry level or the firm level. Most empirical studies find that analysts have industry expertise (e.g., Boni and Womack (2006),and Chan and Hameed (2006)). Other studies, however, document that the information analysts produce is mainly firm specific (e.g., Feng and Li(2011), and Forbes, Huijgen, and Plantinga (2006)).

According to Chinese security market, we investigate where the analysts information come from, A related but broader question is what motivates analysts to produce information in general. Answering these questions could help researchers and practitioners better understand analyst behavior. More importantly, understanding analysts' incentives to produce industry-level and firm-specific information may help investors use the information in analyst research more effectively and potentially improve their investment performance.

By developing a method to decompose the information in analyst research into market, industry, and firm-specific components, I show that the information produced by analysts is mainly at the firm-specific level instead of the industry level. I find evidence consistent with the notion that analysts produce private information to increase the investment value of their research, possibly to benefit their brokerage clients so that their research will bring them more commission fees. My results also offer insights on how to better use analyst research. For example, the investment value of analyst research on firms with high idiosyncratic volatility is greater than that on firms with low idiosyncratic volatility.

Analysts face a trade-off in choosing between producing private information about individual firms within an industry or the industry as a whole. Private information about an entire industry allows investors to profit from multiple firms. I call this the "economy-of-scale effect" of industry information. On the other hand, there is much more information about an industry as a whole than there is for any one firm within the industry. The reason is that public information about individual firms spills over to other firms because all firms in the industry are affected by the same industry factors. Therefore, industry information reflects an aggregation of many such public signals. This "spillover effect" means that it may be more valuable for analysts to produce private firm-specific information because most industry information is already aggregated into the stock price. If analysts' incentives to produce information are influenced by the investment value of their research, several testable hypotheses can be developed that do not depend on whether the spillover effect or the economy-of-scale effect dominates.

Specifically, I hypothesize that analysts' incentives to produce firm-specific information increase with the firm's idiosyncratic volatility because the values of firms with high idiosyncratic volatilities are influenced more by firm-specific information. Therefore, the investment value of private firm-specific information is greater for firms with high idiosyncratic volatilities, which in turn gives analysts incentives to produce more firm-specific information. I also hypothesize that analysts' incentives to produce industry information increase with the absolute value of the firm's industry beta and decrease with the firm's idiosyncratic volatility because the values of firms with large absolute values of industry beta or small values of idiosyncratic volatility are more influenced by industry-level information and less by firm-specific information. Finally, I hypothesize that when a recommendation is issued on a stock, other stocks in the same industry will respond in the same direction as the recommended stock, and the magnitude of the response increases with the absolute value of the industry beta of the recommended stock and that of other stocks in the industry. The reason is that analyst recommendations are informative about the industry factors, which in turn affect all firms in the industry.

I test these hypotheses using analyst stock recommendations from the Wind(China data company). Results show that the firm-specific components of stock returns around analyst recommendations are on average much greater in magnitude than the industry components. For example, I find that the average firm-specific and industry components of 3-day cumulative returns centered around an upgrade are 2.61% and 0.10%, respectively, and those around a downgrade are-2.89% and-0.06%, respectively. If the market reaction around recommendation changes reflects the private information produced by financial analysts, then these numbers show that analysts produce at least 26 times as much firm-specific as industry-level information. Previous studies document post-recommendation drifts that are positively related to returns around recommendation changes (Womack (1996), Mikhail, Walther, and Willis (2004)), and I find that the post-recommendation drifts are also driven mainly by firm-specific instead of industry-level information.

Results reported in this paper also show that the firm-specific components of stock returns around recommendation changes increase in magnitude with the idiosyncratic volatility of the recommended stock. Similarly, the industry components of stock returns around recommendation changes increase in magnitude with the absolute value of the industry beta and decrease in magnitude with the idiosyncratic volatility of the recommended stock. I also find that the prices of other stocks in the same industry as the recommended stock respond in the same direction as the recommendation change, and the magnitude of the response increases with the absolute value of the industry beta of the recommended stock and that of other stocks in the same industry. This paper is related to the vast literature examining the information content of analyst research. My purpose is not to investigate whether analyst research has investment value, but to examine whether the investment value is at the industry level or the firm level.

The results in this paper support the studies documenting that the information analysts produce is mainly firm specific. Interestingly, my results are also consistent with some findings in papers claiming that financial analysts have significant industry expertise. For example, Boni and Womack (2006)find that a portfolio buying firms net upgraded by analysts and shorting firms net downgraded by analysts within each industry outperforms a portfolio buying firms net upgraded by analysts and shorting firms net downgraded by analysts in the whole market. Clearly, the 1st portfolio uses mostly firm-specific information in analyst recommendations, because most market and industry information is canceled out by buying and shorting stocks in the same industry, whereas the 2nd portfolio uses both industry-level and firm-specific information. The results thus imply that using only firm-specific information to form a portfolio is more profitable than using both industry-level and firm-specific information, and this is evidence that firm-specific information in analyst recommendations has more investment value than industry information.

The rest of the paper is organized as follows. Section 2 envelops testable hypotheses. Section3 resents empirical methodologies, results, and investment implications. Section 4 concludes.

2. Hypotheses Development

In this section, I will develop several hypotheses on analysts' incentives to produce industry-level versus firm-specific information. No formal model will be presented. To facilitate exposition, I will use some simple equations. Consider an industry with N firms. The value of firm n's stock is V_n, the expected value of which is $\overline{V}_n$. then:

$$V_n = \overline{V}_n + \beta_n \times I + F_n, n \in \{1,2,\dots,N\}$$

where β_n is the industry beta of stock n, and I and F_n are independent of each other. Suppose here are 3 dates: times 0, 1, and 2. At time 0, one public signal about each firm comes to the market. The public signal could be an earnings announcement, a stock recommendation issued by another analyst, an earnings forecast, or other public news. A price is formed for each stock after that time, Suppose there are three times, at time 0, the stock prices will incorporate public signals on the N firms in the industry. The public signal on every stock is informative about the industry factor because all stocks in the industry are influenced by the industry factor. When there are many firms in the industry, many public signals are available about the industry factor, and as a result, a large fraction of industry-level information is incorporated into stock prices.

