# Analyst Forecasts and the Cross Section of European Stock Returns

By Phillip J. McKnight and Steven K. Todd

We examine revisions to earnings forecasts by equity analysts and their role in predicting stock returns. We provide evidence that European stocks with net upward revised forecasts earn higher future returns than otherwise similar stocks. This effect is not concentrated in small stocks, stocks with low analyst coverage, or stocks with low book-to-market ratios. We find differences in the return continuation patterns of stocks with upward versus downward revisions, namely, bad news travels quickly, but good news travels slowly. This result is consistent with investors' attaching greater significance to poor earnings forecasts, but adopting a wait-and-see approach to good news.

## I. INTRODUCTION

In this paper we analyze the role of earnings forecast revisions by equity analysts in predicting the cross section of European stock returns. We find that stocks with the greatest number of upward revisions in earnings, net of downward revisions, earn significantly higher returns than otherwise similar stocks. In particular, a portfolio of stocks in the highest quintile of net upward revisions outperforms a portfolio of stocks in the lowest quintile of net upward revisions by more than 16% per year. This effect is not concentrated in small stocks, stocks with low analyst coverage, or stocks with low book-to-market ratios. The effect is statistically significant in seven out of the 13 European countries we analyze. Our results likely understate the performance of a trading strategy based on forecast revisions. Although we ignore transaction costs, we evaluate and sort stocks on a monthly basis, acting on forecast revisions data that, on average, has been public for more than several days.

The pattern of returns that we observe when we sort stocks based on forecast revisions complements other findings of momentum, such as the tendency for past winner and loser stocks to repeat (Jegadeesh and Titman, 1993, 2001; Rouwenhurst, 1998) or for stocks with a greater degree of consensus in analysts' earnings forecasts to outperform stocks with more dispersed earnings forecasts (Diether, Malloy, and Scherbina, 2002).

Evidence of stock price momentum has inspired researchers to develop explanations for the phenomenon. These include risk-based explanations (Conrad and Kaul, 1998), underreaction (Chan, Jagadeesh, and Lakonishok, 1996), investors' conservatism bias (Barberis, Shleifer, and Vishny, 1998) the gradual diffusion

of private firm-specific information (Hong and Stein, 1999) and short-sale costs (Miller, 1977). We tentatively offer another explanation: institutional biases in the research generation process. Conflicts of interest generated by investment banking relationships may encourage analysts to report overly optimistic earnings, and investors, who are aware of these biases, may respond by being cynical and adopting a wait-and-see approach when it comes to good news.

Using our measure of forecast revisions, we examine whether good and bad information is processed symmetrically by investors. We find differences in the return continuation patterns for stocks with net upward versus downward forecast revisions. In contrast to Hong, Lim, and Stein (2000), we find that bad news travels quickly, but good news travels slowly. This result is consistent with investors' attaching great significance to poor earnings forecasts, but adopting a wait-and-see approach to good news. This cynicism on the part of investors is perfectly rational, if analysts are biased toward issuing overly optimistic earnings forecasts.

Our study provides an opportunity to assess some of the explanations offered for momentum. We find general support for Barberis, Shleifer, and Vishny (1998) who argue that momentum is rooted in investors' conservatism bias and that investors do not update their beliefs adequately based on the strength and weight of new information. We postulate that our measure of forecast revisions is information with low strength and high weight. Consistent with Barberis, Shleifer, and Vishny (1998), we find that investors underreact to forecast revisions, especially, upward revisions. The return continuation pattern we observe is statistically significant and persists over a 12-month holding period.

On the other hand, our results conflict with Hong, Lim, and Stein (2000), who use U.S. stock returns to test the gradual information diffusion hypothesis of Hong and Stein (1999). Whereas Hong, Lim, and Stein (2000) find that momentum profits are mostly generated by small firms with low analyst coverage, we find that a trading strategy based on forecast revisions produces very large returns for mid-size firms with high analyst coverage. Moreover, the cross section of European stock returns is positively related to residual analyst coverage. In general, our evidence is at odds with arguments that high transaction costs are the drivers of return continuation.

Our paper complements recent studies by Barber, Lehavy, McNichols, and Trueman (2001, 2003) and Jegadeesh, Kim, Krische, and Lee (2004) that document the predictive power of analyst recommendations in the U.S. Like the information contained in consensus recommendations, the information contained in earnings revisions is a robust return predictor. A trading strategy based on this information can be quite profitable. We find that for European stocks, a trading strategy based on forecast revisions dominates a similar strategy based on mean consensus recommendations.

The remainder of the paper is organized as follows. Section II provides a description of our methodology, data set, and trading strategy. Section III contains our main results on return continuation sorted by firm size, residual analyst coverage, and book-to-market ratios. Section IV presents country-specific results. In Section V, we provide possible explanations for our findings. Section VI concludes the paper.

## II. METHODOLOGY

### A Measure of Forecast Revisions

Our measure of forecast revisions is given by expression (1).

$$\begin{aligned}\text{Forecast revision index}_{i,t} = {} & \text{number of upward revisions}_{i,t-1} \\ & - \text{number of downward revisions}_{i,t-1}\end{aligned} \tag{1}$$

At time $t$, for stock $i$, the forecast revision index value is simply the difference between the number of upgrades on stock $i$ and the number of downgrades on stock $i$ over the previous month. Assuming there is not systematic clustering of analyst revisions at month end, our measure of forecast revisions captures information that is, on average, 15 days old.

We choose to not scale our index by the total number of analyst revisions or the total number of analysts covering a stock because we believe investors attach greater significance to the absolute volume of revisions, rather than the relative volume of revisions.[1] By construction, our measure of forecast revisions does not disproportionately assign high or low weightings to low coverage or small stocks. In one sense, our index captures the degree of herding among equity analysts. Such behavior is documented in Welch (2000) and Graham (1999) and is analogous to the herding behavior of institutional money managers documented in Grinblatt, Titman, and Wermers (1995).

