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Analysts' Forecasts and Brokerage-Firm Trading

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ABSTRACT: Using unique data on brokerage-firm trading, I examine whether analysts' earnings forecasts and stock recommendations affect their brokerage firms' share of trading in the forecast stocks. I find that individual analyst's forecasts that differ from the consensus forecast generate significant brokerage-firm trading in the forecast stocks in the two weeks after the forecast release date, affirming that analysts' forecasts affect their brokers' commission revenue. However, I find no evidence that analysts' forecast errors—the difference between forecast earnings and actual earnings— increase brokerage-firm trading. This result suggests that analysts cannot generate trade for their employers simply by adding error to their forecasts. I find that buy recommendations generate relatively more trading, both buying and selling, through the analyst's brokerage firm. Collectively, these results suggest that analysts can generate higher trading commissions through their positive stock recommendations than by biasing their forecasts.

Keywords: *earnings forecasts; trading incentives; brokerage-firm trading.*

Data Availability: *The data are available from I/B/E/S and the Toronto Stock Exchange.*

I. INTRODUCTION

Sell-side research analysts must maintain good relations with company management, assist the investment bank's underwriting department in marketing stock offerings, and serve the institutional clients who provide commission revenue to their brokers. Incentives to meet these goals could potentially bias sell-side analysts' earnings forecasts and recommendations. Recently, concern that brokerage-firms' sell-side analysts issue biased research has driven lawsuits against Credit Suisse First Boston (Craig 2002), Merrill Lynch (Beck 2002), and Salomon Smith Barney (Silverman 2002). The resolution of these

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lawsuits could fundamentally change analysts' research.¹ Much of this controversy centers on whether underwriting relationships bias analysts' research. This paper investigates the largely unexplored question of how incentives to generate brokerage commissions for their employers—hereafter termed *trading incentives*—could affect analysts' earnings forecasts and stock recommendations.

Trading incentives are important because every forecast or recommendation can potentially generate trade for the analyst's employer. For example, Konrad (1989, 118) reports that a sell-side analyst at Morgan Keegan earned 2.5 percent of the brokerage's trading commissions in the 19 stocks the analyst covered. Dorfman (1991) also reports that some brokerage firms include similar trading incentives in analysts' contracts. However, more often brokerage firms conduct a formal poll asking the institutional sales force to rate analysts on how much trade they generate, and the results affect analysts' bonuses (Dorfman 1991; Laderman 1998; Irvine 2000; Lauricella 2001).

I examine whether analysts' forecasts and recommendations influence the amount of trading done by their employers in the forecast stock. I use Toronto Stock Exchange (TSE) data that identifies the broker(s) involved in every trade to calculate brokerage-firm market share of trading in the forecast stock. I apply Hayes' (1998) theoretical model of trading incentives to derive testable hypotheses about the relation between analysts' forecasts and their brokerage-firms' market shares in the forecast stocks. I then test whether, after controlling for analysts' recommendations, analysts' forecasts significantly affect brokerage-firm market share when the forecast is released.

As predicted, I find that the difference between an individual analyst's forecast and the consensus forecast significantly increases a broker's market share of trading in the forecast stock in the two weeks after I/B/E/S receives the analyst's forecast. This conclusion holds after controlling for the issuing analyst's contemporary recommendation on the stock. These findings suggest the possibility that trading incentives encourage analysts to issue forecasts further from the consensus to increase their commission-related compensation. To test whether trading incentives cause analysts to bias their earnings forecasts, I examine whether forecast errors, defined as the difference between an analyst's earnings forecast and actual earnings as reported by I/B/E/S, generate trading in the forecast stock for the analyst's brokerage firm. I find that forecast errors do not increase brokerage-firm market share, so adding error to their forecasts is not an effective way for analysts to generate trade.

Analysts' stock recommendations that accompany earnings forecasts can significantly increase brokerage-firm trading in the forecast stock in the two weeks after I/B/E/S receives the forecast. I find that analysts' buy and strong buy recommendations allow their brokerage-firms' to capture significantly higher market share of trading—both buying and selling—than do hold, sell, or strong sell recommendations. Because buy and strong buy recommendations generate trade effectively, trading incentives could lead analysts to skew their recommendations toward buy and strong buy recommendations. Thus, my findings suggest that, as long as investment bank research is paid for with trading commissions, the potential for biased recommendations remains, even if regulators remove analysts' incentives to promote their firms stock offerings by effectively separating research departments from underwriting departments (Kahn 2002).

Focusing on how analysts' forecasts and recommendations generate trading for their brokerage firms enables me to extend empirical research that directly links analysts' compensation incentives to their forecasts and recommendations. Recent research finds that the

¹ Proposed solutions include splitting research into organizations that are independent from brokerage-firms' underwriting departments (Kahn 2002), or creating a research oversight board (Gasparino and Smith 2002).

probability an analyst will leave her current position increases if her forecasts are less accurate than those of her peers (Mikhail et al. 1999), and that analysts adjust their earnings forecasts in response to underwriting compensation incentives (Dechow et al. 2000). Dechow et al. (2000) find that analysts issue over-optimistic long-term earnings forecasts for clients of their firm's underwriting department when those clients issue common stock. They report that the optimism in analysts' long-term forecasts is positively related to the amount of fee revenue the stock offering generates for the analysts' brokerage firm, an important component of analysts' annual bonuses at many brokers (Lowenstein 1996).

My results are consistent with the theoretical prediction that the incentive to generate trading commissions for their brokerages can be an important influence on analysts' decisions (McNichols and O'Brien 1997). My results are also consistent with Hayes' (1998) prediction that analysts' forecasts affect their brokerage-firms' commission revenues. However, other empirical results are inconsistent with existing theory. Thus, my study also provides a set of empirical results that can guide refinements of theory on how trading incentives affect analysts' forecasts and recommendations.

The paper proceeds as follows. Section II develops hypotheses about how analysts' earnings forecasts affect brokerage-firm trading. Section III describes the sample and key variables used in the empirical tests. Section IV examines the empirical relation between brokerage-firm market share of trading and analysts' forecasts and recommendations. Section V concludes.

II. HYPOTHESES

This section applies existing theory to develop hypotheses that predict how investors' trading demands respond to analysts' earnings forecasts. Admati and Pfleiderer (1990), Allen (1990), Brennan and Chordia (1993), and Hayes (1998) all model how utility-maximizing investors respond to a signal provided by an information seller, such as a sell-side analyst. I focus on Hayes' (1998) model because it explicitly analyzes investors' trading demands using analysts' earnings forecasts as the informative signal.

The Hayes (1998) Model

Hayes (1998) presents a partial equilibrium model of risk-averse investors with negative exponential utility who must allocate their wealth, W_t , between a riskless asset and a risky asset (stock). The analyst provides investors with information about the stock's expected return. The price of the riskless asset and its terminal payoff are normalized to 1. The risky asset's price is P , and its expected terminal payoff is $P + x$, where x is the commonly known expected return, and $x > 0$. The asset's actual terminal payoff is $P + x + \mu$. In her model, investors and the analyst share common prior beliefs about μ , namely that it is distributed normally with mean zero and variance 1. At the beginning of the period, investors own m shares of stock.

Investors allocate their wealth based on the information the analyst provides. Hayes (1998) models the analyst as issuing a report consisting of two components: her posterior expectation of μ , denoted by μ_R , and the variance of this estimate, σ_R . The posterior expectation, μ_R , can be viewed as the analyst's privately held signal about the accuracy of the consensus earnings forecast since, in Hayes' model, the stock's expected return (x) is common knowledge and equals the expected economic earnings for the period. The investor pays a commission, c , to the broker for each share of stock bought and sold.

