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Security analysis and market making

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Abstract

In this paper we analyze the interrelatedness of security analysis and market-making activities. Our results indicate that there exists a bidirectional and positive relation between analyst following and the number of market makers. Using detailed data on analyst and dealer affiliations, we also find that dealers are more likely to make markets in stocks that are tracked by analysts who are affiliated with the same company. Similarly, analysts follow and issue earnings forecasts more proactively for stocks that are handled by affiliated market makers. We interpret these results as evidence that analysts and market makers work as a team to benefit the company. We discuss a possible conflict of interest between investors and brokerage firms that arises from this collaborative endeavor between analysts and dealers.

JEL classification: G14

Keywords: NASDAQ; Analyst following; Dealers; Market making; Earnings forecasts

1. Introduction

Financial analysts have recently been under fire from lawmakers and regulators. In June 2001, the House Financial Services subcommittee on capital markets held a hearing to examine whether analysts make unbiased stock recommendations to investors. Subsequently, the Securities and Exchange Commission issued an investor alert and warned investors

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to take the stock recommendations of financial analysts with caution.[1] In response, the National Association of Securities Dealers proposed rules that would require analysts to disclose potential conflicts of interest when they recommend stocks on television or in other public appearances.

Financial analysts and market makers alike play critical roles in the securities markets. Just like the old saying, behind every successful man is a good woman, behind every successful broker is a good team of analysts. Brokerage firms employ analysts to track stocks and analysts make buy and sell recommendations to their brokers. In turn, brokers pass on these recommendations to their clients who then decide whether to act upon them. Market makers are intermediaries between the buyers and sellers of securities. Market makers provide the immediacy of trading by standing ready to buy and sell a given number of shares at the posted bid and ask prices.

Given the vertical integration of brokerage and dealer operations, a natural question that arises is whether there is a conflict of interest between brokerage firms and investors. We address this question by investigating how security analysis and market-making activities are interrelated and interactively determined. Just as analysts can decide which stocks to track, dealers can decide in which stocks to make markets. Although prior studies examined how analyst following is related to stock characteristics, the interactive nature of analyst following and market-making activities received little attention.[2] Similarly, prior studies of market making (see, e.g., Wahal, 1997 and Weston, 2000) ignored the effect of analyst following on dealer behavior.

Financial analysts and market makers frequently work for the same company and thus their activities are closely intertwined. An analyst's ability to generate revenue and profit for the company is likely to be a significant factor in determining his compensation. Hence, analysts have an incentive to promote stocks that are handled by affiliated market makers, perhaps by providing more information (e.g., frequent earnings forecasts) and making buy or sell recommendations on these stocks. Our study is an attempt to illuminate the interrelatedness of analyst following and market-making activities. Our goal is to contribute to an improved understanding of the incentive structure in the securities industry and its ramifications for investor welfare.

Studies show that equity markets for small companies are characterized by a close relationship between issuers and the underwriters who do the initial public offering. Ellis et al. (2000, 2002) show that underwriters sponsor and support new issues by arranging analyst coverage and acting as the broker-dealer in the secondary markets. Aggarwal (2000) shows that underwriters support new issues through their active engagements in various price stabilization policies. Michaely and Womack (1999) show that buy recommendations issued by underwriter analysts are significantly more optimistic than those by non-underwriter analysts. Our paper complements the findings of these studies from a different perspective.

[1] In early 2002, the New York state attorney general alleged that Merrill Lynch & Co. routinely made stock touts driven largely by its desire to snare lucrative investment banking business. By mid-April, six other major brokerage firms have received subpoenas from the New York state attorney general for similar charges.

[2] See Bhushan (1989a, 1989b), Moyer et al. (1989), O'Brien and Bhushan (1990), Brennan and Hughes (1991), Chung and Jo (1996), and Chung (2000).

We analyze interactions between analyst following and market-making activities using data for a large sample of NASDAQ issues covering a period of 180 months. Our results indicate that analyst following and market-making activities are closely linked and interwoven. We find that a bidirectional and positive relation exists between the number of analysts and the number of dealers. We also find that dealers are more likely to make markets in stocks that are tracked by the analysts affiliated with the same company. Similarly, analysts issue earnings forecasts more proactively for stocks that are handled by affiliated market makers.

Our results underscore a possible conflict of interest between brokerage firms and investors that arises from the vertical integration of brokerage and dealer operations (e.g., internalization) in the sell-side brokerage industry. Although the conflict of interest between brokerage firms and investors created by the lack of independence between brokerage analysts and the investment-banking side of the brokerage business has been well recognized in the literature,[3] the brokerage firm-investor conflict created by the consolidation of brokerage and dealer operations has not received any commensurate attention. To the extent that sell-side analysts recommend stocks to help their brokerage-dealer operations, rather than to help investors, it is important that investors use analysts' recommendations with caution.[4]

The remainder of the paper is organized as follows. In Section 2, we present our conjecture and provide empirical evidence on the relation between analyst following and the number of market makers. Section 3 provides further evidence regarding the analyst-dealer interaction using detailed data on analyst and dealer affiliations. Section 4 examines whether analysts issue overly optimistic earnings forecasts for stocks that are handled by affiliated dealers. Section 5 discusses the result of sensitivity analyses. Section 6 interprets and discusses the major findings of the study. The paper ends with a brief summary and concluding remarks.

2. The relation between analyst following and market making

2.1. Security analysis and market making

Security analysts collect and process data on companies and disseminate valuable information to various market participants. Previous studies show that the information environment differs significantly between firms followed by many analysts and those followed by few. Brennan et al. (1993) show that stocks followed by many analysts react faster to common information than stocks followed by few analysts. Brennan and Subrahmanyam (1995) analyze the relation between the number of analysts following a security and the adverse selection cost of transacting in the security, after controlling for the effects of trading volume, price level, and return volatility. The authors show that market makers incur

[3] See Michaely and Womack (1999), Aggarwal (2000), and Ellis et al. (2000).

[4] Sell-side analysts provide external (buy-side) customers with information on and insight into particular stocks they follow. In contrast, buy-side analysts are employees of mutual funds, commercial banks, and insurance companies who recommend their companies which stocks they should buy.

smaller adverse selection costs from stocks that are followed by many security analysts than by few analysts.

Market makers are at an informational disadvantage when they trade with informed traders. Studies suggest that market makers recoup losses from trades with informed traders through gains from trades with liquidity traders.[5] Although market makers can recover their losses to informed traders by maintaining wide spreads, wide spreads can have detrimental effects on their market-making revenues because liquidity traders may walk away from dealers who maintain wide spreads. Hence, dealers have an incentive to make markets in stocks that are subject to smaller adverse selection costs. To the extent that the adverse selection costs of market making decrease with analyst following, the number of market makers in a given stock is likely to be positively related to the number of analysts following the stock.

Analyst following affects not only the quality of information but also the breadth of investor cognizance. Merton (1987) notes that the portfolios held by actual investors contain only a small subset of the thousands of traded securities and suggests that an investor uses a security in constructing his optimal portfolio only if he knows about the security. Because an important source of information about a particular company is the analysts covering the company, it follows that a stock covered by more analysts is likely to have a broader investor base. To the extent that market-making revenue is likely to be larger for stocks with a broader investor base, dealers have a greater incentive to choose stocks that are followed by more analysts. This constitutes another reason why more dealers are likely to make markets in stocks that are followed by more analysts.

Not only do dealers have a greater incentive to make markets in stocks that are followed by more analysts, security analysts themselves have an incentive to follow stocks with many market makers. The demand for analyst services is likely to be greater for stocks that are chosen by more dealers because both dealers and their customers (i.e., traders) would require more information on these stocks. The aggregate supply of analyst services for a given stock is also likely to be affected by the number of dealers for that stock. Analysts have an incentive to focus on stocks with more market makers because they are widely held and of interest to a greater number of investors. In addition, analysts frequently issue buy and sell recommendations to help generate volume for market makers affiliated with the same company. Hence, more analysts are likely to follow stocks with a greater number of maker makers.

The above discussions suggest a bidirectional and positive relation between the number of analysts following a security and the number of dealers making markets in that security. Larger analyst following leads to greater market-making activities because dealers find it more profitable to make markets in highly followed stocks. Greater market-making activities lead to larger analyst following because analysts find their forecasts more valuable for stocks with greater trading activity. These considerations lead to our first hypothesis:

Hypothesis 1. A positive bidirectional relation exists between the number of analysts following a stock and the number of dealers who make markets in the stock.

[5] See Copeland and Galai (1983) Glosten and Milgrom (1985), and Easley and O'Hara (1987).

2.2. Data sources and descriptive statistics

We obtain the number of market makers in each NASDAQ issue from the data provided by the Center for Research in Security Prices (CRSP) during our study period 1985–1999. The number of analysts following each stock is obtained from the Institutional Brokers Estimate System (IBES). The IBES database contains analysts' forecasts of corporate earnings from approximately 400 leading brokerage firms. We include a stock in the study sample only if it is included in both the CRSP file and the IBES database. For each stock in the study sample, we obtain the number of market makers and the number of analysts who made one-year-ahead earnings forecasts during each month of our study period. We also calculate the market value of equity of each company in the study sample by multiplying the number of shares outstanding by share price at the end of each month.