Using our measure of forecast revisions, we test whether good (i.e., a positive index value) and bad (i.e., a negative index value) information is processed symmetrically by investors. Absent institutional biases in the information generation process, we should not expect differences in the timing or magnitude of investors' reactions to good and bad news.

We compare our measure of forecast revisions to another measure of analyst sentiment examined by researchers. We follow Barber, Lehavy, McNichols, and Trueman (2001) and Jegadeesh, Kim, Krische, and Lee (2004) and focus on mean consensus recommendations. These data measure firm-level mean analyst recommendation values using a 5-point scale, with 1.0 representing a strong buy and 5.0 representing a strong sell.

### Data and Sample Characteristics

We use data provided by the Institutional Brokers Estimate System (I/B/E/S). Our sample period runs from May 1988 to November 2001. The sample consists of monthly stock returns in local currency, converted to pounds sterling using exchange rate information from DataStream. We exclude those countries where analyst coverage began only recently and few firms are covered.[2] The

[1] We obtain qualitatively similar results when we scale our forecast revision index by the number of analyst revisions.

sample excludes all firms whose stock price is below £1 in order to ensure that the bid-ask bounce and/or smaller, illiquid stocks do not influence the results (Jegadeesh and Titman, 2001). We end up with a sample of 3,084 firms from 13 European countries. Country (firm) representation is as follows: Austria (76), Belgium (86), Denmark (107), Finland (100), France (411), Germany (568), Italy (165), Netherlands (155), Norway (102), Spain (149), Sweden (216), Switzerland (160), and U.K. (789).

We use the summary history files from the Institutional Brokers Estimate System (I/B/E/S). These files contain security pricing data, analyst coverage, one-year forward earnings forecasts, revisions up and down, and actual reported earnings per share. As a robustness check, we compare the pricing data in the I/B/E/S file to that provided by DataStream. We find few instances of inconsistency; hence we use the I/B/E/S file as our primary data source.

We also use mean consensus recommendation data from the summary history files of the Institutional Brokers Estimate System (I/B/E/S). These data measure firm-level mean analyst recommendation values using a 5-point scale, with 1.0 representing a strong buy and 5.0 representing a strong sell. These data are compiled by I/B/E/S, updated monthly, and are only available from November 1993 through November 2001.

In Section III we sort on firm size, book-to-market ratios, and a measure of analyst coverage. We measure firm size as the market capitalization for a firm at the start of the year. We compute book-to-market ratios by scaling the book value of a firm's equity at the start of the year by the market value of its equity. In order to examine the impact of analyst coverage, we set coverage equal to the number of analysts providing earnings estimates for the fiscal year one period. Where such a value is missing, we assume coverage is equal to zero. Since firm size and analyst coverage are strongly positively correlated, we regress the natural logarithm of (1 + no. of analysts) on the natural logarithm of market capitalization, and use the residuals from this regression as a proxy for the incremental effect of analyst coverage. (See Bhushan, 1989; Brennan and Hughes, 1991; Hong, Lim, and Stein, 2000).[3] We call this measure of analyst coverage, residual analyst coverage.

Table 1 summarizes analyst coverage information for our sample of European firms. We see that analyst coverage has increased considerably over the sample period. In 1988, 38.1% of European firms were uncovered; by 2001, the number of uncovered firms declined to 6.3%. Because I/B/E/S does not purport to provide data from all research analysts, we cannot say whether this increase in coverage is due to greater research activity on the part of analysts or increased data collection on the part of I/B/E/S. Comparing our sample to that used by Hong, Lim, and Stein (2000), we see that European firms enjoy greater analyst coverage (or more complete analyst reporting) than their American counterparts. For example, in

[2] These countries are Greece, Ireland, and Portugal.

[3] By adding one to the number of analysts, we acknowledge that one additional analyst has a large impact on firms that are not covered (see Hong, Lim, and Stein, 2000).

**Table 1. Descriptive Statistics** Table 1 reports descriptive statistics for the period May 1988 through November 2001 for all stocks representing 13 European countries, excluding those with a share price less than £1. For each year, we report the number of I/B/E/S firms, their mean and median size (in £mils), the number of analysts per firm at coverage percentiles ranging from 10% to 90%, and the percentage of I/B/E/S firms that had no analyst coverage.

| Year | Number of IBES Firms | Mean Firm Size (£mils) | Median Firm Size (£mils) | Number of Analysts at Coverage Percentiles | | | | | | | | | Percent of Firms Not Covered |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | 10 | 20 | 30 | 40 | 50 | 60 | 70 | 80 | 90 | |
| 1988 | 3,226 | 353 | 46 | 0 | 0 | 0 | 1 | 1 | 2 | 4 | 7 | 13 | 38.1 |
| 1989 | 3,398 | 373 | 51 | 0 | 0 | 0 | 1 | 3 | 4 | 6 | 10 | 15 | 31.2 |
| 1990 | 3,228 | 383 | 56 | 0 | 0 | 1 | 2 | 4 | 5 | 8 | 11 | 17 | 25.8 |
| 1991 | 3,401 | 320 | 49 | 0 | 0 | 1 | 2 | 4 | 5 | 8 | 12 | 18 | 25.0 |
| 1992 | 3,616 | 314 | 41 | 0 | 0 | 1 | 2 | 4 | 5 | 9 | 13 | 19 | 24.9 |
| 1993 | 3,604 | 365 | 49 | 0 | 1 | 2 | 3 | 4 | 6 | 9 | 15 | 22 | 19.3 |
| 1994 | 3,602 | 446 | 70 | 0 | 1 | 2 | 3 | 4 | 7 | 10 | 16 | 23 | 19.2 |
| 1995 | 3,989 | 466 | 72 | 0 | 1 | 2 | 3 | 4 | 7 | 10 | 16 | 24 | 19.6 |
| 1996 | 4,022 | 554 | 79 | 0 | 1 | 2 | 3 | 5 | 7 | 11 | 17 | 24 | 18.1 |
| 1997 | 4,302 | 668 | 80 | 0 | 1 | 2 | 3 | 4 | 6 | 9 | 15 | 24 | 18.9 |
| 1998 | 4,402 | 882 | 91 | 0 | 1 | 2 | 2 | 4 | 5 | 8 | 12 | 21 | 14.9 |
| 1999 | 4,500 | 1,080 | 92 | 0 | 1 | 1 | 2 | 3 | 5 | 7 | 11 | 18 | 14.1 |
| 2000 | 4,543 | 1,340 | 126 | 0 | 1 | 1 | 2 | 3 | 5 | 7 | 11 | 17 | 11.7 |
| 2001 | 4,075 | 1,370 | 118 | 1 | 1 | 2 | 3 | 4 | 6 | 9 | 12 | 19 | 6.3 |