As Hayes (1998, 302) demonstrates, an investor chooses the number of shares demanded, n , to maximize his certainty equivalent wealth given the information in the analyst's forecast:

$$(W - nP) + n(P + x + \mu_R) - \frac{\rho}{2} n^2 \sigma_R^2 - c|m - n| \quad (1)$$

where ρ is the coefficient of risk aversion. Hayes (1998) shows that the solution to this problem results in two demand equations. The first equation defines the number of shares bought, n_b , if the analyst's signal is favorable, ($\mu_R > 0$):

$$n_b = \frac{x + \mu_R - c}{\rho \sigma_R^2}. \quad (2)$$

Alternatively, if the information in the analyst's report is unfavorable ($\mu_R < 0$), the number of shares sold, n_s , is given by:

$$n_s = \frac{x + \mu_R + c}{\rho \sigma_R^2}. \quad (3)$$

If trading were costless ($c = 0$), then analysis of investors' demand with respect to the information in the forecast is straightforward. The more positive an analyst's earnings forecast, conditional on the forecast exceeding the consensus earnings expectation, x , (i.e. $\mu_R > 0$), the more investors wish to purchase. The more negative an analyst's earnings forecast, conditional on the forecast falling below the consensus earnings expectation, x , (i.e., $\mu_R < 0$), the more investors wish to sell. Together these results generate the first empirical hypothesis from Hayes' (1998) model:

H1: The greater the absolute deviation in $|\mu_R|$, the greater brokerage-firm trading in the forecast stock.

Differentiating Equations (2) and (3) with respect to σ_R^2 , the variance of the analysts' expectation of the consensus forecast error (μ_R), shows that the number of shares investors wish to buy and sell is decreasing in σ_R^2 . In Hayes' (1988) model, σ_R^2 is the only source of uncertainty; investors, however, are likely to face additional sources of uncertainty. In particular, uncertainty surrounding the accuracy of the consensus forecast. I define total uncertainty surrounding the earnings forecast to include both uncertainty surrounding the analyst's expectation of the consensus forecast error and uncertainty surrounding the accuracy of the consensus, and predict that:

H2: Brokerage-firm trading in the forecast stock decreases in the total uncertainty of the forecast.

Hypothesis 2 is consistent with the common theoretical prediction that the extent to which investors trade on information decreases as the uncertainty of that information increases.²

Trading costs complicate the analysis. Figure 1 adapts Hayes' (1998, 303) diagram of the trading demands derived in Equations (2) and (3). The figure presents the investors' trading demands n , (i.e., the difference between the investor's optimal holdings and his

² Admati and Pfleiderer (1990), Allen (1990), and Brennan and Chordia (1993) all examine how investors respond to uncertain private information. Kim and Verrecchia (1991) extend their results to the case of uncertainty in both private and public information.

FIGURE 1
Investor Trading Demand as a Function of an Analyst's Forecast

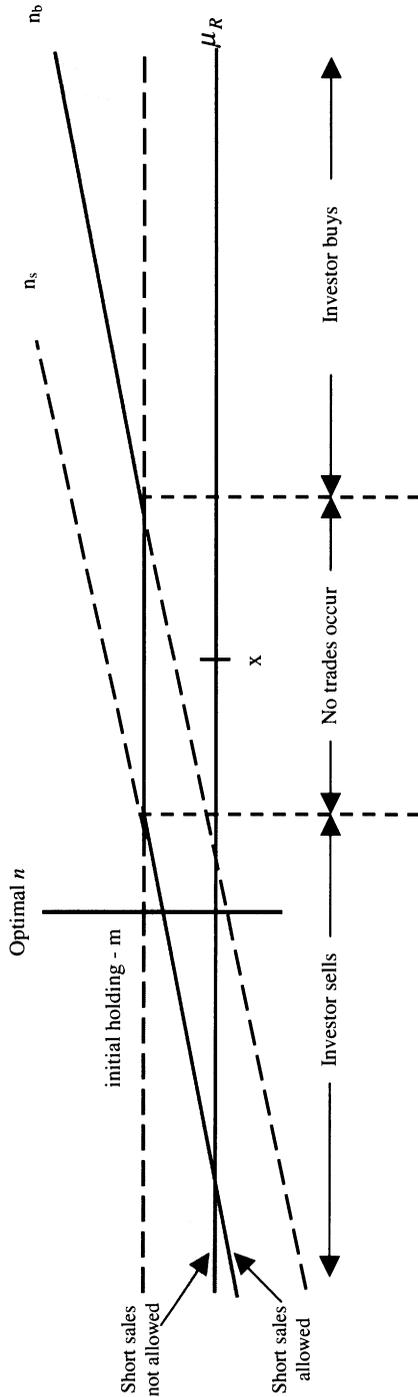


Figure 1, adapted from Hayes (1998, 303). This diagram shows an investor's optimal number of shares, n , as a function of the deviation in an analyst's forecast from the consensus forecast x . m denotes the investor's initial holdings given the consensus forecast, x . n_b , the number of shares the investor buys, is the solution to Equation (2) given that, μ_R , the analyst's estimate of the error in the consensus forecast, is greater than zero. The solid portion of line n_b represents values of μ_R for which n_b is positive and the investor purchases shares. The dashed portion of line n_b represents values of μ_R for which n_b is negative and the investor does not purchase shares. n_s , the number of shares sold, is the solution to Equation (3) given μ_R is less than zero. The solid portion of line n_s represents values of μ_R for which n_s is positive and the investor sells shares. The dashed portion of line n_s represents values of μ_R for which n_s is negative and the investor does not sell shares. Note that: (1) the number of shares traded is not symmetric in $|\mu_R|$ if short selling is constrained, and (2) no trades occur when $|\mu_R| < \text{the commission charge, } c$.

initial holdings, m). Conditional on x , the consensus forecast, investors initially hold m shares. For small deviations between the analyst's forecast and the consensus forecast, $|\mu_R| < c$, a region of no trading exists. When μ_R is large and negative, investors' optimal position in the risky asset falls below zero, and investors sell short. Hayes (1998), following Diamond and Verrecchia (1987), incorporates the fact that some investors, such as mutual funds, are restricted from short selling.³ Restrictions on short selling produces an asymmetry in investors' trading demands between negative and positive values of μ_R .⁴

H3: A positive μ_R generates more brokerage-firm trading than a negative μ_R of the same magnitude.

Hayes (1998), therefore, argues that the marginal return from analysts' efforts in gathering forecast information is greater for stocks that the analyst expects to perform relatively well. As a consequence, she predicts forecast accuracy will be greater for stocks that the analyst expects to perform well in the future. A test of H3 provides evidence on whether asymmetric trading incentives are likely to cause this behavior.

Operationalizing the Theoretical Constructs

To test these hypotheses, I must identify empirical proxies for $|\mu_R|$ and total uncertainty. My proxy for $|\mu_R|$ is the absolute deviation between an analyst's earnings forecast and the consensus earnings forecast. The consensus forecast is the I/B/E/S-reported consensus earnings forecast in the month prior to the analyst's forecast. To scale forecast deviations across firms, I deflate the absolute deviation between the forecast and consensus by the stock price on the day of the forecast. Following H1, I predict that the greater the price-deflated absolute deviation between the analyst's earnings forecast and the consensus forecast (*ABSDEV*), the more likely that investors' valuations will change enough to outweigh the transaction costs of trading. If H1 holds, then I expect *ABSDEV* to be positively related to brokerage-firm trading in the forecast stock.

To calculate an empirical proxy for total uncertainty associated with an analyst's earnings forecast, I use the Barron et al. (1998) (hereafter BKLS) measure of uncertainty, which defines uncertainty over both common (in the consensus) and idiosyncratic (the dispersion across all analysts' forecasts) information:

$$UNCERTAINTY = \left(1 - \frac{1}{N}\right) D + SE \quad (4)$$

where N is the number of forecasts, and D is the sample variance of analysts' forecasts:

$$D = \frac{1}{N-1} \sum_{a=1}^N (F_a - \bar{F})^2. \quad (5)$$

and SE is the sample squared error in the consensus forecast:

³ Even when not completely restricted, investors do not have full use of the proceeds from the short sale, making short sales relatively costly.

⁴ I thank the referee for this comment.

$$SE = (A - \bar{F})^2. \quad (6)$$

In these equations, A is the actual earnings realization, F_a is the forecast by analyst a , and \bar{F} is the consensus forecast.

When making their trading decisions, investors must consider both the analyst's forecast dispersion and the possibility of error in the consensus forecast. BKLS's *UNCERTAINTY* includes proxies for uncertainty in analyst-specific information, (Hayes' [1998] σ_R), through the forecast dispersion component, D , and uncertainty surrounding the accuracy of the consensus forecast through SE . Under H2, if *UNCERTAINTY* captures investors' total uncertainty surrounding the analyst's forecast, then *UNCERTAINTY* will be negatively related to brokerage-firm trading in the forecast stock.