In contrast, the fraction of firm-specific information reflected in a firm's stock price is not directly affected by the number of firms in the industry, because a stock's firm-specific component is not directly affected by public signals on other stocks. Therefore, I expect more industry-level than firm-specific information to be incorporated into stock prices at any time. This is consistent with the empirical finding of Ayers and Freeman (1997) that industry-level earnings information is incorporated into stock prices earlier than firm-specific earnings information. Because more industry-level than firm-specific information is incorporated into stock prices, it is more difficult for the investor to profit from private industry level information and easier to profit from private firm-specific information, which in turn gives the analyst an incentive to produce more firm-specific rather than industry-level information. I call this effect the "spillover effect."

On the other hand, whenever the analyst produces a signal about the industry factor, she can use the signal on all the m stocks that she covers and improves the investment value of all recommendations. As a result, the investor can use the private industry-level information produced by the analyst to trade on and profit from all m stocks. In contrast, the investor can use private firm-specific information to trade on and profit from only 1 particular stock, which gives the analyst an incentive to produce more industry-level rather than firm-specific information. I call this effect the "economy-of-scale effect." Depending on which effect dominates, the analyst may have an incentive to produce more or less industry-level than firm-specific information. If the market reaction around recommendations reflects the private information produced by financial analysts, then the firm specific (industry) component of the market reaction is greater when the spillover (economy-of-scale) effect dominates. Hence, the 1st testable hypothesis is as follows:

Hypothesis 1A. Assuming the spillover effect dominates the economy-of-scale effect, the firm-specific component is greater than the industry component of the market reaction around an analyst recommendation.
Hypothesis 1B. Assuming the economy-of-scale effect dominates the spillover effect, the industry component is greater than the firm-specific component of the market reaction around an analyst recommendation.

The analyst's incentive to produce firm-specific information is also influenced by certain firm characteristics. From equation (1) one can see that the total value of the firm is influenced by both the industry factor and the firm-specific component. Specifically, the variance of firm n's stock value can be decomposed into an industry component, ${\beta_n}^2 \times \mathrm{Var}(I)$, and a firm-specific component,$\mathrm{Var}(F_n)$;

that is,

$$\mathrm{Var}(V_n) = {\beta_n}^2 \times \mathrm{Var}(I) + \mathrm{Var}(F_n), n \in \{1,2,\dots,N\}$$

Consider 2 firms with the same industry beta but different firm-specific variances. The value of the firm with a higher(lower) idiosyncratic volatility is more (less) influenced by the firm-specific component. Therefore, it is easier (harder) for the investor to profit from private firm-specific information about the firm with a higher (lower) idiosyncratic volatility. As a result, the analyst has an incentive to produce more (less) firm-specific information about the firm with a higher (lower) idiosyncratic volatility. If the market reaction around recommendations reflects the private information produced by financial analysts, then the 2nd testable hypothesis is:

Hypothesis2.The firm-specific component of the market reaction around an analyst recommendation increases with the recommended stock's idiosyncratic volatility.

Now consider 2 firms with the same firm-specific variance, $Var(F_n)$, but different industry betas. The value of the firm with a greater (smaller) absolute value of industry beta, $|\beta_n|$, is more (less) influenced by the industry factor. Therefore, it is easier (harder) for the investor to profit from private industry-level information about the firm with a greater (smaller) $|\beta_n|$, which, in turn, gives the analyst an incentive to produce more (less) industry information on the firm with a greater (smaller) $|\beta_n|$. If the market reaction around recommendations reflects the private information produced by financial analysts, then I offer the following testable hypothesis:

Hypothesis 3. The industry component of the market reaction around an analyst recommendation increases with the absolute value of the recommended stock's industry beta.

The value of a firm with a low idiosyncratic volatility is influenced more by the industry factor compared to the value of a firm with a high idiosyncratic volatility. If the analyst covers the firm with a low idiosyncratic volatility, she has an incentive to produce more industry information compared to the case where she covers the firm with a high idiosyncratic volatility. The reason is that it is easier (harder) for the investor to profit from private industry-level information when the investor trades the stock whose value is more (less) influenced by the industry factor. If the market reaction around recommendations reflects the private information produced by financial analysts, then I have the following testable hypothesis:

Hypothesis 4. The industry component of the market reaction around an analyst recommendation decreases with the firm's idiosyncratic volatility.

It is worth noting that even though the 1st hypothesis generates different predictions depending on whether the spillover effect dominates the economy-of scale effect or the other way around, the remaining 4 hypotheses do not depend on either of the 2 effects. As long as analysts' incentives to produce industry level and firm-specific information increase with the investment value of analyst recommendations and the market reaction around recommendations reflects the private information produced by financial analysts, Hypotheses 2–4 should hold.

3. Empirical Evidence

In this section, I empirically test the hypotheses developed in Section II. Specifically, I test whether the market reacts more strongly to industry-level or firm-specific information in analyst recommendations. I also examine market reactions to industry-level and firm-specific information in analyst recommendations among firms with different characteristics.

3.1. Analyst Recommendation Changes

I obtain individual analyst recommendations for Chinese companies from Wind, which collects stock recommendations from brokerage houses and assigns standardized numerical ratings, with numbers 1–5 representing strong buy, buy, hold, underperform, and sell, respectively. If a recommendation has a lower (higher) numerical rating than the previous recommendation issued by the same analyst on the same firm, it is classified as an upgrade (downgrade). Table 1 presents the distribution of analyst recommendation changes over time. The sample covers the years 2003–2011, with12424 upgrades and 12601 downgrades.

