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Analysts' Incentives to Produce Industry-Level versus Firm-Specific Information

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Abstract

Using stock returns around recommendation changes to measure the information produced by analysts, I find that analysts produce more firm-specific than industry-level information. Analysts produce more firm-specific information on stocks with higher idiosyncratic return volatilities. The amount of industry information produced by analysts increases with the absolute value of the stock's industry beta and decreases with the stock's idiosyncratic volatility. Other stocks in the industry also respond to 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 industry. I also offer results on how investors may use analyst research more effectively and potentially improve their investment performance.

I. Introduction

A number of studies document that financial analysts' research has investment value, be it stock recommendations, earnings forecasts, or target prices. Examples include Lys and Sohn (1990), Womack (1996), and Brav and Lehavy (2003).[1] The literature offers different views, however, on whether the information

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[1]Barber, Lehavy, McNichols, and Trueman (2001) raise questions as to whether, after transaction costs, investors can benefit from trading on stock recommendations based on the assumption that investors do not have timely access to the recommendations. However, many institutional investors have access to analyst recommendations before public announcements (see, e.g., Conrad, Johnson, and Wahal (2001), Irvine, Lipson, and Puckett (2007)).

provided by analysts is mainly at the industry level or the firm level. Most empirical studies find that analysts have industry expertise (e.g., Gilson, Healy, Noe, and Palepu (2001), Piotroski and Roulstone (2004), Boni and Womack (2006), and Chan and Hameed (2006)). Other studies, however, document that the information analysts produce is mainly firm specific (e.g., Mikhail, Walther, and Willis (1997), Park and Stice (2000), and Forbes, Huijgen, and Plantinga (2006)).

I join this debate and investigate whether the information produced by financial analysts is mainly at the industry level or the firm level. A related but broader question is what motivates analysts to produce information in general. Answering these questions should 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.[2]

I test these hypotheses using analyst stock recommendations from the Institutional Brokers' Estimate System (IBES). 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.[3] 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

[2]See Section II for detailed arguments behind the previous hypotheses.

[3]For example, Mikhail et al. (1997) show that analyst forecasts become more accurate as analysts' experience in following a specific firm increases. In contrast, there is little relation between forecast accuracy and analysts' concentration in an industry. Park and Stice (2000) find that individual analysts with superior past forecasting track records have greater price impacts on security price than other analysts do, while the price effects do not spill over to other firms followed by the same analyst. Forbes et al. (2006) find that analyst earnings forecasts for individual firms contain information about future stock returns, while earnings estimates aggregated in the industry or country level do not.

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.[4]

The rest of the paper is organized as follows. Section II develops testable hypotheses. Section III presents empirical methodologies, results, and investment implications. Section IV concludes.

II. 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 $\overline{v}_n$. The innovative part of v_n consists of an industry component, I, which affects all N stocks in the industry, and a firm-specific component, F_n;[5] that is,

$$v_n = \overline{v}_n + \beta_n \times I + F_n, \quad n \in \{1, 2, \ldots, N\}, \tag{1}$$

where β_n is the industry beta of stock n, and I and F_n are independent of each other.

There 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. The public signal about firm n is informative about the total value of the firm and takes the form

$$y_n = v_n + e_{yn}, \tag{2}$$

where e_{yn}, the noise in the signal, has 0 mean and is independent of each other and all other variables.

At time 1, an analyst, who covers m stocks in the industry, produces information about the industry component, I, and the firm-specific components of the

[4]Piotroski and Roulstone (2004) and Chan and Hameed (2006) find that firms with more analyst following have higher return synchronicity and claim that this is evidence that analysts help incorporate marketwide and industry-level information into prices. However, their results rely on the assumption that a *higher* idiosyncratic return volatility means *more* information in stock prices, and many recent studies find that a *higher* idiosyncratic return volatility may be an indication of *less* information in stock prices (e.g., Kelly (2005), Ashbaugh-Skaife, Gassen, and LaFond (2005), and Lee and Liu (2011)).

[5]The value of the stock may also be influenced by market factors. One can think of market factors as known constants and as part of $\overline{v}_n$.

m stocks she covers, F_n, where $n \in \{1, 2, \ldots, m\}$ and $2 \leq m \leq N$. The analyst then sells the private information to an investor in the form of recommendations on the m stocks. The investor then trades based on the analyst's recommendations. At time 2, the private information produced by the analyst becomes public, and the market updates stock prices. The investor unwinds her position and pays a fraction of her trading profit to the analyst for the recommendations.[6,7]

The analyst decides how much information to produce about the industry factor and how much about the firm-specific component of each of the m stocks. The more resources the analyst devotes to producing a signal, the more precise it is; that is, it costs the analyst more to produce a more precise signal. At the same time, more precise signals lead to more valuable recommendations, and the investor can make more profits. Because the analyst's compensation is proportional to the investor's profits, the analyst benefits more from producing more precise signals. The analyst weighs the costs and benefits, and she produces information so that the marginal cost of information production equals the marginal benefit.

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.[8] 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

[6]Brokerage firms that sell-side analysts work for often have soft-dollar arrangements with institutional investors, who pay higher commission fees than other investors in exchange for analyst research from brokerage firms. For example, Conrad et al. (2001) document that institutional investors pay 29 (24) basis points (bp) more for small buyer- (seller-) initiated orders to soft-dollar brokers than to other types of brokers. Brennan and Hughes (1991) show that brokerage firms have incentives to produce more information for stocks that bring them more commission fees.

[7]Extant literature documents that analysts have incentives to issue biased (overly optimistic) recommendations to win investment banking business. See, for example, Carleton, Chen, and Steiner (1998), Easterwood and Nutt (1999), Michaely and Womack (1999), Lim (2001), and Chan, Karceski, and Lakonishok (2007). However, as long as analyst compensation increases with the investment value of analyst research, analysts have incentives to increase the investment value of their research.

[8]However, the amount of firm-specific information reflected in the price may be *indirectly* affected by the number of firms N in the following sense. As N increases, investors learn more about the industry factor I, which in turn will help investors infer the value of F_n from the signal y_n because y_n is a linear combination of $\bar{v}_n$, I, F_n, and the error term e_{yn}. I thank an anonymous referee for pointing this out.

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 m 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,

$$(3) \qquad \mathrm{Var}(v_n) \quad = \quad \beta_n^2 \times \mathrm{Var}(I) + \mathrm{Var}(F_n), \quad n \in \{1, 2, \ldots, N\}.$$

Consider 2 firms with the same industry beta but different firm-specific variances (i.e., different idiosyncratic volatilities). 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:

Hypothesis 2. 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, $\mathrm{Var}(F_n)$, 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) $|\beta_n|$.[9] 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.

At time 1, when the analyst issues a recommendation on stock n, the market will update the price of stock n. If the recommendation conveys positive (negative) news, then the price of stock n will go up (down). At the same time, other stocks in the same industry will also respond to the recommendation for the following reason. The recommendation is informative about the total value of stock n, which in turn is influenced by the industry factor I. Consider another stock $j \neq n$ in the same industry as stock n, the value of which is

$$v_j = \bar{v}_j + \beta_j \times I + F_j, \quad \text{where} \quad j \neq n. \tag{4}$$

The recommendation on stock n is also informative about stock j because both are influenced by the industry factor I. Therefore, stock j will also respond to the recommendation on stock n; that is, the price of stock j will go up (down) when a positive (negative) recommendation is issued on stock n. Further, the magnitude of the response increases with the absolute value of stock n's industry beta, $|\beta_n|$, because a higher $|\beta_n|$ means that the value of stock n, hence the recommendation on stock n, is more informative about the industry factor. The magnitude of the response also increases with the absolute value of stock j's industry beta, $|\beta_j|$, because a higher $|\beta_j|$ means that the value of stock j is more sensitive to the industry factor (hence more sensitive to the recommendation on stock n). To summarize, I offer the following testable hypothesis:

[9] The industry component of variance, $\beta_n^2 \times \text{Var}(I)$, increases with $|\beta_n|$ instead of β_n because some firms have negative industry betas. I include firms with $\beta_n < 0$ in the empirical analyses.

Hypothesis 5. When a recommendation is issued on a stock, other stocks in the same industry will respond in the same direction of the recommendation, 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.

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 2–5 should hold.

III. 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 cross-sectionally examine market reactions to industry-level and firm-specific information in analyst recommendations among firms with different characteristics. Finally, I investigate the investment implications of my findings.

A. Analyst Recommendation Changes

I obtain individual analyst recommendations for U.S. companies from IBES, 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 1994–2005, with 55,199 upgrades and 64,662 downgrades.[10]

B. 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

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

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

[10]IBES starts to provide stock recommendations in 1993, but the number of recommendation changes in 1993 is less than half of that in 1994. Therefore, I start my sample in 1994.

