# James Scott

# Some Insider Sales Are Positive Signals

James Scott and Peter Xu

*Not all insider sales are the same. In the study reported here, a variable for shares traded as a percentage of insiders' holdings was used to separate information-driven sales from sales driven by liquidity or risk-reduction needs. In the insider trades from 1987 through 2002, only large sales that also accounted for large percentages of insiders' holdings predicted significantly negative future abnormal returns. Small sales that accounted for small percentages of shares owned not only did not predict poor performance but were correlated with significantly positive abnormal returns. The percentage of shares owned by insiders is also useful for predicting future returns following insider purchases.*

Corporate insiders possess information about their companies before outside investors, and they seem to profit from trading in their own company stock. With the exception of a recent study of stocks on the relatively small Oslo Stock Exchange by Eckbo and Smith (1998), most studies have suggested that insiders have superior information and earn positive abnormal returns (Jaffe 1974; Seyhun 1986, 1998; Rozeff and Zaman 1988; Lin and Howe 1990; Lakonishok and Lee 2001).

Studies of managerial decisions also suggest that managers are better informed than outside investors about their companies' prospects. For example, Ikenberry, Lakonishok, and Vermaelen (1995) found that corporate share repurchases predict high future returns, and Loughran and Ritter (1995) reported poor returns following new equity issues.

Studies on insider trading that investigated whether outside investors can profit by mimicking insider trades reached differing conclusions. Seyhun (1986) and Rozeff and Zaman (1988) showed that after transaction costs are taken into account, imitating insiders produces no abnormal profit. Bettis, Vickrey, and Vickrey (1997), however, found that outsiders can earn abnormal profits after transaction costs by imitating high-ranking insiders who make large-volume trades.

Our study concentrates on the information content of insider trades rather than direct applicability of the findings. For example, we do not address transaction costs for several practical and, we believe, important reasons. First, trading costs change over time as markets evolve, and at any time, different managers have different trading costs, so it is hard to know what level of cost is relevant. As of this writing, some managers can trade for less than 10 bps but others are paying more than 100 bps. More importantly, from the point of view of many professional investment managers, whether a strategy can or cannot cover transaction costs is seldom the issue in decision making. Most active managers use multiple information signals to make buy and sell decisions, so any signal with information content may be useful. In a practical application, the degree to which one signal is correlated with another is often more important than the signal itself. A redundant signal is not useful, whereas an independent, even if weak, signal can provide a competitive advantage. Finally, from the perspective of how markets actually function, and given that managers use multiple signals, the existence of any persistent and statistically significant anomaly is useful because it raises questions about market efficiency.

Most studies show an asymmetry in the prediction of subsequent stock performance between insider sales and insider purchases. Insider purchases are typically associated with positive future abnormal returns, whereas insider sales tend to predict smaller, sometimes insignificant, future abnormal returns. For example, Lakonishok and Lee found in their sample that stocks that experienced net buying by company managers earned an abnormal return of 2.0 percent in the following year but stocks that experienced net selling had an abnormal return of only –0.1 percent in the same interval.

The asymmetry between insider purchases and sales reflects differences in the information content of these actions. When an insider purchases company shares, the primary reason is to make

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money; the buyer probably thinks the stock is undervalued at the time of purchase. So, for that insider purchase to be associated with good future returns is not surprising.

As for insider selling, the motivation most commonly assumed and tested in the literature is the insider's belief that the company stock is overvalued. If the insider possesses useful information, this type of sale should signal poor returns ahead. An insider may sell, however, simply to raise funds for liquidity or to diversify a portfolio. Such sales should not have a negative implication. In fact, if the insider thinks highly of the company's prospects but needs to raise money, the insider might sell only a little of his or her holding and keep the rest in hopes of future appreciation. A small sale, then, would provide a positive signal with respect to future returns.

There is, of course, no way of clearly identifying whether an insider sale is motivated by perceived overvaluation of the stock, the liquidity needs of the owner, or the owner's need to reduce risk by diversifying. On the U.S. SEC forms for insider transactions, insiders do not need to state any reason for their trades. Even if the rules were changed to require the disclosure of intent, such rules would be unenforceable; insiders would be likely to say that their sales were for liquidity needs or risk diversification just to avoid the appearance of trading on insider information.

Most previous studies made no attempt to separate information-driven trades from liquidity- or risk-driven trades. They treated all insider sales the same. Some studies did focus on insider trades involving large numbers of shares, however, on the premise that larger trades are more likely to be motivated by perceived mispricing than are smaller trades (Bettis et al.). Seyhun (1998) reported that larger insider trades are associated with larger subsequent abnormal returns.

In the study reported here, we went a step further by using insiders' share holdings, which are reported on the SEC forms insiders fill out for their trades, to measure the information content of insider sales. Specifically, we calculated the shares traded as a percentage of shares owned and used the ratio to separate informational sales from noninformational sales. We hypothesized that if an insider sells shares because of a negative view on the company's outlook, the seller is likely to sell a larger percentage of his or her holding than if the sale is only for liquidity needs. Thus, we expected insider sales that represent a large percentage of shares owned to be associated with negative future returns. We hypothesized that sales constituting a small fraction of holdings would predict positive future returns.

## Data and Methodology

Our sample covers insider transactions from 1987 through 2002. Data from 1987 through 2000 come from Thomson Financial, and we compiled data for 2001 and 2002 from daily files available from Washington Services. As Lakonishok and Lee did, we included in the sample only open-market transactions of at least 100 shares. We excluded insider purchases of shares through exercise of options but included subsequent open-market sales of these shares. To clean up the data, we excluded all transactions missing a transaction date, report date, or price and those with a transaction date later than the report date. Also, to avoid counting the same transaction multiple times, we excluded amended filings.

Previous studies examined trades by different types of insiders (Rozeff and Zaman 1998; Seyhun 1998; Lakonishok and Lee). Our focus, however, was not on evaluating the strength of the insider trading signal for different types of insiders but on the usefulness of holdings data for understanding the impact of highly informed trades. Therefore, we limited our sample to trades by CEOs, chairs of the board, chief financial officers, presidents, and vice presidents.

Unlike studies that counted each trade reported as a separate transaction, our study combined trades that were executed on the same date but reported separately. We thereby reduced the number of transactions by roughly 20 percent, to 512,133 transactions. **Table 1** reports the number of shares (and their dollar values) bought and sold by insiders each year from 1987 through 2002. Sales accounted for 67 percent of all transactions, 76 percent of all shares, and 93 percent of all values transacted.

A steady increase in insider transactions occurred in the 1987–2002 period up until the end of the 1990s bull market. On average, in each year, insiders transacted trades in 4,704 companies' shares, for an average of 6.8 trades per company.

Whereas most previous studies adopted the event-study methodology to analyze abnormal returns following the report of insider transactions, in this study (following Lakonishok and Lee), we based portfolios on reported insider trades in the six months prior to the portfolio formation date. But unlike Lakonishok and Lee, who used annual rebalances to examine returns in subsequent periods of up to three years, we formed portfolios at the end of each calendar quarter and analyzed the returns in the following quarter. Use of shorter and nonoverlapping periods for performance measurement may have caused us to miss abnormal returns long after insider report dates, but it increased the number of observations and thus improved our

**Table 1. Yearly Insider Trades, 1987–2002**

| | Purchases | | | Sales | | | |
|---|---|---|---|---|---|---|---|
| Year | No. of Trades | No. of Shares (millions) | Value of Trades (millions) | No. of Trades | No. of Shares (millions) | Value of Trades (millions) | No. of Companies |
| 1987 | 9,435 | 43.2 | $ 406.3 | 13,320 | 129.8 | $ 2,655.8 | 3,745 |
| 1988 | 6,189 | 35.8 | 234.2 | 12,038 | 115.8 | 2,181.5 | 3,261 |
| 1989 | 6,040 | 29.8 | 308.2 | 12,589 | 126.8 | 2,313.9 | 3,351 |
| 1990 | 9,844 | 47.0 | 326.1 | 10,478 | 115.8 | 2,184.2 | 3,454 |
| 1991 | 5,827 | 32.9 | 197.8 | 19,048 | 262.2 | 5,848.1 | 3,636 |
| 1992 | 6,454 | 46.0 | 417.7 | 19,959 | 305.4 | 7,366.7 | 3,972 |
| 1993 | 6,791 | 55.7 | 582.1 | 19,209 | 309.2 | 7,016.6 | 4,266 |
| 1994 | 10,136 | 79.7 | 734.8 | 16,069 | 244.9 | 5,640.8 | 4,765 |
| 1995 | 9,513 | 73.2 | 658.9 | 22,825 | 354.3 | 9,468.0 | 5,170 |
| 1996 | 10,025 | 89.7 | 1,222.0 | 22,299 | 461.9 | 14,411.1 | 5,633 |
| 1997 | 11,977 | 121.5 | 1,332.1 | 30,000 | 541.4 | 17,759.8 | 6,195 |
| 1998 | 18,687 | 178.2 | 1,542.4 | 27,817 | 602.3 | 22,627.1 | 6,323 |
| 1999 | 17,310 | 196.2 | 2,407.9 | 25,399 | 727.7 | 33,160.0 | 5,890 |
| 2000 | 14,223 | 212.7 | 1,527.6 | 29,063 | 821.5 | 36,944.4 | 5,602 |
| 2001 | 12,300 | 412.2 | 819.2 | 36,976 | 1,199.3 | 30,756.1 | 5,236 |
| 2002 | 11,450 | 583.2 | 3,200.2 | 28,843 | 844.0 | 18,418.4 | 4,773 |

*Note*: Trades executed before the end of 2002 but reported after February 2003 are not included.

interpretation of the statistical significance of abnormal returns. To avoid skewed returns resulting from transactions in the shares of very small companies, we narrowed our universe to include only stocks that were among the largest 3,000 stocks at the time of portfolio formation.

For every quarter, starting from June 1987, we calculated the *net* total shares purchased or sold for each company over the prior six months. We included trades that were reported before and up to the last day of the quarter for two reasons. First, the processing delay is usually short.[1] Second, no previous study has found meaningful abnormal price movements during short windows around insider trade dates.

For our sample, the average gap between transaction and report date was 31.8 days and the median was 24 days. This gap will shorten dramatically in the future. Until August 2002, insiders had up to the 10th day of the next month to report their trades, but a few high-visibility insider trading and corporate accounting scandals amid the burst of the 1990s stock market bubble caused the SEC to tighten reporting rules. Now, insiders are required to report their trades within 48 hours of the transaction.

To calculate shares traded as a percentage of shares owned, we added up for each company the last reported number of shares owned over the six months for all insiders and added (subtracted) the net total shares sold (purchased). In the case of multiple reports by the same insider, reported holdings plus (minus) shares sold (purchased) are often different from holdings reported on the previous filing. The probable cause is that insiders receive new shares between filings—through either option exercise or stock compensation. Although our choice of inferred beginning-of-period holdings (rather than actual reported holdings from the last filings before the formation period) may seem arbitrary, it has several advantages. First, it does not require that an insider file a prior report before the current formation period. Second, even if an insider filed a report before the current formation period, that report may be outdated. Finally, any new shares received through option exercise or stock compensation during the formation period are likely to have been anticipated and, hence, be a part of the insider's consideration when trading.

Of all reported transactions, about 12 percent did not include holdings data. Some insiders may have used a blank to denote zero shares owned after a sale, but we found that a significant number of purchases also had missing holdings information. For calculating the percentage, we used trades by an insider only if that person reported holdings on his or her last filing during the formation period. But for net total shares purchased or sold, we included all transactions. The example in **Table 2** illustrates our method.