My hypotheses predict that analysts' forecasts affect their brokerage-firm's trade. Hayes (1998, 304) assumes that analysts, through trading commissions, capture the benefits of releasing their forecasts. However, McNichols (1990) correctly maintains that investors are not contractually obligated to trade through the broker from whom they receive the report. Irvine (2000) reports that the market for analysts' research in both the U.S. and Canada is based on "soft-dollar" payments. Instead of paying cash for research services, institutional investors pay through commissions on their trading activity. Irvine (2000) shows that, as a consequence of the "soft-dollar" market, analyst coverage of a particular stock is associated with higher brokerage-firm market share in the covered stock. This result suggests a link between analysts' activities and brokerage-firm trading, but does not determine whether particular analysts' forecasts and recommendations exert a direct affect on brokerage-firm trading. One contribution of the current study is to provide empirical evidence on whether brokers capture *any* incremental commission payments when their analysts' release forecasts and recommendations.

Extensions of the Hayes (1998) Framework

Analysts commonly release investment recommendations along with their earnings forecasts. Substituting analysts' recommendations for the information in analysts' forecasts within Hayes' (1998) framework suggests that positive (buy) and negative (sell) recommendations would generate more brokerage-firm trading in the recommended stock than neutral (hold) recommendations.⁵ If analysts' recommendations subsume the information in their earnings forecasts, then after controlling for the recommendation, neither *ABSDEV* nor *UNCERTAINTY* would predict brokerage-firm trading in the forecast stock. However, Francis and Soffer (1997) find that analysts' earnings forecasts and stock recommendations contain distinct price-relevant information. If analysts' forecasts and stock recommendations both contain distinct price-relevant information, then both could influence brokerage-firm trading in the forecast stock. In Section IV, I examine this issue and find that the deviation between the forecast and consensus consistently predicts brokerage-firm market share in the forecast stock, even after controlling for the analyst's recommendation.

⁵ Practitioners sometimes maintain that hold recommendations are *de facto* sell recommendations. In fact, I show below that no significant difference in brokerage-firm market share exists between hold and sell recommendations.

This result is a natural extension of Francis and Soffer (1997) since investors should consider the price-relevant information in both earnings forecasts and recommendations when making their trading decisions.⁶

Finally, I examine whether analysts' forecast errors, defined as the difference between an analyst's forecast and I/B/E/S reported actual earnings, increase brokerage-firm trading in the forecast stock. If *ABSDEV*, the distance of an analysts' forecast from the consensus forecast, increases brokerage-firm trading, then instead of reporting her true forecast, an analyst could deliberately add error to her forecast in order to increase *ABSDEV* and, therefore, her commission-related compensation. Consider an analyst whose true unbiased forecast of upcoming annual earnings is 10 cents per share, higher than the consensus forecast of 9¢. If the distance of her forecast from the consensus forecast generates trading-commission revenue for her employer, then she could increase her firm's commission revenue by sacrificing forecast accuracy and reporting a forecast further from the consensus, say 11¢. I cannot observe her actual *ex ante* forecast error, but I can observe *ex post* forecast errors—the difference between the analyst's forecast and actual earnings. Thus, I test whether *ex post* forecast errors generate trading flow for the analyst's brokerage firm.

III. DATA

The Toronto Stock Exchange Data Set

This paper uses September 1, 1993 through August 31, 1994 transaction data from the Toronto Stock Exchange (TSE), the largest stock exchange in Canada and the seventh largest in the world. The average daily turnover in 1993 was 59.0 million shares, representing a value of C\$583 million. These measures of average trading grew in 1994, when daily trading averaged 61.5 million shares, or C\$726 million. Trading on the TSE occurs in a market-maker system. Every trade occurs through a seat holder on the exchange, a broker who can trade as an agent or as a principal. The advantage of TSE data is that when the TSE documents a trade, it records, in addition to time, volume, and price information, two brokerage identification codes. The TSE assigns each seat holder a unique two-digit code, which identifies the brokerage firm that sold the security and the brokerage firm that bought the security for each trade.

Irvine (2000) argues that because of the similarities between the sell-side analyst environments in Canada and the U.S., conclusions based on Canadian data are likely to apply to the U.S. market. Specifically, Irvine (2000) reports that: (1) institutional investors are significant traders in both markets, (2) the institutional practice of directing soft-dollar commissions to brokers in return for analyst research enjoys the same safe harbor provisions under the Ontario Securities Act as exist under Section 28(e) of the U.S. Securities Exchange Act of 1934, and (3) that the amount of commission revenue analysts generate for their employers forms an important component of Canadian analysts' compensation.

⁶ Reiterations of previous forecasts or the existence of sophisticated investors do not invalidate the predictions derived from Hayes (1998), but they could reduce the economic importance of the model's predictions. Hayes (1998) assumes that prior to receiving the analyst's earnings forecast, the market's valuation is based entirely on the consensus forecast. There is no mention of reiterations in this framework, but if the analyst's forecast reiterates an earlier forecast, the forecast can generate trade if the reiteration reduces investors' uncertainty about the accuracy of the analyst's forecast. Sophisticated investors, aware of the analyst's trading incentives, could discount forecasts far from the consensus as attempts to generate trade. However, if trading incentives do not completely dominate analysts' incentives to produce accurate forecasts, sophisticated investors would place some weight on the analyst's forecast. Given the evidence in Mikhail et al. (1999) that inaccuracy relative to their peers increases the probability of turnover, it is reasonable to assume that analysts are concerned about the accuracy of their forecasts.

I assign trading volume to the brokerage-firm(s) whose identification code accompanies a trade record.⁷ I then summarize brokerage-firm volume by calculating each firm's market share. Market share is the number of shares traded through the brokerage firm normalized by total shares traded in the stock. Specifically, the daily market share of brokerage firm j for stock k is the total volume traded by brokerage firm j in stock k on day i , divided by the total volume in stock k on day i . In Equation (7), the sum of brokerage-firm volume for all J brokers on the TSE represents total volume for stock k :

$$MKT_SHARE_{j,i}^k = \frac{Broker\ Volume_{j,i}^k}{\sum_{j=1}^J Broker\ Volume_{j,i}^k}. \quad (7)$$

I also calculate buy-side and sell-side *MKT_SHARE* using only buy or sell trades, respectively. For example, a brokerage-firm's buy-side *MKT_SHARE* represents the percentage of all purchases that occur in a particular stock-day executed by that brokerage firm. In untabulated tests, I find that *MKT_SHARE* is significantly positively correlated with the number of shares traded by the brokerage firm ($\rho = 0.71$). *MKT_SHARE* is, therefore, strongly related to commission-based trading revenue, which is most often charged on a cents-per-share basis (Conrad et al. 2001). *MKT_SHARE* has other desirable properties as a measure of brokerage-firm trading: *MKT_SHARE*, unlike raw brokerage-firm volume, is not auto-correlated, and it is also uncorrelated with total trading in the stock; so exogenous changes in total stock volume cannot bias the empirical tests. Summing daily *MKT_SHARE* over any period T produces the total broker *MKT_SHARE* over that period.

The Sample

The TSE sample includes every trade of the largest 100 companies on the TSE between September 1, 1993 and August 31, 1994. These 100 companies represent a significant fraction of the market value of all Canadian-based public companies. Ninety-seven of the 100 companies in the sample are in the TSE 300, the TSE's primary index. These 97 companies make up 78.2 percent of the value of the TSE 300 and include 18 of the 20 most active issues on the exchange (Toronto Stock Exchange 1994).

I obtain analysts' earnings forecasts and recommendations for the sample firms from the I/B/E/S International earnings forecast and recommendation databases. Over the sample period, the I/B/E/S detailed forecast database records a total of 1,224 forecasts of upcoming annual earnings (fiscal year one forecasts) whose issuing brokers also have recommendations on the I/B/E/S detailed recommendations tape. I delete 264 forecasts because the issuing broker was not a member of the Toronto Stock Exchange on July 31, 1993.⁸ In addition, to ensure that earnings announcements do not confound the results, I delete 125 earnings forecasts issued within five trading days before or after an earnings announcement.⁹ The final I/B/E/S sample consists of 835 analysts' earnings forecasts issued through 15 different brokerage firms on 96 of the 100 largest stocks on the TSE.

⁷ The TSE allows brokers to internalize (same broker buying and selling) trades. Therefore, some trades involve two brokers and others only one.