TABLE 1

Distribution of Analyst Recommendation Changes over Time

Table 1 reports the number of analyst recommendation changes (i.e., upgrades and downgrades) from 1994 to 2005. Recommendation changes are classified into upgrades and downgrades based on the changes of recommendations from one category to another, where numbers 1–5 represent strong buy, buy, hold, underperform, and sell, respectively. If a recommendation has a lower (higher) numerical rating than the previous recommendation issued on the same firm by the same analyst, it is classified as an upgrade (downgrade).

Year	Upgrades	Downgrades	Total
1994	2,598	2,490	5,088
1995	4,292	5,630	9,922
1996	4,652	4,765	9,417
1997	4,222	4,900	9,122
1998	4,710	5,825	10,535
1999	5,204	5,068	10,272
2000	4,250	4,881	9,131
2001	4,033	5,449	9,482
2002	4,851	7,710	12,561
2003	5,408	6,810	12,218
2004	5,434	5,752	11,186
2005	5,545	5,382	10,927
Total	55,199	64,662	119,861

category to another, with numbers of observations for each category in parentheses. The most frequent upgrades are from hold to buy (19,060 observations), and the average 3-day return for this type of upgrades is 2.65%, statistically different from 0 at the 1% level. The least frequent upgrades are from sell to underperform (140 observations), with an average 3-day return of 0.68% (not statistically different from 0). The most frequent downgrades are from buy to hold (24,186 observations), and the average 3-day return for this type of downgrades is −2.48%, statistically different from 0 at the 1% level. The least frequent downgrades are from underperform to sell (203 observations), with an average 3-day return of −1.99% (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 Reactions to Upgrades and Downgrades

Table 2 reports the average 3-day cumulative returns (in percentages) around recommendation changes, based on changes of recommendations from one category to another, where numbers 1–5 represent strong buy, buy, hold, underperform, and sell, respectively. The number of observations for each category is reported in parentheses below the average return. * and ** indicate significance at the 5% and 1% levels, respectively.

	To:				
From:	"Strong Buy" 1	2	"Hold" 3	4	"Sell" 5
"Strong Buy" 1	N/A	−1.52**	−2.56**	−2.47**	−2.05**
		(15,442)	(15,913)	(324)	(429)
2	2.38**	N/A	−2.48**	−2.78**	−0.75
	(15,740)		(24,186)	(931)	(350)
"Hold" 3	2.69**	2.65**	N/A	−2.75**	−3.14**
	(12,706)	(19,060)		(4,368)	(2,498)
4	2.02**	2.89**	2.31**	N/A	−1.99*
	(194)	(739)	(3,759)		(203)
"Sell" 5	1.87**	0.02	1.84**	0.68	N/A
	(294)	(257)	(2,310)	(140)	

C. Industry-Level and Firm-Specific Components of Stock Returns around and after Analyst Recommendation Changes

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. The industry classification I use is the 3-digit North American Industry Classification System (NAICS) from Compustat. 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 and β_n^I:

$$(5) \qquad R_{n,t} = \alpha_n + \beta_n^M \times R_t^M + \beta_n^I \times \left(R_t^I - \hat{\beta}_n^{IM} \times R_t^M\right) + \varepsilon_{n,t},$$

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 $t-1$. Here R_t^M is the contemporaneous return on the Center for Research in Security Prices (CRSP) value-weighted market index, and $\hat{\beta}_n^{IM}$ is the market beta of stock n's industry, estimated from the following regression in each calendar year from 1993 to 2004:

$$(6) \qquad R_t^I = \alpha_n^I + \beta_n^{IM} \times R_t^M + \varepsilon_{n,t}^I.$$

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 R_t^I.

The market component of $\mathrm{CR}_{n,(-1,1)}$ is defined as

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

and the industry component is defined as

$$\mathrm{CR}_{n,(-1,1)}^I = \hat{\beta}_n^I \times \left(R_{(-1,1)}^I - \hat{\beta}_n^{IM} \times R_{(-1,1)}^M\right),$$

where $\hat{\beta}_n^M$, $\hat{\beta}_n^I$, and $\hat{\beta}_n^{IM}$ are estimated in the *previous* calendar year; $R_{(-1,1)}^M$ is the 3-day cumulative return on the CRSP value-weighted market index; and $R_{(-1,1)}^I$ 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 $\mathrm{CR}_{n,(-1,1)}$ is defined as

$$\mathrm{CR}_{n,(-1,1)}^F = \mathrm{CR}_{n,(-1,1)} - \hat{\beta}_n^M \times R_{(-1,1)}^M - \hat{\beta}_n^I \times \left(R_{(-1,1)}^I - \hat{\beta}_n^{IM} \times R_{(-1,1)}^M\right).$$

To isolate the effects of each individual recommendation on the stock return, I exclude a recommendation from the sample if another recommendation was issued on the same stock less than 10 days before. I also exclude industries with less than 3 firms at the time of the recommendation change. The final sample has 32,217 upgrades and 36,681 downgrades.[11] Untabulated results show that the industry membership of the sample is diverse, representing 87 different 3-digit NAICS codes.

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 cause of the post-recommendation drifts. The 1-month post-event return on stock n is defined as the cumulative daily stock returns from business day 2 to day 23, $\mathrm{CR}_{n,(2,23)}$, given that 1 calendar month has about 22 business days.[12]

The market component of $\mathrm{CR}_{n,(2,23)}$ is defined as

$$\mathrm{CR}^{M}_{n,(2,23)} \quad = \quad \hat{\beta}^{M}_{n} \times R^{M}_{(2,23)},$$

and the industry component is defined as

$$\mathrm{CR}^{I}_{n,(2,23)} \quad = \quad \hat{\beta}^{I}_{n} \times \left(R^{I}_{(2,23)} - \hat{\beta}^{IM}_{n} \times R^{M}_{(2,23)} \right),$$

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

$$\mathrm{CR}^{F}_{n,(2,23)} \quad = \quad \mathrm{CR}_{n,(2,23)} - \hat{\beta}^{M}_{n} \times R^{M}_{(2,23)} - \hat{\beta}^{I}_{n} \times \left(R^{I}_{(2,23)} - \hat{\beta}^{IM}_{n} \times R^{M}_{(2,23)} \right).$$

I also look at 3-month post-event returns, $\mathrm{CR}_{n,(2,67)}$, and decompose them into market, industry, and firm-specific components similarly.[13]

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 1.07, with a median of 1.03 and a standard deviation of 0.42. The average market and industry betas of upgraded firms are 1.14 and 0.59, respectively. The mean (median) firm-specific

[11] I start with 55,199 upgrades and 64,662 downgrades (as reported in Table 1), and exclude 10,581 upgrades and 13,883 downgrades because another recommendation was issued on the same stock less than 10 days before. Another 8,478 upgrades and 9,648 downgrades are lost because they have no NAICS information from Compustat, and 138 upgrades and 146 downgrades are lost because fewer than 3 firms are in the industry. Finally, I require a stock to have at least 22 daily observations in the previous calendar year to estimate $\hat{\beta}^{M}_{n}$, $\hat{\beta}^{I}_{n}$, and $\hat{\beta}^{IM}_{n}$, and this leads to a loss of 3,785 upgrades and 4,304 downgrades.

[12] Similarly, Womack (1996) uses 21-day cumulative returns, and Mikhail et al. (2004) use 20-day cumulative returns to measure 1-month post-recommendation drifts. All results are unchanged if I use 20- or 21-day cumulative returns.

[13] If the stock does not survive the next 22 or 66 days, I use the CRSP value-weighted market return to substitute for the return on the stock. If I exclude the delisted firms, $\mathrm{CR}^{I}_{n,(2,23)}$ ($\mathrm{CR}^{I}_{n,(2,67)}$) has 31,977 (31,215) observations for upgrades and 36,305 (35,226) observations for downgrades. Results are unchanged if I use only surviving firms.

TABLE 3

Summary Statistics of the Market, Industry, and Firm-Specific Components of Returns around and after Recommendation Changes

Table 3 provides summary statistics of the market, industry, and firm-specific components of returns around (Panels A and B) and after (Panels C and D) recommendation changes. Panels A and C are results for upgrades, and Panels B and D are results for downgrades. All variables are defined in the Appendix. All returns are in percentages.