1996, 36.9% of U.S. firms were uncovered, whereas only 18.1% of European firms were uncovered.

### Trading Strategy

Each month, we form five portfolios by sorting on the prior month's forecast revision index values. Within each portfolio, we weight the stock holdings equally. We end up with portfolios P1, P2, P3, P4, and P5, where P1 (P5) contains those stocks with the lowest (highest) forecast revision index values. The trading strategy we consider is shorting P1 and buying P5, (P5 − P1). We vary the holding period from 1 month up to 12 months.

Table 2 reports mean monthly returns on the five portfolios formed by sorting on the forecast revision index, as well as the trading strategy that sells those stocks in the lowest quintile and buys those stocks in the highest quintile, (P5 − P1). The holding period varies from 1 month to 12 months. For a 1-month holding period, the trading strategy of P5 − P1 generates a 1.37% return per month (with a *t*-statistic = 2.36). This is quite a bit larger than the returns found in pure momentum studies, such as Jegadeesh and Titman (1993, 2000) and Rouwenhorst (1998), or the returns generated from trading strategies based on analyst recommendations, such as Barber, Lehavy, McNichols, and Trueman (2001) and Jegadeesh, Kim, Krische, and Lee (2004). However, like these other studies, our returns ignore transaction costs, which can be quite substantial (see, for example, Lesmond, Schill, and Zhou, 2004, and Keim, 2003).

**Table 2. Forecast Revisions and Return Continuation** Table 2 reports average monthly portfolio returns for the period May 1988 through November 2001 for all stocks representing 13 European countries, excluding those with a share price less than £1. The relative strength portfolios are ranked in ascending order based on the forecast revision index, defined as the difference between the number of upward revisions and the number of downward revisions by analysts since the last monthly production report, as provided by I/B/E/S. Stocks in portfolio P1 (P5) are those that contain the highest number of downward (upward) revisions. The portfolios are equally weighted at formation and held for 1, 3, 6, 9, or 12 months. *T*-statistics are reported in parentheses.

| | **Holding Period** | | | | |
|---|---|---|---|---|---|
| Forecast Revision Index | 1 month | 3 months | 6 months | 9 months | 12 months |
| P1 (Strong Sell) | 0.0026 | 0.0028 | 0.0028 | 0.0028 | 0.0036 |
| P2 | 0.0040 | 0.0038 | 0.0032 | 0.0031 | 0.0035 |
| P3 | 0.0067 | 0.0042 | 0.0057 | 0.0054 | 0.0057 |
| P4 | 0.0105 | 0.0108 | 0.0098 | 0.0088 | 0.0087 |
| P5 (Strong Buy) | 0.0163 | 0.0138 | 0.0116 | 0.0106 | 0.0106 |
| P5 − P1 | 0.0137 | 0.0110 | 0.0088 | 0.0078 | 0.0070 |
| | (2.36) | (3.42) | (3.93) | (4.87) | (5.05) |

As the holding period increases, the mean monthly return generated by our trading strategy decreases, consistent with a gradual diffusion of the information contained in analyst revisions. For a 12-month holding period, the trading strategy of P5 − P1 generates a 0.70% return per month (with a *t*-statistic of 5.05).[4]

If we fix the holding period, we see that monthly returns increase monotonically with the forecast revision index. For example, for a 3-month holding period, the mean monthly returns on P1, P2, P3, P4, and P5 are 0.28%, 0.38%, 0.42%, 1.08%, and 1.38%, respectively. Mean returns on the sell portfolio, P1, are always positive, though considerably smaller than the returns on the neutral portfolio, P3. Focusing on the P5 − P1 trading strategy, less than 30% of that portfolio's return comes from the short side of the trade (i.e., the difference between the returns on portfolios P3 and P1). In other words, it appears that the lion's share of our trading strategy's profit is generated by the long position. This result contrasts sharply with Hong, Lim, and Stein (2000), Barber, Lehavy, McNichols, Trueman (2001), and Jegadeesh, Kim, Krische, and Lee (2004), where the short portfolio generates more than 50% of the profits from the trading strategy.

In Table 3, we compare the performance of a 1-month trading strategy based on the forecast revision index to the performance of a similar strategy based on another measure of analyst sentiment, namely the mean consensus recommendation, a metric examined by Barber, Lehavy, McNichols, Trueman (2001) and Jegadeesh, Kim, Krische, and Lee (2004). The trading strategy based on the forecast revision index dominates a similar strategy based on the mean consensus recommendation, with the latter strategy producing a smaller monthly return (0.81% per month versus 1.37% per month) that is not statistically significant (*t*-statistic = 1.15). The former strategy involves buying large company stocks (mean firm size = £3.199 billion) that are well covered (mean number of analysts per firm = 17.0) and selling large company stocks (mean firm size = £3.066 billion) that are more actively covered (mean number of analysts per firm = 19.3). In contrast, the latter strategy involves buying large company stocks (mean firm size = £3.210 billion) that are well covered (mean number of analysts per firm = 14.0) and selling small company stocks (mean firm size = £0.762 billion) that are less actively tracked (mean number of analysts per firm = 12.6). Compared to studies based on U.S. data (e.g., Hong, Lim, and Stein 2000), both trading strategies involve well-covered stocks.

