Identifying Lead Analysts for Stock Selection

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A firm's expected and realized earnings play a dominant role in the investment decision-making process. It is thus not surprising that investors pay exceptionally close attention to analyst forecasts, with stock prices generally reacting immediately upon revisions to earnings estimates.

The advantage of using superior earnings forecasts for stock selection is well documented (see Herzberg [1998]; Herzberg, Guo, and Brown [1999]). We postulate that certain analysts are particularly influential. Herzberg [2000] proposes alternative methods of identifying influential analysts on an individual stock basis.

Our research compares these methodologies. We introduce a lead analyst model to determine the superior analysts, and provide backtest results that rely on their earnings estimate revisions.

IDENTIFYING INFLUENTIAL ANALYSTS

We use the First Call analyst detail data going back daily to January 1993 to develop methodologies to classify analysts according to their ability to influence stock price movement and the future direction of the consensus. A *lead analyst* for a particular stock is generally described as the first or at least very early on the scene in revising his or her estimates, thus clearly demonstrating a willingness to take risks in announcing forecasts. Our primary objective is to identify these analysts to determine the ones who are respected by the market and truly matter.

Respect is measured in several ways. Stock price reaction to the initial revision is examined in conjunction with subsequent revisions made by other analysts covering the stock. The analyst's skill in terms of forecast accuracy and persistence is also measured. Backtest results suggest that paying attention to such attributes of analysts can enhance stock selection.

Leading versus Following Moves

A crucial element in the analysis is to ascertain when analysts are revealing new information or when they are simply following in the direction of the consensus. A revision toward the consensus, but not beyond, is considered a *following* move. Conversely, moves that are not following by that definition are considered to be *leading.*

For example, if an analyst estimate is at 50 cents per share, and the consensus is at 60, a revision to between 51 and 60 is considered a following move. Revisions to 49 and below or to 61 and above would be considered leading moves.

Leading moves provide an advantage in stock selection because stock prices have not already had an opportunity to react to prior analyst revisions that at the time were leading.

Component Methodologies

We seek out analysts who, on an individual stock basis, tend to make leading moves; that is, revisions away from rather than toward the consensus. Bold or courageous moves are preferable to minor revisions with forecasts tested for accuracy relative to the other analysts. We measure analyst influence by the extent to which other analysts follow a revision, both in terms of direction and magnitude. Ultimately, it is important to gauge each analyst's impact on the stock's price, as well as the length of time that the price reaction persists.

Besides measuring their propensity to make leading moves, we also measure analysts by their skill in: courage, forecast accuracy, influence on other analysts, price reaction, and persistence. Using daily data, we develop algorithms to measure analyst skill for these characteristics, henceforth referred to as *component methodologies.*

We use the results from these algorithms to select analysts each calendar year as leaders in their particular category, and we then select stocks on that basis in the next year. That is, influential or "lead" analysts are selected as of the end of 1993 for stock selection in 1994, and so on. The end-point dates for the identification process are restricted in a manner that avoids any look-ahead bias.

Lead analysts are identified for the stocks in the S&P 1500 universe, and stock selection performance is measured for the prevailing S&P 500, midcap, and small-cap universes, again avoiding look-ahead bias in terms of index constituencies.

Courage. The *courage* measure quantifies the boldness or extent of change of an analyst's revisions for a given stock. Leading moves that are bold in scale are of special interest, since they may be adding important new information to the market.

Kahn and Rudd [1999, p. 7] suggest that "the consensus is contaminated by spurious analyst forecasts that have no information content." The courage algorithm, therefore, also uses means designed to distinguish rebels from true leaders who are adding useful information.

Forecast accuracy. The *forecast accuracy* algorithm measures the analyst's ability to forecast future earnings for the given stock. It is known that the use of more accurate earnings forecasts enhances stock selection performance (e.g., see Herzberg [1998] and Park and Stice [2000]). An analyst is considered more accurate in predictions than others if his or her forecast errors are on average smaller, and if the analyst is more frequently on the right side of the consensus as compared to peers.

Also taken into account is for how long estimates have superior accuracy; the longer, the better. Moreover, the algorithm is designed to give less credit to estimates of analysts who may only be following others and thus turn out to be more accurate. We rank all analysts according to their forecast accuracy skill for the given stock.

Influence. The *influence* algorithm measures the extent to which analysts follow another analyst subsequent to a revision. Trueman [1994] and Mozes and Williams [1999], among others, discuss herding or mimicking behavior in analyst forecasting. There are many reasons for strongly correlated behavior in analysts' earnings revisions. De Bondt and Forbes [1999] and Hong, Kubik, and Salomon [2000] suggest analysts are motivated to avoid regret out of concern for their reputations and careers. True leaders, on the other hand, have the wherewithal to distinguish themselves from other analysts rather than simply mimicking them.