Table 1 Distribution of Analyst recommendation Changes Over Time

Years	Upgrades	Downgrades	Total
2003	553	528	1081
2004	809	775	1584
2005	1392	1108	2500
2006	1457	1236	2693
2007	1503	1632	3135
2008	1462	1785	3247
2009	1357	1894	3251
2010	1853	1769	3622
2011	2038	1874	3912
Total	12424	12601	25025

3.2. The Market Reaction to Analyst Recommendation Changes

The market reactions to analyst recommendation changes are measured with 3-day cumulative returns, which are defined as

$$\mathrm{CR}_{n,(-1,1)} = \left(1 + \mathrm{CR}_{n,-1}\right)\left(1 + \mathrm{CR}_{n,0}\right)\left(1 + \mathrm{CR}_{n,+1}\right) - 1$$

where $R_{n,t}$ is the daily stock return of the recommended stock *n* at day *t*, with day 0 being the recommendation date.

Table 2 reports the average 3-day cumulative returns (in percentages) based on the changes of recommendations from one category to another, with numbers of observations for each category in parentheses. The most frequent upgrades are from hold to buy (3979 observations), and the average 3-day return for this type of upgrades is 2.35%, statistically different from 0 at the 1% level. The least frequent upgrades are from sell to underperform (43 observations), with an average 3-day return of 0.57% (not statistically different from 0). The most frequent downgrades are from buy to hold (5050 observations), and the average 3-day return for this type of downgrades is −2.17%, statistically different from 0 at the 1% level. The least frequent downgrades are from underperform to sell (41 observations), with an average 3-day return of −1.76% (statistically different from 0 at the 5% level). The results are similar to those reported in previous studies (Mikhail et al. (2004), Boni and Womack (2006)).

Table 2 Market reaction to upgrades and downgrades

From	To Strong buy 1	2	Hold 3	4	Sell 5
Strong buy 1		- 1.47** (3224)	- 2.03** (3322)	-2.05** (68)	-1.98** (90)
2	2.38** (3286)		-2.17** (5050)	- 2.21** (194)	-0.73 (73)
Hold 3	2.71** (2653)	2.35** (3979)		- 2.52** (912)	-2.89** (522)
4	2.15** (46)	2.73** (152)	2.42** (782)		-1.76* (41)
Sell 5	1.65** (51)	0.05 (54)	1.97** (482)	0.57 (43)	

3.3. Industry-Level and Firm-Specific Components of Stock Returns around and after Analyst Recommendation Change

To test the amount of industry-level versus firm-specific information produced by analysts, I decompose stock returns around analyst recommendation changes into market, industry, and firm-specific components. In each calendar year from 1993 to 2004, I run the following regression to estimate the market and industry betas of stock n, β_n^M, β_n^I :

$$R_{n,t} = \alpha_n + \beta_n^M \times R_t^M + \beta_n^I \times \left(R_t^I - \hat{\beta}_n^{IM} \times R_t^M\right) + \varepsilon_{n,t}$$

where R_t^I is the return on the industry portfolio in day t for stock n's industry. Following Durnev, Morck, Yeung, and Zarowin (2003) and Durnev, Morck, and Yeung (2004), I construct the industry portfolio without stock n to prevent spurious correlations between firm and industry returns in industries with few firms; remaining stocks are then weighted using the market value at day t-1. $\widehat{B}_n^{IM}$ is the market beta of stock n's industry, estimated from the following regression in each calendar year from2002 to 2010:

$$R_t^I = \alpha_n^I + \beta_n^{IM} \times R_t^M + \varepsilon_{n,t}^I$$

It is worth noting that β_n^{IM} is different for different stocks in the same industry because I exclude stock n when constructing the industry portfolio.

The market component of $CR^{M}_{n,(-1,1)}$ is defined as and the industry component is defined as

$CR^{M}_{n,(-1,1)} = \hat{\beta}^{M}_{n} \times R^{M}_{(-1,1)}$,

and the industry component is defined as:

$CR^{I}_{n,(-1,1)} = \hat{\beta}^{I}_{n} \times (R^{I}_{(-1,1)} - \hat{\beta}^{IM}_{n} \times R^{M}_{(-1,1)}$,

where $\hat{\beta}^{M}_{n}, \hat{\beta}^{I}_{n}, \hat{\beta}^{IM}_{n}$ are estimated in the previous calendar year; $R^{M}_{(-1,1)}$is the 3-day cumulative return on the value-weighted market index; and $R^{I}_{(-1,1)}$is the 3-day cumulative return on the value-weighted industry index in firm n's industry (excluding firm n itself). The firm-specific component of $CR_{n,(-1,1)}$ is defined as:

$$CR^{F}_{n,(-1,1)} = CR_{n,(-1,1)} - \hat{\beta}^{M}_{n} \times R^{M}_{(-1,1)} - \hat{\beta}^{I}_{n} \times (R^{I}_{(-1,1)} - \hat{\beta}^{IM}_{n} \times R^{M}_{(-1,1)})$$

Previous studies document post-recommendation drifts in the direction forecast by analysts (Womack (1996), Mikhail et al. (2004)). Further, the post-event drift is positively related to the market reaction around the recommendation change. To investigate whether the post-recommendation drift is mainly at the industry level or the firm level, I decompose stock returns after recommendation changes into industry and firm-specific components and see which components, if any, are the main causes of the post-recommendation drifts. The 1-month pos-event return on stock n is defined as the cumulative daily stock returns from business day 2 to day 23, $CR^{M}_{n,(2,23)}$, given that 1 calendar month has about 22 business days. The market component of $CR^{M}_{n,(2,23)}$ is defined as: $CR^{M}_{n,(2,23)} = \hat{\beta}^{M}_{n} \times R^{M}_{(2,23)}$,

and the industry component is defined as: $CR^{I}_{n,(2,23)} = \hat{\beta}^{I}_{n} \times (R^{I}_{(2,23)} - \hat{\beta}^{IM}_{n} \times R^{M}_{(2,23)})$.