⁸ Most of the deleted forecasts were issued by U.S.-based brokers or brokers whose firm name in the 1993 TSE record could not be conclusively matched to a name in the I/B/E/S historical names file. In addition, I delete 33 forecasts made by the broker HSBC Securities, which is currently a member of the TSE, but was not a member firm according to TSE records on July 31, 1993 (Toronto Stock Exchange 1993).

⁹ The various news services reporting to Bloomberg supply the earnings announcement dates.

Table 1 presents descriptive statistics on brokerage trading and coverage activity for the 15 I/B/E/S sample brokerage firms in the 100 largest TSE stocks. The 15 brokerage firms constitute a diverse group that trade 54.8 percent of total *MKT_SHARE* in these stocks.¹⁰ The table presents mean daily brokerage-firm volume (C\$) and *MKT_SHARE* per stock, the total number of sell-side analysts each brokerage firm employs (Number of Analysts), the number of sample stocks each brokerage firm covers (Number of Stocks Covered), and the number of sample forecasts (Number of Forecasts in Sample).¹¹ Brokerage firms with larger *MKT_SHARE* tend to cover more stocks. As a consequence, these brokers contribute more forecasts to the sample. All else equal, smaller firms will have less

TABLE 1
Brokerage Trading and Coverage in the 100 Largest Stocks Traded on the Toronto Stock Exchange

Broker	Mean Brokerage \$ Volume	Mean Brokerage-Firm Market Share	Number of Analysts	Number of Stocks Covered	Number of Forecasts in Sample
Barclay De Zoete Wedd	53,767	1.45	9	58	75
Bunting Warburg	107,653	1.96	13	66	2
Burns Fry	538,074	9.64	22	97	160
First Marathon	511,725	6.43	6	41	67
Goepel Shields	25,471	0.46	6	32	9
Levesque Beaubien	111,949	3.61	11	63	145
Loewen Ondaatje	94,882	1.70	7	37	52
Majendie	61,268	1.39	5	40	1
Marleau Lemire	30,385	0.68	13	1	2
Midland Walwyn Capital	270,449	6.00	12	57	45
Research Capital	23,335	0.67	6	43	32
Richardson Greenshields	311,801	5.48	14	81	155
Sanwa McCarthy	18,089	0.49	9	35	18
ScotiaMcLeod	401,223	6.17	15	77	10
Wood Gundy	503,131	8.62	13	82	62

Mean Brokerage \$ Volume = the average daily C\$ share volume per stock traded by the brokerage;
Mean Brokerage-Firm Market Share = the brokerage's average daily *MKT_SHARE* per stock for the 100 largest stocks trades on the Toronto Stock Exchange. The daily *MKT_SHARE* of brokerage firm *j* in stock *k* is the total volume traded by brokerage firm *j* in stock *k* on day *i*, divided by the total volume in stock *k* on day *i*;
Number of Analysts = the total number of sell-side analysts the brokerage firm employs;
Number of Stocks Covered = the number of stocks in the sample the brokerage-firm covers. I determine stock coverage from information the brokerages provide to *Nelson's Directory of Investment Research* (1994); and
Number of Forecasts in Sample = the number of distinct earnings forecasts and recommendations pairs reported in the I/B/E/S International detailed earnings forecast and recommendation databases.

¹⁰ Discount brokers, institutional dealers, and full-service brokers who did not report new forecasts to I/B/E/S during the sample period execute the remaining trades.

¹¹ Stock coverage information comes from the 1994 *Nelson's Directory of Investment Research*, International Edition.

commission revenue available to support a research department. One brokerage firm covers just one sample stock, concentrating instead on small- and mid-cap stocks.

Event Windows

The statistical tests examine four event windows surrounding the release of the forecast:

1. Days -10 through -6 relative to the forecast date
2. Days -5 through -1 relative to the forecast date
3. Days 0 through +5 relative to the forecast date
4. Days +6 through +10 relative to the forecast date.

Discussions with analysts and research directors suggest that a two-week trading window likely captures the immediate effect of analysts' forecasts on investors' trading decisions. I examine period 2, days -5 through -1 relative to the forecast date, because analysts' forecasts could stimulate trading flow through their brokerages in this period if analysts release their forecasts to their best customers before they release them to I/B/E/S. Period 1, days -10 through -6, is a control period when no relation between *ABSDEV* and brokerage-firm trading should exist. Brokerage-firm market share should not be related to analysts' forecasts until the forecast has been prepared and released.

Key Independent Variables

Table 2 presents summary statistics for the 835 analysts' forecasts in the I/B/E/S sample. The price-deflated absolute deviation between the forecast and consensus (*ABSDEV*), and the BKLS measure of uncertainty (*UNCERTAINTY*) are defined above. Mean Market Share, which measures *MKT_SHARE* over all 252 trading days for the unique

TABLE 2
Summary Statistics for 835 I/B/E/S Analysts' Forecasts on 96 Sample Stocks

<u>Variable</u>	<u>Mean</u>	<u>Median</u>	<u>Skewness</u>	<u>Standard Deviation</u>
<i>MARKET SHARE</i>	5.71%	4.31%	1.59	4.74%
<i>ABSDEV</i>	0.69%	0.29%	3.15	1.08%
<i>UNCERTAINTY</i>	0.18	0.04	3.82	0.40
<i>COVERAGE</i>	11.86	11	1.29	5.45
<i>SIZE</i>	2,766	1,599	2.24	2,894
<i>PRICE</i>	25.53	21.97	1.60	13.94

MARKET SHARE = Market Share is $MKT_SHARE_{j,i}^k$ from Equation (7) averaged first over time i for each of the 428 unique brokerage firm-stock $\{j, k\}$ pairs in the sample, then across the brokerage firm-stock pairs;

ABSDEV = the absolute value of the difference between the analyst's fiscal year one earnings forecast and the consensus forecast all divided by the stock price on the forecast date;

UNCERTAINTY = the Barron et al. (1998) measure of uncertainty = $\left(1 - \frac{1}{N}\right) D + SE$, in C\$ per share squared.

N is the number of forecasts, D is the sample variance of analyst's forecasts, and SE is the sample squared error in the consensus forecast;

COVERAGE = the total number of fiscal year one analysts' forecasts reported to I/B/E/S in the month preceding the each stock's initial sample forecast;

SIZE = year-end 1993 market value of the 96 stocks in the sample, in C\$ millions; and

PRICE = a stock's initial forecast date stock price in C\$.

brokerage firm-stock combinations in the sample is 5.71 percent.¹² Mean Market Share reflects the average trading activity of the sample brokerage firms in the forecast stocks. Mean *ABSDEV* is 0.69 percent. Untabulated analyses reveal that the mean (median) absolute difference between the fiscal year one forecast and the consensus forecast is C\$0.14 (\$0.07). Four hundred thirty forecasts are above the consensus forecast, 374 are below, and 31 are equal to the consensus. Mean *UNCERTAINTY* is C\$0.18 per share squared, though the median is much lower (0.04).¹³ The average analyst coverage per stock (*COVERAGE*) is just under 12, the average stock market capitalization per stock (*SIZE*) is just under C\$2.8 billion, and the average share price is C\$25.53. *ABSDEV* is significantly correlated with *UNCERTAINTY* ($\rho = 0.422$), which reflects the fact that forecast dispersion is a component of the BKLS uncertainty measure. This significant correlation between two regressors indicates the need for collinearity diagnostic tests on the regression results.

IV. EMPIRICAL TESTS

Using data from each of the event windows described above, Table 3 presents the results of estimating the following regression:

$$\begin{aligned} \text{SUMSHARE} = & \alpha + \beta_1 \text{ABSDEV} + \beta_2 \text{UNCERTAINTY} \\ & + \sum_{j=3}^7 \beta_j \text{INDDUMMY}_j + \varepsilon_i. \end{aligned} \quad (8)$$

The dependent variable, *SUMSHARE*, is the sum of daily broker *MKT_SHARE* in the stock over the days in each event window. In addition to *ABSDEV* and *UNCERTAINTY*, Equation (8) includes five broad industry classification dummy variables first used by Bhushan (1989a, 1989b): *MINING* (two-digit SIC codes 10–14), *MANUFACTURE* (two-digit SIC codes 15–39), *UTILITY* (two-digit SIC codes 40–49), *TRADE* (two-digit SIC codes 50–59), and *FINANCIAL* (two digit SIC codes 60–67). The impact of a sixth group, the *SERVICES* industry (two-digit SIC codes 70–96), emerges implicitly in the intercept term. These variables effectively control for heteroscedasticity related to the fact that utilities tend to have higher average *SUMSHARE*s. When I include the industry dummy variables in the regression, the results fail to reject the null hypothesis of no heteroscedasticity using White's (1980) test.¹⁴

If the deviation between an analyst's earnings forecast and the consensus forecast affects investors' trading demands, then H1 predicts that the coefficient on *ABSDEV* should be positive. Hypothesis 2 predicts that investors' trading demands are inversely related to the total uncertainty of the forecast. Thus, I expect the coefficient on *UNCERTAINTY* to be negative.