In a sense, the influence algorithm measures the degree of confidence analysts have in one another. One would assume that on a stock-by-stock basis the analysts who cover a given company would be as well informed a group as any to provide judgment as to the quality of the estimates of their peers.

Price reaction and persistence. The *price reaction* algorithm measures the impact an analyst has on a given stock's price when an earnings revision is issued. Many stocks are associated with an "ax," that is to say, an analyst who can have a dramatic impact on the price of a particular stock (see Feinberg [1999]). Price reaction is measured in terms of excess returns relative to the stock's industry peer group. Thus, the stock's price is expected, on average, to increase compared to its peer group for upward revisions and to decline compared to the peer group for downward revisions.

These relative price movements are measured over different holding periods. The longer the price reaction is maintained (that is, its *persistence*), the more highly the analyst is regarded.

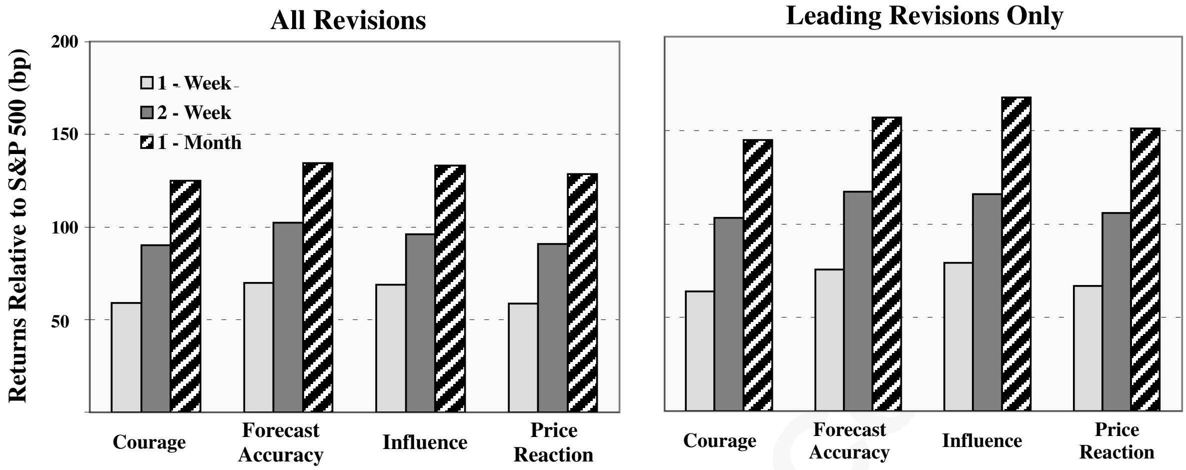
Thus, a strong price reaction in the days following a revision that fades over time is given less weight than a strong price reaction that persists or increases. Similarly, a price reaction accompanied by increased volume over historical norms is also preferable.

Lead Analyst Model

The lead analyst model ranks all the analysts for a given stock. Leaders who have one of the superior attributes often have one or more of the others as well. The

EXHIBIT 1

Average Excess Returns for S&P 1500 Stocks—Component Methodologies



component attributes are therefore aggregated to identify the truly superior leaders from a broader perspective.

Cooper, Day, and Lewis [2000] propose an alternative approach for determining leaders. They examine an analyst's relative timeliness and forecast accuracy (measured differently from our algorithm), as well as impact on trading volume.

Stock selection performance based on our lead analyst model appears to be in general superior to results based only on the individual component methodologies.

HISTORICAL PERFORMANCE

We test the efficacy of the lead analyst model using the S&P 1500 universe for the period 1994 to 2000. Long and short positions are established according to lead analyst revisions: long for upward revisions, and short for downward ones. Positions are initiated at the close of the same day for revisions time-stamped by 3:30 P.M.; otherwise, positions are taken at the close of the following day. No transaction costs are assumed. Total returns are computed for one-week, two-week, and monthly holding periods, and performance is measured according to average excess returns in basis points (bp) relative to the S&P 500.

Exhibit 1 displays average excess one-week, two-week, and monthly holding-period returns relative to the S&P 500 for each of the component methodologies; namely, courage, forecast accuracy, influence, and price reaction for the years 1994 through 2000. We show two sets of results: results achieved by acting on all the lead analyst revisions, and results achieved by acting only on their leading revisions.

It is noteworthy that there is a consistent monotonic pattern, with increasing returns for the one-week, two-week, and monthly holding periods. In the "all revisions" category, the component methodologies perform comparably. Average excess monthly holding returns are in a narrow range, from 125 bp for courage to 133 bp for influence. For the "leading revisions only" category, there is a more discernible difference in performance. Influence has the highest average excess returns relative to the S&P 500 of 168 bp. Courage again does least well, with an average excess monthly holding-period return of 145 bp.