Table 1 shows descriptive statistics of the variables. Panel A shows the results for 1999 and panel B shows the results for the entire study period. There are, on average, five analysts making earnings forecasts and 18 dealers making markets in our study sample of stocks during 1999. There is wide variation in both analyst following and the number of market makers across stocks. The number of analysts following a stock ranges from one to 46, with a median value of 4.0. The number of market makers in a stock ranges from two to 86, with a median value of 15. The average market value of equity ($1317.6 million) is substantially greater than the median ($157 million), indicating a high degree of skewness in the distribution of the market value of equity. We obtain similar results from data for the entire study period.

Table 1
Descriptive statistics

	Mean	Std. dev.	Percentile						
			Minimum	5th	25th	Median	75th	95th	Maximum
A. Results from 1999 data									
No. of analysts	5.2	5.0	1.0	1.0	2.0	4.0	7.0	15.0	46.0
No. of market makers	17.8	11.2	2.0	6.0	10.0	15.0	22.0	40.0	86.0
Market value of equity (millions of dollars)	1317.6	13,314.0	1.5	18.1	62.1	157.0	481.3	3079.5	463,700.0
Trading volume (thousand shares)	6829.2	29,184.3	1.5	96.7	434.5	1305.8	4464.6	23,421.4	803,663.5
B. Results from 1985–1999 data									
No. of analysts	4.1	4.7	1.0	1.0	1.0	2.0	5.0	13.0	52.0
No. of market makers	12.5	8.3	2.0	3.0	7.0	11.0	16.0	28.0	86.0
Market value of equity (millions of dollars)	381.4	4718.4	0.1	5.6	24.7	68.4	212.3	1112.9	463,700.0
Trading volume (thousand shares)	2497.2	12,298.5	0.1	22.6	139.4	469.4	1507.2	8540.5	849,262.3

Note. The average numbers of companies (during each year) in our study sample are 953 (1985), 1162 (1986), 1318 (1987), 1332 (1988), 1305 (1989), 1260 (1990), 1193 (1991), 1189 (1992), 1194 (1993), 1217 (1994), 1269 (1995), 1281 (1996), 1186 (1997), 1870 (1998), and 1691 (1999).

Table 2
Cross-sectional association between analyst following and the number of market makers after controlling for firm size

Firm size deciles	Number of market makers deciles									
	1 (smallest)	2	3	4	5	6	7	8	9	10 (largest)
1 (smallest)	1.3	1.3	1.3	1.3	1.4	1.4	1.5	1.7	1.7	1.4
2	1.5	1.5	1.6	1.7	1.7	1.8	1.8	1.7	1.8	1.8
3	1.7	1.7	1.9	2.0	2.0	2.1	2.1	2.0	2.0	1.9
4	1.8	1.9	2.2	2.3	2.4	2.5	2.5	2.2	2.4	2.4
5	1.9	2.3	2.5	2.7	2.8	2.8	3.0	2.9	2.8	3.0
6	2.0	2.5	2.8	3.1	3.2	3.3	3.7	3.9	3.8	3.4
7	1.8	2.5	3.0	3.4	3.8	4.0	4.3	4.6	5.1	5.0
8	2.1	2.9	3.3	3.9	4.2	5.0	5.4	5.4	6.2	6.7
9	2.4	3.0	3.7	4.5	5.2	6.0	6.6	7.1	8.1	9.9
10 (largest)	3.0	3.4	4.4	5.8	6.8	7.7	8.2	9.9	11.3	17.9

Note. This table shows the number of analysts as a function of the number of market makers after controlling for firm size.

Table 2 shows cross-sectional relation between the number of analysts and the number of market makers. Because analyst following is strongly correlated with firm size,[6] we show the number of analysts as a function of the number of market makers after controlling for firm size. During each month of our study period, we rank stocks according to the market value of equity and cluster them into 10 portfolios. Stocks in each of these 10 portfolios are then further divided into 10 groups according to the number of market makers. We then calculate the average number of analysts within each of the 100 portfolios. Finally, we calculate the time-series mean of the average number of analysts for each portfolio across 180 months. The results indicate that the number of analysts generally increases with the number of market makers within each firm size portfolio.

2.3. Correlation between analyst following and market making after controlling for stock attributes

Although our results in the previous section indicate a positive correlation between analyst following and the number of market makers, we cannot rule out a possibility that the observed correlation between the two variables is driven by their respective correlation with unknown common factors. To examine this issue, we regress the number of market makers and the number of analysts on a common set of stock attributes that have been identified as determinants of analyst following and number of dealers in prior studies.[7]

[6] See, e.g., Bhushan (1989a, 1989b), Moyer et al. (1989), O'Brien and Bhushan (1990), Chung and Jo (1996), and Chung (2000).

[7] We include these control variables based on the findings of previous studies that: (1) the number of market makers in a given stock is significantly related to return volatility, spreads, and trading volume (see Wahal, 1997 and Weston, 2000); and (2) the number of analysts is significantly related to return volatility, the reciprocal of share price, trading volume, and firm size (see Bhushan, 1989a, 1989b; Moyer et al., 1989; O'Brien and Bhushan, 1990; Brennan and Hughes, 1991; Chung and Jo, 1996; Chung, 2000).

Specifically, we estimate the following regression models:

$$\begin{aligned} NMM_{it} &= \alpha_0 + \alpha_1 RISK_{it} + \alpha_2 SPREAD_{it} + \alpha_3 RPRICE_{it} + \alpha_4 \log(VOLUME_{it}) \\ &\quad + \alpha_5 \log(MVE_{it}) + \sum \alpha_k DYEAR_k + \varepsilon_{1it}, \qquad (1) \\ NAF_{it} &= \beta_0 + \beta_1 RISK_{it} + \beta_2 SPREAD_{it} + \beta_3 RPRICE_{it} + \beta_4 \log(VOLUME_{it}) \\ &\quad + \beta_5 \log(MVE_{it}) + \sum \beta_k DYEAR_k + \varepsilon_{2it}, \qquad (2) \end{aligned}$$

where NMM_{it} is the number of market makers in stock i during month t, NAF_{it} is the number of analysts following stock i during t, $RISK_{it}$ is the standard deviation of daily stock returns for stock i during t, $SPREAD_{it}$ is the average bid–ask spread of stock i during t, $VOLUME_{it}$ is the trading volume of stock i during t, $RPRICE_{it}$ is the reciprocal of stock i's average share price during t, MVE_{it} is stock i's market value of equity at the end of month t, and $DYEAR_k$ are dummy variables representing different years.

We estimate the above models using the panel data of monthly time-series and cross-sectional observations in the CRSP file. Because our study period spans a fairly long period (15 years), we include dummy variables representing different years in both equations. We allow different intercepts for different stocks (i.e., fixed effects) by estimating the above model from the data expressed in terms of deviations from group (stock) means. We take this approach instead of including a dummy variable for each stock because the number of stocks exceeds the maximum allowable number of independent variables in SAS. We calculate the coefficient of correlation between the residuals from the above two regression models to determine whether the positive relation between NMM and NAF observed in Table 2 is spurious.

We show the results in Table 3. Panel A shows that both the number of market makers and the number of analysts are strongly correlated with the stock attributes. More importantly, we find that the coefficient of correlation between the residuals from the two regression models is 0.25, which is statistically significant at the 1% level. Hence, we conclude that the positive correlation between the number of market makers and the number of analysts shown in Table 2 is not driven by their respective correlation with the common set of stock attributes.[8]

2.4. A structural model of analyst following and market making

To shed further light on the nature of the relation between the number of market makers and the number of analysts, we estimate the following structural model of market making and analyst following in which both NMM and NAF are treated as endogenous variables:

$$\begin{aligned} NMM_{it} &= \alpha_0 + \alpha_1 NAF_{it} + \alpha_2 RISK_{it} + \alpha_3 SPREAD_{it} + \alpha_4 \log(VOLUME_{it}) \\ &\quad + \alpha_5 \log(MVE_{it}) + \sum \alpha_k DYEAR_k + \varepsilon_{1it}, \qquad (3) \end{aligned}$$

[8] We note that one can never eliminate the possibility that this correlation could still be driven by common correlations with some other variables. The fixed-effects regression controls for this problem to the extent that the omitted variables stay constant through time for each firm.

Table 3
The coefficient of correlation between the residuals from OLS regressions

A. Regression results

$$NMM_{it} = \underset{(-18.75)}{-0.429} + \underset{(79.72)}{1.450}\, RISK_{it}^{***} - \underset{(-15.71)}{3.719}\, SPREAD_{it}^{***} + \underset{(27.25)}{0.691}\, RPRICE_{it}^{***}$$
$$+ \underset{(79.29)}{0.928}\, \log(VOLUME_{it})^{***} + \underset{(33.02)}{0.720}\, \log(MVE_{it})^{***} + \sum \alpha_k DYEAR_k,$$

Adjusted $R^2 = 0.22$

$$NAF_{it} = \underset{(-34.97)}{-0.424} - \underset{(-7.22)}{0.070}\, RISK_{it}^{***} + \underset{(23.83)}{2.990}\, SPREAD_{it}^{***} + \underset{(12.02)}{0.162}\, RPRICE_{it}^{***}$$
$$+ \underset{(21.43)}{0.133}\, \log(VOLUME_{it})^{***} + \underset{(89.45)}{1.034}\, \log(MVE_{it})^{***} + \sum \alpha_k DYEAR_k,$$

Adjusted $R^2 = 0.14$

B. The coefficient of correlation between the residuals from the two regression models

	Residuals from regression model (1)
Residuals from regression model (2)	0.25***

Note. Panel A shows the ordinary least squares (OLS) estimates of the regression models (1) and (2). Numbers in parenthesis are t-statistics. Panel B shows the coefficient of correlation between the residuals from the above two regression models.