Analysts' Forecasts and their Brokerage's Share of Trading: Testing H1 and H2

Table 3 presents OLS estimates of Equation (8).¹⁵ Overall, the results suggest that analysts' earnings forecasts can significantly increase their brokerage-firm's share of trading

¹² Equation (7) shows how to calculate $MKT_SHARE_{j,i}^k$ for each day i , brokerage firm j , and stock k . Mean Market Share is $MKT_SHARE_{j,i}^k$, averaged first over time for each of the 428 unique brokerage firm-stock $\{j, k\}$ pairs in the sample, then across the brokerage firm-stock pairs.

¹³ The units of the square root of the BKLS *UNCERTAINTY* measure are cents per share.

¹⁴ Excluding the industry dummy variables from the regression does not significantly affect any of the study's inferences.

¹⁵ The sample size in the day +6 through +10 period is 829 because analysts issue six forecasts in the last week of the sample year. These forecasts' event days +6 through +10 lie outside the sample period.

TABLE 3
The Effects of the Deviation of Analysts' Earnings Forecasts from Consensus and Total Forecast Uncertainty on Brokerage Market Share

Regression:

$$SUMSHARE = \alpha + \beta_1 ABSDEV + \beta_2 UNCERTAINTY + \sum_{j=3}^7 \beta_j INDDUMMY_j + \epsilon_i$$

Independent Variable	Dependent Variable		Dependent Variable		Dependent Variable	
	Broker Market Share -10 through -6	Broker Market Share -5 through -1	Broker Market Share in Event Days 0 through +5	Broker Market Share in Event Days +6 through +10	Broker Must Share in Event Days +6 through +10	Broker Must Share in Event Days +6 through +10
Intercept	0.23 (5.78)	0.28 (7.01)	0.32 (6.56)	0.32 (7.78)	0.32 (7.78)	0.32 (7.78)
ABSDEV	1.19 (0.96)	2.41 (1.97)	4.28 (2.68)	3.14 (2.42)	3.14 (2.42)	3.14 (2.42)
UNCERTAINTY	-0.03 (-0.89)	-0.05 (-1.29)	-0.07 (-1.73)	-0.09 (-2.59)	-0.09 (-2.59)	-0.09 (-2.59)
Control Variables						
MINING	0.03 (0.64)	-0.04 (-0.98)	-0.06 (-1.05)	-0.07 (-1.71)	-0.07 (-1.71)	-0.07 (-1.71)
MANUFACTURE	0.07 (1.31)	0.04 (0.67)	-0.02 (-0.24)	-0.10 (-1.98)	-0.10 (-1.98)	-0.10 (-1.98)
UTILITY	0.17 (2.65)	0.07 (1.03)	0.18 (2.21)	0.06 (0.84)	0.06 (0.84)	0.06 (0.84)
TRADE	0.02 (0.39)	-0.01 (-0.23)	0.08 (1.12)	-0.05 (-0.78)	-0.05 (-0.78)	-0.05 (-0.78)
FINANCIAL	0.05 (0.94)	-0.01 (-0.10)	0.04 (0.53)	-0.07 (-1.17)	-0.07 (-1.17)	-0.07 (-1.17)

(continued on next page)

TABLE 3 (continued)

R ²	1.22%	1.30%	2.65%	2.13%
Adjusted R ²	0.38%	0.48%	1.83%	1.31%
F-test p-value	0.11	0.22	0.01	0.11
n	835	835	835	829

t-statistics appear in parentheses. F-test p-values are for the joint test of whether the five industry dummy variable coefficients are equal to zero.

SUMSHARE = the sum total of daily brokerage-firm *MKT_SHARE* in the forecast stock in each event window;

ABSDEV = the absolute value of the difference between the analyst's fiscal year one earnings forecast and the consensus forecast, divided by the stock price on the forecast date;

UNCERTAINTY = the Barron et al. (1998) measure of uncertainty $\left(1 - \frac{1}{N}\right) D + SE$, in C\$ per share squared. *N* is the number of forecasts, *D* is the sample variance of analysts' forecasts, and *SE* is the sample squared error in the consensus forecast; and

INDDUMMY = *MINING*, *MANUFACTURE*, *UTILITY*, *TRADE*, and *FINANCIAL* sector dummy variables proposed by Bhushan (1989a, 1989b). The impact of the *SERVICES* industry is implicitly in the intercept term.

in the forecast stock. The more an analyst's forecast differs from the consensus forecast, the greater the broker's market share in the two weeks after forecast publication. Specifically, the coefficient on *ABSDEV* is positive and significant at the 0.05 level in the day -5 through -1 period and the day $+6$ through $+10$ period and is significant at the 0.01 level in the day 0 through $+5$ period. Finding that the deviation between an analyst's forecast and the consensus forecast is associated with the brokerage's share of trading in the stock over days -5 through -1 (before the forecast is released) is consistent with Brown et al. (1991), who find that analysts' clients can only trade profitably if clients receive analysts' forecasts prior to public release. I estimate the economic impact of forecast deviations from consensus by multiplying the coefficient on *ABSDEV* by its mean value (0.0069) and dividing by the number of days in the period. For example, the 4.28 coefficient on *ABSDEV* in the day 0 through $+5$ period represents an increase of 0.5 percent per day in brokerage market share, approximately a 10 percent increase in daily brokerage market share.

The significance of *ABSDEV* in the day -5 through day -1 period is not robust to excluding day -1 from the regression. This finding suggests either that analysts leak the contents of their reports one day before public release, or that some I/B/E/S forecast dates are one day late.

The coefficient on *UNCERTAINTY* is negative and significant at the 0.10 level over the day 0 through $+5$ period and at the 0.01 level over the day $+6$ through $+10$ period.¹⁶ The greater the Barron et al. (1998) measure of total uncertainty surrounding upcoming annual earnings, the less trade an analyst's forecast generates for her brokerage firm. Multiplying the coefficient on *UNCERTAINTY* over the day 0 to $+5$ period by the mean of *UNCERTAINTY* (0.18) and dividing by the number of days in the period shows that *UNCERTAINTY*, at its mean, decreases brokerage-firm market share by 0.2 percent per day. This result is consistent with the common theoretical prediction that magnitude of investors' trading is inversely associated with the level of uncertainty. Neither *ABSDEV* nor *UNCERTAINTY* is significant in the control period, days -10 to -6 . These regression results are consistent with H1 and H2.¹⁷ *ABSDEV* is associated with higher brokerage-firm market share, while *UNCERTAINTY* is associated with lower brokerage-firm market share in the two weeks after the forecast release date.¹⁸

Aggregate Effects and below Consensus Forecasts

Table 4 presents three regression results that extend our understanding of how analysts' forecasts affect brokerage-firm market share.

The first regression is a benchmark for the next two. The benchmark simply replicates the specification in Equation (8) using, as the dependent variable, the sum of a brokerage firm's daily *MKT_SHARE* in the forecast stock over event days 0 through $+10$. Consistent with Table 3, the coefficient on *ABSDEV* is significantly positive at the 0.01 level and the

¹⁶ To test whether the skewness in *UNCERTAINTY* affects the results, I estimate Equation (8) substituting $\ln UNCERTAINTY$ for *UNCERTAINTY*. Using $\ln UNCERTAINTY$ produces similar inferences.

¹⁷ Examination of the regression residuals indicates that intrafirm variation is small relative to interfirm variation. This finding raises the concern that correlation through time in firm-specific variables could affect the significance levels of the OLS t-statistics. I examine several alternative regression specifications that control for firm-specific time-series correlation including: generalized least squares, generalized method of moments, and Froot's (1989) model. These alternatives all produce larger t-statistics for *ABSDEV* and *UNCERTAINTY* than the OLS specification. Thus, the reported OLS test statistics are conservative.