where $R^{M}_{(2,23)}$ is the 22-day cumulative return on the market index; $CR^{I}_{n,(2,23)}$is the 22-day cumulative return on the value-weighted industry portfolio (excluding firm n itself). The firm-specific component of $CR^{F}_{n,(2,23)}$is defined as:

$$CR^{F}_{n,(2,23)} = CR_{n,(2,23)} - \hat{\beta}^{M}_{n} \times R^{M}_{(2,23)} - \hat{\beta}^{I}_{n} \times (R^{I}_{(2,23)} - \hat{\beta}^{IM}_{n} \times R^{M}_{(2,23)})$$

I also look at 3-month post-event returns, $CR^{F}_{n,(2,67)}$, and decompose them into market, industry, and firm-specific components similarly.

Table 3 reports the summary statistics of the market, industry, and firm-specific components of stock returns around and after recommendation changes. Panel A reports results for 3-day cumulative returns around upgrades. The average market beta of the upgraded firm's industry, $\hat{\beta}^{IM}_{n}$ is 1.03, with a median of 1.01 and a standard deviation of 0.37. The average market and industry betas of upgraded firms are 1.12and 0.57, respectively.

The mean (median) firm-specific component of the 3-day cumulative return is 2.49% (1.51%), much greater than the 0.07 (0.01%) for the industry component or the 0.17% (0.21%) for the market component. The standard deviation of the firm-specific component is 8.71, which is also much greater than that of the industry component of 1.73 or that of the market component of 2.51. Panel B reports results for 3-day cumulative returns around downgrades. The average market beta of the downgraded firm's industry, is 1.07, with a median of 1.05 and a standard deviation of 0.41. The average market and industry betas of downgraded firms are 1.12 and 0.55, respectively. The mean (median) firm-specific component of the 3-day cumulative return is-2.82% (-1.59%), much greater in magnitude than the -0.05% (-0.01%) for the industry component or the 0.07% (0.17%) for the market component. The standard deviation of the firm-specific component is 10.17, which is also much greater than that of the industry component of 1.71or that of the market component of 2.61.

Panel C (Panel D) of Table 3 reports results for 1- and 3-month post-recommendation returns for upgrades (downgrades). The average 1- and 3-month post-event total returns are 2.14% and 4.88% for upgrades and 0.69% and 2.92% for downgrades. The average industry components of 1- and 3-month post-event returns for upgrades are-0.01% and 0.07%, not statistically different from the-0.02% and 0.05% for downgrades by t-tests on means (untabulated). The average firm-specific components of 1-and 3-month post-event returns for upgrades are 0.87% and 1.48%. In contrast, the average firm-specific components of 1-and 3-month post-event returns for downgrades are-0.37% and -0.49%.

Table 3 Statistics of the market, industry, and firm-specific component of returns around and after recommendation changes

Variablies	Mean	Std.Dev	75th Percent	Media	25th Percent
A: β and 3-Day cumulative returns around upgrades					
$CR_{n,(-1,1)}$	2.73	8.65	5.78	1.82	-1.37
$\hat{\beta}_n^M$	1.12	0.62	1.43	1.07	0.61
$\hat{\beta}_n^{IM}$	1.03	0.37	1.31	1.01	0.75
$\hat{\beta}_n^I$	0.57	0.55	0.91	0.51	0.15
$R_{(-1,1)}^M$	0.14	1.93	1.21	0.28	-0.85
$R_{(-1,1)}^I$	0.25	2.97	1.74	0.22	-1.21
$CR_{n,(-1,1)}^M$	0.17	2.51	1.17	0.21	-0.75
$CR_{n,(-1,1)}^I$	0.07	1.73	0.44	0.01	-0.36
$CR_{n,(-1,1)}^F$	2.49	8.71	5.37	1.51	-1.22
B：β and 3-Day cumulative returns around downgrades					
$CR_{n,(-1,1)}$	-2.80	11.69	1.57	-1.62	-6.20
$\hat{\beta}_n^M$	1.12	0.67	1.44	1.01	-0.63
$\hat{\beta}_n^{IM}$	1.07	0.41	1.32	1.05	0.82
$\hat{\beta}_n^I$	0.55	0.53	0.87	0.44	0.12
$R_{(-1,1)}^M$	0.12	1.95	1.30	0.31	-0.99
$R_{(-1,1)}^I$	0.01	3.07	1.66	0.15	-1.44
$CR_{n,(-1,1)}^M$	0.07	2.61	1.13	0.17	-0.79
$CR_{n,(-1,1)}^I$	-0.05	1.71	0.35	-0.01	-0.44
$CR_{n,(-1,1)}^F$	-2.82	10.17	1.27	-1.59	-5.67
C：Post-recommend returns for upgrades					
$CR_{n,(2,23)}$	2.14	13.36	9.12	1.67	-4.45
$CR_{n,(2,67)}$	4.88	25.17	16.65	3.10	-7.23
$R_{(2,23)}^M$	1.12	4.57	3.89	1.67	-1.60
$R_{(2,67)}^M$	3.12	7.86	8.55	3.68	-1.44
$R_{(2,23)}^I$	1.18	7.46	5.14	1.33	-2.76
$R_{(2,67)}^I$	3.36	13.01	9.85	3.48	-3.65
$CR_{n,(2,23)}^M$	1.28	5.97	4.06	1.32	-1.23
$CR_{n,(2,67)}^M$	3.66	9.75	8.04	3.06	-1.18
$CR_{n,(2,23)}^I$	-0.01	4.21	1.13	-0.01	-1.15
$CR_{n,(2,67)}^I$	0.07	7.58	1.97	-0.03	-2.16
$CR_{n,(2,23)}^F$	0.87	13.41	6.58	0.39	-5.75
$CR_{n,(2,67)}^F$	1.48	23.74	11.65	0.23	-10.82
D Post-recommend returns for downgrades					
$CR_{n,(2,23)}$	0.69	16.65	7.93	0.41	-7.13
$CR_{n,(2,67)}$	2.92	28.76	15.69	1.92	-12.23
$R_{(2,23)}^M$	1.02	4,76	4.25	1.63	-1.43
$R_{(2,67)}^M$	2.97	8.07	8.52	3.88	-1.65
$R_{(2,23)}^I$	1.07	7.65	5.41	1.29	-2.97
$R_{(2,67)}^I$	2.95	13.04	9.94	3.54	-1.68
$CR_{n,(2,23)}^M$	1.08	6.73	4.07	1.23	-3.26
$CR_{n,(2,67)}^M$	3.37	9.84	8.02	3.26	-3.99
$CR_{n,(2,23)}^I$	-0.02	4.51	1.09	-0.05	-1.04
$CR_{n,(2,67)}^I$	0.05	7.53	2.01	-0.03	-2.31
$CR_{n,(2,23)}^F$	-0.37	13.76	5.64	-0.57	-6.88
$CR_{n,(2,67)}^F$	-0.49	23.87	9.24	-1.33	-12.53