Variables	Mean	Std. Dev.	75th Percentile	Median	25th Percentile
Panel A. Betas and 3-Day Cumulative Returns around Upgrades (N = 32,217)					
$\mathrm{CR}_{n,(-1,1)}$	2.89	9.32	6.18	1.86	–1.44
$\hat{\beta}_n^M$	1.14	0.67	1.50	1.02	0.68
$\hat{\beta}_n^{IM}$	1.07	0.42	1.33	1.03	0.80
$\hat{\beta}_n^I$	0.59	0.58	0.93	0.53	0.17
$R_{(-1,1)}^M$	0.16	1.92	1.23	0.30	–0.88
$R_{(-1,1)}^I$	0.28	3.01	1.79	0.28	–1.26
$\mathrm{CR}_{n,(-1,1)}^M$	0.18	2.52	1.20	0.23	–0.78
$\mathrm{CR}_{n,(-1,1)}^I$	0.10	1.77	0.48	0.01	–0.39
$\mathrm{CR}_{n,(-1,1)}^F$	2.61	8.75	5.41	1.56	–1.25
Panel B. Betas and 3-Day Cumulative Returns around Downgrades (N = 36,681)					
$\mathrm{CR}_{n,(-1,1)}$	–2.86	11.73	1.61	–1.67	–6.21
$\hat{\beta}_n^M$	1.14	0.70	1.50	1.01	0.66
$\hat{\beta}_n^{IM}$	1.08	0.44	1.33	1.03	0.80
$\hat{\beta}_n^I$	0.56	0.58	0.90	0.49	0.15
$R_{(-1,1)}^M$	0.11	1.94	1.20	0.28	–0.97
$R_{(-1,1)}^I$	0.01	3.04	1.62	0.13	–1.50
$\mathrm{CR}_{n,(-1,1)}^M$	0.09	2.65	1.16	0.19	–0.82
$\mathrm{CR}_{n,(-1,1)}^I$	–0.06	1.76	0.37	–0.01	–0.46
$\mathrm{CR}_{n,(-1,1)}^F$	–2.89	11.35	1.23	–1.62	–5.73
Panel C. Post-Recommendation Returns for Upgrades (N = 32,217)					
$\mathrm{CR}_{n,(2,23)}$	2.29	15.38	9.47	1.82	–5.62
$\mathrm{CR}_{n,(2,67)}$	5.25	28.25	17.86	3.80	–9.50
$R_{(2,23)}^M$	1.16	4.64	4.11	1.71	–1.62
$R_{(2,67)}^M$	3.20	7.92	8.69	3.84	–1.52
$R_{(2,23)}^I$	1.21	7.45	5.34	1.42	–2.94
$R_{(2,67)}^I$	3.43	13.13	10.76	3.54	–3.90
$\mathrm{CR}_{n,(2,23)}^M$	1.33	6.17	4.19	1.34	–1.30
$\mathrm{CR}_{n,(2,67)}^M$	3.71	10.39	8.88	3.22	–1.25
$\mathrm{CR}_{n,(2,23)}^I$	–0.01	4.37	1.17	–0.01	–1.25
$\mathrm{CR}_{n,(2,67)}^I$	0.09	7.72	2.05	–0.04	–2.29
$\mathrm{CR}_{n,(2,23)}^F$	0.97	13.47	6.84	0.46	–5.56
$\mathrm{CR}_{n,(2,67)}^F$	1.46	24.86	11.73	0.24	–11.00
Panel D. Post-Recommendation Returns for Downgrades (N = 36,681)					
$\mathrm{CR}_{n,(2,23)}$	0.79	16.89	8.27	0.49	–7.28
$\mathrm{CR}_{n,(2,67)}$	3.03	29.15	15.88	1.95	–12.29
$R_{(2,23)}^M$	1.09	4.90	4.11	1.70	–1.68
$R_{(2,67)}^M$	3.08	8.18	8.67	3.91	–1.72
$R_{(2,23)}^I$	1.15	7.87	5.46	1.35	–3.11
$R_{(2,67)}^I$	3.33	13.51	10.93	3.60	–3.95
$\mathrm{CR}_{n,(2,23)}^M$	1.16	6.88	4.12	1.28	–1.37
$\mathrm{CR}_{n,(2,67)}^M$	3.41	10.93	8.64	3.23	–1.40
$\mathrm{CR}_{n,(2,23)}^I$	–0.01	4.32	1.13	–0.01	–1.18
$\mathrm{CR}_{n,(2,67)}^I$	0.06	7.54	2.05	–0.02	–2.12
$\mathrm{CR}_{n,(2,23)}^F$	–0.36	14.85	5.87	–0.61	–7.17
$\mathrm{CR}_{n,(2,67)}^F$	–0.45	25.81	10.34	–1.42	–13.37

component of the 3-day cumulative return is 2.61% (1.56%), much greater than the 0.10 (0.01%) for the industry component or the 0.18% (0.23%) for the market component. The standard deviation of the firm-specific component is 8.75, which is also much greater than that of the industry component of 1.77 or that of the market component of 2.52. Panel B reports results for 3-day cumulative returns around downgrades. The average market beta of the downgraded firm's industry, $\hat{\beta}_n^{IM}$, is 1.08, with a median of 1.03 and a standard deviation of 0.44. The average market and industry betas of downgraded firms are 1.14 and 0.56, respectively. The mean (median) firm-specific component of the 3-day cumulative return is −2.89% (−1.62%), much greater in magnitude than the −0.06% (−0.01%) for the industry component or the 0.09% (0.19%) for the market component. The standard deviation of the firm-specific component is 11.35, which is also much greater than that of the industry component of 1.76 or that of the market component of 2.65.

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 2.29% and 5.25% for upgrades and 0.79% and 3.03% for downgrades. The average industry components of 1- and 3-month post-event returns for upgrades are −0.01% and 0.09%, not statistically different from the −0.01% and 0.06% for downgrades by *t*-tests on means (untabulated). The average firm-specific components of 1- and 3-month post-event returns for upgrades are 0.97% and 1.46%. In contrast, the average firm-specific components of 1- and 3-month post-event returns for downgrades are −0.36% and −0.45%. 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.

D. 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 Hypothesis 2 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 (5). The 2nd measure is the relative idiosyncratic volatility, 1 − RSQ, which equals 1 minus the adjusted R^2 from regression (5). Results are reported in Table 4.

TABLE 4

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

Table 4 provides results on the relation between idiosyncratic return volatility and firm-specific components of returns around and after recommendation changes. Panel A measures idiosyncratic return volatility using RMSE, whereas Panel B measures idiosyncratic volatility using 1 – RSQ. All variables are defined in the Appendix. All returns are in percentages. * and ** indicate significance at the 5% and 1% levels, respectively.

		Upgrades				Downgrades		
RMSE	N	$CR^F_{n,(-1,1)}$	$CR^F_{n,(2,23)}$	$CR^F_{n,(2,67)}$	N	$CR^F_{n,(-1,1)}$	$CR^F_{n,(2,23)}$	$CR^F_{n,(2,67)}$
Panel A. The Relation between RMSE and Firm-Specific Components of Returns around and after Recommendation Changes								
Decile 1	3,218	0.92**	0.67**	1.11**	3,665	–1.09**	–0.14	–0.03
2	3,218	1.46**	0.65**	0.79**	3,671	–1.50**	–0.05	–0.28
3	3,229	1.66**	0.86**	1.05**	3,666	–1.68**	–0.24	–0.16
4	3,230	1.85**	1.04**	1.89**	3,666	–2.19**	–0.26	–0.27
5	3,215	2.60**	0.92**	1.09**	3,672	–2.49**	–0.11	0.13
6	3,218	2.66**	0.79**	1.21**	3,666	–3.12**	–0.36	–0.47
7	3,220	2.92**	0.96**	2.09**	3,672	–3.43**	–0.21	–0.02
8	3,229	3.31**	0.98**	1.57**	3,671	–3.97**	–0.44	–0.97
9	3,224	3.73**	1.50**	1.50*	3,665	–4.88**	–0.59	–0.92
Highest 10	3,216	4.99**	1.29**	2.33**	3,667	–4.58**	–1.22**	–1.46*
dif(1 – 10)		–4.07**	–0.62*	–1.22*		3.49**	1.08**	1.43*
		Upgrades				Downgrades		
1 – RSQ	N	$CR^F_{n,(-1,1)}$	$CR^F_{n,(2,23)}$	$CR^F_{n,(2,67)}$	N	$CR^F_{n,(-1,1)}$	$CR^F_{n,(2,23)}$	$CR^F_{n,(2,67)}$
Panel B. The Relation between 1 – RSQ and Firm-Specific Components of Returns around and after Recommendation Changes								
Decile 1	3,208	1.00**	0.20	0.12	3,655	–1.33**	–0.21	–0.39
2	3,231	1.71**	0.03	–0.94**	3,680	–2.27**	–0.33	–0.45
3	3,224	2.28**	0.66**	0.31	3,675	–2.57**	0.26	0.72
4	3,222	2.29**	0.69**	0.74	3,660	–2.63**	0.12	0.71
5	3,220	2.76**	0.78**	0.80*	3,670	–3.07**	–0.76**	–0.55
6	3,233	2.43**	0.71**	1.07*	3,674	–3.06**	–0.71**	–0.62
7	3,211	3.15**	1.05**	1.24**	3,665	–2.92**	–0.32	–0.22
8	3,229	3.08**	1.23**	2.15**	3,671	–3.54**	–0.27	–0.88
9	3,226	3.30**	1.88**	3.58**	3,665	–3.68**	–0.58*	–1.20*
Highest 10	3,213	4.09**	2.45**	5.55**	3,666	–3.86**	–0.82**	–1.57**
dif(1 – 10)		–3.09**	–2.25**	–5.43**		2.53**	0.61*	1.18*