¹⁸ Collinearity does not significantly affect these inferences. The largest condition index in the set of regressions is 11.0. The results are not unduly influenced by particular observations. Excluding observations with the ten highest Cook's D statistics does not significantly affect the inferences. An analysis of the DFFITS and DFBETA statistics (Belsley et al. 1980) confirms this finding.

TABLE 4
The Effects of Below-Consensus Forecasts and Analysts' Stock Recommendations on Their Brokerage's Market Share of Trading in the Forecast Stock

<i>Column 1:</i>	$SUMSHARE = \alpha + \beta_1 ABSDEV + \beta_2 UNCERTAINTY + \sum_{j=3}^7 \beta_j INDDUMMY_j + \epsilon_i$																																						
<i>Column 2:</i>	$SUMSHARE = \alpha + \beta_1 ABSDEV + \beta_2 UNCERTAINTY + \beta_3 ABSDEV \times NEG + \sum_{j=4}^8 \beta_j INDDUMMY_j + \epsilon_i$																																						
<i>Column 3:</i>	$SUMSHARE = \alpha + \beta_1 ABSDEV + \beta_2 UNCERTAINTY + \beta_3 BUY + \beta_4 SELL + \sum_{j=5}^9 \beta_j INDDUMMY_j + \epsilon_i$																																						
		<table border="1"> <thead> <tr> <th style="text-align: left;">Dependent Variable</th> <th style="text-align: left;">Broker Market Share in Event Days 0 through +10</th> </tr> </thead> <tbody> <tr> <td>Intercept</td> <td>0.61 (5.60)</td> </tr> <tr> <td>ABSDEV</td> <td>7.92 (3.06)</td> </tr> <tr> <td>UNCERTAIN</td> <td>-0.17 (-2.45)</td> </tr> <tr> <td>ABSDEV × NEG</td> <td></td> </tr> <tr> <td>BUY</td> <td></td> </tr> <tr> <td>SELL</td> <td></td> </tr> <tr> <td>Control Variables</td> <td></td> </tr> <tr> <td>MINING</td> <td>-0.14 (-1.60)</td> </tr> </tbody> </table>	Dependent Variable	Broker Market Share in Event Days 0 through +10	Intercept	0.61 (5.60)	ABSDEV	7.92 (3.06)	UNCERTAIN	-0.17 (-2.45)	ABSDEV × NEG		BUY		SELL		Control Variables		MINING	-0.14 (-1.60)	<table border="1"> <thead> <tr> <th style="text-align: left;">Dependent Variable</th> <th style="text-align: left;">Broker Market Share in Event Days 0 through +10</th> </tr> </thead> <tbody> <tr> <td>Intercept</td> <td>0.41 (3.59)</td> </tr> <tr> <td>ABSDEV</td> <td>6.38 (2.49)</td> </tr> <tr> <td>UNCERTAIN</td> <td>-0.13 (-1.98)</td> </tr> <tr> <td>ABSDEV × NEG</td> <td></td> </tr> <tr> <td>BUY</td> <td></td> </tr> <tr> <td>SELL</td> <td></td> </tr> <tr> <td>Control Variables</td> <td></td> </tr> <tr> <td>MINING</td> <td>-0.08 (-0.92)</td> </tr> </tbody> </table>	Dependent Variable	Broker Market Share in Event Days 0 through +10	Intercept	0.41 (3.59)	ABSDEV	6.38 (2.49)	UNCERTAIN	-0.13 (-1.98)	ABSDEV × NEG		BUY		SELL		Control Variables		MINING	-0.08 (-0.92)
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TABLE 4 (continued)

MANUFACTURE	0.11 (-1.10)	-0.11 (-1.11)	-0.11 (-1.13)
UTILITY	0.26 (1.90)	0.26 (1.89)	0.30 (2.25)
TRADE	0.04 (0.39)	-0.05 (0.40)	0.07 (0.58)
FINANCIAL	-0.01 (-0.09)	-0.01 (-0.06)	-0.01 (-0.10)
R ²	2.91%	2.93%	6.30%
Adjusted R ²	1.85	1.75%	5.05%
F-test p-value			0.001
n	835	835	835

t-statistics appear in parentheses. The F-test p-value is for the test that the BUY coefficient and the SELL coefficient are equal.

SUMSHARE = the sum total of daily brokerage-firm MKT_SHARE in the forecast stock in event days 0 through +10;

ABSDEV = the absolute value of the difference between the analyst's fiscal year one earnings forecast and the consensus forecast all divided by the stock price on the forecast date;

UNCERTAINTY = the Barron et al. (1998) measure of uncertainty = $\left(1 - \frac{1}{N}\right) D + SE$, in C\$ per share squared. N is the number of forecasts, D is the sample variance of analysts' forecasts, and SE is the sample squared error in the consensus forecast;

ABSDEV × NEG = is equal to ABSDEV if the analyst's forecast is below the consensus, and 0 otherwise;

BUY = a dummy variable set to 1 if the analyst's recommendation is a buy or a strong buy;

SELL = a dummy variable set to 1 if the analyst's recommendation is a sell or a strong sell; and

INDDUMMY = MINING, MANUFACTURE, UTILITY, TRADE, and FINANCIAL sector dummy variables proposed by Bhushan (1989a, 1989b). The impact of the SERVICES industry is implicitly in the intercept term.

coefficient on *UNCERTAINTY* is significantly negative at the 0.05 level. Thus, the distance of the individual forecast from consensus, and Barron et al. (1998) uncertainty, are significant determinants of brokerage market share in the two weeks after I/B/E/S receives the forecast.¹⁹

The second column of Table 4 tests whether a positive difference between an analyst's forecast and the consensus generates more trading than a negative difference of the same magnitude. Equation (9a) includes the variable $ABSDEV \times NEG$, which estimates the slope shift in *ABSDEV* if the analyst's forecast is below the consensus. Hypothesis 3 predicts that analysts' forecasts that are below the consensus forecast have less effect on trading because short-sale constraints prevent many investors from trading on the negative information in these forecasts. Thus, H3 suggests the coefficient on $ABSDEV \times NEG$ will be negative.

$$SUMSHARE = \alpha + \beta_1 ABSDEV + \beta_2 UNCERTAINTY + \beta_3 ABSDEV \times NEG + \sum_{j=4}^8 \beta_j INDDUMMY_j + \varepsilon_i \quad (9a)$$

The second column in Table 4, however, shows that the coefficient on $ABSDEV \times NEG$ is not statistically significant.²⁰ Thus, my results are inconsistent with H3, which predicts an asymmetry between the effects of forecasts above the consensus and forecasts below the consensus. This finding is inconsistent with Hayes' (1998) argument that analysts have weaker trading incentives to gather information on stocks they view negatively.

Analysts' Forecasts, Stock Recommendations, and Brokerage-Firm Market Share

Equation (9b) examines whether H1 and H2 hold after controlling for analysts' contemporaneous buy and sell recommendations.

$$SUMSHARE = \alpha + \beta_1 ABSDEV + \beta_2 UNCERTAINTY + \beta_3 BUY + \beta_4 SELL + \sum_{j=5}^9 \beta_j INDDUMMY_j + \varepsilon_i \quad (9b)$$

BUY is a dummy variable set to 1 if the analyst's recommendation is a buy or strong buy. *SELL* is a dummy variable set to 1 if the analyst's recommendation is a sell or strong sell. There are 490 buy or strong buy recommendations in the sample and 82 sell or strong sell recommendations.

The third column in Table 4 presents the results of estimating Equation (9b). H1 and H2 still hold after controlling for analysts' stock recommendations. The coefficient on *ABSDEV* is positive (p-value < 0.01), and the coefficient on *UNCERTAINTY* is negative (p-value < 0.05). Given that the coefficient on *ABSDEV* is 6.38, at the mean (0.0069) *ABSDEV* increases market share by 0.4 percent per day.

Analysts' stock recommendations also produce a significant impact on brokerage-firm trading in the forecast stock. The 0.26 coefficient on *BUY* is significant at the 0.01 level

¹⁹ Including *MKT_SHARE* on event day -1 in the dependent variable does not affect the results.