The lead analyst model combines analyst scores from the component methodologies to identify a single lead analyst on a stock-by-stock basis for firms in the S&P 1500 universe. Average excess one-week, two-week, and monthly holding-period returns relative to the S&P 500 for the years 1994 through 2000 are displayed in Exhibit 2. We can see that the model is positive in all years for all three holding periods; the best returns are in the three most recent years of the study. For the entire period, the average excess returns of all transactions for the three holding periods of one week, two week, and monthly are 68, 96, and 151 bp, respectively, when acting on all lead analyst revisions.

When we act only on the leading moves made by these analysts (that is, only when the revisions are away from the consensus), the results, although similar, reveal an overall improvement. For the entire period, we obtain average excess returns of 80, 112, and 180 bp for the one-week, two-week, and monthly holding periods, respectively. Thus, the combination of the methodologies in the form of the lead analyst model produces better per-

EXHIBIT 2
Average Excess Returns for S&P 1500 Stocks—Lead Analyst Model

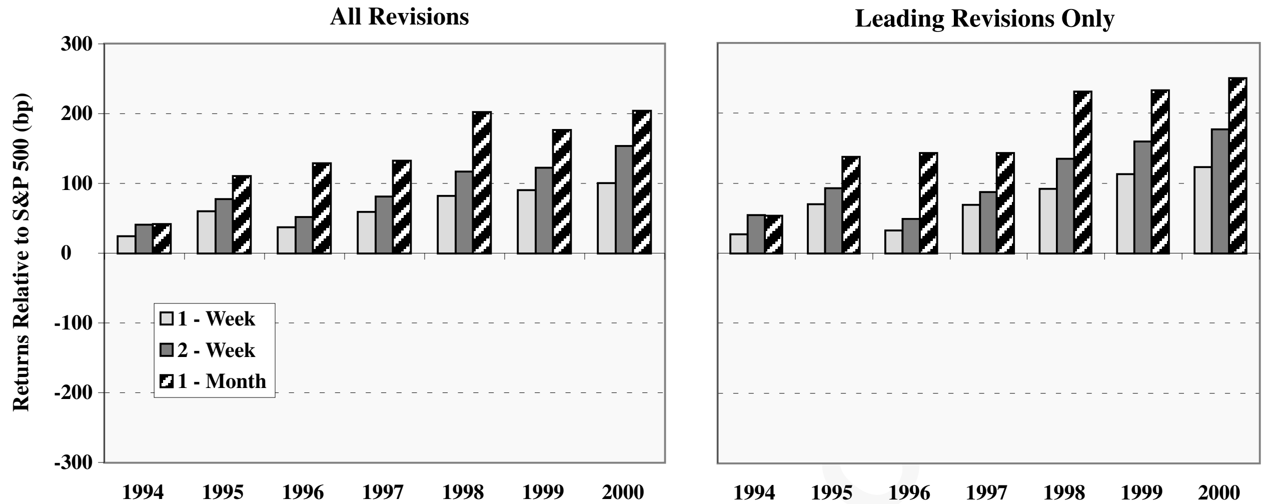
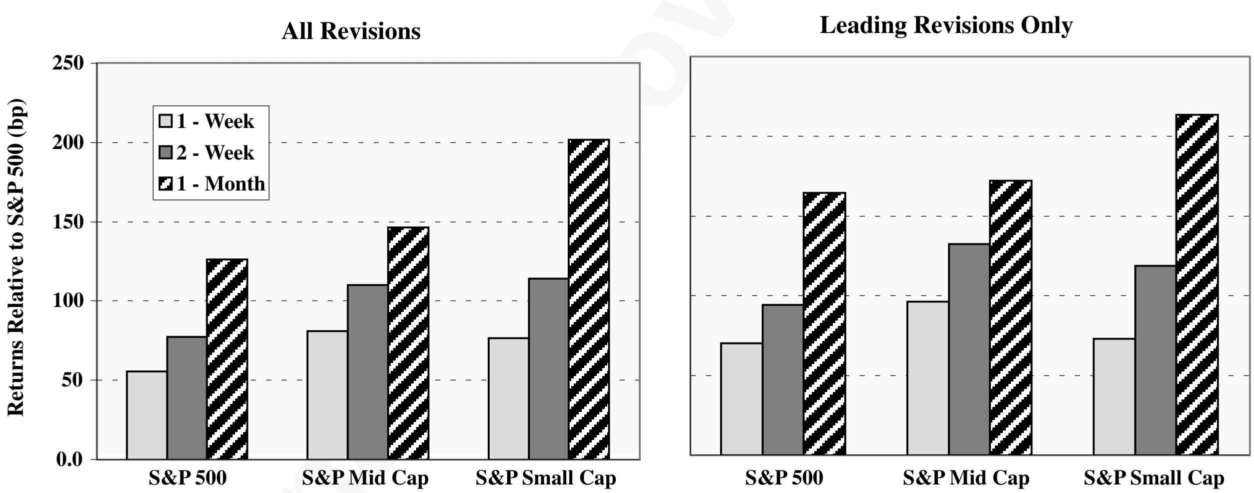


EXHIBIT 3
Average Excess Returns for S&P Universes—Lead Analyst Model



formance than any of the individual components.