Table 2 reflects five insider trades by three insiders during the six months ending June 1995. The net total number of shares sold is 14,000, simply

**Table 2. Illustration of Calculation of Net Total Shares Traded and Percentage of Shares Owned**

| Trader | Trade | Shares | Date | Report Date | Holdings |
|---|---|---|---|---|---|
| Insider A | Bought | 1,000 | 04/06/95 | 05/08/95 | 1,000 |
| Insider B | Sold | 5,000 | 01/15/95 | 01/23/95 | 5,000 |
| Insider B | Sold | 2,000 | 04/15/95 | 05/02/95 | |
| Insider B | Sold | 3,000 | 04/16/95 | 05/02/95 | 2,000 |
| Insider C | Sold | 5,000 | 05/02/95 | 05/10/95 | NA |

*Notes*: The net total shares sold by insiders for whom we have holdings information is 9,000. The derived beginning shares owned by insiders with holdings information is 12,000. The figure for shares sold as a percentage of shares owned is 75 percent.

NA = not available.

the sum of all sold trades minus the bought trades. Insider B reported twice and received 2,000 new shares between the two filings. Her second and more recent filing indicates that she has 2,000 shares left after selling 5,000 shares in April. Insider C did not report his holdings; thus, his trade is excluded from the calculation of percentage of holdings.

Our methodology of using aggregate insider trades and holdings to calculate percentage of shares owned gives more weight to those insiders who trade and own larger shares of the company. This approach is reasonable if these significant insiders are more influential and better informed than insiders who own few shares.

## Insider Trading and Future Returns

At the end of each quarter from June 1987 through September 2002, we calculated net total shares traded in each stock in the prior six months. **Table 3** reports summary statistics for, separately, stocks with net insider purchases and stocks with net insider sales over the six-month formation period. Note the much greater number of net total shares sold than of net total shares purchased.

**Table 3. Characteristics of Stocks Based on Net Total Shares Traded, 1987–2002**

| Characteristic | Net Purchases | Net Sales |
|---|---|---|
| Average net total shares traded | 28,894 | 133,608 |
| Average prior six-month return (%) | 4.94 | 16.23 |
| Average book-to-price ratio | 0.62 | 0.41 |
| Average market capitalization ($ millions) | 1,348.9 | 4,680.5 |
| Average next three-month return (%) | 4.05 | 2.36 |
| Average next three-month excess return (%) | 0.83 | 0.16 |
| No. of observations (company-quarters) | 20,740 | 60,002 |

Based on average book-to-price ratios (B/Ps), the two groups also exhibit a significant difference in valuation. In addition, the stocks with net purchases were the stocks of smaller companies than were the stocks with net sales.

To calculate returns, we formed 62 quarterly portfolios (one of net purchases and one of net sales) in the June 1987–September 2002 period, for a total of 80,742 company-quarters with insider trading. Consistent with previous research, Table 3 shows that insiders appear to be contrarian investors: They sell when prices seem high and buy when they seem low. Insiders seem better informed than the market. The stocks with net purchases earned, for raw sales in subsequent three-month periods, an average 1.69 percentage points more than the stocks with net sales. This difference in average absolute returns is partly a result, however, of insiders' ability to time the overall market (see Lakonishok and Lee). To measure insiders' pure stock-selection ability, therefore, we calculated excess returns, which we defined as raw returns minus the average return of all stocks in the universe in each quarter. As Table 3 shows, the difference in average excess returns between the portfolios of net sales and net purchases is considerably smaller than the difference in raw returns.

What may be surprising is that stocks with net insider sales produced positive (although not statistically significant) average excess returns in the subsequent three months. This finding differs from the findings of earlier studies, which reported negative relative performance of stocks after insider sales (see Seyhun 1986; Lin and Howe). We believe our results reflect the fact that a small volume of sales simply to raise money for the executive is a positive statement about the company's future: The executive likes the prospects of her company and so sells as little as possible to raise the money she needs. The results are perhaps clearer in our study than in previous studies because our sample includes the more recent period, when stock and option compensation became common and more central to an executive's compensation package than in the past. The work of Lakonishok and Lee perhaps supports this reasoning. They used data as recent as 1995 and found that stocks with more sales than purchases produced the same subsequent six-month returns as stocks with no insider trading at all.

The suggestion that insider sales of different volumes have different informational implications brings up the major point of this article: Not all insider sales are the same. To explore the idea that large sales may be driven by perceived overvaluation (and thus provide a negative signal) but many small sales are carried out to raise money or to reduce risk, we used shares traded as a percentage of shares owned to separate trades that may signal negative information from those that signal positive information. For stocks with net sales, we report the results for two groups—transactions of more than 100,000 net total shares sold and those of fewer shares sold.

**Table 4** shows the results. For the most part, the larger the percentage of shares owned, the larger the magnitude of excess returns. The group of stocks with net total sales exceeding 100,000 shares had an average excess return of –0.55 percent, but of that group, those stocks for which shares sold accounted for more than half of shares owned had average excess return of –1.17 percent. Excess returns on stocks with the same level of shares sold but a lower percentage of holdings were negative but statistically insignificant. Among stocks with net total sales of fewer than 100,000 shares, those that accounted for at least half of shares owned had small and insignificant excess returns but those that accounted for less than half of the holdings had statistically significant positive excess returns.

In summary, we believe that both total number of shares sold and percentage of shares owned are proxies for the motivation of insider sales. When insiders sell a large number of shares and a large portion of what they own, they are likely to be motivated by perceived overpricing of their stocks. When insiders sell a small number of shares and also a small portion of their holdings, they are likely to be simply raising money to spend or to be modestly diversifying their holdings.

As Table 4 shows, percentage of shares owned is also useful for differentiating insider purchases. As net insider purchases increase as a percentage of shares already owned, positive excess returns increase. For stocks with only initial purchases, we could not, of course, calculate a percentage value of holdings. Initial insider purchases, however, do not seem to earn excess returns. For net new purchases, we found an insignificant excess return of 0.05 percent from 2,625 observations.

## Size- and B/P-Adjusted Returns

Prior studies have found that market cap and book-to-price ratio are significant factors for explaining cross-sectional variation in stock returns (Fama and French 1992). Thus, to refine the information provided by insider trades, we added adjustments for size and B/P. These findings may be especially interesting because, as Table 3 shows, stocks with net sales and stocks with net purchases differ substantially in average market cap and B/P.

We ranked the stocks in our universe each quarter independently by size and by B/P and separated them into three groups containing an equal number of stocks for each attribute. The result was

**Table 4. Excess Returns Based on Shares Traded as Percentage of Shares Owned, 1987–2002**

| | Percentage of Shares Originally Owned | | |
|---|---|---|---|
| Group | Less than 10% | 10–50% | More than 50% |
| *Net shares sold* | | | |
| Over 100,000 shares | –0.48 | –0.24 | –1.17** |
| No. of observations | 3,932 | 7,776 | 4,397 |
| 0–100,000 shares | 0.65** | 0.44** | 0.04 |
| No. of observations | 14,191 | 20,295 | 9,411 |
| *Net shares purchased* | 0.44* | 1.24** | 1.56** |
| No. of observations | 8,468 | 5,175 | 4,472 |

*Note*: Excess returns are in percentages.
*Significantly different from zero at the 5 percent level.
**Significantly different from zero at the 1 percent level.

nine portfolios. We then subtracted from the three-month return on each stock with insider trading the average return of all stocks in the same group in which that particular stock fell. We call these returns the "size- and B/P-adjusted excess return."

The average quarterly (three-month) returns on the size- and B/P portfolios are shown in **Table 5**. As in numerous other studies, the high-B/P stocks outperformed the low-B/P stocks. Over the 1987–2002 period, large-cap stocks had higher average returns than small-cap stocks, but the difference is small. Also, note that the number of observations in the cells along the diagonal is greater than the number across any row or down any column, which indicates that size and B/P are correlated; the smaller-cap stocks tend to have the higher B/Ps.

**Table 6** reports size- and B/P-adjusted excess returns for the stocks subject to insider trading. Because stocks with net sales had lower B/Ps and stocks with net purchases had higher B/Ps than the average stock, the size- and B/P-adjusted returns are smaller than the simple excess returns shown in Table 4. Nevertheless, the results are qualitatively similar.[2]

Finally, we ran a cross-sectional regression of size- and B/P-adjusted returns on insider trading measures. We defined three dummy variables—*LrgSale*, *SmlSale*, and *Buy*—which equaled 1 if the net total shares traded fell into the corresponding level defined in Tables 4 and 6 and equaled 0 otherwise. To measure the effect of percentage holding, we added interaction terms consisting of each of the three dummy variables multiplied by *PcntOwn*. The term *PcntOwn* was assigned a value of 0, 1, or 2 for each respective level of percentage holding defined in Tables 4 and 6.[3] Because we defined dummy variables for all levels of net total shares traded, we used no intercept for the regression. We chose this specification of the regression equation because it would allow us to clearly interpret the parameter estimates.

**Table 7** reports the regression results. The coefficients on the dummy variables are average excess returns for small-percentage trades in each level of net total shares traded. For example, the coefficient on *LrgSale* is 0.20, suggesting that the small-percentage large insider sales earned an average abnormal return of 0.20 percent. These

**Table 5. Average Quarterly Returns on Portfolios Based on Size and B/P, 1987–2002**

| Size | Low B/P | Medium B/P | High B/P | All B/P Groups |
|---|---|---|---|---|
| Large (%) | 2.54 | 2.42 | 3.09 | 2.64 |
| No. of observations | 22,947 | 22,317 | 16,736 | 62,000 |
| Medium (%) | 1.52 | 2.36 | 3.42 | 2.44 |
| No. of observations | 20,417 | 21,159 | 20,424 | 62,000 |
| Small (%) | 1.65 | 1.97 | 3.26 | 2.39 |
| No. of observations | 18,636 | 18,524 | 24,840 | 62,000 |
| All size groups (%) | 1.94 | 2.26 | 3.27 | 2.49 |
| No. of observations | 62,000 | 62,000 | 62,000 | 186,000 |

*Note*: Stocks with missing returns were not included in calculating the means.

**Table 6. Size- and B/P-Adjusted Excess Returns on Shares Traded as Percentage of Shares Owned, 1987–2002**

| | Percentage of Shares Originally Owned | | |
|---|---|---|---|
| Shares Traded | Less than 10% | 10–50% | More than 50% |
| *Net shares sold* | | | |
| Over 100,000 shares | –0.06 | 0.08 | –0.81* |
| 0–100,000 shares | 0.68** | 0.44** | 0.06 |
| *Net shares purchased* | 0.38 | 1.06** | 1.42** |

*Notes*: Excess returns are in percentages, and numbers of observations are the same as reported in Table 4. For net new purchases, excess return was an insignificant 0.10 percent from 2,625 observations.

*Significantly different from zero at the 5 percent level.
**Significantly different from zero at the 1 percent level.

**Table 7. Regression of Size- and B/P-Adjusted Excess Returns on Insider Trading Measures**

| Statistic | *LrgSale* | *SmlSale* | *Buy* | *PcntOwn* × *LrgSale* | *PcntOwn* × *SmlSale* | *PcntOwn* × *Buy* |
|---|---|---|---|---|---|---|
| Coefficient | 0.20 | 0.74 | 0.41 | –0.39 | –0.30 | 0.54 |
| *t*-Statistic | 0.64 | 4.08 | 1.75 | –1.54 | –2.01 | 2.58 |

*Note*: The dependent variable is excess return.

results show that, on the one hand, even large insider sales did not predict negative abnormal returns if they represented only a small fraction of insider holdings. On the other hand, if insiders sold a small number of shares that also represented a small fraction of their holdings, the average future abnormal return was positive and statistically significant (as shown by the positive and significant coefficient on *SmlSale*). The coefficients on the three interaction terms all have the predictable sign. Insider sales and purchases contain stronger signals when shares traded account for a larger percentage of insider holdings.