²⁰ In Hayes' (1998) framework, investors are only affected by short sale constraints when analysts forecast a large negative deviation from consensus. To test the robustness of my result, I examine whether large negative deviations from consensus (rather than all negative deviations from consensus), generate a slope shift in *ABSDEV*. In alternative specifications, I used the 25th, 10th, and 5th percentiles of the forecast deviation from consensus to define $ABSDEV \times NEG$. In every case, the coefficient on $ABSDEV \times NEG$ is insignificant.

and indicates that, over the day 0 through +10 period, buy recommendations generate approximately 2.4 percent per day higher market share in the recommended stock than do hold recommendations, whose effects are implicit in the intercept. The coefficient on *SELL* is not significant, so sell recommendations do not generate significantly more trading than hold recommendations. However, an F-test of the equality of the *BUY* and *SELL* coefficients is rejected (p -value < 0.01). This result shows that the analyst's recommendation choice significantly affects brokerage market share in the stock in the two weeks after the forecast is released. Thus, both positive stock recommendations and earnings forecasts that deviate from the consensus can significantly increase brokerage-firm market share in the forecast stock. This finding is consistent with Francis and Soffer's (1997) conclusion that analysts' forecasts and recommendations both contain distinct price-relevant information.

The difference between the effects of *BUY* and *SELL* recommendations on trades flowing through the analyst's broker is large, relative to the effects of deviations from the consensus forecast, *ABSDEV*. Thus, analysts can generate higher trading commissions through positive recommendations than with earnings forecasts that deviate from the consensus.

Analysts' Stock Recommendations and Buy-Side versus Sell-Side Broker Market Share

The TSE data show whether the broker was on the buy-side or the sell-side of a trade. Thus, I calculate each brokerage's daily buy-side *MKT_SHARE* from Equation (7), though using only stock *purchases* in the forecast stock. I calculate each brokerage's daily sell-side *MKT_SHARE* from Equation (7), though using only stock *sales* in the forecast stock. Then I test whether analysts' forecasts, recommendations, and recommendation changes affect the amount of buy and sell trading that flows through the analyst's brokerage firm in the two weeks after publication of the analyst's forecast. The dependent variable in Equation (10a), *SUMBUY*, is the brokerage's buy-side *MKT_SHARE* aggregated over the day 0 through +10 period. In Equation (10b) the dependent variable, *SUMSELL*, is the brokerage's sell-side *MKT_SHARE* aggregated over the day 0 through +10 period:

$$\begin{aligned} \text{SUMBUY} = & \alpha + \beta_1 \text{ABSDEV} + \beta_2 \text{UNCERTAINTY} + \beta_3 \text{BUY} + \beta_4 \text{SELL} \\ & + \beta_5 \text{UPTOBUY} + \beta_6 \text{DOWNTOSELL} + \sum_{j=7}^{11} \beta_j \text{INDDUMMY}_j \\ & + \epsilon_i. \end{aligned} \quad (10a)$$

$$\begin{aligned} \text{SUMSELL} = & \alpha + \beta_1 \text{ABSDEV} + \beta_2 \text{UNCERTAINTY} + \beta_3 \text{BUY} + \beta_4 \text{SELL} \\ & + \beta_5 \text{UPTOBUY} + \beta_6 \text{DOWNTOSELL} + \sum_{j=7}^{11} \beta_j \text{INDDUMMY}_j \\ & + \epsilon_i. \end{aligned} \quad (10b)$$

Equations (10a) and (10b) include dummy variables for the stock recommendation levels (*BUY* and *SELL*) and dummy variables for recommendation upgrades and downgrades. *UPTOBUY* is a dummy variable that equals 1 if the recommendation is an upgrade to strong buy ($n = 107$). *DOWNTOSELL* is a dummy variable that equals 1 if the recommendation is a downgrade to sell or strong sell ($n = 20$).²¹

²¹ The results are similar if *UPTOBUY* includes upgrades to buy as well as strong buy ($n = 129$) or if *DOWNTOSELL* includes downgrades to hold, as well as sell and strong sell ($n = 68$).

Table 5 presents the results of estimating Equations (10a) and (10b). My key finding is that analyst's earnings forecasts and recommendations have similar effects on both purchases and sales flowing through the analyst's brokerage firm.

First, after including all of the recommendation variables, analysts' forecasts are still important determinants of brokerage market share. In the *SUMBUY* regression, the coefficient on *ABSDEV* is positive (p-value = 0.05), while the coefficient on *UNCERTAINTY* is negative (p-value = 0.07). In the *SUMSELL* regression, the coefficient on *ABSDEV* is positive (p-value = 0.01), while the coefficient on *UNCERTAINTY* is negative (p-value = 0.22). *ABSDEV* and *UNCERTAINTY* are jointly significant in the *SUMBUY* regression (p-value = 0.07) and in the *SUMSELL* regression (p-value = 0.02). Second, the coefficient on *BUY* is positive and significant (p-value < 0.01) in both regressions, and a t-test fails to reject the null hypothesis that the coefficients are equal (p-value = 0.48).²² Analysts' buy recommendations generate more buy-side market share through the analysts' brokerage firm than do other recommendations, but they also generate more sell-side market share. Conversations with institutional money managers reveal that managers often use the liquidity associated with buy recommendations to sell when they want to rebalance their portfolios. Thus, analysts' buy recommendations generate increased commissions from both client buying and client selling. The dummy variables for upgrades to strong buy and downgrades to sell are jointly insignificant in both the *SUMBUY* regression (p-value = 0.49) and the *SUMSELL* regression (p-value = 0.15). However, the coefficient on *UPTOBUY* is negative and marginally significant (p-value = 0.10) in the *SUMSELL* regression, suggesting that upgrades to strong buy generate less selling activity than do other buy recommendations.

Together, the results in Tables 3, 4, and 5 show that both the distance of analysts' forecasts from the consensus and analysts' buy recommendations significantly increase their brokerage-firms' buying and selling activity in the forecast stock.²³

The Effect of Analysts' Forecast Errors on their Brokerage's Market Share

Finally, I examine whether larger forecast errors (i.e., the difference between an analyst's forecast and I/B/E/S actual earnings) increase the brokerage's share of trading in the forecast stock. Evidence that a larger *ABSDEV* increases the brokerage's share of trading in the forecast stock raises the question whether analysts could increase their commission-related compensation by intentionally adding error to their forecasts to increase the distance between their forecast and the consensus. I cannot directly observe whether analysts add error to their forecasts to generate trading, but I can observe *ex post* forecast errors and examine whether forecast errors generate trading through the analysts' employer.

Table 6 examines whether an analyst's *FORECAST ERROR* is related to her brokerage-firm's market share of trading in the forecast stock. *FORECAST ERROR* is defined as the

²² The fact that the *BUY* coefficients are conditioned on the same information (i.e., the independent variables are identical in both regressions) allows me to construct a difference-in-means test using the estimated coefficients and standard errors from Equations (10a) and (10b).

²³ Do buy recommendations increase brokerage-firm trading, or do analysts issue buy recommendations on stocks their brokerage-firms trade heavily? The event-study research design in the paper is limited in its ability to answer this question. In untabulated tests, I examine brokerage-firm trading in the period before the analyst's forecast is released, event days -10 through -2. I find that average daily *MKT_SHARE* for both buy and sell recommendations is significantly lower in the prior period than in the period from event day 0 through +10 (p-value < 0.01), and that *MKT_SHARE* for favorable (buy and strong buy) recommendation is insignificantly different than for unfavorable (hold, sell, or strong sell) recommendations (p-value = 0.16). These results suggest that analysts' recommendations cause brokerage-firm trading to increase. However, a full examination of the direction of causality is left for future work.

TABLE 5
The Effect of Analysts' Stock Recommendation Upgrades and Downgrades on Their Brokerage's Market Share of Buy and Sell Trading

Column 1:

$$SUMBUY = \alpha + \beta_1 ABSDEV + \beta_2 UNCERTAINTY + \beta_3 BUY + \beta_4 SELL + \beta_5 UPTOBUY + \beta_6 DOWNTOSELL + \sum_{j=7}^{11} \beta_j INDDUMMY_j + \epsilon_i$$

Column 2:

$$SUMSELL = \alpha + \beta_1 ABSDEV + \beta_2 UNCERTAINTY + \beta_3 BUY + \beta_4 SELL + \beta_5 UPTOBUY + \beta_6 DOWNTOSELL + \sum_{j=7}^{11} \beta_j INDDUMMY_j + \epsilon_i$$

Independent Variable	Dependent Variable	Dependent Variable
	<i>SUMBUY</i> , Broker Buy-Side Market Share in Event Days 0 through +10	<i>SUMSELL</i> , Broker Sell-Side Market Share in Event Days 0 through +10
Intercept	0.49 (4.87)	0.49 (5.33)
<i>ABSDEV</i>	5.57 (1.93)	7.40 (2.74)
<i>UNCERTAINTY</i>	-0.13 (-1.87)	-0.09 (-1.23)
<i>BUY</i>	0.33 (4.95)	0.26 (4.26)
<i>SELL</i>	-0.02 (-0.18)	-0.07 (-0.65)
<i>UPTOBUY</i>	-0.02 (-0.20)	-0.14 (-1.71)
<i>DOWNTOSELL</i>	-0.24 (-1.18)	-0.18 (-0.93)
R ²	6.20%	6.35%
Adjusted R ²	4.95%	5.10%
n	835	835

t-statistics appear in parentheses.