Exhibit 3 displays the performance of the model for the three subsets of the S&P 1500 universe, that is, for the S&P 500, midcap, and small-cap universes. Here, too, leading revisions generally outperform all revisions, and the model shows better returns for small-caps than mid- or large-capitalization stocks. For leading moves only, the average excess monthly holding-period returns are 164, 172, and 212 bp for the S&P 500, midcap, and small-cap universes, respectively.

Exhibit 4 compares the performance of the component methodologies by sector for stocks in the S&P 1500 universe. By and large, for many of the sectors the component methodologies perform comparably, although for some sectors performance does vary.

For example, in the communications sector, influence performs very well, with an average excess return of 250 bp, while courage returns a negative 147 bp, and price reaction is also marginally negative relative to the S&P 500. Forecast accuracy is the best-performing component methodology for health care, with an average excess return of 234 bp, while courage performs least well, with a return of 34 bp.

Exhibit 5 shows that the lead analyst model works

EXHIBIT 4

Average Excess Monthly Returns for S&P 1500 Sectors—Component Methodologies—Leading Revisions Only

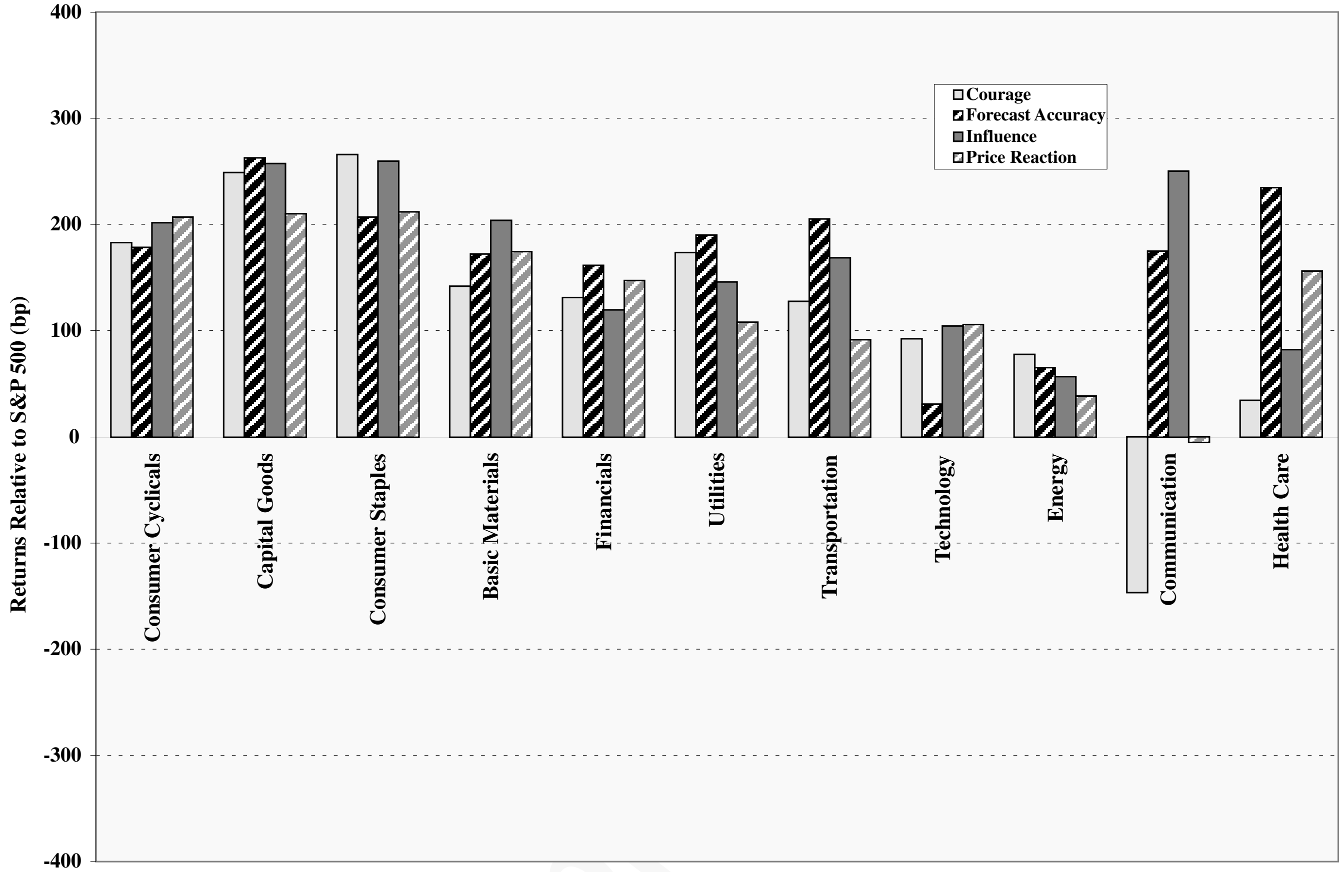


EXHIBIT 5

Average Excess Monthly Returns for S&P 1500 Sectors—Lead Analyst Model

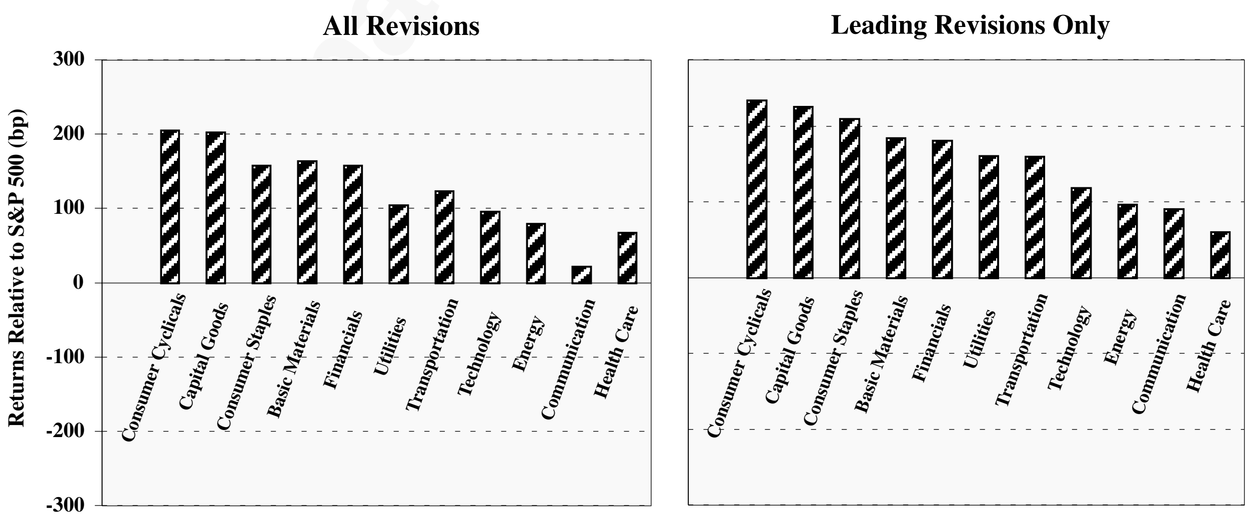


EXHIBIT 6

Average Excess Returns for S&P 500 Value and Growth Universes—Component Methodologies