*** Significant at the 1% level.

$$NAF_{it} = \beta_0 + \beta_1 NMM_{it} + \beta_2 RISK_{it} + \beta_3 RPRICE_{it} + \beta_4 \log(VOLUME_{it}) + \beta_5 \log(MVE_{it}) + \sum \beta_k DYEAR_k + \varepsilon_{2it}. \tag{4}$$

Our model specification is based on the finding of prior studies that the number of market makers is significantly related to return volatility, spreads, and trading volume (see Wahal, 1997 and Weston, 2000) and the number of analysts is significantly related to return volatility, the reciprocal of share price, trading volume, and firm size (see Bhushan, 1989a, 1989b; Moyer et al., 1989; O'Brien and Bhushan, 1990; Brennan and Hughes, 1991; Chung and Jo, 1996; Chung, 2000).

To the extent that dealers have a greater incentive to make markets in stocks with larger spreads, the number of dealers is likely to be spuriously correlated with share price because the spread and share price are highly correlated. However, there is no reason that share price exerts a *direct* impact on dealer behavior.[9] Consequently, we exclude $RPRICE_{it}$ from the market maker equation. Likewise, although the spread is likely to have an indirect effect on analyst following through its impact on the number of dealers, there is no apparent reason to believe that the spread exerts a *direct* impact on the number of analysts. Hence, we exclude $SPREAD_{it}$ from the analyst following equation.

We estimate the above structural model using the panel data of monthly time-series and cross-sectional observations. We allow different intercepts for different stocks by estimating the above model from the data expressed in terms of deviations from group (stock) means. We estimate the model using both the two-stage (2SLS) and three-stage least

[9] Again, we cannot rule out the possibility that the number of dealers and share price are related to each other for some unknown reasons.

Table 4
A structural model of analyst following and market making

$$NMM_{it} = \underset{(-4.38)}{-0.823} + \underset{(54.67)}{23.228}\, NAF_{it}^{***} - \underset{(-4.31)}{14.343}\, RISK_{it}^{***} + \underset{(54.93)}{168.303}\, SPREAD_{it}^{***} + \underset{(55.85)}{4.974}\, \log(VOLUME_{it})^{***} + \underset{(18.35)}{3.493}\, \log(MVE_{it})^{***} + \sum \alpha_k DYEAR_k$$

$$NAF_{it} = \underset{(-2.10)}{-0.055} + \underset{(74.87)}{0.964}\, NMM_{it}^{***} + \underset{(40.20)}{18.164}\, RISK_{it}^{***} + \underset{(39.51)}{0.967}\, RPRICE_{it}^{***} - \underset{(-13.51)}{0.155}\, \log(VOLUME_{it})^{***} + \underset{(104.57)}{1.780}\, \log(MVE_{it})^{***} + \sum \alpha_k DYEAR_k$$

System weighted $R^2 = 0.30$

Note. This table shows the results of the structural model of market making and analyst following Eqs. (3)–(4). Numbers in parenthesis are t-statistics.

*** Significant at the 1% level.

squares (3SLS) regressions and obtain qualitatively identical results. Hence, for brevity, we report only the results of the 3SLS regression.[10]

We show the results in Table 4. The results show that the estimated coefficient for the number of analysts in the market-maker equation is positive and significant. Similarly, the estimated coefficient for the number of market makers in the analyst-following equation is also positive and significant. These results indicate that there is a positive bidirectional relation between market making and analyst following, as stipulated in this study.

The number of market makers is negatively and significantly related to return volatility and positively to trading volume and firm size, indicating that dealers have greater (smaller) incentives to make markets in high-volume (high-risk) stocks. The positive relation between the number of market makers and the spread is consistent with the notion that more dealers are likely to make markets in stocks with wider spreads since, all else being equal, wider spreads imply greater market-making profits.[11] Consistent with the finding of prior research, we find that analyst following is positively related to firm size and return volatility and negatively to share price.

To assess the robustness of our results with respect to different variable measurements, we estimate the structural model using the number of analysts making long-term earnings forecasts. Although the overall explanatory power (system weighted $R^2 = 0.13$) of the model decreases with this alternative measure of analyst following, the main results are qualitatively similar to those reported in Table 4.[12]

[10] To assess the sensitivity of our results to different estimation methods, we also estimate the structural model using the cross-sectional data for each month and calculate the mean regression coefficients and the z-statistic. We obtain the z-statistic by adding the individual regression t-statistics across time and dividing the sum by the square root of the number of regression coefficients. (See Dodd and Warner, 1983; Warner et al., 1988; Meulbroek, 1992.) The results from this approach are qualitatively identical to those reported here.

[11] Earlier, we showed in Table 3 that NMM is negatively related to SPREAD. This may be explained by the fact that (1) the OLS regression fails to capture the endogeneity of NMM and NAF and (2) the results in Table 3 are based on a model specification that is different from the one used in Table 4.

[12] The results are available from the authors upon request.

2.5. Difference in analyst following between NASDAQ and NYSE stocks

This section presents an alternative test of our hypothesis using a sample of NASDAQ and NYSE stocks. Instead of comparing analyst following across NASDAQ stocks that differ in the number of dealers, we compare analyst following between NASDAQ and NYSE stocks after controlling for the effects of stock attributes. Because the NYSE is artificially constrained to have a single market maker (i.e., the specialist) while there are at least two dealers in any NASDAQ issue, testing the difference in the number of analysts between NASDAQ and NYSE stocks provides a natural controlled experiment on the effect of market making on analyst following.

To determine whether the number of analysts for NASDAQ stocks is greater than the corresponding figure for NYSE stocks, we estimate the following regression model for each year using the pooled sample of NASDAQ and NYSE stocks:

$$\begin{aligned} NAF_{it} = {} & \gamma_0 + \gamma_1 RISK_{it} + \gamma_2 RPRICE_{it} + \gamma_3 \log(VOLUME_{it}) + \gamma_4 \log(MVE_{it}) \\ & + \gamma_5 NASDAQ_{it} + \upsilon_{it}, \end{aligned} \tag{5}$$

where NAF_{it} is the number of analysts, $RISK_{it}$ is the standard deviation of daily returns, $RPRICE_{it}$ is the reciprocal of share price, $VOLUME_{it}$ is the trading volume, and MVE_{it} is the market value of equity for stock i. $NASDAQ_{it}$ is a dummy variable which equals one for NASDAQ stocks and zero for NYSE stocks. We multiply the share volume of NYSE stocks by two to make it comparable to the reported share volume of NASDAQ stocks.[13]

The regression results (see Table 5) show that the estimated coefficient for the NASDAQ dummy variable is positive and statistically significant in all years. This indicates that, all else being equal, NASDAQ stocks are more likely to be followed by financial analysts than are NYSE stocks. Overall, our results suggest that analyst following is determined, at least in part, by market-making considerations.

3. Analyst and dealer affiliations and the interdependence of their activities

In this section, we provide additional evidence on the relation between analyst following and market-making activities using data on analyst and dealer affiliations. While our analysis in the previous section relied solely on information regarding how many dealers and analysts cover each stock over time, this section utilizes data on dealer and analyst affiliations and examines how their affiliations affect stock selection, trading volume, and the frequency and accuracy of earnings forecasts.

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[13] To ensure that our study sample of NASDAQ and NYSE stocks are reasonably homogeneous, we include in the study sample only those NYSE stocks that are similar in market capitalization to one of our NASDAQ stocks.