The above findings show that there is no post-recommendation drift for industry level information but there is post-recommendation drift for firm-specific information. Together with results in Panels A and B that the market reacts more strongly to firm-specific than to industry-level information in analyst research, the results on post-event drifts are also consistent with previous findings that the post-recommendation drift is positively related to the market reaction around recommendation changes.

To summarize, Table 3 shows that the firm-specific component of returns around recommendation changes is much greater in magnitude than the industry component. If the market reaction around recommendation changes reflects the private information produced by financial analysts, then the evidence shows that analysts on average produce more firm-specific information and less industry level information. The evidence seems to support Hypothesis 1A instead of Hypothesis 1B, suggesting that the spillover effect dominates the economy-of-scale effect. Results on post-event drifts are also broadly consistent with Hypothesis 1A in the sense that there is evidence of post-event drift for firm-specific information, but not for industry-level information.

3.4. Idiosyncratic Volatility and Firm-Specific Components of Returns around and after Recommendation Changes

Hypothesis 2 predicts that the firm-specific component of the market reaction around an analyst recommendation increases with the recommended stock's idiosyncratic volatility. Further, if the firm-specific information produced by analysts is not fully incorporated into the price during the 3-day window around the recommendation change and there is a post-recommendation drift proportional to the amount of private information produced by analysts, then Hypothesis2 also predicts a positive relation between idiosyncratic return volatility and the magnitude of firm-specific components of post-recommendation returns. To test this hypothesis, I use 2 measures of idiosyncratic return volatility. The 1st measure is the absolute idiosyncratic volatility for firm n, RMSE, which is the root mean square error from regression[1]. The 2nd measure is the relative idiosyncratic volatility, 1-RSQ, which equals 1 minus the adjusted R^2 from regression[2]. Results are reported in Table4.

Table4 The Relation between Idiosyncratic Return Volatility and Firm-Specific Components of Returns around and after Recommendation Changes

	Upgrades			Downgrades		
RMSE	$CR^F_{n,(-1,1)}$	$CR^F_{n,(2,23)}$	$CR^F_{n,(2,67)}$	$CR^F_{n,(-1,1)}$	$CR^F_{n,(2,23)}$	$CR^F_{n,(2,67)}$
1	0.91**	0.65**	1.13**	-1.06**	-0.13	-0.03
2	1.42**	0.63**	0.76**	-1.46**	-0.03	-0.27
3	1.65**	0.79**	1.03**	-1.61**	-0.27	-0.17
4	1.87**	1.03**	1.81**	-2.17**	-0.25	-0.28
5	2.65**	0.92**	1.03**	-2.43**	-0.12	0.15
6	2.71**	0.77**	1.21**	-3.15**	-0.35	-0.49
7	2.88**	0.89**	2.03**	-3.44**	-0.25	-0.03
8	2.97**	0.91**	1.51**	-3.86**	-0.46	-0.96
9	3.35**	1.48**	1.46**	-4.81**	-0.53	-0.93
10	4.74**	1.29**	2.35**	-4.57**	-1.25**	-1.44*
	Upgrades			Downgrades		
1-RSQ	$CR^F_{n,(-1,1)}$	$CR^F_{n,(2,23)}$	$CR^F_{n,(2,67)}$	$CR^F_{n,(-1,1)}$	$CR^F_{n,(2,23)}$	$CR^F_{n,(2,67)}$
1	1.03**	0.17	0.13	-1.35**	-0.21	-0.33
2	1.65**	0.02	-0.97**	-2.27**	-0.35	-0.41
3	1.92**	0.64**	0.32	-2.43**	0.29	0.67
4	2.03**	0.67**	0.65	-2.58**	0.14	0.72
5	2.15**	0.75**	0.81**	-3.01**	-0.73**	-0.52
6	2.48**	0.65**	1.05**	-3.12**	-0.71**	-0.64
7	2.87**	1.03**	1.20**	-2.88**	-0.32	-0.17
8	2.91**	1.18**	2.16**	-3.57**	-0.27	-0.68
9	3.31**	1.75**	3.55**	-3.62**	-0.55*	-1.37*
10	3.86**	2.08**	4.41**	-3.54**	-0.69**	-1.52**

[1] $R_{n,t} = \alpha_n + \beta_n^M \times R_t^M + \beta_n^I \times \left(R_t^I - \hat{\beta}_n^{IM} \times R_t^M\right) + \varepsilon_{n,t}$