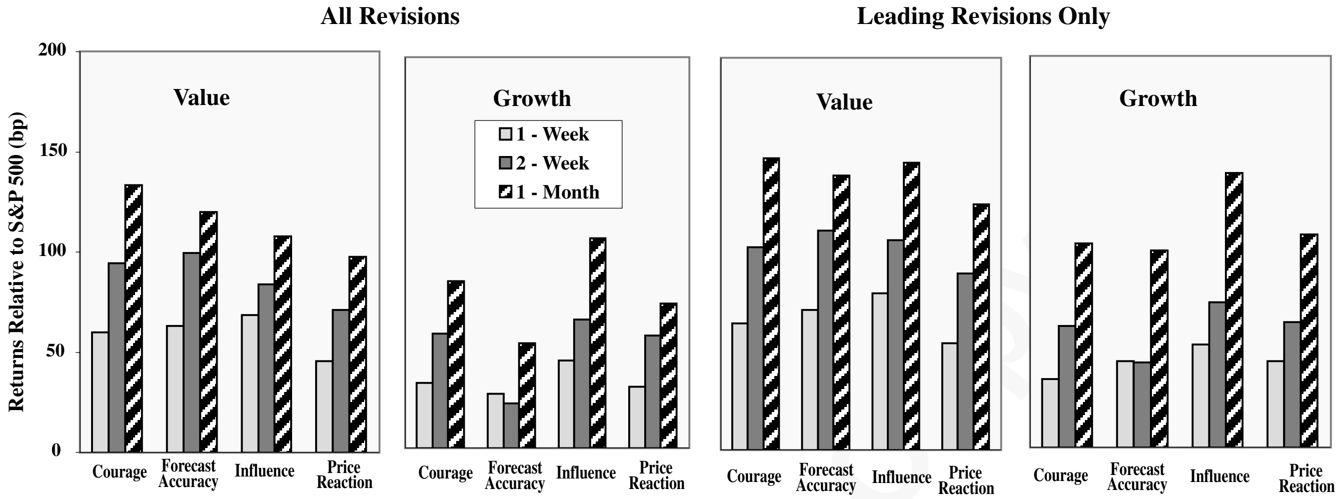
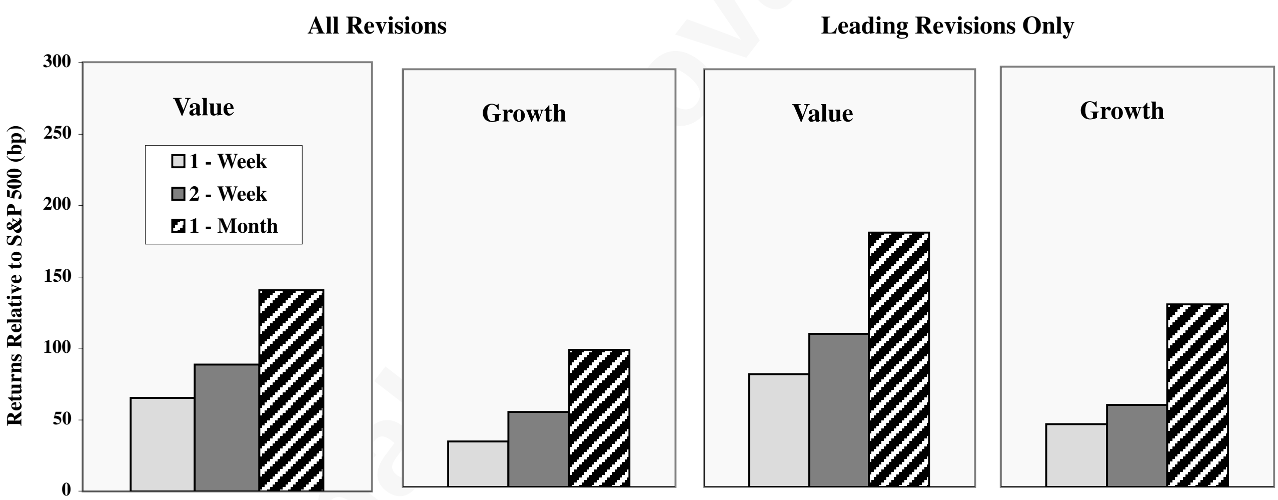


EXHIBIT 7

Average Excess Returns for S&P 500 Value and Growth Universes—Lead Analyst Model



best for consumer cyclicals (an average excess return of 233 bp) and least well for health care (return of 60 bp).

Performance of the component methodologies and the lead analyst model for value and growth stocks of the S&P 500 universe is compared in Exhibits 6 and 7. It is interesting to note that both the component methodologies and the lead analyst model achieve better average excess returns for value stocks than for growth stocks. Average excess monthly holding-period returns for value versus growth are 140 to 98 bp for all revisions and 183 to 130 bp for leading revisions only.