Table 5
Difference in analyst following between NASDAQ and NYSE stocks (Eq. (5))

Year	γ_0	γ_1	γ_2	γ_3	γ_4	γ_5	Adjusted R^2
1985	−56.281***	9.917**	0.985***	1.467***	3.518***	0.295***	0.47
	(−93.19)	(2.36)	(5.74)	(40.51)	(60.55)	(4.17)	
1986	−58.412***	−20.210***	1.754***	1.925***	3.165***	0.274***	0.44
	(−88.37)	(−4.91)	(7.17)	(48.38)	(52.94)	(3.47)	
1987	−63.650***	−14.267***	2.229***	1.956***	3.448***	0.808***	0.47
	(−84.63)	(−5.05)	(6.51)	(47.26)	(50.63)	(9.29)	
1988	−64.674***	−31.548***	1.198***	1.986***	3.554***	1.336***	0.48
	(−75.94)	(−6.70)	(4.21)	(43.82)	(45.29)	(13.91)	
1989	−68.067***	−63.666***	1.722***	2.135***	3.658***	1.537***	0.48
	(−69.68)	(−10.58)	(3.98)	(42.21)	(41.61)	(14.26)	
1990	−68.908***	−18.528***	0.863***	1.972***	3.892***	0.793***	0.54
	(−73.18)	(−3.42)	(3.07)	(37.42)	(44.02)	(7.20)	
1991	−70.316***	−19.157***	2.305***	1.727***	4.178***	0.258**	0.57
	(−85.27)	(−3.75)	(5.40)	(34.54)	(54.30)	(2.55)	
1992	−73.080***	−54.669***	4.543***	1.791***	4.279***	0.339***	0.56
	(−83.76)	(−9.91)	(7.22)	(33.29)	(52.39)	(3.17)	
1993	−72.850***	−78.150***	3.538***	1.863***	4.158***	0.907***	0.53
	(−79.29)	(−12.84)	(4.92)	(32.43)	(47.94)	(7.99)	
1994	−67.779***	−70.458***	2.906***	1.707***	3.946***	0.636***	0.53
	(−88.45)	(−13.32)	(3.68)	(34.49)	(53.26)	(6.65)	
1995	−66.441***	−92.665***	6.904***	1.734***	3.751***	0.519***	0.52
	(−86.77)	(−19.34)	(6.11)	(33.42)	(50.29)	(5.27)	
1996	−67.297***	−105.116***	11.183***	1.889***	3.556***	0.893***	0.53
	(−89.44)	(−26.26)	(7.83)	(38.32)	(49.34)	(9.23)	
1997	−66.625***	−70.321***	10.336***	1.949***	3.345***	1.095***	0.54
	(−88.37)	(−17.88)	(6.51)	(41.43)	(47.07)	(11.92)	
1998	−63.181***	−13.264***	9.650***	1.969***	2.947***	0.976***	0.54
	(−83.84)	(−3.85)	(5.72)	(39.48)	(40.45)	(10.32)	
1999	−59.701***	−47.342***	18.253***	1.893***	2.831***	1.143***	0.56
	(−91.36)	(−15.20)	(10.31)	(33.97)	(40.52)	(11.82)	

** Significant at the 5% level.
*** Idem., 1%.

Internalization or "self preferencing" is the vertical integration of brokerage and market-making operations within a single entity.[14] Frequently a brokerage firm has enough order flow to profitably take a position against it instead of routing its orders to a market maker. In this case, the brokerage branch of the firm routes its order flow to the market-making branch (i.e., affiliated dealers) of the same firm. In what follows, we develop testable impli-

[14] Studies show that the bid–ask spreads of NASDAQ stocks are larger than those of comparable NYSE-listed stocks (see Huang and Stoll, 1996; Bessembinder and Kaufman, 1997a, 1997b; Bessembinder, 1999). The large NASDAQ spreads are believed to be a result of the high degree of "preferencing" on NASDAQ (see Godek, 1996; Huang and Stoll, 1996; Chung et al., 2001). Brokers and market makers on NASDAQ are allowed to direct or preference an order to any market maker who has agreed to execute orders at the best quoted price, regardless of the price quoted by the market maker to whom the order is directed.

cations regarding the relation between analyst following and market-making activities by considering incentive structures in the brokerage and market-making industries that arise from the vertical integration.

3.1. Statement of hypotheses

We hold that dealers have a stronger incentive to make markets in stocks that are covered by affiliated analysts than stocks that are not covered by these analysts. To the extent that dealers and analysts who are affiliated with the same company interact and share information, dealers are likely to be more comfortable making markets in stocks that are covered by affiliated analysts than those that are not covered. Dealers are likely to incur smaller adverse selection costs from these stocks because they can obtain more information regarding these stocks from affiliated analysts.[15] In addition, stocks covered by affiliated analysts are likely to have greater volumes than those not covered due to promotional activities performed by these analysts.[16] Hence, dealers may find it more profitable to make markets in stocks followed by affiliated analysts.

Similarly, analysts have an incentive to follow stocks that are handled by their affiliated market makers. Effective marketing of a stock by a brokerage firm requires that at least one of the firm's analysts must follow the stock. Chung and Jo (1996) and Chung (2000) hold that analyst following can be best understood by viewing analysts as working together with brokers as part of a brokerage firm's marketing team. In a similar vein, we conjecture that analysts help increase the market-making revenues of affiliated dealers by promoting stocks chosen by their affiliated dealers. Analysts have an incentive to promote these stocks because an analyst's ability to generate revenue and profit for the company is likely to be a significant factor in determining his own compensation. These considerations lead to the following hypotheses:

Hypothesis 2a. Dealers are more likely to make markets in stocks that are followed by affiliated analysts than those that are not followed.

Hypothesis 2b. Analysts are more likely to follow stocks that are handled by affiliated dealers than those that are not handled.

We conjecture that, for a given stock, the trading volume of a market maker who has an affiliated analyst following the stock is larger than the average volume of other market makers without such an affiliated analyst. For example, suppose that stock i is followed by six analysts (whose affiliations are A, B, C, D, E, and F) and five dealers (whose affiliations are B, L, M, N, and O, respectively) are making markets in the stock. Note that there is

15 In a similar spirit, Schultz (2000) holds that dealers may make markets in stocks where they have an informational advantage. In support of his conjecture, Schultz shows that dealers tend to concentrate their market making in stocks that belong to particular industries and as well as in stocks they underwrote.

16 Schultz (2000) holds that dealers tend to make markets in stocks with large expected order flow. In support of his conjecture, Schultz finds evidence that dealers are more likely to make markets in stocks that their brokerage customers want to trade, stocks of local companies, and stocks they underwrote.

only one matching analyst-dealer with an identical affiliation (B). We hold that stock i's volume accounted for by the dealer who is affiliated with B will be greater than the average volume of other dealers who also make markets in stock i.

Similarly, we hold that analysts are more proactive in marketing stocks that are handled by affiliated dealers by issuing more frequent earnings forecasts for those stocks. Because more frequent updates of earnings forecasts will tend to generate greater investor interests and thus larger trading volumes, analysts help their affiliated dealers to generate more market-making revenues. These considerations lead to the following hypotheses:

Hypothesis 3a. For a given stock, the trading volume of a dealer who has an affiliated analyst following the stock is larger than the trading volume of other dealers without such an analyst.

Hypothesis 3b. For a given stock, the frequency of earnings forecasts by an analyst who has an affiliated dealer in the stock is greater than the frequency of earnings forecasts by other analysts who do not have such an affiliated dealer.

3.2. Data sources

We obtain each dealer's affiliation and monthly trading volume from the data provided by NASDAQ. We obtain the affiliation of each analyst from the data (detail history tapes) provided by the IBES. Because the NASDAQ data contain dealer-by-dealer trading volumes for each stock from January 1996, and because our holding of the IBES detail history tapes is limited to the pre-1998 period, we perform our analysis using data from January 1996 through December 1997. Note that our Hypotheses 2 and 3 mainly concern inter-dealer and inter-analyst differences in stock selection, trading volume, and the frequency of earnings forecasts. To the extent that dealer and analyst behavior on these dimensions is reasonably stable over time, our selection of the two-year study period is not likely to pose a significant problem in research design.

For each dealer firm, we examine whether there is at least one analyst whose affiliation is identical to the dealer firm in question. By repeating this process for every dealer in our database, we identify all the dealers and analysts whose affiliations are identical. Among 544 dealers included in the NASDAQ data, we find that 143 dealers employ at least one analyst included in the IBES database at the end of 1997. This indicates that, on average, one out of every four dealers in our sample has an affiliated analyst whose earnings forecasts were included in the IBES database.

3.3. Empirical results: Hypothesis 2a

To examine whether dealers are more likely to make markets in stocks that are followed by affiliated analysts, we cluster our study sample of stocks into 10 portfolios according to the number of analysts so that stocks in each portfolio have the similar number of an-

Table 6
Testing whether dealers are more likely to make markets in stocks that are followed by affiliate analysts than those not followed (Eq. (6))

Analyst deciles	$(1/K)\sum_k FDD(k)$	$(1/K)\sum_k FDN(k)$	$(1/K)\sum_k FDD(k) - (1/K)\sum_k FDN(k)$	t-value
1	0.7262	0.0342	0.6920***	50.90
2	0.7076	0.0347	0.6729***	55.15
3	0.7210	0.0414	0.6796***	60.44
4	0.6960	0.0526	0.6434***	61.76
5	0.6652	0.0592	0.6060***	57.27
6	0.6047	0.0793	0.5254***	52.58
7	0.5624	0.1189	0.4435***	38.51
8	0.5532	0.1727	0.3805***	36.80
9	0.5639	0.2534	0.3105***	30.51
10	0.5229	0.3356	0.1873***	30.75

*** Significant at 1% level.

alysts.[17] Within each portfolio, we then identify stocks that are followed by each analyst who has an affiliated dealer. Similarly, we identify stocks that are not followed by each analyst who has an affiliated dealer. We then calculate the proportion (*FDD*) of the first group of stocks that are handled by the affiliated dealer and the proportion (*FDN*) of the second group of stocks that are handled by the affiliated dealer. For example, suppose analyst k follows 10 of the 200 stocks in portfolio 1 during a given month. Suppose also that the dealer who is affiliated with analyst k makes a market in six of the 10 stocks and seven of the remaining 190 (i.e., $200 - 10$) stocks. Then we have $FDD = 6/10$ and $FDN = 7/190$. According to Hypothesis 2a, we expect

$$\frac{1}{K}\sum_k FDD(k) - \frac{1}{K}\sum_k FDN(k) > 0, \tag{6}$$

where $FDD(k)$ and $FDN(k)$, respectively, are the values of FDD and FDN for analyst k, $\sum_k$ is the summation over k, and K is the number of analysts with an affiliated dealer.