A trading strategy based on forecast revisions results in sell and buy portfolios with forecast revision index values of −4.72 and +3.62 respectively. In contrast, a trading strategy based on recommendations results in sell and buy portfolios with mean consensus recommendation values of 3.34 and 1.66 respectively. Since analysts are reluctant to issue "sell" recommendations, a strategy based on consensus recommendations involves shorting many stocks that are rated "hold."

A trading strategy based on forecast revisions might dominate a similar strategy based on recommendations because the latter measure of analyst sentiment is

[4] If we extend the holding period, we find that returns on the trading strategy continue to decline. At 36 months, the trading strategy of P5 − P1 generates a 0.29% return per month (with a *t*-statistic of 3.74). There is no evidence of a return reversal over this 36-month holding period.

**Table 3. Portfolio Returns and Descriptive Statistics: Forecast Revisions Versus Mean Consensus Recommendations** Table 3 reports average monthly portfolio returns and descriptive statistics for the periods May 1988 through November 2001 (Panel A) and November 1993 through November 2001 (Panel B) for all stocks representing 13 European countries, excluding those with a share price less than £1. In Panel A, portfolios are formed by sorting on the forecast revision index, defined as the difference between the number of upward revisions and the number of downward revisions by analysts since the last monthly production report, as provided by I/B/E/S; stocks in portfolio P1 (P5) are those which contain the highest number of net downward (upward) revisions. In Panel B, portfolios are formed by sorting on the mean consensus recommendation, with 1.0 representing a strong buy, and 5.0 representing a strong sell; stocks in portfolio P1 (P5) are those with the highest (lowest) mean analyst recommendation. The portfolios are equally weighted at formation and held for 1 month. *T*-statistics are reported in parentheses.

**Panel A: Portfolios Based on the Forecast Revision Index**

| Forecast Revision Index | 1-Month Holding Period Return | Mean Number of Analysts | Mean Forecast Revision Index | Mean Firm Size (£mils) |
|---|---|---|---|---|
| P1 (Strong sell) | 0.0026 | 19.3 | −4.72 | 3,066 |
| P2 | 0.0040 | 13.6 | −1.41 | 1,409 |
| P3 | 0.0067 | 9.9 | −0.55 | 1,108 |
| P4 | 0.0105 | 10.6 | 0.90 | 1,218 |
| P5 (Strong buy) | 0.0163 | 17.0 | 3.62 | 3,199 |
| P5 − P1 | 0.0137 | | | |
| | (2.36) | | | |

**Panel B: Portfolios Based on the Mean Consensus Recommendation**

| Mean Consensus Recommendation | 1-Month Holding Period Return | Mean Number of Analysts | Mean Consensus Recommendation | Mean Firm Size (£mils) |
|---|---|---|---|---|
| P1 (Strong sell) | 0.0046 | 12.6 | 3.34 | 762 |
| P2 | 0.0070 | 16.7 | 2.74 | 2,420 |
| P3 | 0.0069 | 16.4 | 2.41 | 2,891 |
| P4 | 0.0082 | 15.1 | 2.11 | 2,928 |
| P5 (Strong buy) | 0.0127 | 14.0 | 1.66 | 3,210 |
| P5 − P1 | 0.0081 | | | |
| | (1.15) | | | |

sticky. When analysts initiate coverage for a firm, they often produce a report that lists a 1-year (or longer-term) share price target. Recommendations often accompany and summarize these price targets. Analysts may be reluctant to revise their recommendations frequently and appear flippant. In fact, Barber, Lehavy, McNichols, and Trueman (2001) show that nearly half of all recommendations are left unchanged when they are revisited, approximately 300 days after they were

first made. Earnings forecasts, in contrast, are generally more responsive to short-term news events. Richardson, Teoh, and Wysocki (2004) show that analysts often revise their earnings forecasts on a quarterly (or monthly) basis.

If analysts revise earnings forecasts more frequently than they revise recommendations, and if earnings forecasts are informative, then a trading strategy based on forecast revisions will dominate one based on recommendations or changes in recommendations. We find that our trading strategy dominates a similar strategy based on monthly changes in the mean consensus recommendation. In the next section, we explore this issue in more detail by performing a Fama and MacBeth (1973) cross-sectional analysis of European stock returns in Table 7.

Combining the information in Tables 2 and 3, we see that our trading strategy of sorting P1 and buying P5 is heavily skewed toward large company stocks with high analyst coverage. This result conflicts with Hong, Lim, and Stein (2000) who find that momentum strategies work best for small-sized firms with low analyst coverage. The evidence also conflicts with Diether, Malloy, and Scherbina (2002) who find an inverse relation between dispersion in analysts' forecasts and future stock returns, especially pronounced for small stocks, where short-sale constraints are likely binding. Because our trading strategy does not disproportionately favor small or illiquid stocks with short-sale constraints, we would expect the transaction costs associated with it to be lower than the transaction costs associated with pure momentum strategies.

## III. SORTS BY SIZE, BOOK-TO-MARKET AND ANALYST COVERAGE

In this section, we test whether standard multi-factor risk-based explanations account for the relation we see between forecast revisions and future returns.