The difference in performance is lessened when we use leading revisions only. This might be explained by recognizing that, for growth stocks, it is especially important to be early with a revised forecast before the stock's price has had a chance to react. It is also noteworthy that, for value stocks, courage is the best-performing methodology of the components and price reaction the weakest.

Performance of the lead analyst model for upward and downward revisions separately is measured two ways. The results are displayed in Exhibit 8. The model generates average excess monthly holding returns of 199 bp for positions initiated by the upward revisions and 171 bp for the downward revision positions. On the other hand, the

EXHIBIT 8
Lead Analyst Model Performance for S&P 1500 Stocks—Leading Revisions Only

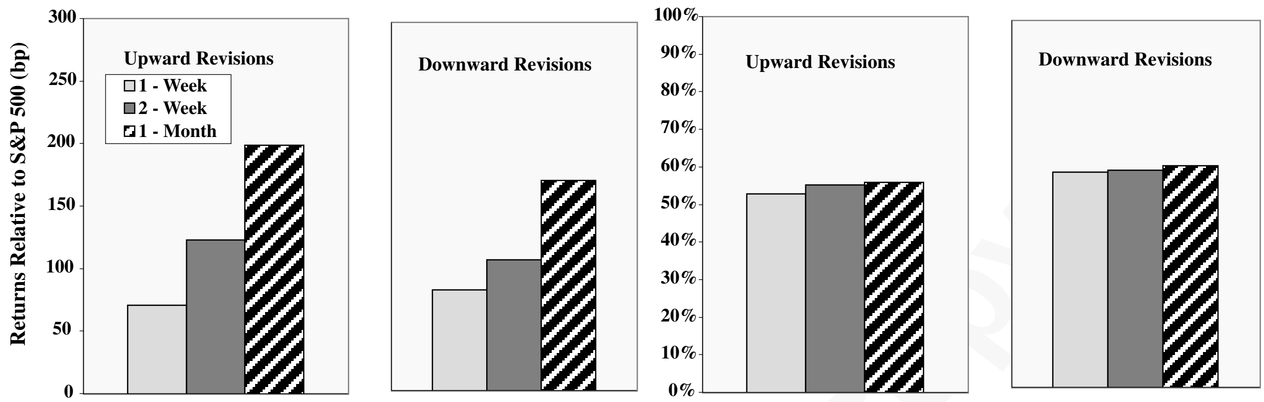


EXHIBIT 9
Percentage Commonality of Leading Analysts Across Methodologies for S&P 500 Universe