## Conclusions and Future Research

We used shares traded as a percentage of insiders' holdings to separate information-driven sales from other (liquidity- or risk-motivated) sales. We hypothesized that not all insider trades are the same. When insiders have negative information about their companies' business prospects, their sales are likely to be large in volume and to account for a large portion of their holdings. A small volume of sales that represents a small portion of insiders' holdings may indicate that the owners need to raise money but think highly of their company and, therefore, limit the amount of the holdings they sell. If so, a small volume of sales provides a positive signal for future stock returns.

The empirical results support our hypothesis. Using insider transaction data from 1987 through 2002, we found that only large sales that also accounted for large percentages of insiders' holdings predicted significantly negative future abnormal returns. Small sales that represented small percentages of shares owned not only did not predict poor performance but were associated with significantly positive abnormal returns.

Although the association of positive future performance with small volume/small percentage of sales may have been specific to the time period we studied (because option and stock compensation became common in the period), we believe that comparing shares traded with shares held is useful for differentiating the motivation and likely signaling of insider sales. Moreover, our findings may not be time specific, because we found percentage of shares owned to be useful also for differentiating the expected future return from insider purchases, which would not have been affected by increasing option and stock compensations. We found that insider purchases that were small relative to shares already owned predicted lower positive future returns than purchases that were large relative to shares already owned.

We chose to investigate the size and relative importance (to the insider) of insider trades, but other aspects of insider trading may also prove fruitful. For example, the length of the holding period may matter. Sales of shares that the insider has just received may contain less information than sales of shares that have been held for a long time. Or sales of shares obtained through exercise of options that are far from the expiration dates may indicate a negative view on the stock. Finally, although we used only trades and holdings of insiders who traded during the months of portfolio formation to calculate percentage of holdings, an aggregate measure of all insiders, including those who did not trade, might be a better predictor for the information content of insider trades. In short, the field of insider trading analysis still holds untested hypotheses.

## Notes

1. For the insider trades in 2001 and 2002 for which we had data, the average processing delay from the report date to when the information was electronically available to all investors, or the keypunch date, was 1.8 days. The median delay was 1 day.
2. We also adjusted the returns on the insider trading portfolios for size and earnings/price and, separately, used a three-factor risk model that encompassed size, B/P, and prior-six-month momentum. In both cases, we found results very similar to those reported here.
3. Because the variable *PcntOwn* could not be defined for initial purchases, they were not included in the regression.

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# News, Not Trading Volume, Builds Momentum

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*Recent research has found that price momentum and trading volume appear to predict subsequent stock returns in the U.S. market and that they seem to do so in a nonlinear fashion. Specifically, the effect of momentum appears more pronounced among high-volume stocks than among low-volume stocks. This effect would suggest the existence of an exploitable deviation from market efficiency. We argue that this phenomenon is a result of the underreaction of investors to earnings news—an effect that is most pronounced for high-growth companies. We show that, after earnings-related news and a stock's growth rate have been controlled for, the interaction between momentum and volume largely disappears.*

Recent research (Lee and Swaminathan 2000) found that momentum and trading volume appear to predict subsequent returns in the U.S. equity market and that they seem to do so in a nonlinear fashion. Specifically, the effect of momentum appears more pronounced among high-volume stocks than among low-volume stocks. This effect suggests the existence of a predictable deviation from market efficiency. Furthermore, because both volume and momentum are standard tools of technical analysis, these findings also suggest that investors can use technical analysis to earn abnormal profits.

We also found a momentum–volume effect in the research reported here. We propose a different explanation from that of Lee and Swaminathan, however—an explanation based on investor reaction to news about company fundamentals. First, we argue that news about a company's earnings often creates volume and a change in stock price (i.e., price momentum). Furthermore, news creates greater volume and greater momentum for growth stocks. Second, investor overconfidence delays some of the reaction because investors are slow to adjust their beliefs. Just as the initial reaction is greater for growth stocks, the delayed reaction also is greater for growth stocks. This nonlinear reaction to earnings news by stocks with different growth rates creates the nonlinearities in the momentum–volume effect. In short, we believe that the momentum–volume interaction is explainable as a delayed reaction to news about company fundamentals.

We begin with reporting the result we found from replicating earlier findings that suggested a momentum–volume interaction. We then offer our alternative explanation and provide various tests of the two hypotheses. Distinguishing between such closely related hypotheses is difficult. We believe our case is persuasive, but we leave it to readers to decide between the two.

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## Data

For the study we report, our sample consisted of stocks of the largest 1,500 publicly traded companies in the United States each quarter between 1981 and 1998. The sample starts in 1981 because that was the year I/B/E/S International began reporting long-term expected earnings growth.[1] For a stock to be included in our sample, we required that a long-term earnings growth forecast be available and that the stock have return and volume data for at least one year prior to portfolio formation. The result was 91,356 total observations, or an average 1,324 observations a quarter. We formed portfolios at the end of each quarter on the basis of data (e.g., expected earnings growth) available at that time.[2]

We defined "average monthly trading volume" as the average of the monthly trading volume over the year preceding portfolio formation. Monthly trading volume is the total number of shares traded each month as a percentage of the total number of shares outstanding at the end of the month. We obtained monthly volume and return data from FactSet Data Systems. We adjusted the data for stock splits.

We defined excess return as the difference between a stock's return in any quarter and the equal-weighted average return of all stocks in the sample in that quarter.

## Momentum–Volume Interaction

The quarterly data on U.S. stocks for 1981–1998, reported in **Table 1**, are consistent with the momentum–volume interaction found by previous research. Table 1 ranks stocks independently on both price momentum and average monthly trading volume and reports the average excess returns of stocks in each momentum–volume quintile. The average excess return for any momentum–volume portfolio is simply the equal-weighted average of excess returns of all the stocks in the portfolio. As in the momentum-related studies of Lee and Swaminathan and others (Jegadeesh and Titman 1993; Rouwenhorst 1998), we used a one-year ranking interval and measured excess returns over the subsequent quarter. The rightmost column in Table 1 shows that stocks in the highest-momentum quintile outperformed the average stock by 1.09 percentage points in the ensuing quarter whereas stocks in the lowest-momentum quintile subsequently lagged the average stock by 1.24 pps.

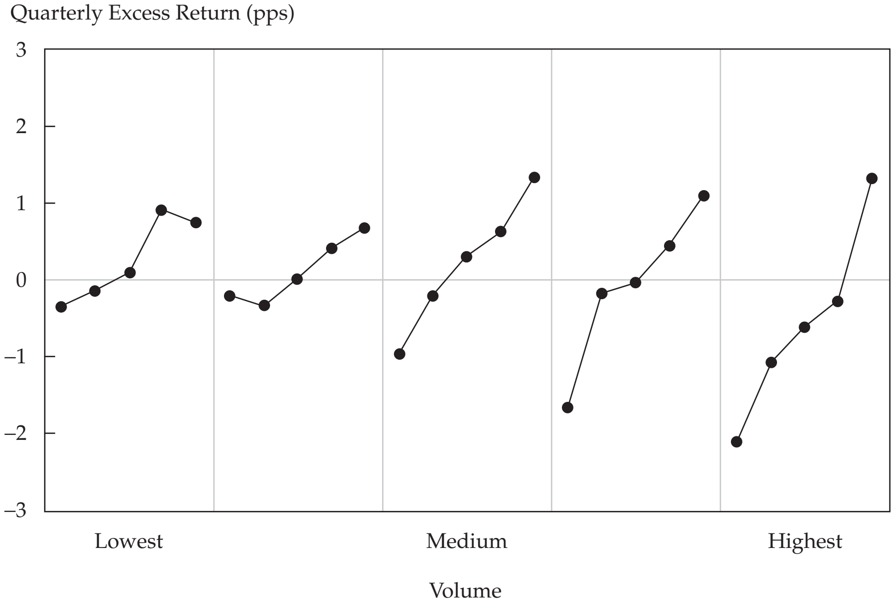
Table 1 also shows that volume is related to future returns. Although the relationship is not monotonic, the bottom row in Table 1 shows that overall trading volume was negatively correlated with subsequent stock returns in the 1981–98 period.

More important than trading volume and momentum individually, however, is the interaction between them. Simply put, most of the payoff from momentum investing in this period came from high-volume stocks. Table 1 shows that for stocks in the highest-volume quintile, the difference in excess return between the lowest- and highest-momentum stocks is 3.41 pps. Conversely, the return spread for momentum is only 1.08 pps for stocks in the lowest-volume quintile.[3] This disparity is easier to see in **Figure 1**, which depicts graphically the results shown in Table 1. Each vertical panel in Figure 1 represents a volume quintile. Within each panel is a plot of quarterly excess return against past momentum; the top circles identify the highest-momentum group, and the bottom circles, the lowest-momentum group. The lengthening of the line from the left panel to the right in Figure 1 shows

**Table 1. Quarterly Excess Returns on Momentum and Volume Portfolios, 1981–98**
(excess returns in percentage points; data in parentheses are *t*-statistics; numbers below *t*-statistics are number of observations in each quintile)

| | Trading Volume | | | | | |
|---|---|---|---|---|---|---|
| Momentum | 0 (low) | 1 | 2 | 3 | 4 (high) | All |
| 0 (low) | –0.34 | –0.21 | –0.95 | –1.64 | –2.09 | –1.24 |
| | (–1.20) | (–0.66) | (–3.29) | (–5.95) | (–6.70) | (–9.00) |
| | 2,824 | 2,598 | 3,249 | 4,356 | 5,216 | 18,243 |
| 1 | –0.14 | –0.35 | –0.21 | –0.18 | –1.06 | –0.34 |
| | (–0.69) | (–1.82) | (–0.96) | (–0.69) | (–2.62) | (–3.10) |
| | 4,224 | 4,148 | 3,933 | 3,464 | 2,517 | 18,286 |
| 2 | 0.09 | 0.01 | 0.30 | –0.04 | –0.61 | 0.01 |
| | (0.49) | (0.07) | (1.47) | (–0.16) | (–1.44) | (0.13) |
| | 4,366 | 4,713 | 4,002 | 3,067 | 2,139 | 18,287 |
| 3 | 0.91 | 0.41 | 0.63 | 0.46 | –0.28 | 0.49 |
| | (4.75) | (2.25) | (3.13) | (1.84) | (–0.68) | (4.72) |
| | 4,163 | 4,265 | 3,978 | 3,401 | 2,479 | 18,286 |
| 4 (high) | 0.74 | 0.67 | 1.34 | 1.09 | 1.32 | 1.09 |
| | (2.69) | (2.26) | (5.07) | (4.05) | (4.43) | (8.16) |
| | 2,666 | 2,562 | 3,125 | 3,998 | 5,903 | 18,254 |
| All | 0.25 | 0.08 | 0.21 | –0.11 | –0.44 | 0.00 |
| | (2.58) | (0.87) | (2.05) | (–0.95) | (–2.76) | (0.00) |
| | 18,243 | 18,286 | 18,287 | 18,286 | 18,254 | 91,356 |

**Figure 1. Excess Returns within Volume Categories for Increasing Levels of Momentum**




that the momentum effect becomes more pronounced at higher levels of volume—largely because negative momentum is particularly strong for stocks with high trading volumes.

One of the possible explanations of these results, discussed in Lee and Swaminathan, is the "momentum life cycle" hypothesis. According to this hypothesis, stocks cycle sequentially through intervals of glamour and neglect, with high trading volume during periods of glamour and low trading volume during periods of neglect. For example, high-volume stocks with low momentum are considered to be in the early stages of a move from glamour to neglect and thus have lower subsequent returns than low-volume, low-momentum stocks, which are considered to be near the end of a period of neglect. The momentum life-cycle hypothesis is similar to the "earnings expectation" hypothesis postulated by Bernstein (1993).

Although the momentum life-cycle hypothesis can explain some of the empirical results, we found it to be unsatisfactory and believe trading volume per se should not convey any information. In the next section, we present an alternative hypothesis for what we think is behind the interaction between momentum and volume.