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.[14] I then calculate the average firm-specific components of stock returns around and after

[14]For example, I first rank all upgraded firms in 1994 based on the RMSE estimated in 1993. Ranking RMSE within each calendar year reduces the influence of changes of RMSE over time on

analyst recommendation changes in each decile. For upgrades, the average value of $\mathrm{CR}^F_{n,(-1,1)}$ increases monotonically with RMSE deciles. The average 3-day firm-specific reaction to an upgrade is 4.99% for firms with the highest RMSE, and 0.92% 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, $\mathrm{CR}^F_{n,(2,23)}$ and $\mathrm{CR}^F_{n,(2,67)}$, 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 $\mathrm{CR}^F_{n,(2,67)}$ is 2.33% for firms with the highest RMSE, and 1.11% 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 $\mathrm{CR}^F_{n,(-1,1)}$, $\mathrm{CR}^F_{n,(2,23)}$, and $\mathrm{CR}^F_{n,(2,67)}$ 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 −4.58% for firms with the highest RMSE, and −1.09% 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 −1.22% for firms with the highest RMSE, and −0.14% for firms with the lowest RMSE, with the difference statistically significant at the 1% level by *t*-tests on means.

In Panel B of Table 4, I sort firms into 10 deciles each year based on the estimated $1-\mathrm{RSQ}$ of the firm from equation (5) 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 $\mathrm{CR}^F_{n,(-1,1)}$, $\mathrm{CR}^F_{n,(2,23)}$, and $\mathrm{CR}^F_{n,(2,67)}$ increase with $1-\mathrm{RSQ}$ deciles with few exceptions. For downgrades, the average values of $\mathrm{CR}^F_{n,(-1,1)}$, $\mathrm{CR}^F_{n,(2,23)}$, and $\mathrm{CR}^F_{n,(2,67)}$ tend to decrease with $1-\mathrm{RSQ}$ 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.

E. 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 from equation (5) in the previous calendar year. I then calculate the average industry components of stock returns around and

the cross-sectional comparison. All results are unchanged if I use pooled ranking instead of ranking within each calendar year.

TABLE 5

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

Panel A of Table 5 reports results on the relation between the absolute value of the industry beta and industry components of returns around and after recommendation changes. Panel B examines the relation between the absolute value of the industry beta and abnormal industry returns. All variables are defined in the Appendix. All returns are in percentages. * and ** indicate significance at the 5% and 1% levels, respectively.

	Upgrades				Downgrades			
$\lvert\hat{\beta}_n^I\rvert$	N	$\mathrm{CR}^I_{n,(-1,1)}$	$\mathrm{CR}^I_{n,(2,23)}$	$\mathrm{CR}^I_{n,(2,67)}$	N	$\mathrm{CR}^I_{n,(-1,1)}$	$\mathrm{CR}^I_{n,(2,23)}$	$\mathrm{CR}^I_{n,(2,67)}$
Panel A. The Relation between the Absolute Value of the Industry Beta and Industry Components of Returns around and after Recommendation Changes								
Decile 1	3,222	0.00	0.00	0.01	3,664	0.00	–0.02	0.06
2	3,219	0.01	0.00	–0.01	3,664	0.00	–0.06	0.01
3	3,221	0.02	–0.03	–0.07	3,674	–0.03	–0.18	–0.35
4	3,220	0.04*	–0.01	0.03	3,674	–0.02	0.26	0.32
5	3,224	0.03	0.02	–0.02	3,646	–0.05**	0.19	0.31
6	3,224	0.06**	0.08	0.15	3,685	–0.04*	–0.11	0.14
7	3,227	0.05*	–0.02	0.12	3,671	–0.07**	0.08	0.01
8	3,227	0.22**	0.13	0.46**	3,677	–0.12**	0.58	0.66
9	3,216	0.22**	0.15	0.42*	3,659	–0.13**	–0.27	0.95
Highest 10	3,217	0.35**	–0.40**	–0.25	3,667	–0.14**	–0.06	–0.31
dif(1 – 10)		–0.35**	0.40**	0.26		0.14**	0.04	0.37

	Upgrades				Downgrades			
$\lvert\hat{\beta}_n^I\rvert$	N	$\mathrm{AR}^I_{n,(-1,1)}$	$\mathrm{AR}^I_{n,(2,23)}$	$\mathrm{AR}^I_{n,(2,67)}$	N	$\mathrm{AR}^I_{n,(-1,1)}$	$\mathrm{AR}^I_{n,(2,23)}$	$\mathrm{AR}^I_{n,(2,67)}$
Panel B. The Relation between the Absolute Value of the Industry Beta of the Recommended Stock and Abnormal Industry Returns								
Decile 1	3,222	0.07	–0.07	–0.33	3,664	–0.01	–0.15	–0.56
2	3,219	0.07	0.00	0.09	3,664	–0.05	–0.20	0.09
3	3,221	0.04	–0.13	–0.39*	3,674	–0.08*	–0.52	–0.82
4	3,220	0.12**	–0.15	–0.18	3,674	–0.10**	–0.03	0.11
5	3,224	0.07*	–0.03	–0.17	3,646	–0.10**	–0.01	0.04
6	3,224	0.08*	0.04	0.03	3,685	–0.08*	–0.08	0.34
7	3,227	0.06	–0.04	0.10	3,671	–0.09**	0.09	0.01
8	3,227	0.22**	0.12	0.38*	3,677	–0.12**	0.15	0.93
9	3,216	0.21**	0.13	0.38*	3,659	–0.12**	–0.30	0.96
Highest 10	3,217	0.21**	–0.20*	–0.09	3,667	–0.12**	0.06	0.06
dif(1 – 10)		–0.14**	0.13	–0.24		0.11**	–0.21	–0.62

after recommendation changes in each decile. For upgrades, the average value of $\mathrm{CR}^I_{n,(-1,1)}$ tends to increase with $|\hat{\beta}_n^I|$ deciles. The average 3-day industry reaction to an upgrade is 0 for firms with the smallest $|\hat{\beta}_n^I|$, and 0.35% for firms with the largest $|\hat{\beta}_n^I|$, with the difference statistically significant at the 1% level by t-tests on means. For downgrades, the average value of $\mathrm{CR}^I_{n,(-1,1)}$ decreases with $|\hat{\beta}_n^I|$ deciles, even though not strictly monotonically. The average 3-day industry reaction to a downgrade is 0 for firms with the smallest $|\hat{\beta}_n^I|$, and -0.14% for firms with the largest $|\hat{\beta}_n^I|$, 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. I also examine the relation between $|\hat{\beta}_n^I|$ and industry components of post-event drifts. The average values of $\mathrm{CR}^I_{n,(2,23)}$ and $\mathrm{CR}^I_{n,(2,67)}$ have no relation with $|\hat{\beta}_n^I|$ deciles for either upgrades or downgrades. In fact, for upgrades, the average value of $\mathrm{CR}^I_{n,(2,23)}$ in the smallest

$|\hat{\beta}_n^I|$ decile is significantly greater than that in the largest $|\hat{\beta}_n^I|$ decile, opposite to the relation between $\text{CR}_{n,(-1,1)}^I$ and $|\hat{\beta}_n^I|$. 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 $\hat{\beta}_n^I$ and $(R^I - \hat{\beta}_n^{IM} \times R^M)$ (i.e., $\text{CR}_n^I = \hat{\beta}_n^I \times (R^I - \hat{\beta}_n^{IM} \times R^M)$), there might be a natural positive relation between $|\hat{\beta}_n^I|$ and the absolute value of CR_n^I that has nothing to do with analysts' incentives to produce industry information. To address this concern, I test in Panel B of Table 5 the relation between $|\hat{\beta}_n^I|$ and the abnormal industry return, $\text{AR}_n^I = R^I - \hat{\beta}_n^{IM} \times R^M$. Results in Panel B show that the average value of $\text{AR}_{n,(-1,1)}^I$ increases with $|\hat{\beta}_n^I|$ deciles for upgrades and decreases with $|\hat{\beta}_n^I|$ deciles for downgrades, even though not strictly monotonically. The differences in the average value of $\text{AR}_{n,(-1,1)}^I$ 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 $|\hat{\beta}_n^I|$ and average values of $\text{AR}_{n,(2,23)}^I$ and $\text{AR}_{n,(2,67)}^I$ 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.

F. 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, $1 - \text{RSQ}$, and industry components of stock returns around and after analyst recommendation changes.