### Sorting by Size

We sort firms into five size portfolios, with the smallest firms placed in quintile S1 and the largest firms in quintile S5. Table 4 reports mean monthly returns for the $5 \times 5$ matrix of portfolios sorted by firm size and forecast revisions. Panel A reports 1-month holding period returns; Panel B reports 12-month holding period returns. For the 1-month holding period, the P5 $-$ P1 trading strategy produces positive and significant returns for all size portfolios, except S5. Mid-size firms generate the largest returns, with S2 producing a mean monthly return of 1.68% and S3 producing a mean monthly return of 1.60%. Moreover, within each size quintile, returns increase with the forecast revision index. Thus it does not appear that we are simply picking up a size effect, since the two-way sorts still produce a strong positive relation between forecast revisions and average returns. In contrast, within each forecast revision quintile, there is no monotonic relation between firm size and return.

In Panel C, we report mean size, coverage, and forecast revisions statistics for the five size quintiles. We see that coverage increases with size, but mean forecast

**Table 4. Portfolio Returns and Descriptive Statistics: Forecast Revision Index by Firm Size** Table 4 reports average monthly portfolio returns and descriptive statistics for the period May 1988 through November 2001 for all stocks representing 13 European countries, excluding those with a share price less than £1. We first rank stocks into quintiles based on market capitalization. Stocks in the S1 (S5) quintile are those with the lowest (highest) market capitalization values. Then, within each size quintile, we sort stocks by the forecast revision index, defined as the difference between the number of upward revisions and the number of downward revisions by analysts since the last monthly production report, as provided by I/B/E/S. Stocks in portfolio P1 (P5) are those that contain the highest number of net downward (upward) revisions. The portfolios are equally weighted at formation and held for 1 month (Panel A) or 12 months (Panel B). *T*-statistics are reported in parentheses.

**Panel A: 1-Month Holding Period**

| Forecast Revision Index | All Stocks | S1 | S2 | S3 | S4 | S5 |
|---|---|---|---|---|---|---|
| P1 (Strong sell) | 0.0026 | 0.0007 | 0.0005 | 0.0029 | 0.0000 | 0.0075 |
| P2 | 0.0040 | 0.0045 | 0.0013 | 0.0057 | 0.0044 | 0.0038 |
| P3 | 0.0067 | 0.0070 | 0.0077 | 0.0067 | 0.0050 | 0.0082 |
| P4 | 0.0105 | 0.0117 | 0.0147 | 0.0099 | 0.0111 | 0.0083 |
| P5 (Strong buy) | 0.0163 | 0.0141 | 0.0173 | 0.0189 | 0.0125 | 0.0146 |
| P5 − P1 | 0.0137 | 0.0134 | 0.0168 | 0.0160 | 0.0125 | 0.0071 |
| | (2.36) | (2.15) | (2.76) | (2.30) | (1.90) | (1.26) |

**Panel B: 12-Month Holding Period**

| Forecast Revision Index | All Stocks | S1 | S2 | S3 | S4 | S5 |
|---|---|---|---|---|---|---|
| P1 (Strong sell) | 0.0036 | −0.0008 | 0.0014 | 0.0027 | 0.0031 | 0.0064 |
| P2 | 0.0035 | 0.0032 | 0.0048 | 0.0041 | 0.0041 | 0.0061 |
| P3 | 0.0057 | 0.0042 | 0.0046 | 0.0044 | 0.0055 | 0.0078 |
| P4 | 0.0087 | 0.0091 | 0.0088 | 0.0070 | 0.0069 | 0.0090 |
| P5 (Strong buy) | 0.0106 | 0.0100 | 0.0108 | 0.0094 | 0.0094 | 0.0109 |
| P5 − P1 | 0.0070 | 0.0108 | 0.0093 | 0.0067 | 0.0064 | 0.0045 |
| | (5.05) | (6.39) | (5.16) | (4.09) | (4.37) | (3.24) |

**Panel C: Descriptive Statistics**

| | S1 | S2 | S3 | S4 | S5 |
|---|---|---|---|---|---|
| Mean firm size (£ mils) | 55 | 178 | 418 | 1,111 | 8,239 |
| Mean number of analysts | 6.7 | 10.5 | 13.4 | 16.9 | 22.8 |
| Mean forecast revision index | −0.46 | −0.46 | −0.43 | −0.43 | −0.36 |

revisions are invariant to size, consistent with our earlier claim that the index does not disproportionately assign high or low values to small size firms. Also worth noting, forecast revisions are net negative over the sample period, indicating more downgrades than upgrades.

### Sorting by Size and Residual Analyst Coverage

We continue our analysis by performing a three-way sort on firm size and residual analyst coverage. First, we sort stocks into three portfolios based on firm size (small, mid, and large); next, we sort each portfolio into three portfolios based on residual analyst coverage (low, medium, and high); finally, we sort each portfolio into five portfolios based on the forecast revision index. Table 5 (Panel A) reports mean 1-month holding period returns for the resulting $5 \times 3 \times 3$ matrix. We observe that the P5 $-$ P1 trading strategy produces positive and significant 1-month holding period returns in 4 out of 9 of the size/coverage portfolios. Mid-size firms with high analyst coverage generate the largest returns, 1.83% per month (with a $t$-statistic of 2.56).

If we fix firm size and residual analyst coverage (i.e., move down a column), returns generally increase with the forecast revision index. Thus it does not appear that we are simply picking up firm size or analyst coverage effects since the three-way sorts still produce a strong positive relation between forecast revisions and average returns. In contrast, if we fix the forecast revisions quintile (i.e., move across a row), there are no simple relations between firm size and return, and residual analyst coverage and return.

In Panel B, we report mean forecast revision statistics for the sell, neutral, and buy portfolios (P1, P3, and P5, respectively) sorted by firm size and residual analyst coverage. We see that the forecast revision index takes on the most extreme positive and negative values for large firms with high coverage. Large firms with high analyst coverage receive a mean forecast revision index value of $-7.487$ ($+6.064$) for the P1 (P5) portfolio. In contrast, the smallest firms with the least analyst coverage generate a smaller spread in index values, with mean forecast revision index values of $-1.701$ for the sell portfolio and $+1.493$ for the buy portfolio.