## Delayed Reaction to Fundamental News

The first part of our explanation relies on well-known empirical research that has found a delayed reaction on the part of investors to earnings information. Latane and Jones (1979) and Bernard and Thomas (1989, 1990) showed that stock prices do not fully reflect the information in earnings announcements. Several other studies have found a similar delayed reaction to other public information (Desai and Jain 1997; Ikenberry, Lakonishok, and Vermaelen 1995; Womack 1996.)

This partially delayed reaction to fundamental news is consistent with the theoretical arguments of Daniel, Hirshleifer, and Subrahmanyam (1998), as well as of Scott, Stumpp, and Xu (1999). Daniel et al. argued that the delay is caused by the influence of investors who are overconfident in their own predictions and, as a result, are overly slow in adjusting to new information.

The second part of our explanation is that earnings-related information should have a greater impact on the valuation of more rapidly growing stocks because the more rapidly a stock grows, the more its valuation depends on estimates of the speed and profitability of its growth.[4] Information that causes changes in those estimates will have dramatic effects on valuation.[5] The price reaction is greater for such companies at the time of the information release and also in the delayed response. Earnings news in one quarter, for example, results in volume and momentum change in that quarter, and the effect is greatest on growth stocks. In the next quarter, a second, delayed reaction to the news of the previous quarter occurs, and this reaction also affects growth stocks the most. We believe this nonlinear reaction to information explains most, if not all, of the momentum–volume interaction effect documented by Lee and Swaminathan.

**Table 2** contains data on quarterly excess returns that are consistent with our hypothesis. The table presents next quarter's stock returns as they relate to this quarter's earnings news and the company's expected long-term earnings growth rates from I/B/E/S. We used estimates available at the time of portfolio formation to group stocks. Our measure of earnings news was the proportion of security analysts revising earnings forecasts upward. To be consistent with the measurement of trading volume and momentum in Table 1, revision activity was calculated over the one-year interval prior to portfolio formation. We subtracted the total number of downward revisions from the total number of upward revisions over the previous year and then divided by the number of earnings forecasts at the end of the year. The resulting measure is essentially the number of times the average analyst revised a forecast upward (downward if the figure is negative) over the one-year period. For example, suppose that a stock was followed by five analysts and over the prior year, each of them changed his or her earnings estimate upward four times and downward twice. Then, the total net number of upward revisions would be 10 and, when divided by the number of analysts, the resulting measure of news would be 2.

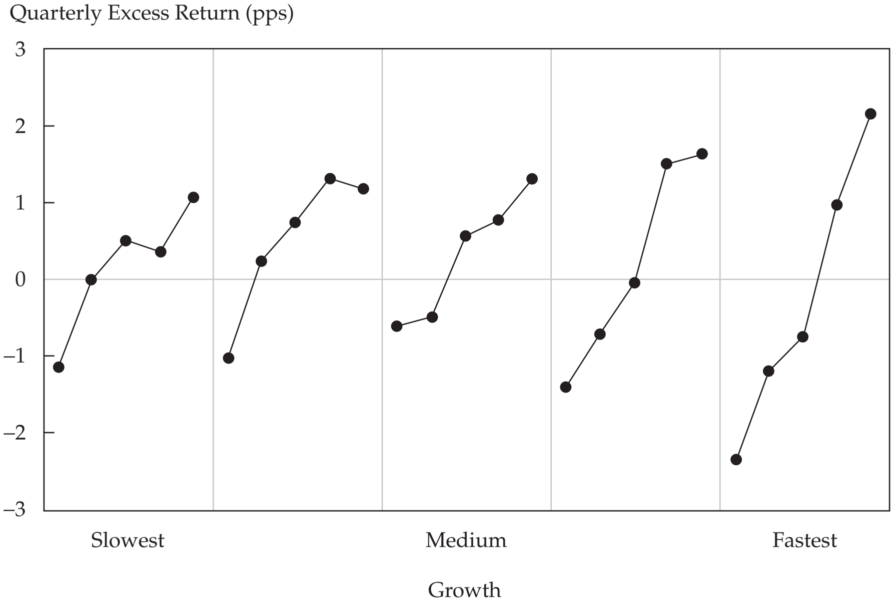
We separated stocks into five categories on the basis of this measure of news. If this measure was 2 or larger, we categorized the stock as having "very good" news. If this measure was between 1 and 2, we defined the news as "good." "Bad" and "very bad" news were defined similarly. Because analysts tend to revise their forecasts downward, we had substantially more observations in the negative-news categories than in the positive-news categories.

The results in Table 2 show a delayed reaction to earnings news that increases as growth rates increase. Like the momentum–volume effect, this relationship is nonlinear; the delayed effect of earnings news is strongest for growth stocks. **Figure 2** presents these data graphically in a manner similar to Figure 1. Each vertical panel represents a long-term growth quintile. Within each panel, excess returns over the quarter after portfolio formation are plotted against news (net upward estimate revisions). The leftmost point in each line shows the excess return for very bad news; the rightmost point shows the excess return following the very best news.

**Table 2. Quarterly Excess Returns on News and Growth Portfolios, 1981–98**
(excess returns in percentage points; data in parentheses are *t*-statistics; numbers below *t*-statistics are number of observations in each quintile)

| | Growth Rate | | | | | |
|---|---|---|---|---|---|---|
| News | 0 (low) | 1 | 2 | 3 | 4 (high) | All |
| Very bad | –1.12 | –1.02 | –0.58 | –1.39 | –2.33 | –1.24 |
| | (–4.13) | (–5.01) | (–2.57) | (–5.52) | (–6.45) | (–10.75) |
| | 3,594 | 4,924 | 4,638 | 4,446 | 3,609 | 21,211 |
| Bad | –0.01 | 0.24 | –0.48 | –0.69 | –1.18 | –0.40 |
| | (–0.05) | (1.00) | (–1.94) | (–2.45) | (–3.03) | (–3.17) |
| | 3,345 | 3,210 | 3,361 | 3,172 | 2,813 | 15,901 |
| Neutral | 0.50 | 0.74 | 0.57 | –0.03 | –0.74 | 0.22 |
| | (3.53) | (4.64) | (3.47) | (–0.15) | (–3.03) | (2.76) |
| | 7,878 | 6,585 | 6,778 | 6,550 | 6,605 | 34,396 |
| Good | 0.36 | 1.31 | 0.78 | 1.50 | 0.96 | 0.98 |
| | (1.36) | (4.71) | (2.73) | (4.65) | (2.11) | (6.58) |
| | 2,159 | 2,065 | 1,907 | 2,162 | 2,221 | 10,514 |
| Very good | 1.05 | 1.17 | 1.30 | 1.62 | 2.14 | 1.58 |
| | (2.92) | (3.60) | (3.44) | (4.10) | (5.12) | (8.56) |
| | 1,234 | 1,556 | 1,620 | 1,941 | 2,983 | 9,334 |
| All | 0.11 | 0.28 | 0.17 | –0.12 | –0.44 | 0.00 |
| | (1.06) | (2.82) | (1.65) | (–1.02) | (–2.83) | (0.00) |
| | 18,210 | 18,340 | 18,304 | 18,271 | 18,231 | 91,356 |

**Figure 2. Excess Returns within Growth Categories for Increasing Good News**




Visually, the relationships in Figure 2 are very similar to those in Figure 1. To gain further insight into the competing hypotheses, we investigated the effect of earnings news and expected growth rates on volume and momentum.

## News, Growth, and the Momentum–Volume Effect

How is the momentum–volume effect related to growth and news? To begin to answer this question, we started by looking at what happened if we replaced volume by growth in Table 1. We wanted to know whether there is a momentum–growth interaction that resembles the momentum–volume interaction.

**Table 3** is identical to Table 1 except that growth has replaced volume. We divided stocks into different quintiles with respect to both prior momentum and growth. Table 3 indicates that, just as we found a momentum–volume interaction, we found a momentum–growth interaction. In fact, the momentum–growth interaction appears to be the somewhat stronger effect. Comparing Tables 1 and 3 suggests that stocks in the highest-growth quintile display a stronger momentum effect than stocks in the highest-volume quintile.

**Table 4** reveals the effect of news and momentum on subsequent performance. Not surprisingly, most of the observations in this table lie on or close to the diagonal. In other words, most stocks that suffered bad news in the past experienced negative momentum and good-news stocks had positive momentum. This relationship strongly suggests that momentum may be largely a surrogate for news about future earnings.

Furthermore, the impact of news on subsequent performance appears to be slightly stronger than the impact of momentum. In our sample, very bad news always resulted in significantly negative subsequent performance whereas very low momentum did not. In addition, regardless of momentum, stocks with very good news had subsequent returns that were either significantly positive or insignificantly different from zero, which was not the case for momentum. These results, which suggest that a substantial portion of the momentum effect can be explained as investors' delayed reaction to news, are consistent with those found by Chan, Jegadeesh, and Lakonishok (1996).

Our measure of news does not, however, explain all of the momentum effect. For example, in the Neutral column, the average excess return in the subsequent quarter increases monotonically from the lowest- to the highest-momentum quintile. As discussed in Chan et al., this apparently independent momentum effect is likely to be caused by underreaction to news that is not captured in our measure of earnings estimate revisions.

The results in Tables 3 and 4 suggest that the momentum–volume interaction in Table 1 may be explainable by the effects of news and growth on the momentum effect. To test this hypothesis, we examined more closely how trading volume is related to growth and news.

**Table 3. Quarterly Excess Returns on Momentum and Growth Portfolios, 1981–98**
(excess returns in percentage points; data in parentheses are *t*-statistics; numbers below *t*-statistics are number of observations in each quintile)

| | Growth Rate | | | | | |
|---|---|---|---|---|---|---|
| Momentum | 0 (low) | 1 | 2 | 3 | 4 (high) | All |
| 0 (low) | 0.13 | –1.02 | –0.12 | –1.52 | –3.09 | –1.24 |
| | (0.42) | (–3.55) | (–0.41) | (–5.46) | (–9.00) | (–9.00) |
| | 3,340 | 3,274 | 3,359 | 3,985 | 4,285 | 18,243 |
| 1 | –0.09 | 0.26 | –0.48 | –0.48 | –1.26 | –0.34 |
| | (–0.45) | (1.36) | (–2.27) | (–1.90) | (–3.13) | (–3.10) |
| | 4,067 | 4,163 | 3,976 | 3,467 | 2,613 | 18,286 |
| 2 | –0.24 | 0.49 | 0.14 | –0.16 | –0.32 | 0.01 |
| | (–1.39) | (2.54) | (0.73) | (–0.65) | (–0.79) | (0.13) |
| | 4,488 | 4,118 | 4,012 | 3,383 | 2,286 | 18,287 |
| 3 | 0.31 | 0.73 | 0.61 | 0.65 | 0.04 | 0.49 |
| | (1.60) | (3.76) | (2.89) | (2.80) | (0.10) | (6.58) |
| | 3,857 | 3,961 | 3,964 | 3,585 | 2,919 | 18,286 |
| 4 (high) | 0.75 | 0.91 | 0.83 | 0.99 | 1.50 | 1.09 |
| | (2.58) | (3.41) | (2.92) | (3.46) | (5.39) | (8.56) |
| | 2,458 | 2,824 | 2,993 | 3,851 | 6,128 | 18,254 |
| All | 0.11 | 0.28 | 0.17 | –0.12 | –0.44 | 0.00 |
| | (1.06) | (2.82) | (1.65) | (–1.02) | (–2.83) | (0.00) |
| | 18,210 | 18,340 | 18,304 | 18,286 | 18,231 | 91,356 |