I divide firms into 10 deciles according to the value of $1 - \text{RSQ}$ estimated from equation (5) in 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 $\text{CR}_{n,(-1,1)}^I$ decreases monotonically (except from decile 4 to decile 5) with $1 - \text{RSQ}$ deciles. The average 3-day industry reaction to an upgrade is 0.43% for firms with the smallest $1 - \text{RSQ}$, and around 0 for firms with the largest $1 - \text{RSQ}$, with the difference statistically significant at the 1% level by t-tests on means. For downgrades, the average value of $\text{CR}_{n,(-1,1)}^I$ tends to increase with $1 - \text{RSQ}$ deciles, even though not strictly monotonically. The average 3-day industry reaction to a downgrade is -0.23% for firms with the smallest $1 - \text{RSQ}$, and -0.01% for firms with the largest$1 - \text{RSQ}$,

TABLE 6

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

Panel A of Table 6 reports results on the relation between relative idiosyncratic return volatility, 1 – RSQ, and industry components of stock returns around and after recommendation changes. Panel B examines how relative idiosyncratic return volatility affects abnormal industry returns around and after recommendation changes. All variables are defined in the Appendix. All returns are in percentages. * and ** indicate significance at the 5% and 1% levels, respectively.

		Upgrades				Downgrades		
1 – RSQ	N	$\text{CR}^I_{n,(-1,1)}$	$\text{CR}^I_{n,(2,23)}$	$\text{CR}^I_{n,(2,67)}$	N	$\text{CR}^I_{n,(-1,1)}$	$\text{CR}^I_{n,(2,23)}$	$\text{CR}^I_{n,(2,67)}$
Panel A. The Relation between Idiosyncratic Volatility and Industry Components of Returns around and after Recommendation Changes								
Decile 1	3,208	0.43**	0.16*	0.83**	3,655	–0.23**	0.76	1.68
2	3,231	0.25**	0.06	0.45*	3,680	–0.08*	–0.27	–0.05
3	3,224	0.14**	–0.02	–0.16	3,675	–0.11**	–0.05	–0.04
4	3,222	0.01	0.00	–0.05	3,660	–0.02	0.15	0.43
5	3,220	0.04	–0.21**	–0.19	3,670	–0.01	–0.17	–0.19
6	3,233	0.04	0.06	0.19	3,674	–0.04*	–0.26	0.57
7	3,211	0.04	–0.03	–0.08	3,665	–0.05*	0.24	–0.41
8	3,229	0.02	0.02	0.02	3,671	–0.02	0.06	0.09
9	3,226	0.02	–0.09*	–0.12	3,665	–0.02	–0.35	–0.67
Highest 10	3,213	0.00	–0.03	–0.03	3,666	–0.01	0.03	–0.15
dif(1 – 10)		0.43**	0.19	0.86**		–0.22**	0.73	1.83

		Upgrades				Downgrades		
1 – RSQ	N	$\text{AR}^I_{n,(-1,1)}$	$\text{AR}^I_{n,(2,23)}$	$\text{AR}^I_{n,(2,67)}$	N	$\text{AR}^I_{n,(-1,1)}$	$\text{AR}^I_{n,(2,23)}$	$\text{AR}^I_{n,(2,67)}$
Panel B. The Relation between Idiosyncratic Volatility and Abnormal Industry Returns								
Decile 1	3,208	0.34**	0.30**	0.96**	3,655	–0.20**	0.91	1.83
2	3,231	0.22**	0.07	0.34	3,680	–0.11**	–0.05	0.26
3	3,224	0.15**	–0.13	–0.43**	3,675	–0.16**	0.40	0.05
4	3,222	0.05	–0.06	–0.22	3,660	–0.08*	–0.58	–0.67
5	3,220	0.04	–0.33**	–0.43**	3,670	–0.06	–0.17	0.71
6	3,233	0.05	0.11	0.21	3,674	–0.08*	–0.96	0.09
7	3,211	0.08*	–0.12	–0.33*	3,665	–0.08*	–0.07	–0.48
8	3,229	0.11**	0.08	0.21	3,671	–0.05	–0.07	–0.02
9	3,226	0.00	–0.15	–0.39*	3,665	–0.02	–1.04	–1.10
Highest 10	3,213	0.10*	–0.12	–0.10	3,666	–0.04	0.72	1.02
dif(1 – 10)		0.24**	0.42**	1.06**		–0.16**	0.19	0.81

with the difference statistically significant at the 1% level by t-tests on means. For upgrades, the average value of $\text{CR}^I_{n,(2,23)}$ shows no relation with $1 - \text{RSQ}$ deciles, while that of $\text{CR}^I_{n,(2,67)}$ tends to decrease with $1 - \text{RSQ}$ deciles. For downgrades, the average values of $\text{CR}^I_{n,(2,23)}$ and $\text{CR}^I_{n,(2,67)}$ show a weak negative relation with $1 - \text{RSQ}$, opposite to the relation between $\text{CR}^I_{n,(-1,1)}$ and $1 - \text{RSQ}$.

Because the industry component of stock returns around and after analyst recommendation changes, $\text{CR}^I_n = \hat{\beta}^I_n \times (R^I - \hat{\beta}^{IM}_n \times R^M)$, increases in magnitude with $|\hat{\beta}^I_n|$, while $1 - \text{RSQ} = (\text{Var}(F_n))/((\hat{\beta}^I_n)^2 \times \text{Var}(I) + \text{Var}(F_n))$ decreases with $|\hat{\beta}^I_n|$, there might be a natural negative relation between $1 - \text{RSQ}$ 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 $1 - \text{RSQ}$ and abnormal industry returns ($\text{AR}^I_{n,(-1,1)}$, $\text{AR}^I_{n,(2,23)}$, and $\text{AR}^I_{n,(2,67)}$). Results in Panel B show that the average value of $\text{AR}^I_{n,(-1,1)}$ decreases with $1 - \text{RSQ}$ deciles for upgrades and increases with $1 - \text{RSQ}$ deciles for downgrades, even though not strictly monotonically. The differences in the average value of $\mathrm{AR}^{I}_{n,(-1,1)}$ 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 $\mathrm{CR}^{I}_{n,(2,23)}$ and $\mathrm{CR}^{I}_{n,(2,67)}$ tend to decrease with $1-\mathrm{RSQ}$ deciles for upgrades. For downgrades, however, the average values of $\mathrm{CR}^{I}_{n,(2,23)}$ and $\mathrm{CR}^{I}_{n,(2,67)}$ show no relation with $1-\mathrm{RSQ}$ 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.

G. Response of Other Stocks in the Same Industry

Hypothesis 5 predicts 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 both the recommended stock and other stocks in the industry. To test this prediction, I first run the following regression in each calendar year from 1993 to 2004 for each stock:

$$R_{j,t} \quad = \quad \alpha_j + \beta^M_j \times R^M_t + \beta^I_j \times \left(R^I_t - \hat{\beta}^{IM}_j \times R^M_t\right) + \varepsilon_{j,t}, \tag{7}$$

where $R_{j,t}$ is the return in day t on firm j in the same industry as the recommended firm n; R^M_t is the CRSP value-weighted market return in day t; and R^I_t is the contemporaneous return on the industry portfolio. The industry portfolio is constructed without stock j; remaining stocks are then value-weighted using size in day $t-1$. Here $\hat{\beta}^{IM}_j$ is estimated in a similar fashion as $\hat{\beta}^{IM}_n$ in equation (6) except that the industry portfolio excludes stock j instead of the recommended stock n.

In Panel A of Table 7, I divide other stocks in the industry into 10 deciles each year based on the absolute value of the estimated $\hat{\beta}^I_n$ of the recommended stock from equation (5) in the previous calendar year.[15] I then calculate the average abnormal stock returns around and after recommendation changes in each decile. The 3-day abnormal return of stock j around a recommendation change on stock n is defined as

$$\mathrm{AR}^{n}_{j,(-1,1)} \quad = \quad R_{j,(-1,1)} - \hat{\beta}^M_j \times R^M_{(-1,1)},$$

[15]Because for each recommended stock, the number of firms in the same industry is different, the number of nonrecommended stocks is quite different in different deciles when one groups nonrecommended stocks based on recommended stocks' characteristics (this also applies to Panel C of Table 7). The number of observations becomes similar across deciles in Panels B and D where one groups nonrecommended stocks based on their own characteristics.

TABLE 7

The Response of Other Stocks in the Same Industry to Analyst Recommendation Changes

Table 7 reports how other stocks in the same industry as the recommended stock respond to recommendation changes, as a function of the absolute value of the industry beta or the size of the recommended stock or other stocks in the industry. All variables are defined in the Appendix. All returns are in percentages. * and ** indicate significance at the 5% and 1% levels, respectively.