	Courage	Forecast Accuracy	Influence	Price Reaction	Lead Analyst Model
Courage	100.0	23.2	25.7	8.4	35.1
Forecast Accuracy	44.6	100.0	32.2	10.5	44.6
Influence	48.1	58.8	100.0	13.7	47.1
Price Reaction	21.7	25.3	30.9	100.0	38.3
Lead Analyst Model	56.2	74.9	72.2	67.2	100.0

Top Analyst

Top 2 Analysts

model is more frequently positive for downward revisions: 60.31% of the time for monthly holding positions, as compared to 55.95% for upward revisions.

Exhibit 9 displays the percentage commonality of leading analysts across methodologies for the S&P 500 universe. We observe that only 8.4% of the price reaction leaders also turn out to be the courage leaders. Of the component methodologies, forecast accuracy and influence leaders have the greatest commonality at 32.2%, which might suggest that the analysts to whom peers tend to pay attention and follow are the ones who rank highly in forecast accuracy for a given stock.

We also show the percentages that result by considering the number of stocks with at least one match between the two pairs of the top two ranked analysts. Here, too, price reaction and courage have the least overlap at 21.7%, and influence with forecast accuracy has the greatest overlap at 58.8%. Influence and courage are the component methodologies with the highest and lowest percentages, respectively, of their leaders turning into leaders as determined by the lead analyst model; 47.1% of influence leaders and 35.1% of courage leaders turn into lead analyst model leaders.

In the case of two leaders per category, the distinc-

Exhibit 10

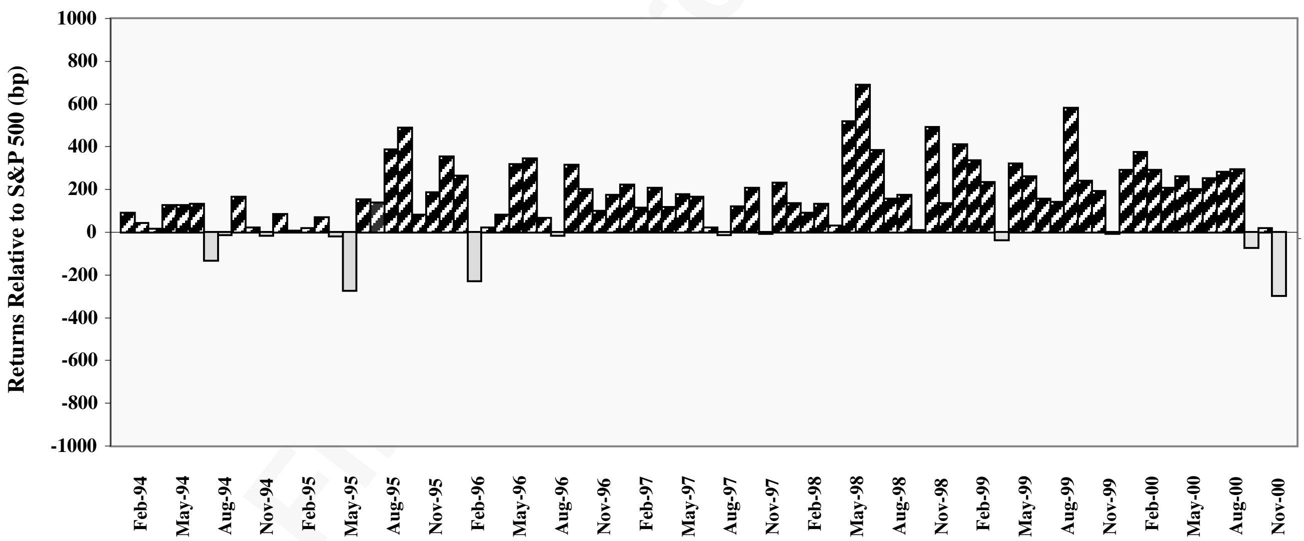
Performance Correlation Across Methodologies for S&P 1500 Universe—Average Excess Monthly Returns

	Courage	Forecast Accuracy	Influence	Price Reaction	Lead Analyst Model
Courage	1.00	0.77	0.81	0.63	0.73
Forecast Accuracy	0.73	1.00	0.81	0.56	0.73
Influence	0.76	0.77	1.00	0.67	0.83
Price Reaction	0.58	0.51	0.59	1.00	0.81
Lead Analyst Model	0.66	0.65	0.73	0.82	1.00