**Table 4. Quarterly Excess Returns on Momentum and News Portfolios, 1981–98**
(excess returns in percentage points; data in parentheses are *t*-statistics; numbers below *t*-statistics are number of observations in each quintile)

| | News | | | | | |
|---|---|---|---|---|---|---|
| Momentum | Very Bad | Bad | Neutral | Good | Very Good | All |
| 0 (low) | –1.58 | –1.01 | –0.77 | –0.07 | –1.47 | –1.24 |
| | (–8.23) | (–3.42) | (–2.70) | (–0.09) | (–1.20) | (–9.00) |
| | 9,620 | 3,894 | 3,938 | 530 | 261 | 18,243 |
| 1 | –0.92 | –0.12 | –0.09 | –0.14 | 0.61 | –0.34 |
| | (–4.84) | (–0.49) | (–0.52) | (–0.29) | (0.93) | (–3.10) |
| | 5,722 | 4,178 | 6,648 | 1,142 | 596 | 18,286 |
| 2 | –0.95 | –0.08 | 0.22 | 0.69 | 0.51 | 0.01 |
| | (–3.80) | (–0.36) | (1.54) | (2.34) | (1.08) | (0.13) |
| | 3,327 | 3,637 | 8,293 | 1,983 | 1,047 | 18,287 |
| 3 | –0.82 | –0.17 | 0.57 | 1.08 | 1.23 | 0.49 |
| | (–2.26) | (–0.59) | (3.96) | (4.50) | (3.78) | (4.72) |
| | 1,764 | 2,706 | 8,703 | 3,036 | 2,077 | 18,286 |
| 4 (high) | –1.64 | –0.82 | 0.67 | 1.54 | 2.18 | 1.09 |
| | (–2.30) | (–1.80) | (3.16) | (5.60) | (8.25) | (8.16) |
| | 778 | 1,486 | 6,841 | 3,823 | 5,353 | 18,254 |
| All | –1.24 | –0.40 | 0.22 | 0.98 | 1.58 | 0.00 |
| | (–10.75) | (–3.17) | (2.76) | (6.58) | (8.56) | (0.00) |
| | 21,211 | 15,901 | 34,396 | 10,514 | 9,334 | 91,356 |

## News, Growth, and Volume

Trading should take place because investors need liquidity or have received new information.[6] The primary catalyst for the second type of trading should be an event that alters the rate at which rational investors discount the future or, more importantly, news relating to future profitability.

**Figure 3** indicates the dependence of trading volume on growth and earnings news. We used analysts' earnings revisions as a proxy for news and used analysts' forecasts of future growth as a proxy for growth. Figure 3 shows that both growth and news have a significant effect on volume. As one would expect, the more important (more extreme) the news and the higher the growth rate, the higher the volume. The relationship is also strongly nonlinear. The effect of news on volume appears to be particularly pronounced for rapidly growing stocks.

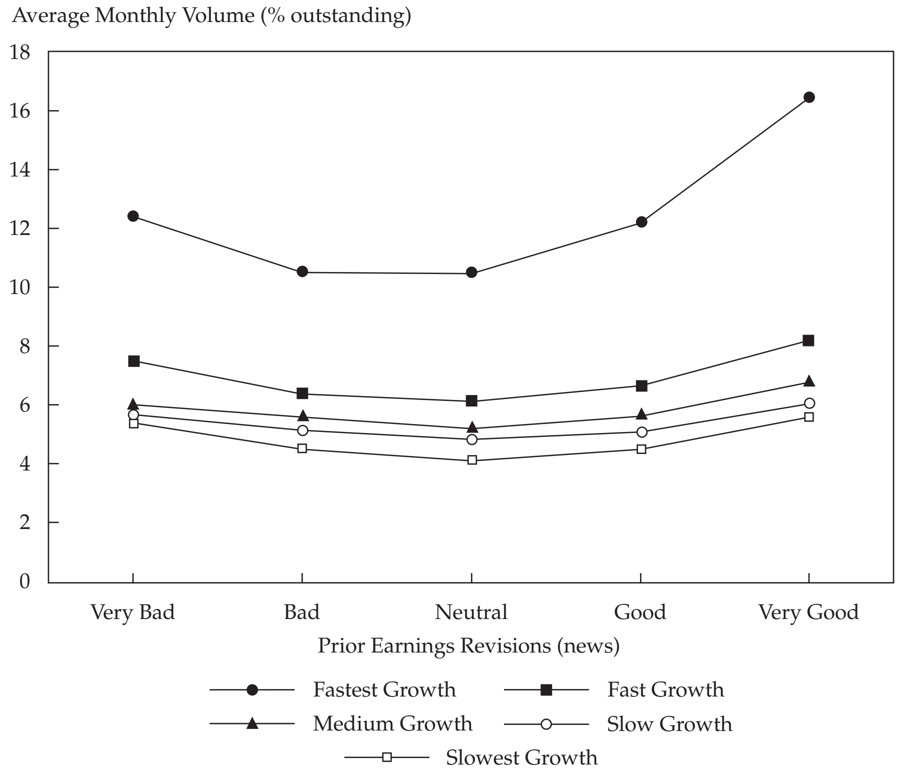
Because our measure of news was net upward revisions as a percentage of the total number of forecasts and could be either positive or negative, the relationship between trading volume and this news measure in Figure 3 is U-shaped. Intuitively, however, trading volume should be better explained by the total number of revisions than by downward or upward revisions. For instance, a stock in the "neutral" news category may have had a lot of both upward and downward revisions over the year and would thus be likely to have had high trading volume. Therefore, we examined the relationship between trading volume and an alternative measure of news based on the total (not net) number of revisions. As expected, we found that trading volume increased monotonically with the total revision activity in each growth category.[7]

## Relative Importance of Volume

Does volume matter even after growth and news are controlled for? The results shown in Figure 3 are strong, but finding that important news and high growth lead to high volume is not surprising. The more interesting question is whether expected growth rate and news, two fundamental variables, explain the momentum–volume effect.

We started by calculating "residual" volume for each stock, where residual volume equals the difference between a stock's actual trading volume and the average volume for each point plotted in Figure 3. Simply put, residual volume controls for the average amount of trading for stocks with similar revisions and similar rates of growth. We did

**Figure 3. Volume Increases with Prior News and the Importance of News (Growth)**



this calculation for each quarter in the sample period, thereby normalizing volume for the type of stock and amount of news. We then replicated the analysis in Table 1 but replaced absolute trading volume with this measure of residual volume.

The results, reported in **Table 5**, demonstrate that the interactions among volume, momentum, and subsequent returns disappear when volume is controlled for news and growth. The spread in excess returns between the high- and low-momentum quintiles now varies randomly across columns (i.e., across residual volume ranks).

**Table 6** presents results from cross-sectional regressions of quarterly excess returns of individual stocks on volume and momentum. To facilitate a comparison, we ran two regressions. The first row shows results when price momentum and unadjusted average monthly trading volume were the independent variables; the second row shows results when price momentum and residual trading volume adjusted for earnings growth and news were the independent variables. In both regressions, the dependent variable was the excess return of individual stocks in the quarter after they were ranked on one-year price momentum and trading volume. The independent variables were quintile ranks of momentum and volume, which were assigned integer values of 0 through 4. To test the statistical significance of the interaction effect between momentum and volume (that is, to test whether the momentum effect varied with different levels of volume), we included an interaction term, namely, the product of the momentum and volume ranks.

Consistent with the results shown in Table 1, the first row of Table 6 shows a strong positive interaction effect between momentum and trading volume when trading volume was not adjusted for earnings growth and news. The coefficient on the interaction term, 0.13, is positive and statistically significant. The coefficient for the momentum rank, 0.26, implies that the momentum effect for the lowest-volume quintile is about half the momentum effect for the average-volume quintile and a third that for the highest-volume quintile.

**Table 5. Quarterly Excess Returns on Momentum and Residual Volume Portfolios, 1981–98**
(excess returns in percentage points; data in parentheses are *t*-statistics)

| Momentum | Residual Trading Volume 0 (low) | 1 | 2 | 3 | 4 (high) | Average |
|---|---|---|---|---|---|---|
| 0 (low) | –1.32 | –0.95 | –0.88 | –1.44 | –1.42 | –1.24 |
| | (–4.42) | (–3.26) | (–2.92) | (–4.98) | (–4.53) | (–9.00) |
| 1 | –0.70 | –0.14 | –0.18 | –0.05 | –0.75 | –0.34 |
| | (–2.84) | (–0.72) | (–0.87) | (–0.22) | (–2.11) | (–3.10) |
| 2 | 0.05 | 0.03 | 0.11 | 0.32 | –0.70 | 0.01 |
| | (0.19) | (0.17) | (0.62) | (1.43) | (–1.97) | (0.13) |
| 3 | 0.79 | 0.55 | 0.54 | 0.49 | –0.07 | 0.49 |
| | (3.23) | (2.80) | (2.82) | (2.36) | (–0.20) | (4.72) |
| 4 (high) | 1.16 | 1.23 | 0.75 | 1.34 | 0.98 | 1.09 |
| | (4.34) | (4.16) | (2.49) | (4.73) | (3.23) | (8.16) |
| Average | 0.03 | 0.13 | 0.07 | 0.11 | –0.34 | 0.00 |
| | (0.25) | (1.30) | (0.67) | (0.96) | (–2.24) | (0.00) |

**Table 6. Momentum–Volume Interaction Effect: Evidence from Cross-Sectional Regressions, 1981–98**
(*t*-statistics in parentheses)

| Volume | INT | MM | VOL | MM×VOL | $R^2$ | $F$ |
|---|---|---|---|---|---|---|
| Unadjusted for growth and news | –0.19 | 0.26 | –0.42 | 0.13 | 0.0029 | 86.9 |
| | (–1.12) | (3.70) | (–6.60) | (4.97) | | |
| Adjusted for growth and news | –0.96 | 0.55 | –0.06 | –0.00 | 0.0024 | 73.3 |
| | (–6.02) | (8.51) | (–1.01) | (–0.09) | | |

*Note*: INT is the intercept; MM is momentum; VOL is volume; MM×VOL is the interaction term.

The second row shows that the interaction effect between momentum and volume completely vanishes when residual volume (which was adjusted for growth and news) was used in the regression. This finding is consistent with the data in Table 5. These results suggest that the interaction between news and earnings growth explains the momentum–volume effect.[8]

Finally, the coefficient for trading volume in the first row is negative and significant. The reason is that trading volume is correlated with earnings growth and slow-growth stocks tended to outperform fast-growth stocks in the period studied (see Lakonishok, Shleifer, and Vishny 1994). As shown in the second row, when trading volume was adjusted for growth, the coefficient for volume became no longer significant.

## Conclusions

Our evidence suggests that once the company's growth rate is controlled for, the momentum–volume effect is largely explainable by news. That is, the apparent deviation from market efficiency that has been dubbed the momentum–volume effect should be considered a delayed reaction by investors to fundamental news, not a technical trading rule driven by volume or momentum.