		Upgrades				Downgrades		
$\lvert\hat{\beta}_n^I\rvert$	N	$AR^n_{j,(-1,1)}$	$AR^n_{j,(2,23)}$	$AR^n_{j,(2,67)}$	N	$AR^n_{j,(-1,1)}$	$AR^n_{j,(2,23)}$	$AR^n_{j,(2,67)}$
Panel A. Response as a Function of the Absolute Value of the Recommended Stock's Industry Beta								
Decile 1	163,231	0.15**	0.39**	1.44**	170,214	0.03*	0.19**	0.88**
2	152,670	0.06**	0.46**	1.11**	174,924	–0.03**	0.18**	0.62**
3	168,094	0.06**	0.39**	1.50**	173,266	–0.03**	0.07*	0.41**
4	161,738	0.11**	0.35**	1.31**	186,500	–0.03**	0.15**	0.77**
5	163,665	0.12**	0.42**	1.44**	172,083	–0.04**	–0.03	0.50**
6	172,057	0.12**	0.24**	0.61**	191,423	–0.04**	0.08**	0.51**
7	148,990	0.11**	0.63**	1.29**	173,261	–0.05**	0.11**	0.43**
8	155,635	0.22**	0.64**	1.46**	175,256	–0.03*	0.01	0.39**
9	132,962	0.15**	0.52**	1.21**	155,969	–0.04**	–0.14**	0.59**
Highest 10	158,990	0.37**	0.48**	1.62**	177,206	–0.11**	–0.24**	–0.01
dif(1 – 10)		–0.22**	–0.09	–0.18		0.14**	0.43**	0.89**

		Upgrades				Downgrades		
$\lvert\hat{\beta}_j^I\rvert$	N	$AR^n_{j,(-1,1)}$	$AR^n_{j,(2,23)}$	$AR^n_{j,(2,67)}$	N	$AR^n_{j,(-1,1)}$	$AR^n_{j,(2,23)}$	$AR^n_{j,(2,67)}$
Panel B. Response as a Function of the Absolute Value of the Industry Beta of Other Stocks in the Industry								
Decile 1	157,904	0.13**	0.72**	1.96**	175,730	0.05**	0.44**	1.57**
2	158,017	0.11**	0.51**	1.70**	174,906	0.05**	0.29**	1.13**
3	157,983	0.11**	0.53**	1.33**	174,766	0.01	0.08**	0.58**
4	157,521	0.10**	0.48**	1.31**	174,874	0.01	0.23**	0.81**
5	157,705	0.15**	0.51**	1.39**	174,968	–0.03*	0.20**	0.73**
6	158,275	0.12**	0.53**	1.62**	175,280	0.00	0.09**	0.67**
7	157,471	0.13**	0.52**	1.27**	174,560	–0.05**	–0.03	0.15
8	157,985	0.17**	0.36**	0.89**	175,358	–0.09**	–0.13**	0.22**
9	157,540	0.22**	0.51**	1.59**	174,882	–0.10**	–0.03	0.47**
Highest 10	157,631	0.24**	–0.02	0.42	174,778	–0.19**	–0.71**	–1.02**
dif(1 – 10)		–0.11**	0.74**	1.54**		0.24**	1.15**	2.59**

		Upgrades				Downgrades		
$SIZE_n$	N	$AR^n_{j,(-1,1)}$	$AR^n_{j,(2,23)}$	$AR^n_{j,(2,67)}$	N	$AR^n_{j,(-1,1)}$	$AR^n_{j,(2,23)}$	$AR^n_{j,(2,67)}$
Panel C. Response as a Function of the Recommended Stock's Market Capitalization								
Decile 1	163,088	0.21**	0.20**	0.62**	174,937	–0.10**	–0.15**	0.22**
2	174,353	0.15**	0.49**	1.40**	181,661	–0.03*	0.07*	0.40**
3	162,825	0.16**	0.44**	1.00**	179,501	–0.05**	–0.10**	0.25**
4	167,792	0.10**	0.54**	2.18**	178,853	–0.01	–0.12**	0.22**
5	165,560	0.11**	0.37**	0.89**	181,423	–0.03*	0.09**	0.64**
6	163,338	0.14**	0.67**	1.56**	179,097	–0.07**	0.01	0.65**
7	148,249	0.17**	0.53**	1.14**	173,860	–0.03*	0.05	0.43**
8	150,056	0.14**	0.29**	1.44**	176,745	–0.02	0.29**	0.70**
9	162,159	0.19**	0.48**	1.55**	176,644	–0.03*	0.15**	0.64**
Highest 10	120,612	0.08**	0.57**	1.39**	147,381	–0.01	0.14**	1.05**
dif(1 – 10)		0.13**	–0.37**	–0.77**		–0.09**	–0.29**	–0.83**

		Upgrades				Downgrades		
$SIZE_j$	N	$AR^n_{j,(-1,1)}$	$AR^n_{j,(2,23)}$	$AR^n_{j,(2,67)}$	N	$AR^n_{j,(-1,1)}$	$AR^n_{j,(2,23)}$	$AR^n_{j,(2,67)}$
Panel D. Response as a Function of the Market Capitalization of Other Stocks in the Industry								
Decile 1	158,088	0.43**	2.00**	5.31**	174,963	–0.11**	–0.01	0.91**
2	157,353	0.19**	0.77**	2.60**	175,148	–0.05**	–0.06	0.91**
3	157,825	0.15**	0.59**	2.17**	174,177	–0.03*	–0.05	–0.24**
4	157,792	0.10**	0.27**	0.99**	175,345	–0.03*	–0.05	0.67**
5	157,560	0.09**	0.18**	0.88**	175,223	–0.01	0.08*	0.74**
6	157,338	0.10**	0.29**	1.06**	174,848	–0.02	0.17**	0.69**
7	158,249	0.10**	0.11**	0.33**	175,230	–0.04**	0.09**	0.36**
8	158,056	0.11**	0.10**	0.05	175,718	–0.03*	0.06	0.27**
9	158,159	0.10**	0.10**	0.03	174,614	–0.06**	0.12**	0.33**
Highest 10	157,612	0.07**	–0.03	–0.43**	174,836	0.01	0.07	0.74**
dif(1 – 10)		0.36**	2.03**	5.74**		–0.12**	–0.08	0.17

where $R_{j,(-1,1)}$ is the 3-day cumulative return of firm j; $\hat{\beta}_j^M$ is the market beta of firm j estimated in the previous calendar year; and $R^M_{(-1,1)}$ is the 3-day cumulative return of the CRSP value-weighted market index.[16] I define 1- and 3-month abnormal returns of firm j, $\text{AR}^n_{j,(2,23)}$ and $\text{AR}^n_{j,(2,67)}$, similarly.

Results in Panel A of Table 7 indicate that when a firm is upgraded (downgraded), other firms in the same industry have positive (negative) abnormal returns around the recommendation change, with the exception of decile 1 for downgrades. Further, the magnitude of the abnormal return tends to increase with the absolute value of the industry beta of the recommended stock. For example, the average 3-day abnormal return associated with an upgrade is 0.37% for the highest $|\hat{\beta}_n^I|$ decile and 0.15% for the lowest $|\hat{\beta}_n^I|$ decile, with the difference statistically significant at the 1% level by t-tests on means. For downgrades, the average 3-day abnormal return is -0.11% for the highest $|\hat{\beta}_n^I|$ decile and 0.03% for the lowest $|\hat{\beta}_n^I|$ decile, with the difference also statistically significant at the 1% level by t-tests on means. The 1- and 3-month abnormal returns, $\text{AR}^n_{j,(2,23)}$ and $\text{AR}^n_{j,(2,67)}$, have no relation with $|\hat{\beta}_n^I|$ for upgrades, while they tend to decrease with $|\hat{\beta}_n^I|$ for downgrades.

In Panel B of Table 7, I divide firms into 10 deciles each year based on the absolute value of $\hat{\beta}_j^I$ estimated from equation (7) in the previous calendar year. I then calculate the average abnormal stock returns around and after recommendation changes in each decile. The value of $\text{AR}^n_{j,(-1,1)}$ tends to increase (decrease) with $|\hat{\beta}_j^I|$ for upgrades (downgrades). For example, the average $\text{AR}^n_{j,(-1,1)}$ associated with downgrades is -0.19% for the highest $|\hat{\beta}_j^I|$ decile and 0.05% for the lowest $|\hat{\beta}_j^I|$ decile, with the difference statistically significant at the 1% level by t-tests on means. The average values of $\text{AR}^n_{j,(2,23)}$ and $\text{AR}^n_{j,(2,67)}$ decrease with $|\hat{\beta}_j^I|$ deciles for *both* upgrades and downgrades. The results in Panel B indicate that the abnormal returns around recommendation changes, but not those after, increase in magnitude with $|\hat{\beta}_j^I|$.