Returns (upper triangle); Return Ranks (lower triangle)

Exhibit 11

Average Excess Monthly Returns for S&P 1500 Stocks based on Lead Analyst Model—Leading Revisions Only



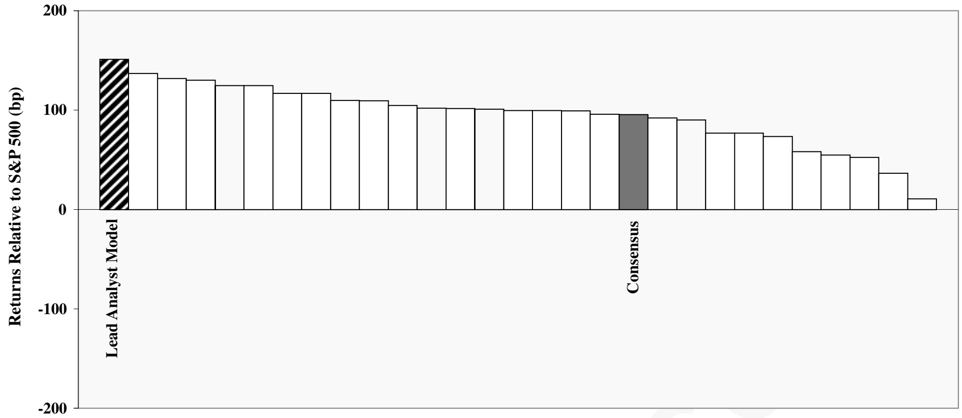
tion is even slighter, with a range from 67.2% to 74.9% for price reaction, influence, and forecast accuracy. Courage again lags at 56.2%.

The performance correlation matrix across methodologies based on average excess monthly returns for the 84 months of the study is displayed in Exhibit 10. Correlation results are computed both for returns and return ranks. There appears to be an overall positive consistency in performance across methodologies.

Exhibit 11 presents average excess monthly returns relative to the S&P 500 for positions initiated during the given month and held for one month for the seven-year period 1994 through 2000, using leading revisions only. The model is positive in 74 of 84 months, or 84.5% of the time. The minimum return is a negative 296 bp (December 2000), and the maximum return relative to the S&P

EXHIBIT 12

Average Excess Monthly Returns for Lead Analyst Model, Consensus, and by Broker for S&P 1500 Stocks—All Revisions



Firms intentionally not identified.

500 is 689 bp (June 1998). The average excess return for all transactions over the entire period is 180 bp.

We also examine brokerage firm research departments separately and compute average excess returns obtained by acting on all of their analyst revisions for the years 1994 through 2000; and similarly compute returns based on all consensus revisions. These results are displayed in Exhibit 12. (Firm identities are not revealed.)

Acting on all consensus revisions produces an average excess return relative to the S&P 500 of 95 bp. It turns out, though, that by cherry-picking the best analysts from each of the brokerage firms on an individual stock basis and acting on all their revisions, the lead analyst model outperforms both the consensus and the brokers, with an average excess return of 151 bp. These results improve to 180 bp if we restrict positions to leading revisions only. This appears to suggest that the lead analyst model is effective in identifying superior analysts.

CONCLUSIONS

Analyst forecast revisions are the basis for many quantitative investment strategies. If we can distinguish among analysts and their forecasts, we ought to be able to improve stock selection performance. We propose methodologies to identify superior analysts on an individual stock basis, and provide stock selection backtest results that rely on the estimate revisions of these superior analysts. We look for analysts who tend to make revisions away from rather than toward the consensus and develop algorithms to measure their skill for attributes such as courage, forecast accuracy, and influence on other analysts, as well as price reaction to their forecasts. These component methodologies are shown to generate superior stock selection performance.

The lead analyst model ranks all the analysts for a given stock. By aggregating the component attributes the model is better able to identify the truly superior leaders for each stock, thereby generating backtest returns better than those produced by the component methodologies. For the period 1994–2000, when acting on all lead analyst revisions, the model's average excess monthly holding return over the S&P 500 is 151 bp. These results are better than those achieved by any individual brokerage firm examined when acting on all their analyst revisions. This demonstrates that it is possible to outperform the brokerage firms by cherry-picking their best analysts. The model is profitable in 74 of 84 months. The average excess return of all transactions increases to 180 bp when acting only on leading revisions.

There are a variety of intuitive approaches for determining lead analysts. Our model uses a combination of methodologies based on courage, superior forecast accuracy, and influence on other analysts, as well as market-adjusted stock price reaction to forecasts. We find that leading revisions are more informative than following ones. Backtest results suggest that stock selection based on earnings estimate revisions of lead analysts is effective in generating superior returns.

ENDNOTE

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