[2] $R_{n,t} = \alpha_n + \beta_n^M \times R_t^M + \beta_n^I \times \left(R_t^I - \hat{\beta}_n^{IM} \times R_t^M\right) + \varepsilon_{n,t}$

In Panel A of Table 4, I first divide firms into 10 deciles each year based on the estimated RMSE of the firm from the previous calendar year. I then calculate the average firm-specific components of stock returns around and after analyst recommendation changes in each decile. For upgrades, the average value of $CR^{F}_{n,(-1,1)}$increases monotonically with RMSE deciles. The average 3-day firm-specific reaction to an upgrade is 4.74% for firms with the highest RMSE, and 0.91% for firms with the lowest RMSE, with the difference statistically significant at the 1% level by t-tests on means. The average 1- and 3-month firm-specific post-event drifts, $CR^{F}_{n,(2,23)}$) and $CR^{F}_{n,(2,67)}$, also tend to increase with RMSE deciles, even though the results are not as strong as those for announcement returns.

For example, the average value of $CR^{F}_{n,(2,67)}$ is 1.29% for firms with the highest RMSE, and 0.65% for firms with the lowest RMSE, with the difference statistically significant at the 5% level by t-tests on means. For downgrades, the average magnitudes of $CR^{F}_{n,(-1,1)}$, $CR^{F}_{n,(2,23)}$) and $CR^{F}_{n,(2,67)}$ also tend to increase with RMSE deciles, though not strictly monotonically. The results for announcement returns are stronger than those for post-recommendation returns. For example, the average 3-day firm-specific reaction to a downgrade is -4.57% for firms with the highest RMSE, and -1.06% for firms with the lowest RMSE, with the difference statistically significant at the 1% level by t-tests on means. The average 1-month firm-specific post-event return following a downgrade is-1.44% for firms with the highest RMSE, and -0.03% for firms with the lowest RMSE, with the difference statistically significant at the 5% level by t-tests on means.

In Panel B of Table 4, I sort firms into 10 deciles each year based on the estimated 1-RSQ of the firm from equation[3] in the previous calendar year, and I calculate the average firm-specific components of stock returns around and after analyst recommendation changes in each decile. The results are similar to those in Panel A. For upgrades, the average values of $CR^{F}_{n,(-1,1)}$, $CR^{F}_{n,(2,23)}$) and $CR^{F}_{n,(2,67)}$ increase with 1-RSQ deciles with few exceptions. For downgrades, the average values of $CR^{F}_{n,(-1,1)}$, $CR^{F}_{n,(2,23)}$) and $CR^{F}_{n,(2,67)}$ tend to decrease with 1-RSQ deciles. Further, for both upgrades and downgrades, the results for announcement returns are stronger than those for post-recommendation returns.

To summarize, consistent with Hypothesis 2, I find a positive relation between idiosyncratic return volatility and the magnitude of firm-specific components of stock returns around recommendation changes. There is also a positive, albeit weaker, relation between idiosyncratic return volatility and the magnitude of firm-specific components of post-recommendation returns.

3.5. Industry Beta and Industry Components of Returns around and after Recommendation Changes

Hypothesis 3 predicts a positive relation between the absolute value of the stock's industry beta and the magnitude of the industry component of the market reaction to the recommendation change. I test this prediction in Table 5.

In Panel A of Table 5, I first divide firms into 10 deciles each year based on the absolute value of $\hat{\beta}^{I}_{n}$ estimated in the previous calendar year. I then calculate the average industry components of stock returns around and after recommendation changes in each decile. For upgrades, the average value of $CR^{I}_{n,(-1,1)}$tends to increase with $\left|\hat{\beta}^{I}_{n}\right|$deciles. The average 3-day industry reaction to an upgrade is 0 for firms with the smallest$\left|\hat{\beta}^{I}_{n}\right|$, and 0.38% for firms with the largest$\left|\hat{\beta}^{I}_{n}\right|$, with the difference statistically significant at the 1% level by t-tests on means. For downgrades, the average value of $CR^{I}_{n,(-1,1)}$decreases with$\left|\hat{\beta}^{I}_{n}\right|$deciles, even though not strictly monotonically. The average 3-day industry reaction to a downgrade is 0 for firms with the smallest$\left|\hat{\beta}^{I}_{n}\right|$,and -0.17% for firms with the largest$\left|\hat{\beta}^{I}_{n}\right|$, with the difference statistically significant at the 1% level by t-tests on means. These results show that the industry component of stock returns around recommendation changes increases in magnitude with the absolute value of the recommended stock's industry beta.

[3] $R_{n,t} = \alpha_n + \beta^{M}_{n} \times R^{M}_{t} + \beta^{I}_{n} \times \left(R^{I}_{t} - \hat{\beta}^{IM}_{n} \times R^{M}_{t}\right) + \varepsilon_{n,t}$

I also examine the relation between $\left|\hat{\beta}_n^I\right|$ and industry components of post-event drifts. The average values of $CR^I_{n,(2,23)}$ and $CR^I_{n,(2,67)}$ have no relation with $\left|\hat{\beta}_n^I\right|$ deciles for either upgrades or downgrades. In fact, for upgrades, the average value of $CR^I_{n,(2,23)}$ in the smallest $\left|\hat{\beta}_n^I\right|$ decile is significantly greater than that in the largest $\left|\hat{\beta}_n^I\right|$ decile, opposite to the relation between $CR^I_{n,(-1,1)}$ and $\left|\hat{\beta}_n^I\right|$.