Table 6 shows the mean values of $(1/K)\sum_k FDD(k)$ and $(1/K)\sum_k FDN(k)$ during our 24-month study period. The table shows whether the mean value of $(1/K)\sum_k FDD(k)$ is significantly greater than the mean value of $(1/K)\sum_k FDN(k)$ within each portfolio. On average, a typical dealer makes markets in 50 to 70 percent of those stocks that are followed by the affiliated analyst. In contrast, for those stocks that are not followed by the analyst, the corresponding figure is less than 10 percent. Overall, these results support our conjecture that dealers are more likely to make markets in stocks that are followed by affiliated analysts.

[17] It is possible that dealers and analysts are drawn to the same stocks, regardless of affiliation. Hence, we examine whether the dealer is more likely to make a market in the stock followed by his affiliated analyst amongst stocks with the similar number of analysts.

3.4. Empirical results: Hypothesis 2b

To examine whether analysts are more likely to follow stocks that are handled by their affiliated dealers, we cluster our study sample of stocks into 10 portfolios according to the number of dealers so that stocks in each portfolio have the similar number of dealers.[18] Within each portfolio, we identify stocks that are handled by each dealer who has an affiliated analyst. Similarly, we identify stocks that are not handled by each dealer who has an affiliated analyst. We then calculate the proportion (*FAD*) of the first group of stocks that are followed by the affiliated analyst and the proportion (*FAN*) of the second group of stocks that are followed by the affiliated analyst. For example, suppose that dealer j makes a market in 50 of the 200 stocks in portfolio 1 during a given month. Suppose also that the analyst who is affiliated with dealer j follows eight of the 50 stocks and 15 of the remaining 150 (i.e., $200 - 50$) stocks. Then we have $FAD = 8/50$ and $FAN = 15/150$. According to Hypothesis 2b, we expect

$$\frac{1}{J}\sum_{j} FAD(j) - \frac{1}{J}\sum_{j} FAN(j) > 0, \tag{7}$$

where $FAD(j)$ and $FAN(j)$, respectively, are the values of *FAD* and *FAN* for dealer j, $\sum_j$ is the summation over j, and J is the number of dealers who have an affiliated analyst.

We show the results in Table 7. The table shows whether the mean value of $(1/J)\sum_j FAD(j)$ is significantly greater than the mean value of $(1/J)\sum_j FAN(j)$ within each portfolio. On average, a typical analyst follows nearly five to seven percent of stocks that are handled by the affiliated dealer. In contrast, for those stocks that are not handled by the affiliated dealer, the corresponding figure is less than one percent. Overall, these results

Table 7
Testing whether analysts are more likely to follow stocks that are handled by affiliated dealers (Eq. (7))

Dealer deciles	$(1/J)\sum_j FAD(j)$	$(1/J)\sum_j FAN(j)$	$(1/J)\sum_j FAD(j) - (1/J)\sum_j FAN(j)$	t-value
1	0.0703	0.0003	0.0700***	9.25
2	0.0595	0.0001	0.0594***	9.10
3	0.0737	0.0003	0.0734***	10.39
4	0.0625	0.0003	0.0622***	11.90
5	0.0550	0.0002	0.0548***	8.55
6	0.0524	0.0002	0.0522***	10.04
7	0.0410	0.0002	0.0408***	8.27
8	0.0379	0.0001	0.0378***	8.16
9	0.0403	0.0002	0.0401***	8.88
10	0.0168	0.0001	0.0167***	5.53

*** Significant at 1% level.

[18] Again, because it is possible that dealers and analysts are drawn to the same stocks regardless of affiliation, we examine whether the analyst is more likely to follow the stock handled by his affiliated dealer amongst stocks with the similar number of dealers.

support our conjecture that financial analysts are more likely to follow stocks that are dealt by affiliated market makers.

3.5. Empirical results: Hypothesis 3a

To examine whether dealers trade more actively for stocks that are followed by affiliated analysts than those that are not followed, we identify all the stocks that are handled by each dealer who has at least one affiliated analyst. We cluster these stocks into 10 portfolios according to monthly trading volume. Stocks in each of these 10 portfolios are then further divided into 10 portfolios according to the number of analysts. We then classify stocks within each cell (i.e., volume-analyst deciles) into two groups: the first group consists of stocks that are followed by an analyst who is affiliated with the dealer and the second group consists of stocks that are not followed by such an analyst. Note that stocks within each cell have the similar number of analysts and trading volume. This allows us to examine whether the dealer's market share in a stock is larger when the stock is followed by an affiliated analyst amongst stocks with the similar number of analysts and trading volume.

According to Hypothesis 3a, we expect that the dealer's market share in the first group of stocks is greater than his market share in the second group of stocks, i.e.,

$$\frac{1}{J}\sum_{j}\left\{\frac{1}{K}\sum_{k}V(j,k)\right\}-\frac{1}{J}\sum_{j}\left\{\frac{1}{H}\sum_{h}V(j,h)\right\}>0, \tag{8}$$

where $V(j,k)$ is dealer j's market share in stock k when stock k is followed by an analyst who is affiliated with dealer j, $V(j,h)$ is dealer j's market share in stock h when stock h is not followed by an analyst who is affiliated with dealer j, K is the number of stocks that are covered by both dealer j and his affiliated analyst, H is the number of stocks that are covered by dealer j but not by his affiliated analyst, J is the number of dealers with at least one affiliated analyst, $\sum_j$ denotes the summation over j, $\sum_k$ denotes the summation over stocks that are followed by an affiliated analyst of dealer j, and $\sum_h$ denotes the summation over stocks that are not followed by an affiliated analyst of dealer j.

Table 8 shows whether the mean value of $A = (1/J)\sum_j\{(1/K)\sum_k V(j,k)\}$ is greater than the mean value of $B = (1/J)\sum_j\{(1/H)\sum_h V(j,h)\}$ during the 24-month study period. The majority (86 of 100 cells) of the observed differences $(A - B)$ are positive and statistically significant at the 5% level. This indicates that the average volume accounted for by dealers who have an affiliated analyst following the stock is significantly greater than the corresponding figure by dealers without such an affiliated analyst. These results are in line with our expectation that market makers have a greater incentive to trade stocks that are followed by affiliated analysts than those that are not.[19]

3.6. Empirical results: Hypothesis 3b

To examine whether analysts issue earnings forecasts more actively for stocks that are handled by affiliated dealers, we identify all the stocks that are followed by each

[19] In the same spirit, Irvine (2001) shows that brokerage volume is significantly higher in stocks that are covered by affiliated analysts than those not covered for a sample of Canadian stocks.

Table 8
Testing whether dealers trade more actively for stocks that are followed by affiliated analysts than those not followed (Eq. (8))