Previous studies (Stickel (1995), Mikhail et al. (2004)) find that the market reaction to recommendation changes is weaker (stronger) if the size of the recommended stock is larger (smaller) because more information is available for large firms than for small firms. In Panel C of Table 7, I examine whether the stock returns on other firms in the industry are affected by the size of the recommended firm. I first divide recommended firms into 10 deciles each year based on their market capitalizations at the end of the previous calendar year, SIZE_n. I then calculate average abnormal stock returns of other firms in the same industry around and after recommendation changes ($\text{AR}^n_{j,(-1,1)}$, $\text{AR}^n_{j,(2,23)}$, and $\text{AR}^n_{j,(2,67)}$) in each decile. The average value of $\text{AR}^n_{j,(-1,1)}$ tends to decrease with SIZE_n deciles for upgrades and increase with SIZE_n deciles for downgrades. For example, the

[16]Essentially, $\text{AR}^n_{j,(-1,1)}$ is the sum of industry and firm-specific components of $R_{j,(-1,1)}$. Results are similar if I use $R_{j,(-1,1)}$ instead of $\text{AR}^n_{j,(-1,1)}$. An alternative way of testing is to use the industry component of $R_{j,(-1,1)}$. However, this alternative test is close to the tests in Panel B of Tables 5 and 6 where the abnormal industry returns are used.

average $AR^n_{j,(-1,1)}$ associated with upgrades (downgrades) is 0.21% (−0.10%) for the smallest $SIZE_n$ decile and 0.08% (−0.01%) for the largest $SIZE_n$ decile, with the difference statistically significant at the 1% level by t-tests on means. The average values of $AR^n_{j,(2,23)}$ and $AR^n_{j,(2,67)}$ increase with $SIZE_n$ deciles for *both* upgrades and downgrades, suggesting that the abnormal returns of other stocks in the same industry after recommendation changes may not be related to the size of the recommended stock.

In Panel D of Table 7, I examine whether the return on stock j in the recommended stock n's industry is affected by its own size, $SIZE_j$. Because less information is available for smaller stocks than for larger stocks, the stock price of smaller firms is less informative. As a result, I expect the response of stock j to decrease with its own size. To test this prediction, I first divide other stocks in the industry into 10 deciles each year based on their market capitalization at the end of the previous calendar year. I then calculate the average abnormal returns around and after recommendation changes in each decile. The returns around recommendation changes decrease with $SIZE_j$ deciles for upgrades and increase with $SIZE_j$ deciles for downgrades. For example, the average $AR^n_{j,(-1,1)}$ associated with upgrades (downgrades) is 0.43% (−0.11%) for firms in the smallest $SIZE_j$ decile and 0.07% (0.01%) for firms in the largest $SIZE_j$ decile, with the difference statistically significant at the 1% level by t-tests on means. The average values of $AR^n_{j,(2,23)}$ and $AR^n_{j,(2,67)}$ decrease with $SIZE_j$ deciles for upgrades, and they are not related to $SIZE_j$ deciles for downgrades. Overall, results in Panel D show that small (large) firms react more (less) strongly to recommendations on other stocks in the same industry around, but not after, recommendation changes.

To summarize, results in Table 7 support Hypothesis 5 that other firms in the same industry as the recommended stock respond positively (negatively) to upgrades (downgrades) around recommendation changes. Further, the magnitude of the response increases with the absolute value of industry beta of the recommended stock and that of other stocks in the industry. The magnitude of the response also decreases with the size of the recommended stock and the size of other stocks in the industry.

H. Investment Implications

The findings presented in this paper show that the incremental information in analyst recommendations is mainly at the firm level instead of the industry level. Further, analysts have incentives to produce more firm-specific information on firms with greater idiosyncratic volatilities. Therefore, investors can potentially use these findings to maximize the investment value of analyst recommendations. To test the investment implications of the above results, I examine returns to different investment strategies after recommendation changes based on firms' idiosyncratic volatilities.

In Panel A of Table 8, I divide upgraded firms into 10 deciles each year based on the estimated 1 − RSQ of the firm from equation (5) in the previous calendar year. I then buy the upgraded stock and short the same dollar amount of the value-weighted industry portfolio at the beginning of day 1, where day 0 is the recommendation date.[17] The industry classification is the 3-digit NAICS, and the industry portfolio excludes the recommended stock itself. I then hold this 0-investment portfolio for 10, 22, or 66 business days and compute the average returns to and the Sharpe (1966) ratios of this investment strategy.[18] To avoid the look-ahead bias, I replace the stock with the CRSP value-weighted market index if the stock is delisted before the end of the investment period, as I have done in Table 3.[19]

TABLE 8

Investment Strategies Based on Idiosyncratic Volatility

Table 8 reports the performance of investment strategies using recommendation changes for firms with different idiosyncratic return volatilities. Sharpe (1966) ratios of these investments (defined as the average return of the portfolio divided by the standard deviation of the return) are also reported. In Panels A and C, I buy upgraded stocks and short the value-weighted industry index the day after the upgrade and hold the 0-investment portfolio for 10, 22, or 66 days. In Panels B and D, I short downgraded stocks and buy the value-weighted industry index the day after the downgrade and hold the 0-investment portfolio for 10, 22, or 66 days. Firms are sorted by 1 – RSQ in Panels A and B and by RMSE in Panels C and D. All variables are defined in the Appendix. All returns are in percentages.

		$\mathrm{CR}_n - R^I$			$\frac{\mathrm{CR}_n - R^I}{\mathrm{std}(\mathrm{CR}_n - R^I)}$		
1 – RSQ	*N*	(1,10)	(1,22)	(1,66)	(1,10)	(1,22)	(1,66)
Panel A. Portfolio Returns from Buying Upgraded Stocks and Shorting the Industry Index Based on 1 – RSQ							
All	32,217	1.02	1.43	2.11	0.11	0.11	0.09
Decile 1	3,208	0.53	0.57	0.91	0.07	0.05	0.04
2	3,231	0.51	0.63	0.10	0.06	0.04	0.01
3	3,224	0.67	1.41	1.57	0.08	0.12	0.08
4	3,222	0.88	1.28	1.77	0.10	0.11	0.09
5	3,220	0.89	1.30	1.70	0.10	0.10	0.08
6	3,233	0.90	1.11	1.85	0.11	0.09	0.08
7	3,211	1.28	1.51	2.01	0.14	0.11	0.09
8	3,229	1.10	1.53	2.32	0.12	0.11	0.10
9	3,226	1.46	2.15	3.91	0.15	0.16	0.15
Highest 10	3,213	1.93	2.77	4.87	0.18	0.18	0.16

		$R^I - \mathrm{CR}_n$			$\frac{R^I - \mathrm{CR}_n}{\mathrm{std}(R^I - \mathrm{CR}_n)}$		
1 – RSQ	*N*	(1,10)	(1,22)	(1,66)	(1,10)	(1,22)	(1,66)
Panel B. Portfolio Returns from Shorting Downgraded Stocks and Buying the Industry Index Based on 1 – RSQ							
All	36,681	0.57	0.56	0.52	0.07	0.05	0.04
Decile 1	3,655	0.21	0.22	0.22	0.03	0.03	0.02
2	3,680	0.38	0.29	0.43	0.06	0.02	0.03
3	3,675	0.49	0.28	0.42	0.06	0.03	0.02
4	3,660	0.54	0.34	0.26	0.07	0.02	0.02
5	3,670	0.38	0.34	–0.05	0.04	0.02	0.00
6	3,674	0.70	0.57	0.18	0.08	0.04	0.01
7	3,665	0.58	0.68	0.08	0.07	0.06	0.01
8	3,671	0.42	0.61	0.83	0.05	0.06	0.06
9	3,665	0.85	0.94	0.54	0.08	0.07	0.05
Highest 10	3,666	1.15	1.36	2.28	0.15	0.14	0.15

(continued on next page)

[17] To ensure that the investment strategy is implementable, I form portfolios the day after the recommendation change. When constructing the industry portfolio, I use firm size at the beginning of day 1 (i.e., size at the end of day 0) as weight so that no rebalancing on the portfolio is needed.

[18] The Sharpe (1966) ratio is defined as the average return on a portfolio divided by the standard deviation of the return.

[19] Because one does not know which stocks will be delisted when forming the portfolio, excluding the delisted stocks ex post will create a look-ahead bias. Results are similar if I replace the returns on the delisted stocks with 0 or the industry returns.