### Sorting by Size and Book-to-Market Ratios

We continue our analysis by performing a three-way sort on firm size and book-to-market ratio. First, we sort stocks into three portfolios based on firm size (small, mid, and large); next, we sort each portfolio into three portfolios based on book-to-market ratios (low, medium, and high); finally, we sort each portfolio into five portfolios based on the forecast revision index. Table 6 (Panel A) reports mean monthly returns for the resulting $5 \times 3 \times 3$ matrix. We observe that the P5 $-$ P1 trading strategy produces positive and significant 1-month holding period returns in 4 out of 9 of the size/book-to-market portfolios. Mid-size stocks with medium book-to-market ratios generate the largest returns, 2.02% per month (with a $t$-statistic of 2.89).[5]

If we fix firm size and book-to-market ratio (i.e., move down a column), returns generally increase with the forecast revision index. Thus it does not appear that we are simply picking up firm size or book-to-market effects since the three-way

[5] We obtain similar results when we sort on earnings-to-price ratios.

**Table 5. Portfolio Returns: Forecast Revision Index by Firm Size by Residual Analyst Coverage** Table 5 reports average monthly portfolio returns (Panel A) and mean forecast revision index values (Panel B) for the period May 1988 through November 2001 for all stocks representing 13 European countries, excluding those with a share price less than £1. We first sort stocks into three portfolios based on firm size (small, mid, and large). Next we sort each portfolio into three portfolios based on residual analyst coverage (low, medium, and high), where the residuals come from month-by-month cross-sectional regressions of log (1 + no. of analysts) on log (firm size). We then sort each portfolio into five portfolios based on the forecast revision index, defined as the difference between the number of upward revisions and the number of downward revisions by analysts since the last monthly production report, as provided by I/B/E/S. Stocks in portfolio P1 (P5) are those that contain the highest number of downward (upward) revisions. The portfolios are equally weighted at formation and held for 1 month. *T*-statistics are reported in parentheses.

**Panel A: 1-Month Holding Period Returns**

| Coverage<br>Firm Size | Low<br>Small | Low<br>Mid | Low<br>Large | Medium<br>Small | Medium<br>Mid | Medium<br>Large | High<br>Small | High<br>Mid | High<br>Large |
|---|---|---|---|---|---|---|---|---|---|
| P1 | 0.0038 | 0.0044 | 0.0064 | 0.0026 | −0.0011 | 0.0049 | 0.0054 | −0.0007 | 0.0050 |
| P2 | 0.0041 | 0.0011 | 0.0029 | 0.0042 | 0.0046 | 0.0055 | −0.0013 | 0.0042 | 0.0051 |
| P3 | 0.0072 | 0.0065 | 0.0026 | 0.0004 | 0.0108 | 0.0094 | 0.0033 | 0.0052 | 0.0110 |
| P4 | 0.0134 | 0.0072 | 0.0096 | 0.0152 | 0.0128 | 0.0107 | 0.0082 | 0.0117 | 0.0162 |
| P5 | 0.0135 | 0.0210 | 0.0120 | 0.0168 | 0.0150 | 0.0114 | 0.0173 | 0.0176 | 0.0137 |
| P5 − P1 | 0.0097 | 0.0166 | 0.0056 | 0.0142 | 0.0161 | 0.0065 | 0.0119 | 0.0183 | 0.0087 |
| (t-stat.) | (1.42) | (2.60) | (0.96) | (2.19) | (2.31) | (1.04) | (1.66) | (2.56) | (1.36) |

**Panel B: Mean Forecast Revision Index**

| Coverage<br>Firm Size | Low<br>Small | Low<br>Mid | Low<br>Large | Medium<br>Small | Medium<br>Mid | Medium<br>Large | High<br>Small | High<br>Mid | High<br>Large |
|---|---|---|---|---|---|---|---|---|---|
| P1 | −1.701 | −2.601 | −5.056 | −2.759 | −4.221 | −6.185 | −4.973 | −6.127 | −7.487 |
| P3 | −0.568 | −0.272 | −0.319 | −0.773 | −0.539 | −0.366 | −0.885 | −0.647 | −0.382 |
| P5 | 1.493 | 2.258 | 4.195 | 1.927 | 3.144 | 5.199 | 2.752 | 4.198 | 6.064 |

**Table 6. Portfolio Returns: Forecast Revision Index by Firm Size by Book-to-Market** Table 6 reports average monthly portfolio returns (Panel A) and mean forecast revision index values (Panel B) for the period May 1988 through November 2001 for all stocks representing 13 European countries, excluding those with a share price less than £1. We first sort stocks into three portfolios based on firm size (small, mid, and large). We next sort each portfolio into three portfolios based on book-to-market ratios (low, medium, and high). We then sort each portfolio into five portfolios based on the forecast revision index, defined as the difference between the number of upward revisions and the number of downward revisions by analysts since the last monthly production report, as provided by I/B/E/S. Stocks in portfolio P1 (P5) are those that contain the highest number of downward (upward) revisions. The portfolios are equally weighted at formation and held for 1 month. *T*-statistics are reported in parentheses.