SUMBUY = the sum total of daily brokerage-firm buy-side *MKT_SHARE* traded in event days 0 through +10;

SUMSELL = the sum total of daily brokerage-firm sell-side *MKT_SHARE* traded in event days 0 through +10;

ABSDEV = the absolute value of the difference between the analyst's fiscal year one earnings forecast and the consensus forecast, divided by the stock price on the forecast date;

UNCERTAINTY = the Barron et al. (1998) measure of uncertainty = $\left(1 - \frac{1}{N}\right) D + SE$, in C\$ per share squared.

N is the number of forecasts, *D* is the sample variance of analysts' forecasts, and *SE* is the sample squared error in the consensus forecast;

BUY = a dummy variable set to 1 if the analyst's recommendation is a buy or a strong buy;

SELL = a dummy variable set to 1 if the analyst's recommendation is a sell or a strong sell;

UPTOBUY = a dummy variable set to 1 if the analyst's recommendation is an upgrade to strong buy;

DOWNTOSELL = a dummy variable set to 1 if the analyst's recommendation is a downgrade to sell or strong sell; and

INDDUMMY = *MINING*, *MANUFACTURE*, *UTILITY*, *TRADE*, and *FINANCIAL* sector dummy variables are included in the regression specification, but for clarity, they are not tabulated.

TABLE 6
The Effects of Analysts' Forecast Errors and Stock Recommendations on Their Brokerage's Market Share of Trading in the Forecast Stock

Regression:

$$SUMSHARE = \alpha + \beta_1 FORECAST \ ERROR + \beta_2 BUY + \beta_3 SELL + \sum_{j=4}^8 \beta_j INDDUMMY_j + \epsilon_i$$

<u>Dependent Variable</u>	<u>Independent Variable</u> <u>Broker Market Share in Event</u> <u>Days 0 through +10</u>
Intercept	0.51 (5.71)
<i>FORECAST ERROR</i>	-2.14 (-1.64)
<i>BUY</i>	0.27 4.91)
<i>SELL</i>	-0.09 (-1.04)
R ²	5.71%
Adjusted R ²	4.80%
n	835

t-statistics appear reported in parentheses.

SUMSHARE = the sum total of daily brokerage-firm *MKT_SHARE* in the forecast stock in event days 0 through +10;

FORECAST ERROR = absolute value of: the analyst's fiscal year one earnings forecast less the I/B/E/S reported actual fiscal year one earnings per share, divided by the price on the forecast date; and

INDDUMMY = the *MINING*, *MANUFACTURE*, *UTILITY*, *TRADE*, and *FINANCIAL* industry dummy variables are included in the regression specification, but for clarity, they are not tabulated.

price-deflated absolute difference between the upcoming year's earnings forecast and the firm's actual earnings as reported on I/B/E/S. Equation (11) regresses *SUMSHARE*, calculated over the day 0 through +10 period, on *FORECAST ERROR*, *BUY*, and *SELL*. I include the recommendation dummy variables because buy recommendations increase brokerage-firm trading, and thus provide an alternative to biasing forecasts for an analyst who wishes to increase her trading-related compensation.

$$SUMSHARE = \alpha + \beta_1 FORECAST \ ERROR + \beta_2 BUY + \beta_3 SELL + \sum_{j=4}^8 \beta_j INDDUMMY_j + \epsilon_i \quad (11)$$

The results in Table 6 indicate that *MKT_SHARE* is not positively related to forecast error. Estimating Equation (11) shows that *FORECAST ERROR* is marginally *negatively* related to *SUMSHARE* (p-value = 0.10). This finding indicates that larger absolute forecast errors *reduce* the amount of trading that the analysts' brokerage-firm executes in the forecast stock. The coefficient on *BUY* is positive (p-value < 0.01). Thus, after controlling for forecast error, analysts' buy and strong buy recommendations still significantly increase their brokerage-firms' market share.

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The results in Table 6 suggest that biasing forecasts is unlikely to increase analysts' trading-related compensation. Thus, I interpret this result as suggesting that issuing buy and strong buy recommendations is a more effective way for analysts to increase their trading-related compensation than biasing their forecasts.^{24,25}

V. CONCLUSION

Using data on brokerage-firm trading from the Toronto Stock Exchange, I examine how analysts' earnings forecasts and their stock recommendations affect their employers' share of trading in the forecast stocks. Analysts' earnings forecasts can significantly increase brokerage-firm market share in the two weeks after the forecast release date. I find that: (1) consistent with Hayes (1998), the further an analyst's earnings forecast diverges from the consensus forecast, the greater the analyst's brokerage-firm's market share of trading, and (2) consistent with the common theoretical prediction that greater uncertainty about the accuracy of a forecast reduces investors' trading, the higher the total uncertainty surrounding the analyst's earnings forecast, the lower the analyst's brokerage-firm's market share of trading.

Contrary to Hayes' (1998) contention, I find that analysts' forecasts below the consensus forecast do not generate less trading commission revenue for the analysts' brokerage firms than do analysts' forecasts above the consensus. I also find no evidence that analysts can generate trade by adding error to their earnings forecasts. Forecast errors produce no significant effect on brokerage-firm market share. However, analysts' buy and strong buy recommendations generate significantly higher trading-commission revenue than other recommendations. I conclude that analysts are more likely to generate trading commissions for their employers by making favorable stock recommendations rather than by upward-biasing their earnings forecasts.

My study generates a set of empirical results that can guide refinements of theory on how trading incentives affect analysts' forecasts and recommendations. To reiterate, I find that analysts' forecasts and stock recommendations exert a significant effect on their brokerage-firms' market share of trading in the forecast stock. This result strengthens the link developed by McNichols and O'Brien (1997) and Hayes (1998) between analysts' actions and their trading-related compensation. Moreover, this result is consistent with Hayes' (1998) contention that the distance of an analyst's forecast from the consensus forecast predicts investors' trading. However, my results are inconsistent with Hayes' (1998) contention that analysts' forecasts below the consensus forecast generate less trading commission revenue than do analysts' forecasts above the consensus. Finally, I report the unpredicted result that analysts' buy recommendations increase both *buying* and *selling* market shares of trading through the analysts' brokerage-firms.

I cannot observe directly whether analysts are biasing their forecasts. As a result, my conclusion that trading incentives are unlikely to affect analysts' forecasts is based partly on the indirect evidence obtained from analyzing *ex post* forecast errors. Neither can I observe trading by investors who receive an analyst's earnings forecast or stock recommendation and choose to trade with a different brokerage-firm. Thus, my results should not be interpreted as representing the total effect of analysts' forecasts and recommendations on their investors' trading. Despite these limitations, my study establishes that investors

²⁴ I find similar results using *SUMBUY* or *SUMSELL* as the dependent variable in Equation (11).

²⁵ Including *ABSVAR* and *UNCERTAINTY* in the regression specification does not affect the inferences. If included in the regression, then the coefficient on *ABSVAR* is always significantly positive, but the coefficient on *UNCERTAINTY* is not significant. The insignificant coefficient on *UNCERTAINTY* is due to the correlation between *UNCERTAINTY* and *FORECAST ERROR*.

trade on the information in analysts' forecasts, and that analysts' favorable stock recommendations increase their employers' market share of trading in the recommended stock. Thus, my results suggest that, as long as the amount of trading done by their employers is a factor in analysts' compensation, then the potential for biased recommendations remains, even if regulators remove analysts' incentives to promote their firms' stock offerings by effectively separating research departments from underwriting departments.

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