Table 5 The Relation between Industry Beta and Industry Components of Returns around and after Recommendation Changes

	Upgrades			Downgrades		
$\left\|\hat{\beta}_n^I\right\|$	$CR^I_{n,(-1,1)}$	$CR^I_{n,(2,23)}$	$CR^I_{n,(2,67)}$	$CR^I_{n,(-1,1)}$	$CR^I_{n,(2,23)}$	$CR^I_{n,(2,67)}$
1	0.00	0.00	0.00	0.00	-0.01	-0.05
2	0.01	0.00	0.01	-0.00	-0.05	-0.01
3	0.03	-0.02	-0.05	-0.02	-0.17	-0.37
4	0.04**	-0.00	0.04	-0.01	0.26	0.33
5	0.02	0.01	-0.02	-0.05**	0.22	0.36
6	0.03	0.07	0.17	-0.04*	-0.13	0.15
7	0.06**	-0.01 **	0.44**	-0.05**	0.07	0.01
8	0.19**	0.13**	0.42*	-0.12**	0.56	0.68
9	0.21**	0.15	0.43**	-0.14**	-0.22	0.87
10	0.38**	-0.37**	-0.23**	-0.17**	-0.04	-0.24
	Upgrades			Downgrades		
$\left\|\hat{\beta}_n^I\right\|$	$AR^I_{n,(-1,1)}$	$AR^I_{n,(2,23)}$	$AR^I_{n,(2,67)}$	$AR^I_{n,(-1,1)}$	$AR^I_{n,(2,23)}$	$AR^I_{n,(2,67)}$
1	0.05	-0.05	-0.35	0.00	-0.13	-0.55
2	0.44	0.00	0.09	0.03	-0.17	0.07
3	0.06	-0.11	-0.37*	-0.06*	-0.55	-0.77
4	0.15**	-0.13	-0.15	-0.10*	-0.07	0.15
5	0.08*	-0.01	-0.14	-0.12*	-0.09	0.07
6	0.07*	0.02	0.02	-0.06**	-0.07	0.01
7	0.04	-0.03	0.10	-0.12**	0.13	0.88
8	0.22**	-0.08	0.39*	-0.15**	-0.24	-0.92
9	0.23**	0.12	0.42*	-0.17*	-0.30	0.95
10	0.25**	-0.17*	-0.06	-0.15**	0.03	0.07

The results in Panel A indicate that the industry components of stock returns around recommendation changes, but not those after, increase in magnitude with the absolute value of the recommended stock's industry beta. Because the industry component of stock returns around and after analyst recommendation changes is defined as a product of $\hat{\beta}_n^I$, $R^I_{(-1,1)} - \hat{\beta}_n^{IM} \times R^M_{(-1,1)}$ (i.e., $CR^I_{n,(-1,1)} = \hat{\beta}_n^I \times (R^I_{(-1,1)} - \hat{\beta}_n^{IM} \times R^M_{(-1,1)})$), there might be a natural positive relation between $\left|\hat{\beta}_n^I\right|$ and the absolute value of CR^I_n, that has nothing to do with analysts' incentives to produce industry information. To address this concern, I test in Panel B of the relation between $\left|\hat{\beta}_n^I\right|$ and $AR^I_n (R^I - \hat{\beta}_n^{IM} \times R^M)$. Results in Panel B show that the average value of AR^I_n increases with $\left|\hat{\beta}_n^I\right|$ deciles for upgrades and decreases with $\left|\hat{\beta}_n^I\right|$ deciles for downgrades, even though not strictly monotonically. The differences in the average value of $AR^I_{n(-1,1)}$ between the top and bottom deciles are statistically significant at the 1% level, even though smaller in magnitude compared to those in Panel A. There is no relation between $\left|\hat{\beta}_n^I\right|$ and average values of $AR^I_{n(2,23)}$ and $AR^I_{n(2,26)}$ for either upgrades or downgrades.

Results in Table 5 show that the industry components of stock returns around recommendation changes increase in magnitude with the absolute value of the recommended stock's industry beta, which supports Hypothesis 3. Results in Table 5 also show that the industry components of returns after recommendation changes have no relation with the absolute value of the recommended stock's industry beta, which is consistent with the result in Table 3 that there is no post-recommendation drift for industry information.

3.6. Idiosyncratic Volatility and Industry Components of Returns around and after Recommendation Changes

Hypothesis 4 predicts that the industry component of the market reaction to recommendations decreases in magnitude with the idiosyncratic volatility of the stock. Table 6 tests this prediction by examining the relation between relative idiosyncratic return volatility, 1-RSQ, and industry components of stock returns around and after analyst recommendation changes.

I divide firms into 10 deciles according to the value of 1-RSQ estimated from the previous calendar year, and I calculate the average industry components of stock returns around and after recommendation changes in each decile. For upgrades, the average value of $CR^{I}_{n(-1,1)}$ decreases monotonically with 1-RSQ deciles. The average 3-day industry reaction to an upgrade is 0.47% for firms with the smallest 1-RSQ, and around 0 for firms with the largest 1-RSQ, with the difference statistically significant at the 1% level by t-tests on means. For downgrades, the average value of $CR^{I}_{n(-1,1)}$ tends to increase with 1- RSQ deciles, even though not strictly monotonically.