**Panel A: 1-Month Holding Period Returns**

| B/M<br>Firm Size | Low<br>Small | Low<br>Mid | Low<br>Large | Medium<br>Small | Medium<br>Mid | Medium<br>Large | High<br>Small | High<br>Mid | High<br>Large |
|---|---|---|---|---|---|---|---|---|---|
| P1 | −0.0040 | −0.0012 | 0.0031 | −0.0023 | −0.0007 | 0.0094 | 0.0086 | 0.0056 | 0.0043 |
| P2 | −0.0013 | 0.0031 | 0.0062 | 0.0036 | 0.0072 | 0.0072 | 0.0118 | 0.0067 | 0.0067 |
| P3 | 0.0095 | 0.0072 | 0.0078 | 0.0055 | 0.0064 | 0.0074 | 0.0085 | 0.0058 | 0.0024 |
| P4 | 0.0130 | 0.0106 | 0.0084 | 0.0098 | 0.0155 | 0.0160 | 0.0183 | 0.0096 | 0.0109 |
| P5 | 0.0136 | 0.0163 | 0.0154 | 0.0170 | 0.0195 | 0.0152 | 0.0171 | 0.0148 | 0.0146 |
| P5 − P1 | 0.0176 | 0.0175 | 0.0123 | 0.0193 | 0.0202 | 0.0058 | 0.0085 | 0.0092 | 0.0103 |
| (t-stat.) | (2.43) | (2.31) | (1.80) | (2.64) | (2.89) | (0.77) | (1.32) | (1.32) | (1.75) |

**Panel B: Mean Forecast Revision Index**

| B/M<br>Firm Size | Low<br>Small | Low<br>Mid | Low<br>Large | Medium<br>Small | Medium<br>Mid | Medium<br>Large | High<br>Small | High<br>Mid | High<br>Large |
|---|---|---|---|---|---|---|---|---|---|
| P1 | −3.421 | −4.666 | −6.112 | −3.765 | −4.868 | −7.161 | −2.975 | −4.353 | −6.118 |
| P3 | −0.557 | −0.365 | 0.112 | −0.851 | −0.552 | −0.225 | −0.742 | −0.534 | −0.608 |
| P5 | 2.552 | 3.741 | 6.315 | 2.089 | 3.330 | 5.965 | 1.894 | 3.315 | 4.281 |

sorts still produce a strong positive relation between forecast revisions and average returns. In contrast, if we fix the forecast revisions quintile, (i.e., move across a row), there is no simple relation between firm size and return, although returns are mostly increasing with book-to-market ratios.

In Panel B, we report mean forecast revisions statistics for the sell, neutral, and buy portfolios (P1, P3, and P5, respectively) sorted by firm size and book-to-market ratios. We see that the forecast revision index takes on its most negative (positive) values for large size firms with medium (low) book-to-market ratios.

### Cross-Sectional Regression Analysis

We continue our analysis by performing a Fama and MacBeth (1973) cross-sectional regression of European stock returns. Our dependent variable is firm return over the period $(t-1, t)$. Our independent variables include measures of firm size, book-to-market ratio, return momentum, residual analyst coverage, and analyst sentiment (the forecast revision index, the mean consensus recommendation value, and the monthly change in the mean consensus recommendation value). Beginning with the multivariate regressions (Panel B), Table 7 shows that European stock returns are positively related to our measure of forecast revisions (with a $t$-statistic of 4.35 or higher). When one analyst upgrades a firm that firm enjoys a 7-basis point increase in its return over the subsequent month.

The other measures of analyst sentiment are not statistically significant in predicting future returns. The mean consensus recommendation is negatively related to returns (– higher values are associated with greater bearish sentiment) as we would expect, but the coefficient is not statistically significant. The coefficient on the monthly change in the mean consensus recommendation is positive, but insignificant. These results differ from Jegadeesh, Kim, Krische, and Lee (2004) who find that quarterly changes in the mean consensus recommendation are a robust return predictor for U.S. stocks.

The multivariate results in Table 7 show that European stock returns are positively related to residual analyst coverage. Coverage is useful in generating and disseminating heretofore private information. Though the information may be negative or positive, disseminating it is helpful. Stocks with higher residual analyst coverage enjoy higher returns. This result contrasts with Hong, Lim, and Stein (2000) where stocks with lower analyst coverage and slower information diffusion exhibit a more pronounced momentum.

In our sample of European firms, value firms outperform growth firms (there is a positive relation between returns and book-to-market ratios), a result that is consistent with Fama and French (1992). In contrast, Jegadeesh, Kim, Krische, and Lee (2004) find that growth firms outperform value firms in the U.S. during an overlapping period of time.

The multivariate results in Table 7 also show that return momentum is not statistically significant in explaining the cross section of European stock returns. This contrasts sharply with Jegadeesh and Titman (1993, 2001) and Jegadeesh,

**Table 7. Fama–MacBeth Regressions Describing the Cross Section of Stock Returns** Table 7 reports regression coefficients and Newey–West adjusted *t*-statistics in parentheses. The sample period is May 1988 through November 2001, except when the mean consensus recommendation variable or its change is included, in which case, the sample period is November 1993 through November 2001. The sample includes all stocks representing 13 European countries, excluding those with a share price less than £1. We regress monthly firm returns over the period ($t-1$, $t$) on the following set of explanatory variables: ln(ME), the natural logarithm of the market value of the equity at time $t-1$; ln(B/M), the natural logarithm of the ratio of the matching year book value to the market value of the equity at time $t-1$; residual analyst coverage, where the residuals come from month-by-month cross-sectional regressions of log (1 + no. of analysts) on log (firm size); firm past return over the period ($t-7$, $t-1$); the forecast revision index, defined as the difference between the number of upward revisions and the number of downward revisions by analysts since the last monthly production report; mean consensus recommendation at time $t-1$, with 1.0 representing a strong buy and 5.0 representing a strong sell; the monthly change in the mean consensus recommendation over the period ($t-2$, $t-1$). * (**) [***] denote significance at the 10% (5%) [1%] level.