Trading volume deciles		Number of analysts deciles: 1 (smallest)	2	3	4	5	6	7	8	9	10 (largest)
1 (smallest)	*A*	0.2707	0.2948	0.2279	0.2481	0.2425	0.2056	0.1799	0.2293	NA	0.0850
	B	0.1886	0.1486	0.1067	0.1558	0.1004	0.0648	0.1108	0.0646	NA	0.0335
	A − *B*	0.0821***	0.1462***	0.1212***	0.0923***	0.1422***	0.1408***	0.0691	0.1647	NA	0.0515**
	(*t*-value)	(4.78)	(7.95)	(5.90)	(4.99)	(4.93)	(4.30)	(1.96)	(1.89)	NA	(2.45)
2	*A*	0.2931	0.2697	0.2782	0.2187	0.2500	0.1882	0.1725	0.1306	0.1123	0.0780
	B	0.2082	0.1785	0.1753	0.1322	0.0968	0.1105	0.0824	0.0400	0.0855	0.0387
	A − *B*	0.0849***	0.0912***	0.1029***	0.0866***	0.1531***	0.0777***	0.0902***	0.0906***	0.0268	0.0393
	(*t*-value)	(5.24)***	(5.77)	(5.80)	(6.01)	(7.15)	(3.62)	(3.23)***	(3.12)	(0.91)	(1.66)
3	*A*	0.2182	0.2226	0.1939	0.1717	0.1763	0.1489	0.1350	0.1524	0.1280	0.0969
	B	0.1514	0.1622	0.1378	0.1123	0.1110	0.0925	0.0750	0.0606	0.0357	0.0461
	A − *B*	0.0668***	0.0604***	0.0561***	0.0594***	0.0654***	0.0565***	0.0599***	0.0917***	0.0923***	0.0509
	(*t*-value)	(5.21)	(4.04)	(4.24)	(5.43)	(4.96)	(3.97)	(4.06)	(3.64)	(3.42)	(1.17)
4	*A*	0.2105	0.2105	0.1869	0.1371	0.1651	0.1400	0.1319	0.1316	0.0992	0.0923
	B	0.1752	0.1343	0.1284	0.0949	0.0905	0.0778	0.0830	0.0641	0.0386	0.0148
	A − *B*	0.0352**	0.0762***	0.0584***	0.0422***	0.0746***	0.0622***	0.0490***	0.0675***	0.0606***	0.0775***
	(*t*-value)	(2.02)	(6.32)	(4.95)	(4.40)	(6.77)	(5.48)	(2.83)	(5.42)	(3.62)	(3.93)
5	*A*	0.1773	0.1724	0.1737	0.1201	0.1384	0.1197	0.1005	0.1131	0.1224	0.0869
	B	0.1247	0.1295	0.1038	0.0819	0.0940	0.0613	0.0541	0.0462	0.0470	0.0092
	A − *B*	0.0526***	0.0430***	0.0699***	0.0382***	0.0444***	0.0584***	0.0464***	0.0669***	0.0754***	0.0777***
	(*t*-value)	(3.23)	(3.05)	(5.71)	(4.05)	(4.08)	(6.53)	(5.77)	(7.60)	(3.21)	(4.05)
6	*A*	0.1526	0.1336	0.1252	0.1150	0.1104	0.1065	0.0985	0.1053	0.0906	0.0744
	B	0.1169	0.0993	0.0896	0.0832	0.0704	0.0743	0.0604	0.0604	0.0369	0.0326
	A − *B*	0.0357	0.0343**	0.0356***	0.0318***	0.0399***	0.0323***	0.0381***	0.0449***	0.0537***	0.0418***
	(*t*-value)	(1.81)	(2.64)	(3.15)	(3.36)	(4.62)	(3.89)	(4.71)	(4.76)	(5.20)	(3.03)
7	*A*	0.1866	0.1013	0.1147	0.0826	0.1106	0.0889	0.0852	0.0771	0.0596	0.0691
	B	0.0706	0.0764	0.0858	0.0692	0.0693	0.0568	0.0515	0.0527	0.0406	0.0314
	A − *B*	0.1161***	0.0249**	0.0289**	0.0134	0.0412***	0.0322***	0.0337***	0.0244***	0.0189***	0.0377***
	(*t*-value)	(3.12)	(2.00)	(2.35)	(1.48)	(4.70)	(5.26)	(5.38)	(3.47)	(3.38)	(3.26)

(*continued on next page*)

Table 8 (*Continued*)

Trading volume deciles		Number of analysts deciles									
		1 (smallest)	2	3	4	5	6	7	8	9	10 (largest)
8	*A*	0.1216	0.1101	0.0955	0.0524	0.0880	0.0755	0.0738	0.0592	0.0474	0.0392
	B	0.1353	0.1054	0.0742	0.0622	0.0562	0.0537	0.0475	0.0413	0.0314	0.0282
	$A - B$	−0.0138	0.0048	0.0213**	−0.0097	0.0318***	0.0218***	0.0263***	0.0179***	0.0160***	0.0111***
	(t-value)	(−0.35)	(0.18)	(2.08)	(−0.81)	(4.09)	(3.70)	(4.74)	(4.81)	(5.47)	(2.85)
9	*A*	NA	0.0511	0.0732	0.0895	0.0713	0.0490	0.0484	0.0468	0.0376	0.0310
	B	NA	0.0749	0.0726	0.0358	0.0553	0.0426	0.0413	0.0368	0.0272	0.0216
	$A - B$	NA	−0.0238	0.0007	0.0537	0.0160	0.0064	0.0071	0.0100***	0.0104***	0.0094***
	(t-value)	NA	(−0.89)	(0.03)	(1.49)	(1.55)	(1.33)	(1.82)	(3.26)	(4.29)	(4.92)
10 (largest)	*A*	NA	NA	0.0161	0.0895	0.0283	0.0381	0.0429	0.0333	0.0264	0.0163
	B	NA	NA	0.0135	0.0358	0.0328	0.0416	0.0269	0.0264	0.0215	0.0129
	$A - B$	NA	NA	0.0026	0.0537	−0.0044	−0.0035	0.0160***	0.0068**	0.0049***	0.0035***
	(t-value)	NA	NA	(0.44)	(1.49)	(−0.31)	(−0.31)	(2.70)	(2.54)	(3.53)	(6.24)

Note. NA: not applicable due to lack of observations.

** Significant at the 5% level.

*** Idem., 1%.

analyst who has an affiliated dealer. We cluster these stocks into four portfolios according to the number of analysts.[20] Stocks in each of these four portfolios are then further divided into four portfolios according to trading volume. Then, using stocks within each cell (i.e., analyst-volume quartile), we calculate the average number of forecasts $[A = (1/I)\sum_i\{(1/J)\sum_j F(i,j)\}]$ issued by analysts who have an affiliated dealer making a market in the same stock and the average number of forecasts $[B = (1/I)\sum_i\{(1/G)\sum_g F(i,g)\}]$ issued by analysts without such an affiliated dealer.

According to Hypothesis 3b, we expect

$$\frac{1}{I}\sum_i\left\{\frac{1}{J}\sum_j F(i,j)\right\} - \frac{1}{I}\sum_i\left\{\frac{1}{G}\sum_g F(i,g)\right\} > 0, \tag{9}$$

where $F(i,j)$ is the number of forecasts for stock i by analyst j who has an affiliated dealer making a market in stock i, $F(i,g)$ is the number of forecast for stock i by analyst g without such an affiliated dealer, I is the number of stocks with at least one affiliated analyst-dealer, J is the number of analysts with an affiliated dealer for stock i, G is the number of analysts who do not have an affiliated dealer in stock i, $\sum_i$ denotes the summation over i, $\sum_j$ denotes the summation over analysts for stock i with an affiliated dealer who makes a market in stock i, and $\sum_g$ denotes the summation over analysts for stock i who do not have an affiliated dealer making a market in stock i.

We show the results in Table 9. For analyst-volume cell $(1,1)$, the average number of earnings forecasts for a given stock issued by an analyst who has an affiliated dealer making a market in the same stock is 2.59 in 1996, whereas the corresponding figure by an analyst who does not have such an affiliated dealer is 2.05. The difference between the two figures is statistically significant at the 1% level. For analyst-volume cell $(4,4)$, the corresponding figures are 26.03 and 4.28, respectively, and the difference is statistically significant at the 1% level.

The average number of earnings forecasts for stocks issued by analysts who have affiliated dealers making markets in the same stocks is significantly greater than the average of number earnings forecasts issued by analysts who do not have such dealers in 14 of 16 analyst-volume cells. For the 16 analyst-volume cells as a whole we find that z-score is 12.23, which is significant at the 1% level.[21] We find similar results from the 1997 data. These results are consistent with our hypothesis that analysts are proactive in marketing stocks that are handled by affiliated dealers by issuing frequent earnings forecasts.

4. Do analysts issue more optimistic forecasts for stocks handled by affiliated dealers?

The previous section shows that analysts favor stocks that are handled by affiliated dealers in terms of both coverage and forecast frequency. Do analysts also issue more favorable

[20] The number of stocks followed by an analyst is, on average, substantially smaller than the number of stocks handled by a dealer. Hence, we cluster stocks into analyst quartiles instead of analyst deciles.

[21] We calculate z-score by adding t-values across 16 analyst-volume cells and then dividing the sum by the square root of the number of t-values.

Table 9
Testing whether analysts issue earnings forecasts more frequently for stocks that are handled by affiliated market makers (Eq. (9))

Year	Number of analysts quartiles		Trading volume quartiles 1	2	3	4
1996	1	Affiliated (A)	2.59	2.13	2.03	1.81
		Non-affiliated (B)	2.05	1.62	1.54	1.72
		$(A)-(B)$	0.54***	0.52***	0.49***	0.09
		(t-value)	(3.12)	(3.31)	(2.66)	(0.25)
	2	Affiliated (A)	3.13	2.96	3.09	2.83
		Non-affiliated (B)	2.31	1.74	1.72	1.86
		$(A)-(B)$	0.83**	1.23***	1.37***	0.97**
		(t-value)	(1.99)	(4.57)	(4.33)	(2.31)
	3	Affiliated (A)	3.84	4.61	6.38	8.92
		Non-affiliated (B)	3.27	2.66	2.80	2.62
		$(A)-(B)$	0.56	1.95***	3.59***	6.30***
		(t-value)	(0.62)	(3.68)	(5.41)	(6.27)
	4	Affiliated (A)	4.75	7.16	10.89	26.03
		Non-affiliated (B)	14.57	6.92	4.37	4.29
		$(A)-(B)$	−9.82	0.24	6.52***	21.74***
		(t-value)	(−1.5)	(0.11)	(3.28)	(7.02)
				z-score = 12.23***		
1997	1	Affiliated (A)	1.80	1.75	1.97	1.50
		Non-affiliated (B)	1.71	1.40	1.19	1.00
		$(A)-(B)$	0.09	0.35**	0.78***	0.50
		(t-value)	(0.53)	(2.05)	(2.90)	(1.32)
	2	Affiliated (A)	2.76	2.36	2.49	3.12
		Non-affiliated (B)	1.90	1.80	1.34	1.56
		$(A)-(B)$	0.86	0.56	1.15***	1.56**
		(t-value)	(1.12)	(1.71)	(3.93)	(2.41)
	3	Affiliated (A)	3.14	3.35	3.49	6.22
		Non-affiliated (B)	4.89	1.68	1.58	1.84
		$(A)-(B)$	−1.75	1.67***	1.91***	4.38***
		(t-value)	(−0.89)	(2.63)	(3.84)	(4.77)
	4	Affiliated (A)		9.71	7.85	14.29
		Non-affiliated (B)	NA	4.50	3.00	2.91
		$(A)-(B)$		5.21	4.85**	11.38***
		(t-value)		(1.35)	(2.40)	(4.12)
				z-score = 9.06***		