Table6 The Relation between Relative Idiosyncratic Return Volatility and Industry Components of Returns around and after Recommendation Changes

	Upgrades			Downgrades		
1-RSQ	$CR^{I}_{n,(-1,1)}$	$CR^{I}_{n,(2,23)}$	$CR^{I}_{n,(2,67)}$	$CR^{I}_{n,(-1,1)}$	$CR^{I}_{n,(2,23)}$	$CR^{I}_{n,(2,67)}$
1	0.47**	0.19*	0.81**	-0.26**	0.71	1.67
2	0.32**	0.06	0.66*	-0.11*	-0.23	-0.04
3	0.21**	0.02	-0.13	-0.17**	-0.05	-0.06
4	0.03	0.03	-0.07	-0.02	0.17	0.48
5	0.04	-0.24**	-0.15	-0.01	-0.19	-0.17
6	0.02	0.07	0.17	-0.07*	-0.26	0.61
7	0.03	-0.05	-0.08	-0.05*	0.17	-0.47
8	0.02	0.03	0.03	-0.01	0.05	0.08
9	0.01	-0.11*	-0.11	-0.02	-0.33	-0.51
10	0.01	-0.02	-0.02	-0.01	0.03	-0.09
	Upgrades			Downgrades		
1-RSQ	$AR^{I}_{n,(-1,1)}$	$AR^{I}_{n,(2,23)}$	$AR^{I}_{n,(2,67)}$	$AR^{I}_{n,(-1,1)}$	$AR^{I}_{n,(2,23)}$	$AR^{I}_{n,(2,67)}$
1	0.35**	0.27**	0.93**	-0.22**	0.92	1.59
2	0.27**	0.06	0.31	-0.13**	-0.07	0.18
3	0.19**	-0.11	-0.47**	-0.15**	-0.35	-0.03
4	0.05	-0.05	0.24	-0.08*	-0.53	0.32
5	0.04	-0.37**	-0.49**	-0.05	-0.14	0.67
6	0.04	0.15	0.16	-0.09*	-0.92	0.06
7	0.05	-0.14	-0.27	-0.10*	-0.05	-0.28
8	0.14**	0.06	0.15	-0.05	0.06	0.03
9	0.02	-0.14	-0.42*	-0.03	-1.02	-1.12
10	0.06	-0.11	-0.08	-0.02	0.76	1.04

The average 3-day industry reaction to a downgrade is -0.26% for firms with the smallest 1-RSQ, and-0.01% for firms with the largest1-RSQ with the difference statistically significant at the 1% level by t-tests on means. For upgrades, the average value of $CR^{I}_{n(2,23)}$ shows no relation with 1 – RSQ deciles, while that of $CR^{I}_{n(2,67)}$tends to decrease with 1-RSQ deciles. For downgrades, the average values of $CR^{I}_{n(2,23)}$ and $CR^{I}_{n(2,67)}$ show a weak negative relation with 1-RSQ, opposite to the relation between $CR^{I}_{n(-1,1)}$ and 1- RSQ.

Because the industry component of stock returns around and after analyst recommendation changes, $CR^{I}_{n} = \hat{\beta}^{I}_{n} \times (R^{I}_{n} - \hat{\beta}^{IM}_{n} \times R^{M})$, increases in magnitude with$\hat{\beta}^{I}_{n}$, while $1 - RSQ = Var(F_n)/((\hat{\beta}^{I}_{n})^2 \times Var(I) + Var(F_n))$ decreases with $\hat{\beta}^{I}_{n}$, there might be a natural negative relation between 1-RSQ and the absolute value of CR^{I}_{n} that has nothing to do with analysts' incentives to produce industry information.

To address this concern, I test in Panel B of Table 6 the relation between 1-RSQ and abnormal industry returns AR_n^I,Results in Panel B show that the average value of $AR_{n,(-1,1)}^I$ decreases with 1-RSQ deciles for upgrades and increases with 1-RSQ deciles for downgrades, even though not strictly monotonically. The differences in the average value of $AR_{n,(-1,1)}^I$ between the top and bottom deciles are statistically significant at the 1% level by t-tests on means for both upgrades and downgrades, even though the differences are smaller than those in Panel A. The average values of $CR_{n(2,23)}^I$ and $CR_{n(2,67)}^I$ tend to decrease with 1-RSQ deciles for upgrades. For downgrades, however, the average values of $CR_{n(2,23)}^I$ and $CR_{n(2,67)}^I$ show no relation with 1-RSQ deciles.

To summarize, results in Table 6 show that the industry component of stock returns around recommendation changes decreases in magnitude with the idiosyncratic return volatility of the recommended stock. The above findings support Hypothesis 4. Results in Table 6 also show that the industry components of stock returns after recommendation changes have little relation with the idiosyncratic volatility of the recommended stock.

4. Conclusion

Most finance and accounting researchers have found that analyst research has had investment value. They have different views, however, on whether the information provided by analysts is mainly at the industry level or at the firm level. This paper joins the debate and attempts to shed light on this issue. Because analysts' compensation is positively related to the commission fees that their research brings to their brokerage firms (Brennan and Hughes (1991), Conrad et al.(2001)), analysts have incentives to produce private information to increase the investment value of their research to benefit their brokerage clients. The fact that industry-level information affects all firms in the same industry has two opposite effects on analysts' incentives to produce industry-level information. On the one hand, investors receive more public signals about industry-level than firm-specific information because public events about all firms in the industry are informative about the industry factor. In contrast, only public events about 1 firm are directly informative about the firm-specific component of the stock.

As a result, more industry-level than firm-specific information is aggregated into stock prices. This "spillover effect" of industry-level information should make it harder for investors to profit from private industry-level information and easier to profit from private firm-specific information. On the other hand, investors can use the private industry-level information produced by analysts to trade on and profit from more than 1 stock in the industry. In contrast, investors can use the private firm-specific information to profit from only 1 particular stock. This "economy of- scale effect" of industry-level information should make it easier for investors to profit from private industry-level instead of firm-specific information. Therefore, depending on whether the spillover effect or the economy-of-scale effect dominates, analysts may have incentives to produce more firm-specific or more industry-level information. Using analyst stock recommendations from Wind, I find that analysts on average produce much more firm-specific than industry level information.

I also find evidence that analysts' incentives to produce firm-specific information increase with the firm's idiosyncratic volatility. Analysts' incentives to produce industry-level information increase with the absolute value of the firm's industry beta and decrease with the firm's idiosyncratic volatility.

This paper also offers insights on how to use analyst research more effectively. For example, investors may potentially improve their performance by focusing on firms with high idiosyncratic volatility instead of all firms covered by analysts.

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