## Notes

1. The I/B/E/S forecasts are three- to five-year earnings growth forecasts made by sell-side security analysts.
2. The sample includes companies that were delisted, went bankrupt, or merged after the quarter under investigation; a small fraction, 0.8 percent, of the observations were eliminated from the sample because they did not have a return in the quarter following portfolio formation. This circumstance raises the possibility of survivorship affecting the results. Although survivorship may have influenced our findings, the impact is likely to be small because of the small number of excluded companies and our use of equal weighting. Only two companies were dropped because they went bankrupt—too few to affect our results. Most of the deletions from the study were the result of missing returns and were companies involved in mergers in the quarter following portfolio formation. A majority of them fell in the high-momentum/high-volume category in the period preceding portfolio formation (the rest were distributed evenly among the quintiles). Although we have no reason to believe that returns would be especially unusual for these stocks, a merger-related "bounce" in the missing quarter would strengthen our conclusions. Note that we lost only the terminal quarters of bankruptcies and mergers; they were included in prior quarters, when these (pending) events were also likely to elicit strong price responses. Finally, we also examined whether the exclusion of small stocks from the sample might skew our results. We broke the sample in half by market capitalization and recompiled the tables. Results for the large-cap sample and for the sample containing mid-sized and small-cap stocks were similar. Although very-small-cap stocks might exhibit a different result, we believe that the results shown are probably robust to variations in company size.
3. Lee and Swaminathan examined the momentum–volume interaction effect for various subperiods from 1965 through 1995. They found that for the 1985–95 period, high-momentum stocks with high volume (measured over the preceding six months) tended to subsequently outperform high-momentum stocks with low volume. They also showed that the opposite held for earlier time periods. As we show later in this article, volume is a proxy for growth. Thus, the difference in results reported by Lee and Swaminathan for different periods may have been driven by the relative performance of slow-growth stocks (many of which can be characterized as "value stocks") versus fast-growth stocks. In the periods prior to 1985, growth stocks underperformed value stocks, whereas the opposite tended to hold in the late 1990s.
4. In 1961, Miller and Modigliani made a distinction between companies that are "expanding" and companies that are "growing." Expanding companies simply get larger, whereas growing companies get larger profitably. In other words, expanding companies get larger by accepting projects that have net present values of zero; growing companies grow by accepting projects with positive NPVs. We do not make this distinction here: Whether the company's expansion is profitable or not, it is growing in our terminology. Technically, our theory is based on different expansion rates.
5. A simple growth-stock formula makes this point: If stock price equals $d/(r - g)$, where $d$ is next period's expected dividend, $r$ is the cost of equity, and $g$ is the expected rate of growth of dividends per share, any change in $g$ can have dramatic effects on valuation (see Scott et al. for a fuller discussion).
6. See Harris and Raviv (1993) and Kandel and Pearson (1995) for a discussion of information effects.
7. These results are not reported here. We chose to report the results found when we used net upward revision in order to be consistent with the news measure in Tables 2 and 4. The choice of news measure had virtually no effect on the results in the next section.
8. Because news appears to predict future performance, our empirical results raise the possibility that investors could pursue a profitable revisions-based trading strategy. We are aware of practitioners pursuing both volume- and revisions-based trading strategies, but simulating a revisions-based strategy and testing whether it could outperform a volume-based approach is beyond our intent in this article.

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# Behavioral Bias, Valuation, and Active Management

James Scott, Mark Stumpp, and Peter Xu

*We examine the consequences of behavioral biases in the context of valuation theory. Although the biases we consider have been well documented elsewhere, the framework we provide is new. It not only allows a rationalization of previous findings, but it also makes possible identification of the types of stocks for which specific biases will be strongest. We provide empirical evidence concerning the ability of an array of commonly used active investment strategies, such as value and growth tilts, to exploit biases. We also use the framework to test the relative importance of prospect theory and the overconfidence hypothesis as justification for momentum investing.*

A large and rapidly growing body of literature attributes various stock market anomalies to behavioral biases. Most articles focus on individual anomalies, such as the low-P/E effect or the behavior of stock prices subsequent to earnings announcements. Little work has been conducted to link the anomalies to, or discuss them within, the framework of a broad model of security prices. For example, recent empirical work suggests that the low-P/E effect may be the result of a tendency of investors to overextrapolate past problems into the future—a finding that provides important support for value, or low-P/E, investing (Lakonishok, Shleifer, and Vishny 1994). Many other widely used—and frequently successful—alternatives to low-P/E investing exist, however, including buying high-momentum growth stocks. Moreover, many behavioral biases exist in addition to overextrapolation.

We examine the consequences of two types of behavioral bias in the context of valuation theory. Although the biases we examine have been documented elsewhere, the framework we provide is new. It allows us not only to rationalize previous findings but also to suggest the types of stocks for which various biases will be strongest. We suggest that behavioral finance offers much more than a simple prescription to own value stocks. We provide empirical evidence about the ability of an array of commonly used active investment strategies to exploit biases. In addition, we use the framework to empirically test the relative importance of prospect theory and the overconfidence hypothesis for momentum investing. Finally, we suggest some criteria investors might use to assess active managers.

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## Behavioral Biases

Although the overextrapolation effect (Lakonishok, Shleifer, and Vishny) is the most well known of behavioral biases, behavioral science is replete with examples of other biases that can affect decision making and, possibly, security prices. Biases are many, but they can be grouped into two general categories: (1) overconfidence and (2) prospect theory.

**Overconfidence.** We use the term "overconfidence" to characterize a broad group of human foibles. Studies have demonstrated that humans tend to ascribe an unduly high probability of success to their forecasts (Kahneman and Tversky 1973). Similarly, individuals are poor Bayesians: They overemphasize their own judgmental forecasts relative to unbiased probabilities (Grether 1980). Some researchers (Kahneman and Tversky 1972) have referred to this trait as "representativeness bias," which, simply put, means that people tend to think "if it walks like a duck and quacks like a duck, it must be a duck." People's preferences also depend on how an argument, or situation, is framed (Kahneman and Tversky 1984), which suggests that choice does not always reflect a dispassionate analysis. Finally, people tend to overreact to dramatic events (De Bondt and Thaler 1985); that is, they tend to attach unduly high probabilities to, for example, aircraft and stock market crashes, which are spectacular but rare. In short, human beings develop, and stick to, stronger views than warranted by impartial analysis of the data.

An overconfidence bias also suggests that investors adjust their expectations only slowly (Daniel, Hirshleifer, and Subrahmanyam 1998). In this sense, overconfidence implies that, because investors adjust to new information with a lag, a postevent drift in stock prices should be evident.

**Prospect Theory.** In prospect theory, utility functions are more complex than those supporting conventional microeconomic models. Prospect theory posits that utility depends on deviations from moving reference points (Kahneman and Tversky 1979) rather than on absolute levels of wealth or consumption. Recent empirical studies have suggested that people fear losses more than they value gains—that losing $1 is about twice as painful as the pleasure of gaining $1 (Kahneman and Tversky 1991). Prospect theory predicts that people will tend to gamble in losses; that is, investors will tend to hold on to losing positions in the hope that prices will eventually recover. Prospect theory also predicts that investors will be risk averse in gains. When they make money, investors will move too quickly to "take some chips off the table."

Prospect theory predicts a payoff to momentum investing. To understand the connection, assume that some investors behave as if they have utility functions for losses and gains for each individual stock in their portfolios. If investors view stocks on an individual basis, then risk aversion in gains will cause them to sell too quickly into rising stock prices, thereby depressing prices relative to fundamentals. In other words, positive momentum sets the stage for a further rise in price when stock prices return to fundamental values. Conversely, risk seeking in losses will cause investors to hold on too long when prices decline, thereby causing the prices of stocks with negative momentum to overstate fundamental values.

## Bias and Valuation Theory

Behavioral science tells us what biases to look for. Valuation theory tells us where to look for them. To clarify this concept, we use a simplified valuation model that presents the value of a share of stock in terms of two components—a part that represents the present value of earnings from existing assets and a part that represents the present value of future growth opportunities.

In 1961, Miller and Modigliani showed that if one assumes a company will have the opportunity to invest in projects that earn average returns of $\rho^*$ for the next $T$ years and if, during that time, the investments are a constant proportion of earnings, then the stock price, $P$, can be given by

$$P \cong \frac{NE}{\rho} + I\left(\frac{\rho^* - \rho}{\rho}\right)T, \tag{1}$$

where $NE$ is normalized earnings, $I$ is annualized net investment, and $\rho$ is the cost of equity, or the equity discount rate. Conceptually, $\rho$ in the growth portion (the second term) of Equation 1 may differ from $\rho$ in the first term if the systematic risk for the company's growth opportunities differs from the systematic risk for current earnings.

Because $I\rho^* = gNE$, where $g$ is the rate of growth of earnings, Equation 1 can also be expressed as

$$P \cong \frac{NE}{\rho} + \left(\frac{gNE}{\rho} - I\right)T. \tag{2}$$

As discussed in the next section, the second term, or growth portion, in Equation 1 or Equation 2 determines how an individual classifies stocks. As is well known, this term will be positive if a company's expected growth is profitable—that is, if $\rho^*$, the return on incremental equity, exceeds $\rho$, the cost of equity.

Suppose cognitive biases affect estimates of both the level of normalized earnings, $NE$, and growth in normalized earnings, $g$. Now, consider the implications of such biases for fast-growth and slow-growth companies. For slow-growth companies, Equation 2 shows that normalized earnings have an important effect on price whereas the term involving $g$ is trivial. Consequently, any bias in price should involve primarily estimates of normalized earnings. Our hypothesis is that a bias in the stock price of a slow-growth company is likely to occur when enough overconfident investors believe a story about the company—either favorable or not—that is inconsistent with its lack of growth prospects and reasonable estimates of its normalized earnings.

Conversely, for fast-growth stocks, Equation 2 shows that the first term—the present value of normalized earnings—is trivial when compared with the present value of future growth opportunities. For these stocks, biased prices are more often associated with biased estimates of future growth. Unlike for their slow-growth counterparts, for which news may often relay information about random deviations from normalized earnings, news for fast-growth companies often conveys information about prospects for future growth. News may signal changed investment opportunities or, more importantly, changes in $\rho^*$, the return on incremental equity. Our hypothesis is that a bias in the stock price of a fast-growth company is likely to occur when enough overconfident investors cling to their beliefs about the future growth prospects of the company despite the release of news that is inconsistent with those beliefs.

The higher the growth rate, $g$, the bigger the potential impact of a shift in perceived profitability. Viewed in this context, the importance of news increases with the company's growth rate. Biased responses to news should have a larger impact on market prices of rapidly growing companies. Biased estimates of normalized earnings should have a profound impact on the stock prices of slowly growing companies but a relatively small impact on the stock prices of rapidly growing companies.

## Stock Classification

To investigate bias, we needed to identify slow-growth and fast-growth companies. To do so, we used past and expected growth rates. Then, we placed companies in a matrix shown in **Exhibit 1**.[1]

Because cognitive biases are most clearly associated with expectational extremes, we focused on stocks that lie in the four corners of the matrix. "Dogs" are companies that have grown slowly in the past and are expected to grow slowly in the future. "Stars" represent the opposite. Although most observations fall along the diagonal between Dogs and Stars, a few fall into the off-diagonal corners—"Fallen Angels" or "Old Dogs with New Tricks." In those cells, the future is expected to significantly diverge from the past. Companies in those cells are typically undergoing change for the better, or worse, and investor expectations are undergoing corresponding changes. Whether a company is a Fallen Angel or an Old Dog with New Tricks depends on the direction of the company's change.

**Dogs.** Earnings-to-price ratios (E/Ps) or book-to-price ratios (B/Ps) can be viewed as measures of investor overconfidence for slow-growth companies. According to Equation 2, price is proportional to normalized earnings (i.e., $P \approx NE/\rho$) because $g$ is small for these companies. Furthermore, because normalized earnings tend to be relatively stable, earnings or book value can be used to derive noisy estimates of normalized earnings (although, in many cases, functions of earnings and book value may provide the best estimates). When investors overextrapolate past failure, price will be low relative to normalized earnings and, consequently, E/P and B/P will be high. When investors are too optimistic, E/P and B/P will be low. Thus, we would predict that for slow-growth companies, cheap stocks should appreciate and expensive stocks should fall in price.

**Stars.** In our taxonomy, Stars are companies that have grown quickly in the past and are expected to do so in the future. Normalized earnings for Stars are less important than they are for Dogs. The value of Star stocks is concentrated in estimates of the present value of future growth, and the value of the first term in Equation 1 or Equation 2 is trivial in comparison with the value of the stock. Consequently, earnings or book value, and thus E/P and B/P multiples, convey little information about value. News, however, can have profound consequences because it may provide information about uncertain future growth prospects. If bias affects the price of growth stocks, we would expect to discover the effect in the stocks' response to news.