Note. NA: not applicable due to lack of observations.
** Significant at 5% level.
*** Idem., 1%.

earnings forecasts for these stocks? Prior studies show that analysts' buy recommendations contain significant optimism biases when the recommendations involve their current or prospective corporate customers. Dugar and Nathan (1995) find that analysts tend to issue more optimistic recommendations on a company when they work for investment banking firms that have underwriting relationships with the company. Lin and McNichols (1993, 1998) show that analysts offer more favorable long-term earnings forecasts and recommendations on companies that are underwriting clients to their brokerage firm. Similarly, Dechow et al. (1999) show that sell-side analysts' long-term growth forecasts are overly optimistic around seasoned equity offerings and analysts affiliated with the lead underwriter make the most optimistic forecasts.

Carleton et al. (1998) show that both regional and national brokerage firms, which have conflicts of interest emerging from their activities in both underwriting securities and making investment recommendations, tend to produce more optimistic recommendations than non-brokerage firms. Michaely and Womack (1999) find that stocks underwriter analysts recommend perform poorly compared to buy recommendations by unaffiliated brokers.

In this section, we examine whether analysts' earnings forecasts for stocks that are handled by affiliated dealers differ in bias and accuracy from those for stocks that are not handled by affiliated dealers. Because analysts have an incentive to promote stocks that are handled by affiliated dealers, they may exhibit a tendency to issue more optimistic earnings forecasts for those stocks.[22] The incentive to inflate earnings forecasts, however, may be offset by analysts' concern for the value of their reputation capital, which is partly dependent upon delivering an unbiased investment research report. If the concern for reputation capital is large enough to offset the incentive to promote the market-making business of affiliated dealers, we may not observe a significant difference in forecast bias between the two groups of stocks. If, on the other hand, the concern for reputation capital is smaller than the incentive to inflate earnings forecasts, we may observe a difference in forecast bias between the two groups.

To examine whether analysts issue more optimistic earnings forecasts for stocks that are handled by affiliated dealers, we identify all the stocks that are followed by each analyst who has an affiliated dealer. We group these stocks into four portfolios according to the number of analysts. Stocks in each of these four portfolios are then further divided into four portfolios according to trading volume. Then, using stocks within each cell (i.e., analyst-volume quartile), we calculate the mean analyst forecast bias $[A = (1/I)\sum_i \{(1/J)\sum_j FB(i,j)\}]$ for stocks that are handled by affiliated dealers and the mean analyst forecast bias $[B = (1/I)\sum_i \{(1/G)\sum_g FB(i,g)\}]$ for stocks that are not handled affiliated dealers.

If analysts exhibit a tendency to issue more optimistic earnings forecasts for stocks that are handled by affiliated dealers than for those that are not handled by affiliated dealers, we expect

$$\frac{1}{I}\sum_i \left\{\frac{1}{J}\sum_j FB(i,j)\right\} - \frac{1}{I}\sum_i \left\{\frac{1}{G}\sum_g FB(i,g)\right\} > 0, \tag{10}$$

where $FB(i,j)$ is the observed forecast bias ((Forecast − Actual)/|Actual|) for stock i by analyst j who has an affiliated dealer for stock i, $FB(i,g)$ is the observed forecast bias for stock i by analyst g without such an affiliated dealer, I is the number of stocks with at

[22] An implicit assumption behind this conjecture is that analysts make more buy than sell recommendations. Indeed, prior studies find a significant positive bias in analysts' recommendations. For example, Stickel (1995) shows that the ratio of buy recommendations to sell recommendations exceeds 4.5.

least one affiliated analyst-dealer, J is the number of analysts with an affiliated dealer for stock i, G is the number of analysts who do not have an affiliated dealer for stock i, $\sum_i$ denotes the summation over i, $\sum_j$ denotes the summation over analysts for stock i with an affiliated dealer for stock i, and $\sum_g$ denotes the summation over analysts for stock i without such an affiliated dealer.

We report the results in panel A of Table 10. The results show that analysts tend to issue optimistic earnings forecasts for both groups of stocks. Moreover, during 1996, the

Table 10
Earnings forecast bias and error of affiliated and unaffiliated analysts (Eq. (10))

Year	Number of analysts quartiles		Trading volume quartiles 1	2	3	4
			A. Forecast bias (FB) = (Forecast − Actual)/|Actual|			
1996	1	Affiliated (A)	0.1143	0.1067	0.1019	0.0564
		Non-affiliated (B)	0.0909	0.0781	0.0704	0.0438
		(A) − (B)	0.0234	0.0286***	0.0315**	0.0126
		(t-value)	(0.83)	(5.03)	(2.01)	(0.50)
	2	Affiliated (A)	0.1444	0.1199	0.0906	0.0436
		Non-affiliated (B)	0.0928	0.0497	0.0601	0.0611
		(A) − (B)	0.0516	0.0702***	0.0305	−0.0175
		(t-value)	(1.60)	(4.91)	(2.23)**	(−1.06)
	3	Affiliated (A)	0.2234	0.1383	0.0702	0.1137
		Non-affiliated (B)	0.0806	0.0180	0.0498	0.0484
		(A) − (B)	0.1428***	0.1203***	0.0204	0.0653***
		(t-value)	(3.82)	(5.13)	(1.48)	(4.40)
	4	Affiliated (A)	0.0473	−0.0030	0.0959	0.0864
		Non-affiliated (B)	0.1346	0.0544	0.0325	0.0616
		(A) − (B)	−0.0873**	−0.0574	0.0634***	0.0248**
		(t-value)	(−2.80)	(−1.76)	(3.55)	(2.37)
			z-score = 8.62***			
1997	1	Affiliated (A)	0.0515	0.0917	0.0545	0.0048
		Non-affiliated (B)	0.0450	0.0273	0.0222	0.0159
		(A) − (B)	0.0065	0.0644***	0.0323	−0.0111
		(t-value)	(0.13)	(3.51)	(1.54)	(−0.36)
	2	Affiliated (A)		0.0477	0.0626	−0.0230
		Non-affiliated (B)	NA	0.0222	0.0448	0.0066
		(A) − (B)		0.0255	0.0178	−0.0296
		(t-value)		(1.17)	(0.85)	(−1.23)
	3	Affiliated (A)	−0.0420	0.1499	0.0302	−0.0430
		Non-affiliated (B)	0.0484	0.0339	0.0873	0.0187
		(A) − (B)	−0.0904***	0.1160***	−0.0571***	−0.0617***
		(t-value)	(−4.63)	(4.22)	(−3.02)	(−3.73)
	4	Affiliated (A)		0.0560	0.0576	0.1189
		Non-affiliated (B)	NA	0.0003	0.0088	0.0203
		(A) − (B)		0.0557	0.0488	0.0986***
		(t-value)		(1.46)	(1.39)	(6.42)
			z-score = 2.06**			

(*continued on next page*)

Table 10 (*Continued*)