TABLE 8 (continued)

Investment Strategies Based on Idiosyncratic Volatility

RMSE	N	$CR_n - R^I$ (1,10)	$CR_n - R^I$ (1,22)	$CR_n - R^I$ (1,66)	$\frac{CR_n - R^I}{std(CR_n - R^I)}$ (1,10)	$\frac{CR_n - R^I}{std(CR_n - R^I)}$ (1,22)	$\frac{CR_n - R^I}{std(CR_n - R^I)}$ (1,66)
Panel C. Portfolio Returns from Buying Upgraded Stocks and Shorting the Industry Index Based on RMSE							
All	32,217	1.02	1.43	2.11	0.11	0.11	0.09
Decile 1	3,218	0.61	0.71	1.04	0.08	0.06	0.05
2	3,218	0.76	0.79	0.82	0.10	0.06	0.03
3	3,229	0.65	0.95	0.86	0.08	0.08	0.03
4	3,230	0.93	1.28	1.99	0.12	0.12	0.11
5	3,215	0.90	1.39	1.48	0.12	0.12	0.07
6	3,218	1.04	1.41	2.25	0.11	0.11	0.10
7	3,220	0.82	1.43	3.06	0.09	0.11	0.13
8	3,229	1.25	1.80	2.88	0.13	0.13	0.12
9	3,224	1.59	2.23	3.14	0.16	0.15	0.12
Highest 10	3,216	1.60	2.25	3.57	0.15	0.14	0.12

RMSE	N	$R^I - CR_n$ (1,10)	$R^I - CR_n$ (1,22)	$R^I - CR_n$ (1,66)	$\frac{R^I - CR_n}{std(R^I - CR_n)}$ (1,10)	$\frac{R^I - CR_n}{std(R^I - CR_n)}$ (1,22)	$\frac{R^I - CR_n}{std(R^I - CR_n)}$ (1,66)
Panel D. Portfolio Returns from Shorting Downgraded Stocks and Buying the Industry Index Based on RMSE							
All	36,681	0.57	0.56	0.52	0.07	0.05	0.04
Decile 1	3,665	0.37	0.44	0.48	0.05	0.06	0.04
2	3,671	0.42	0.37	0.74	0.07	0.04	0.05
3	3,666	0.55	0.53	0.60	0.08	0.06	0.04
4	3,666	0.50	0.45	0.53	0.07	0.04	0.03
5	3,672	0.44	0.49	0.05	0.04	0.04	0.01
6	3,666	0.49	0.39	0.44	0.05	0.03	0.02
7	3,672	0.68	0.28	0.01	0.07	0.01	0.01
8	3,671	0.77	0.58	0.62	0.07	0.05	0.04
9	3,665	0.64	0.69	0.24	0.08	0.06	0.04
Highest 10	3,667	0.84	1.40	1.47	0.11	0.10	0.08

If one holds the portfolio for 10 days, the average return is 1.02%, with a Sharpe (1966) ratio of 0.11. The average returns are different for firms in different 1 − RSQ deciles. The average return is 0.53% for firms with the lowest 1 − RSQ rankings and 1.93% for firms with the highest 1 − RSQ rankings. Therefore, by focusing only on firms in the largest 1 − RSQ decile, one can improve the average 10-day return from 1.02% to 1.93%, and the Sharpe ratio from 0.11 to 0.18. Results for returns in the next 1 or 3 months (i.e., 22 or 66 business days) are similar. For example, by focusing only on firms in the largest 1 − RSQ decile, one can improve the average 3-month return from 2.11% to 4.87%, and the Sharpe ratio from 0.09 to 0.16.

In Panel B of Table 8, I first divide downgraded firms into 10 deciles each year based on the estimated 1 − RSQ of the firm from equation (5) in the previous calendar year. I then short the downgraded stock and buy the value-weighted industry portfolio at the beginning of day 1, and hold this 0-investment portfolio for 10, 22, or 66 business days. I compute the average returns to and the Sharpe (1966) ratios of this investment strategy. The average returns tend to increase with 1 − RSQ deciles, even though not strictly monotonically. For example, the 10-day, 1-month, and 3-month average returns are 0.21%, 0.22%, and 0.22%, respectively, for firms with the lowest 1 − RSQ rankings, and 1.15%, 1.36%, and

2.28%, respectively, for firms with the highest 1 − RSQ rankings. By focusing only on firms with the highest 1 − RSQ rankings instead of all downgraded firms, one can improve the average return to and the Sharpe ratio of the investment strategy.

I replace the relative idiosyncratic return volatility, 1 − RSQ, with the absolute idiosyncratic return volatility, RMSE, repeat the analyses, and find similar results. Panel C of Table 8 shows that if one focuses only on firms in the largest RMSE decile instead of all upgraded firms, one can improve the average 1-month return from 1.43% to 2.25%, and the Sharpe (1966) ratio from 0.11 to 0.14. Panel D shows that if one focuses only on firms in the largest RMSE decile instead of all downgraded firms, one can improve the average 3-month return from 0.52% to 1.47%, and the Sharpe ratio from 0.04 to 0.08.

To summarize, the results in Table 8 show that investors may potentially use the findings in this paper to improve their investment performance. Specifically, by focusing on firms with high idiosyncratic return volatilities instead of all upgraded or downgraded firms, investors may potentially improve the average returns to and the Sharpe (1966) ratios of their investments.

IV. 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 IBES, 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. Finally, I find that other stocks in the same industry as the recommended stock also respond to the recommendation, 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. 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.

Appendix. Definition of Variables in Empirical Tests

I define the variables used in the empirical part of the paper here to facilitate reading the tables.

$\mathrm{CR}_{n,(-1,1)}$: 3-day cumulative return on the recommended stock n from day -1 to day 1, where day 0 is the recommendation date; $\mathrm{CR}_{n,(2,23)}$ and $\mathrm{CR}_{n,(2,67)}$ are defined similarly.

$\hat{\beta}_n^M$: market beta of the recommended stock n.

$\hat{\beta}_n^I$: industry beta of the recommended stock n.

$\hat{\beta}_n^{IM}$: market beta of the recommended stock n's industry.

$R_{(-1,1)}^M$: 3-day cumulative return on the CRSP value-weighted market index; $R_{(2,23)}^M$ and $R_{(2,67)}^M$ are defined similarly.

$R_{(-1,1)}^I$: 3-day cumulative return on the value-weighted industry index (excluding the recommended stock n); $R_{(2,23)}^I$ and $R_{(2,67)}^I$ are defined similarly.

$\mathrm{CR}_{n,(-1,1)}^M$: market component of $\mathrm{CR}_{n,(-1,1)}$, equal to $\hat{\beta}_n^M \times R_{(-1,1)}^M$; $\mathrm{CR}_{n,(2,23)}^M$ and $\mathrm{CR}_{n,(2,67)}^M$ are defined similarly.

$\mathrm{CR}_{n,(-1,1)}^I$: industry component of $\mathrm{CR}_{n,(-1,1)}$, equal to $\hat{\beta}_n^I \times (R_{(-1,1)}^I - \hat{\beta}_n^{IM} \times R_{(-1,1)}^M)$; $\mathrm{CR}_{n,(2,23)}^I$ and $\mathrm{CR}_{n,(2,67)}^I$ are defined similarly.

$\mathrm{CR}_{n,(-1,1)}^F$: firm-specific component of $\mathrm{CR}_{n,(-1,1)}$, equal to $\mathrm{CR}_{n,(-1,1)} - \mathrm{CR}_{n,(-1,1)}^M - \mathrm{CR}_{n,(-1,1)}^I$; $\mathrm{CR}_{n,(2,23)}^F$ and $\mathrm{CR}_{n,(2,67)}^F$ are defined similarly.

RMSE: root mean square error from the regression of the firm's daily stock return on market and industry returns (i.e., the firm's absolute idiosyncratic return volatility).

$1 - \mathrm{RSQ}$: 1 minus the adjusted R^2 from the regression of the firm's daily stock return on market and industry returns (i.e., the firm's relative idiosyncratic return volatility).

$\mathrm{AR}_{n,(-1,1)}^I$: 3-day abnormal industry return, defined as $\mathrm{AR}_{n,(-1,1)}^I = R_{(-1,1)}^I - \hat{\beta}_n^{IM} \times R_{(-1,1)}^M$, where $R_{(-1,1)}^I$, $\hat{\beta}_n^{IM}$, and $R_{(-1,1)}^M$ are defined above; $\mathrm{AR}_{n,(2,23)}^I$ and $\mathrm{AR}_{n,(2,67)}^I$ are defined similarly.

$\hat{\beta}_j^I$: industry beta of stock j, which is in the same industry as the recommended stock n.

$\mathrm{AR}_{j,(-1,1)}^n$: 3-day abnormal cumulative return of stock j, which is in the same industry as the recommended stock n; defined as $\mathrm{AR}_{j,(-1,1)}^n = R_{j,(-1,1)} - \hat{\beta}_j^M \times R_{(-1,1)}^M$; $\mathrm{AR}_{j,(2,23)}^n$ and $\mathrm{AR}_{j,(2,67)}^n$ are defined similarly.

SIZE_n: market capitalization of the recommended stock n at the end of the previous calendar year.

SIZE_j: market capitalization of stock j, which is in the same industry as the recommended stock n.

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