## Empirical Results

The overconfidence hypothesis suggests that value investing should work for slow-growth companies. These companies, with their high E/Ps and B/Ps, should outperform their low-E/P and low-B/P counterparts. The overconfidence hypothesis also suggests that a delayed reaction to news should be most important for fast-growth companies. To examine these hypotheses, we constructed portfolios of stocks based on E/P and on new information about future earnings growth. We used consensus estimates of EPS forecasts from the I/B/E/S International database for each quarter between 1989

**Exhibit 1. EPS–Sales Growth Matrix**

| Historical Five-Year Sales Growth Quartile | Forecasted Long-Term EPS Growth Quartile | | | |
|---|---|---|---|---|
| | 1 (low) | 2 | 3 | 4 (high) |
| 4 (high) | Fallen Angels | | | Stars |
| 3 | | | | |
| 2 | | | | |
| 1 (low) | Dogs | | | Old Dogs with New Tricks |

and 1997 and ranked the 1,000 largest publicly traded stocks into quartiles on the basis of five-year sales growth and mean forecasts for EPS growth over the next five years.[2] Because new information is unobservable, we used revisions of earnings forecasts made by security analysts, as well as earnings surprises, as proxies. E/P ratios were calculated using the average of consensus I/B/E/S EPS estimates for the next two fiscal years, where each estimate was weighted by the time remaining until earnings were actually reported.[3] Companies with a data history of less than five years and companies with fewer than three analysts following them were excluded from the sample. In the portfolio construction, we used both revisions and surprises reported in the three months prior to portfolio formation. We used revisions of fiscal year earnings estimates and revisions of estimated earnings for the upcoming calendar quarter. We considered earnings revisions to be positive when EPS estimates for the current fiscal quarter were not falling and at least 40 percent of annual EPS estimates were being revised upward.[4] Earnings reports were considered favorable if they met or exceeded consensus estimates.

**Fast-Growth Stocks.** Average returns on portfolios of Star stocks ranked by E/P and EPS revisions are provided in **Table 1**. For each type of revision, the first row, μ, is average excess return over the three months following portfolio formation; the second row, *se*, is the standard error; and the third row, *n*, is the number of observations. We defined excess return as the total return on a security minus the equally weighted average return of all stocks in the universe.[5] **Table 2** shows similar results for a two-way classification on E/P and earnings surprises.

*E/P and Stars*. Tables 1 and 2 suggest that only a weak relationship exists between E/P and subsequent performance of Stars.[6] Returns are not monotonic in E/P, and in fact, some of the cheaper (second E/P quintile) Stars tended to lag their more expensive counterparts in this period. Although surprising at first, this result is entirely consistent with valuation theory, which would predict that near-term earnings are a poor measure of value for these stocks.

*News and Stars*. In contrast to E/P, signals about future growth were found to be strongly related to subsequent performance. Tables 1 and 2 show that Star stocks experiencing downward estimate revisions, or negative earnings surprises, significantly underperformed the average Star. Keep in mind that these portfolios were constructed in the calendar quarter *following* either the revision or the earnings surprise, and consequently, they exclude the immediate price response to these unanticipated events. In a perfectly efficient market, we would expect an immediate response to unanticipated news but would not expect to see postannouncement drift.

**Table 1. Average Quarterly Excess Returns for Portfolios of Stars Constructed on the Basis of E/P and EPS Estimate Revisions, 1989–97**

| EPS Estimate Revision | E/P Quintile 1 (high) | 2 | 3 | 4 | 5 (low) | All |
|---|---|---|---|---|---|---|
| Negative | | | | | | |
| μ | 0.21 | –3.91 | –0.49 | –3.58 | –3.20 | –1.92 |
| *se* | 1.32 | 1.27 | 1.33 | 1.60 | 1.33 | 0.63 |
| *n* | 321 | 217 | 165 | 150 | 185 | 1,038 |
| Neutral | | | | | | |
| μ | 1.45 | –0.40 | –0.76 | 0.62 | –0.71 | 0.01 |
| *se* | 1.43 | 1.24 | 1.09 | 0.87 | 0.77 | 0.47 |
| *n* | 321 | 255 | 279 | 340 | 490 | 1,685 |
| Positive | | | | | | |
| μ | 2.48 | 2.52 | 5.27 | 0.99 | 3.80 | 2.98 |
| *se* | 1.82 | 1.59 | 1.55 | 1.16 | 1.34 | 0.66 |
| *n* | 206 | 175 | 185 | 236 | 280 | 1,082 |
| All | | | | | | |
| μ | 1.23 | –0.79 | 1.09 | –0.13 | 0.15 | 0.33 |
| *se* | 0.86 | 0.79 | 0.76 | 0.65 | 0.62 | 0.33 |
| *n* | 848 | 647 | 629 | 726 | 955 | 3,805 |

*Note*: Quarterly returns include dividends and were calculated by Factset Data Systems. Returns equal the average of equally weighted returns for each cell less the corresponding equally weighted return on the entire sample for each quarter. Average excess returns equal the average quarterly excess returns on portfolios rebalanced each quarter.

 

**Table 2. Average Quarterly Excess Returns for Portfolios of Stars Constructed on the Basis of E/P and Earnings Surprise, 1989–97**

| | E/P Quintile | | | | | |
|---|---|---|---|---|---|---|
| Earnings Surprise | 1 (high) | 2 | 3 | 4 | 5 (low) | All |
| Negative | | | | | | |
| μ | –0.62 | –1.91 | –1.02 | –1.75 | –2.64 | –1.61 |
| *se* | 1.53 | 1.33 | 1.42 | 1.44 | 1.15 | 0.63 |
| *n* | 269 | 203 | 142 | 172 | 264 | 1,050 |
| Nonnegative | | | | | | |
| μ | 2.10 | –0.28 | 1.70 | 0.37 | 1.22 | 1.07 |
| *se* | 1.04 | 0.97 | 0.89 | 0.72 | 0.73 | 0.39 |
| *n* | 579 | 444 | 487 | 554 | 691 | 2,755 |
| All | | | | | | |
| μ | 1.23 | –0.79 | 1.09 | –0.13 | 0.15 | 0.33 |
| *se* | 0.86 | 0.79 | 0.76 | 0.65 | 0.62 | 0.33 |
| *n* | 848 | 647 | 629 | 726 | 955 | 3,805 |

*Note*: An earnings surprise was negative if reported quarterly earnings fell short of the average EPS estimate available just prior to the report date.

In contrast to the results for E/P, the findings about news are strongly monotonic and significant. Prices of stocks that have already experienced negative information about future growth might continue to fall for two behavioral reasons. First, overconfident investors might be slow to sell when provided with information that contradicts their prior optimistic beliefs about future growth. Second, prospect theory (see Kahneman and Tversky 1979 or, more recently, Statman 1995) suggests that individuals tend to gamble in losses. Growth stock prices frequently plummet on negative earnings surprises and analyst downgrades. These sharply lower prices, relative to the preannouncement reference prices, may induce loss-averse investors to hold on in the hopes of recouping lost gains. Prospect theory, however, as we will demonstrate later, appears to play a minor role.

Taken together, our results provide only limited support for investing in cheap Stars. Although the average excess return for the cheapest growth stocks is positive, it is not significantly different from zero. Therefore, successful GARP (growth-at-a-reasonable-price) investors must emphasize more than extremely cheap growth stocks. They must also hold only those stocks experiencing nonnegative earnings surprises. Those stocks may be tough to find, however, because shares with such characteristics constituted only 2 percent of the entire sample (which implies holding a portfolio of 20 stocks when drawn from a 1,000-stock universe). An easier and more profitable approach in this period would have been to invest only in the most expensive Stars experiencing positive news.

**Slow-Growth Stocks.** The analysis applied to the fast-growth Stars is repeated for the slow-growth Dogs in **Table 3** and **Table 4**.

*E/P and Dogs*. In our taxonomy, Dogs have grown slowly in the past and are expected to grow slowly in the future. As mentioned, we view E/P as a measure of investor overextrapolation. For these stocks, the first term in the valuation equation, which measures the value of normalized earnings, should dominate and the growth term should be insignificant.

Taken as a whole, Dogs tend to outperform the average stock. Moreover, as hypothesized, and in contrast to the findings for Stars, we found a strong relationship between E/P and subsequent performance. Although the average excess return on high-priced Dogs is negative, it is not significantly different from zero.

*News and Dogs*. News plays a secondary role for Dogs. We found, consistent with Equation 1, that the average excess return on Dogs experiencing positive revisions was not significantly different from Dogs experiencing negative revisions.[7] Perversely, Dogs with mixed revisions (Mutts?) exhibited the highest average return. Dogs experiencing negative revisions tended to underperform other Dogs, but neither negative revisions nor negative surprises led to significantly negative excess returns. Finally, the average return for Dogs with negative earnings surprises was significantly positive. Taken as a whole, the reaction of Dogs to news is consistent with the premise that investors view earnings news largely as information about the variability, not the mean, of normalized earnings.

**Table 3. Average Quarterly Excess Returns for Portfolios of Dogs Constructed on the Basis of E/P and EPS Estimate Revisions, 1989–97**

| EPS Estimate Revision | E/P Quintile 1 (high) | 2 | 3 | 4 | 5 (low) | All |
|---|---|---|---|---|---|---|
| Negative | | | | | | |
| μ | 1.64 | 2.17 | –0.83 | –0.30 | –1.46 | 0.09 |
| *se* | 1.21 | 0.81 | 0.61 | 0.78 | 1.09 | 0.40 |
| *n* | 156 | 228 | 282 | 192 | 258 | 1,116 |
| Neutral | | | | | | |
| μ | 3.75 | 1.28 | 0.80 | 0.07 | 1.41 | 1.15 |
| *se* | 1.00 | 0.53 | 0.43 | 0.66 | 1.29 | 0.30 |
| *n* | 174 | 410 | 552 | 333 | 193 | 1,661 |
| Positive | | | | | | |
| μ | 2.97 | 0.12 | 0.34 | –1.65 | –0.32 | 0.33 |
| *se* | 1.22 | 1.01 | 1.22 | 0.98 | 1.26 | 0.51 |
| *n* | 119 | 106 | 93 | 118 | 98 | 534 |
| All | | | | | | |
| μ | 2.80 | 1.39 | 0.26 | -0.35 | –0.25 | 0.66 |
| *se* | 0.66 | 0.41 | 0.34 | 0.45 | 0.72 | 0.22 |
| *n* | 449 | 744 | 927 | 643 | 548 | 3,311 |

**Table 4. Average Quarterly Excess Returns for Portfolios of Dogs Constructed on the Basis of E/P and Earnings Surprise, 1989–97**

| Earnings Surprise | E/P Quintile 1 (high) | 2 | 3 | 4 | 5 (low) | All |
|---|---|---|---|---|---|---|
| Negative | | | | | | |
| μ | 2.84 | 1.12 | 0.56 | 0.38 | –1.54 | 0.70 |
| *se* | 1.12 | 0.61 | 0.49 | 0.75 | 1.10 | 0.34 |
| *n* | 172 | 330 | 400 | 251 | 242 | 1,395 |
| Nonnegative | | | | | | |
| μ | 2.78 | 1.60 | 0.03 | –0.83 | 0.82 | 0.63 |
| *se* | 0.81 | 0.55 | 0.47 | 0.56 | 0.95 | 0.29 |
| *n* | 277 | 414 | 527 | 392 | 306 | 1,916 |
| All | | | | | | |
| μ | 2.80 | 1.39 | 0.26 | –0.35 | –0.25 | 0.66 |
| *se* | 0.66 | 0.41 | 0.34 | 0.45 | 0.72 | 0.22 |
| *n* | 449 | 744 | 927 | 643 | 548 | 3,311 |

**Fallen Angels and Old Dogs with New Tricks.** Cognitive bias potentially plays a role for the off-diagonal stocks. The tendency for individuals to be overconfident suggests that investor expectations may reflect bias whenever forecasts materially diverge from historical experience. In our framework, the outlook may be too pessimistic for Fallen Angels and too optimistic for Old Dogs with New Tricks.