Year	Number of analysts quartiles		Trading volume quartiles 1	2	3	4
			B. Forecast error (FE) = |Forecast − Actual|/|Actual|			
1996	1	Affiliated (A)	0.2912	0.2652	0.2696	0.2336
		Non-affiliated (B)	0.2621	0.2095	0.1603	0.1294
		$(A)-(B)$	0.0291	0.0557***	0.1093***	0.1042***
		(t-value)	(1.26)	(5.03)	(8.17)	(4.80)
	2	Affiliated (A)	0.2929	0.2445	0.2324	0.1789
		Non-affiliated (B)	0.2271	0.1908	0.1590	0.1344
		$(A)-(B)$	0.0658**	0.0537***	0.0734***	0.0445***
		(t-value)	(2.40)	(4.36)	(6.24)	(3.11)
	3	Affiliated (A)	0.2887	0.2462	0.1817	0.2277
		Non-affiliated (B)	0.2202	0.1642	0.1742	0.1198
		$(A)-(B)$	0.0685**	0.0820***	0.0075	0.1079***
		(t-value)	(1.99)	(3.95)	(0.63)	(8.28)
	4	Affiliated (A)	0.2185	0.1290	0.1625	0.2020
		Non-affiliated (B)	0.2452	0.2285	0.2094	0.1743
		$(A)-(B)$	−0.0267	−0.0995***	−0.0469***	0.0277***
		(t-value)	(−1.03)	(−3.74)	(−2.96)	(3.07)
			z-score = 12.18***			
1997	1	Affiliated (A)	0.0597	0.2305	0.1899	0.1583
		Non-affiliated (B)	0.1839	0.1573	0.1141	0.1025
		$(A)-(B)$	−0.1242***	0.0732***	0.0758***	0.0558**
		(t-value)	(−2.72)	(4.61)	(4.11)	(2.07)
	2	Affiliated (A)		0.1625	0.1637	0.1456
		Non-affiliated (B)	NA	0.1306	0.1430	0.0704
		$(A)-(B)$		0.0319	0.0207	0.0752***
		(t-value)		(1.68)	(1.11)	(3.50)
	3	Affiliated (A)	0.0419	0.2246	0.1454	0.1266
		Non-affiliated (B)	0.1518	0.1251	0.1612	0.0797
		$(A)-(B)$	−0.1099***	0.0995***	−0.0158	0.0469***
		(t-value)	(−5.77)	(4.10)	(0.94)	(3.19)
	4	Affiliated (A)		0.1207	0.1784	0.2061
		Non-affiliated (B)	NA	0.0862	0.1097	0.1143
		$(A)-(B)$		0.0345	0.0687**	0.0918***
		(t-value)		(1.21)	(2.22)	(6.77)
			z-score = 6.72***			

Note. NA: not applicable due to lack of observations.
** Significant at 5% level.
*** Idem., 1%.

mean analyst forecast bias for stocks that are handled by affiliated dealers is significantly greater than the corresponding figure for stocks that are not handled by affiliated dealers in 9 of 16 analyst-volume cells. For the 16 cells as a whole, we find a z-score of 8.62, which is significant at the 1% level. The results show that analysts tended to issue optimistic forecasts during 1997 and the mean bias is greater for stocks that are handled by affiliated dealers. The observed difference, however, is less significant (z-score is only 2.06) than the corresponding figure in 1996. Overall, our results are in line with the hypothesis that analysts help the market-making operation of affiliated dealers by issuing optimistic earnings forecasts.[23]

To determine whether the accuracy of forecasts differs between the two groups of stocks, we also calculate the mean analyst forecast error $[A = (1/I)\sum_i\{(1/J) \times \sum_j FE(i, j)\}]$ for stocks that are handled by affiliated dealers and the corresponding figure $[B = (1/I)\sum_i\{(1/G)\sum_g FE(i, g)\}]$ for stocks that are not handled by affiliated dealers, where $FE(i, j)$ is the observed forecast error (|Forecast − Actual|/|Actual|) for stock i by analyst j who has an affiliated dealer making a market in stock i, $FE(i, g)$ is the observed forecast error for stock i by analyst g without such an affiliated dealer, and all other variables are the same as previously defined.

The results (see panel b, Table 10) show that the mean analyst forecast error for stocks that are handled by affiliated dealers is greater than the corresponding figure for stocks that are not handled by affiliated dealers—we find that z-scores are positive and significant at the 1% level during both 1996 and 1997. This result may be explained in part by the fact that analysts tend to issue more optimistic earnings forecasts for the first group of stocks.

Overall, our empirical results suggest that analysts help affiliated dealers through more proactive coverage of stocks that are chosen by their dealers and also by issuing more optimistic earnings forecasts for these stocks. The bias in analysts' forecasts may be attributed at least in part to their desire to generate greater investor interest and trading volumes for stocks that are handled by their affiliated broker-dealers and thereby help increase brokerage commissions and market-making revenues for the company.

5. Are the results driven by the underwriter effect?

Prior studies show that underwriters support new issues by arranging analyst coverage, making optimistic recommendations, and acting as the broker-dealer in the secondary markets (see, e.g., Ellis et al., 2000, 2002; Michaely and Womack, 1999). Taken together, the results of these studies imply that when a firm is the underwriter, its dealer is likely to have a large market share and its analyst is likely to follow the stock and issue optimistic recommendations. Consequently, one might suspect that the collaborative activities between analysts and market makers shown in our study could have resulted from this "underwriter effect."

To shed some light on this issue, we obtain data on the initial and seasoned equity offering dates from the SDC database for our study sample of firms during the study period. We identify a total of 6926 initial and seasoned equity offerings for our study sample. We then exclude the data for each company during the first 12 months following the initial public offering from the study sample. Similarly, we exclude the data for each company during the first 12 months following each seasoned equity offering. Finally, we repeat our

[23] We note that this result is open to alternative interpretations. For instance, the observed optimism may simply be an inadvertent consequence of analysts' genuine (but false) beliefs about the stock's potential. The very fact that a stock is chosen by an analyst as well as his associate (i.e., dealer) may reflect the analyst's true optimism about the stock. Regardless of whether the observed optimism is due to analysts' marketing motives or false beliefs, the implication of our findings remains the same.

empirical analyses using this reduced study sample and replicate Table 3 through Table 10. We find that the results from the reduced sample are qualitatively similar to those reported above.[24] Hence, we conclude that our results are not driven by the underwriter effect.

6. Interpretations and discussions

The conflict of interest between information intermediaries (i.e., analysts) and their clients (i.e., investors) addressed in this paper has similar analogies in other areas. For example, an appraisal of an artwork may not be very useful to potential buyers if the appraiser works for the dealer who owns the artwork. Similarly, a rating of a motion picture issued by a movie critic who is affiliated with the company that produced the movie may not be completely objective.

Obviously, this conflict of interest will be minimized if the information intermediaries are independent agents. Whether it is an artwork appraisal or movie rating, credibility would be higher if it came from an independent source. Likewise, analysts' reports and stock recommendations that come from independent research houses (such as Value Line and Standard and Poor's) could be considered more credible than those provided by analysts who are affiliated with the broker-dealer firms. Analysts who do not have vested interests would be more objective in determining which stocks to follow, and subsequently, which stocks to recommend among them. In contrast, analysts who are affiliated with the broker-dealer firms are likely to focus their coverage on those issues that are handled by their dealers (as shown in this paper) and, as a consequence, their reports and stock recommendations are likely to be subject to significant selection biases.

Although the above discussion suggests that the vertical integration of brokerage and dealer operations can pose a significant conflict of interest between analysts and investors, it may have some positive ramifications for investor welfare. For example, close collaboration between brokers and dealers may benefit investors through smaller execution costs (e.g., narrower bid–ask spreads) to the extent that analysts help dealers to avoid large adverse selection costs by providing timely and valuable information. In this case, dealers can better serve their clients by being able to charge lower spreads. In addition, brokerage firms may be able to better serve their clients when they also run dealer operations by providing prompt and reliable execution of customer orders. Traders may also receive better price improvements when brokers route their orders to affiliated market makers.

Considering these potential costs and benefits, the net effect of the broker-dealer integration on investor welfare is unclear. The accurate quantification of these costs and benefits is likely to be difficult and is well beyond the scope of our paper. However, our results should alert investors to recognize these potential problems and thereby interpret and act upon analysts' recommendations accordingly.

[24] The results are available from the authors upon request.

7. Summary and concluding remarks

Financial analysts and market makers are important intermediaries in securities markets. Analysts collect and process data on select stocks and issue buy and sell recommendations to their clients and the general public. Dealers provide liquidity by standing ready to trade select securities with any buyers and sellers. A financial analyst (market maker) does not follow (trade) all stocks, however, any more than a department store carries all clothing labels. A typical analyst (dealer) follows (trades) only a small subset of available securities and it is unclear what motivates them to choose certain stocks and not others. Our study sheds some light on this question.

Our empirical results indicate that there is a positive and bidirectional relation between analyst following and the number of market makers. We also find that dealers are more likely to make markets in stocks that are covered by affiliated analysts. Likewise, analysts provide more proactive coverage and optimistic earnings forecasts for stocks that are handled by affiliated dealers. We interpret these results in the context of incentive structures in the securities industry.

Several recent studies report significant biases in analyst recommendations that arise from coordinated efforts between brokerage analysts and the investment-banking branch of the brokerage firm on behalf of their client companies that went public. In contrast, our study underscores a possible conflict of interest between investors and brokerage firms arising from the vertical integration of brokerage and dealer operations. To the extent that sell-side analysts follow and promote stocks to help their brokerage-dealer operations rather than to help outside investors, it is important for investors to use analysts' stock recommendations with caution.

Analyst behavior has recently been under the close scrutiny of lawmakers, regulators, and the investment community in general. In addition, securities industry has enacted various self-imposed guidelines for 'best practices' to ensure that analysts provide investors with unbiased stock recommendations and earnings forecasts. A fruitful area for future research would be an investigation into whether the collaborative behavior between analysts and market makers that could pose a threat to investor interest has declined as a result of these events and actions. Another area of future research would be an examination of the positive impact of analyst-dealer collaboration on investor welfare. As pointed out earlier, close collaboration between analysts and dealers may benefit investors through smaller trading cost as well as fast and reliable executions. Empirical estimates of these benefits would help assess the full ramification of analyst-dealer collaboration for investor welfare.

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