**Table 5** shows average quarterly excess returns for equally weighted portfolios constructed using the classification matrix. Note that far fewer observations, $n$, fall in the off-diagonal corner cells ($n$ = 525 and $n$ = 324) than in the Dog cell ($n$ = 3,332) and Star cell ($n$ = 3,822). Nevertheless, average excess returns were found to be positive for Fallen Angels and negative for Old Dogs with New Tricks—a finding consistent with the overconfidence hypothesis.

Fallen Angels tend to behave more like growth stocks. These companies have exhibited rapid rates of growth in the past, but their growth is expected to slow in the future. Our research (not shown here) suggests that news is much more important than E/P for these stocks. Although the sample studied here is quite small, we did find the average return to be negative (positive) for Fallen Angels experiencing bad (good) news. We found no apparent relationship to E/P.

Investing in Old Dogs with New Tricks is dangerous. Expectations are high for these stocks, despite the fact that they have been among the slowest growers in the past. Taken as a whole, these stocks generated a significant negative return over the period studied. These stocks tended to underperform all other categories regardless of news or E/P.

 

**Table 5. Average Quarterly Excess Returns by Company Classification, 1989–97**

| Historical Five-Year Sales Growth | Forecasted Long-Term EPS Growth 1 (low) | 2 | 3 | 4 (high) | All |
|---|---|---|---|---|---|
| 4 (high) | | | | | |
| μ | 0.75 | –1.20 | –0.12 | 0.32 | 0.07 |
| *se* | 0.62 | 0.47 | 0.38 | 0.33 | 0.22 |
| *n* | 525 | 815 | 1,622 | 3,822 | 6,784 |
| 3 | | | | | |
| μ | –0.13 | 0.38 | –0.03 | –0.07 | 0.11 |
| *se* | 0.37 | 0.26 | 0.26 | 0.51 | 0.16 |
| *n* | 1,165 | 2,055 | 2,598 | 1,024 | 6,842 |
| 2 | | | | | |
| μ | –0.75 | –0.08 | 0.33 | –0.31 | –0.25 |
| *se* | 0.23 | 0.23 | 0.33 | 0.91 | 0.15 |
| *n* | 2,520 | 2,411 | 1,541 | 367 | 6,839 |
| 1 (low) | | | | | |
| μ | 0.63 | 0.16 | –0.63 | –1.60 | 0.18 |
| *se* | 0.22 | 0.28 | 0.40 | 0.87 | 0.16 |
| *n* | 3,332 | 2,015 | 1,109 | 324 | 6,780 |
| All | | | | | |
| μ | 0.10 | –0.01 | –0.07 | 0.10 | 0.03 |
| *se* | 0.14 | 0.14 | 0.17 | 0.26 | 0.09 |
| *n* | 7,542 | 7,296 | 6,870 | 5,537 | 27,245 |

**Prospect Theory versus Overconfidence.** So far, we have emphasized the impact of overconfidence on stock prices, but as mentioned previously, prospect theory suggests that stocks with positive (negative) momentum should subsequently outperform (underperform). So, controlling for the type of stock, we compared whether overconfidence or prospect theory was the better explanation for stock price movements.

**Table 6** shows the relationship between past performance and news for Stars. The bottom section (labeled "All") suggests a univariate relationship

**Table 6. Average Quarterly Excess Returns for Portfolios of Stars Constructed on the Basis of EPS Revisions and 12-Month Excess Returns, 1989–97**

| EPS Estimate Revision | Alpha Quintile 1 (low) | 2 | 3 | 4 | 5 (high) | All |
|---|---|---|---|---|---|---|
| Negative | | | | | | |
| μ | –1.15 | –2.95 | –2.89 | –1.52 | –2.22 | –1.92 |
| *se* | 1.09 | 1.35 | 1.56 | 1.61 | 1.49 | 0.63 |
| *n* | 422 | 166 | 153 | 132 | 158 | 1,040 |
| Neutral | | | | | | |
| μ | –1.75 | 0.59 | –0.99 | 1.48 | 0.29 | 0.01 |
| *se* | 1.32 | 1.08 | 1.15 | 0.98 | 0.84 | 0.47 |
| *n* | 276 | 236 | 241 | 356 | 581 | 1,697 |
| Positive | | | | | | |
| μ | 1.24 | –1.09 | 0.73 | –0.03 | 4.47 | 2.95 |
| *se* | 3.39 | 2.39 | 2.70 | 1.42 | 0.84 | 0.66 |
| *n* | 52 | 69 | 66 | 174 | 718 | 1,085 |
| All | | | | | | |
| μ | –1.20 | –0.90 | –1.59 | 0.48 | 2.09 | 0.32 |
| *se* | 0.82 | 0.80 | 0.88 | 0.72 | 0.56 | 0.33 |
| *n* | 750 | 471 | 460 | 662 | 1,454 | 3,800 |

*Note*: Momentum was measured as the intercept (alpha) from a regression of 52 weekly returns against the corresponding return on the value-weighted NYSE index. For any stock, the alpha quintile represents the quintile ranking of the intercept from a regression of weekly returns against the value-weighted NYSE for the 52 weeks prior to the portfolio formation date.

between past and future performance—a finding that is consistent with a number of recent empirical studies (see, for example, Jegadeesh and Titman 1993; Lee and Swaminathan 1998). However, most of the relationship is explained by a lagged response to news; that is, past performance seems to be proxying for past news. To see this relationship, note that most of the stocks with negative momentum (Column 1) had negative or neutral earnings revisions and that their subsequent returns were negative. The stocks with negative momentum but with positive revisions had positive subsequent returns, but there were too few of them to outweigh the sheer number of stocks with bad news. The same logic applies to the high-momentum stocks. Finally, note that the relationship between past momentum (alpha) and future return appears randomly distributed across any μ row (where each row controls for the direction of "news"). The differences in mean returns between high- and low-momentum stocks across any μ row are insignificant. We found similar results for Dogs.

Rather than negative momentum causing poor performance, the data suggest that bad news causes these stocks to underperform (thereby creating negative momentum). Then, a lagged reaction to bad news resulting from overconfidence causes the stocks to underperform in the next quarter.

## Implications for Active Investors

These results suggest that some investment strategies are more likely to succeed than others and that value investing is not the only route to exploiting bias. The preceding framework also provides interesting implications for several popular investment strategies.

- *Growth investing*. Because current valuation measures such as E/P have little meaning, growth managers must seek out cheap growth stocks. Furthermore, because investors react slowly to news, growth stock managers should ride winners and look for good news. Sell disciplines, however, are critical for growth managers. Successful growth managers should be quick to sell and should rapidly revise forecasts of future earnings following any evidence of faltering growth.
- *GARP*. Pursuing growth at a reasonable price represents the intersection of value and growth investing. GARP should emphasize stocks for which expectations are diametrically opposed to past performance—for example, stocks that have had among the highest growth in the past but are now expected to have among the slowest. Stars provide some opportunities for GARP investors, but more prospects lie in the Fallen Angel category. Because Fallen Angels have characteristics that closely resemble growth stocks, GARP investors should emphasize Fallen Angels that are experiencing some evidence of a turnaround (i.e., positive news).
- *Value investing*. Value investors are lucky because they swim with the tide. As Tables 3 and 4 show, a randomly constructed portfolio of Dogs tends to outperform—even if it includes some expensive Dogs with negative news. Consequently, holding value index funds may make sense. Actively managed value portfolios should emphasize cheap Dogs. Although looking for signs of a turnaround (e.g., rising EPS estimates and positive surprises) may help performance, most of the value investor's effort should be focused on finding low-priced stocks and on constructing estimates of normalized earnings. Value portfolios can also hold GARP stocks, which may not be especially cheap but for which expectations significantly diverge from historical experience.
- *Old Dogs with New Tricks*. All investors should avoid the well-framed story suggesting that an old dog has learned new tricks. The exception is short sellers, who might find this quadrant fertile ground to plow. This warning also applies to initial public offerings and other special situations in which investors may be subject to representativeness bias and carefully framed reasons to buy.
- *Momentum*. Although risk and loss aversion may create bias in stock prices, our research suggests that the momentum effect may actually have more to do with an overconfidence bias. We found little behavioral support for strategies that rely exclusively on momentum, other than as a once-removed cousin of a strategy that responds to news.

## Notes

1. Most analysts and practitioners classify stocks into growth and value categories. In one conventional classification, growth stocks are companies that are expensive and value stocks are companies that are cheap relative to earnings or book value. Although nothing is wrong with this conventional approach, it blends the type of stock (either fast or slow growth) with the market's assessment of the company. The value category, for example, can include growth stocks (as evidenced by the popular GARP, growth-at-a-reasonable-price, strategy). We were interested specifically in the market's assessment of expected growth and, consequently, did not want to mix the two characteristics.

We used historical sales growth rather than historical EPS growth as the measure of past growth because expectations appear to be more aligned with sales than the more variable earnings growth—especially for rapidly growing companies with a history of low earnings.

We weighted year-over-year sales growth for each of the past five years with the more recent years receiving the higher weight. Specifically, we assigned sales growth for five years ago a weight of 1/15 and last year's sales growth a weight of 5/15. This methodology is similar to that used in Lakonishok, Shleifer, and Vishny.

2. Although we would have preferred to study a longer interval, quarterly EPS estimate revisions and earnings surprises from I/B/E/S (used later in the analysis) were not available until 1989.
3. For example, for a company that reported earnings in February, at the end of September, current fiscal year earnings forecasts received a weight of 5/12 and the next fiscal year's earnings forecasts received a weight of 7/12. Time weighting earnings in this manner provides a constant 12-month-ahead EPS forecast.
4. Specifically, we wanted to capture good long-term news that was not rendered ambiguous by contrary short-term news. The following two conditions were required to hold for revisions to be considered positive. First, the net (up minus down) number of revisions for the current fiscal year made over the prior three months exceeded 40 percent of the total number of analysts following the stock. Second, the net number of EPS estimate revisions for the latest fiscal quarter made over the prior three months was nonnegative.
5. Returns were unavailable for companies that vanished (e.g., merged or were delisted) during a quarter, and these companies were excluded from the analysis. Because most mergers and potential bankruptcies are known some time in advance, we assumed that most information on mergers and bankruptcies was captured in returns over prior quarters.

We measured E/P using 12-month-ahead consensus EPS forecasts, which we believe more accurately represent expectations than trailing earnings. These EPS forecasts were estimated by time weighting individual EPS estimates (from I/B/E/S) for each of the next two fiscal years by the time remaining until annual results were reported. We "normalized" E/P by grouping stocks into quintiles by expected long-term earnings growth and then ranking stocks by E/P within each group. Consequently, the E/P quintiles for Stars shown in Tables 1 and 2 represent rankings relative to other fast-growth companies.

For any quarter, excess return on a stock equaled the total return on the stock (including dividends) minus the equally weighted average return on all stocks in the entire universe.

6. We view this result as a refinement of Lakonishok, Shleifer, and Vishny. They concluded that overextrapolation of past success causes "glamour" stocks (companies with high historical sales growth that are trading at low E/Ps) to subsequently underperform. Our study focused on a subset of glamour stocks—companies that grew quickly in the past *and are expected to grow quickly in the future* (i.e., Stars).
7. One nonbehavioral explanation for this lack of difference is that past estimate revisions may be better predictors of future revisions for Stars than for Dogs. We found no difference, however, in the serial correlation of surprises between Dogs and Stars.

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