**Panel A: Univariate Regressions**

| Parameter | Model A1 | Model A2 | Model A3 | Model A4 | Model A5 | Model A6 | Model A7 |
|---|---|---|---|---|---|---|---|
| LN (ME) | 0.0007<br>(2.35)** | | | | | | |
| LN (B/M) | | 0.0005<br>(2.27)** | | | | | |
| Residual analyst coverage | | | 0.0035<br>(2.91)*** | | | | |
| Prior 6-month return | | | | 0.0114<br>(0.67) | | | |
| Forecast revision index | | | | | 0.0007<br>(4.43)*** | | |
| Mean consensus recommendation | | | | | | −0.0012<br>(1.33) | |
| Change in mean recommendation | | | | | | | 0.0005<br>(0.20) |

**Table 7.** (Continued)

| Panel B: Multivariate Regressions | | | | | | |
|---|---|---|---|---|---|---|
| Parameter | Model B1 | Model B2 | Model B3 | Model B4 | Model B5 | Model B6 |
| LN (ME) | 0.0007 | 0.0007 | 0.0007 | 0.0008 | 0.0007 | 0.0007 |
| | (2.44)** | (2.48)** | (2.42)** | (2.67)** | (2.33)** | (2.48)** |
| LN (B/M) | 0.0005 | 0.0009 | 0.0009 | 0.0008 | 0.0009 | 0.0009 |
| | (2.39)** | (3.70)*** | (3.46)*** | (3.47)*** | (3.69)*** | (3.70)*** |
| Residual analyst coverage | | 0.0050 | 0.0051 | 0.0047 | 0.0052 | 0.0051 |
| | | (3.75)*** | (3.64)*** | (3.54)*** | (3.75)*** | (3.75)*** |
| Prior 6-month return | | 0.0062 | 0.0081 | 0.0089 | 0.0059 | 0.0066 |
| | | (0.37) | (0.47) | (0.52) | (0.34) | (0.38) |
| Forecast revision index | | 0.0007 | | | 0.0007 | 0.0007 |
| | | (4.60)*** | | | (4.35)*** | (4.61)*** |
| Mean consensus recommendation | | | −0.0014 | | −0.0007 | |
| | | | (1.58) | | (0.83) | |
| Change in mean recommendation | | | | 0.0007 | | 0.0021 |
| | | | | (0.28) | | (0.86) |

**Table 8. Forecast Revisions and Return Continuation by Country** Table 8 reports average monthly portfolio returns for the period May 1988 through November 2001 for all stocks representing 13 European countries, excluding those with a share price less than £1. We first sort stocks by country. We then sort each country portfolio by the forecast revision index, defined as the difference between the number of upward revisions and the number of downward revisions by analysts since the last monthly production report, as provided by I/B/E/S. Stocks in portfolio P1 (P5) are those which contain the highest number of downward (upward) revisions. This table reports returns on the P5 − P1 strategy. The portfolios are equally weighted at formation and held for 1, 3, 6, 9, or 12 months. *T*-statistics are reported in parentheses and adjusted for autocorrelation.

| | Holding Period | | | | |
|---|---|---|---|---|---|
| Country | 1 month | 3 months | 6 months | 9 months | 12 months |
| United Kingdom | 0.0118 | 0.0083 | 0.0079 | 0.0069 | 0.0069 |
| | (2.09) | (2.46) | (3.69) | (4.45) | (5.36) |
| Norway | −0.0122 | 0.0055 | 0.0025 | 0.0061 | 0.0042 |
| | (−1.34) | (1.01) | (0.64) | (1.90) | (1.46) |
| Austria | 0.0156 | 0.0045 | −0.0007 | 0.0006 | −0.0008 |
| | (1.73) | (0.84) | (−0.15) | (0.17) | (−0.25) |
| Switzerland | 0.0170 | 0.0102 | 0.0093 | 0.0096 | 0.0084 |
| | (2.34) | (2.33) | (2.85) | (3.35) | (3.33) |
| Germany | 0.0169 | 0.0116 | 0.0100 | 0.0089 | 0.0077 |
| | (2.32) | (2.99) | (3.62) | (4.09) | (4.05) |
| Belgium | 0.0135 | 0.0125 | 0.0101 | 0.0094 | 0.0084 |
| | (1.89) | (2.80) | (2.95) | (3.73) | (2.82) |
| Netherlands | 0.0184 | 0.0159 | 0.0116 | 0.0090 | 0.0075 |
| | (3.20) | (4.60) | (4.41) | (4.15) | (4.14) |
| Denmark | 0.0129 | 0.0141 | 0.0109 | 0.0081 | 0.0063 |
| | (1.70) | (3.44) | (2.79) | (2.60) | (2.36) |
| France | 0.0065 | 0.0071 | 0.0083 | 0.0084 | 0.0078 |
| | (0.81) | (1.55) | (2.92) | (3.74) | (4.00) |
| Finland | 0.0130 | 0.0068 | 0.0044 | 0.0038 | 0.0061 |
| | (1.13) | (0.99) | (0.97) | (1.06) | (1.89) |
| Sweden | −0.0023 | 0.0027 | 0.0005 | −0.0024 | −0.0027 |
| | (−0.23) | (0.47) | (0.87) | (−0.76) | (−1.08) |
| Italy | 0.0115 | 0.0110 | 0.0074 | 0.0044 | 0.0032 |
| | (0.98) | (1.73) | (1.96) | (1.57) | (1.25) |
| Spain | −0.0005 | 0.0091 | 0.0054 | 0.0048 | 0.0041 |
| | (−0.04) | (1.70) | (1.52) | (1.91) | (1.65) |

Kim, Krische, and Lee (2004), where return momentum is an important predictor of future stock returns in the U.S.

The univariate regressions (Panel A) produce similar results. In summary, it appears that information contained in the forecast revision index is helpful in predicting the cross section of European stock returns.

## IV. RETURN CONTINUATION BY COUNTRY

It is entirely possible that our trading strategy benefits from favorable exchange rate movements in the pound. Hence, in this section, we provide country-specific data. Table 8 reports mean monthly returns by country for the trading strategy that sells those stocks in the lowest forecast revisions quintile and buys those stocks in the highest forecast revisions quintile, (P5 − P1). The holding period varies from 1 month, up to 12 months. Here, we see that one or two countries alone are not driving our trading strategy's positive performance. Over short-term holding periods, returns are significantly positive in all countries, except Norway, France, Finland, Sweden, Italy, and Spain. Over long-term holding periods, returns are significantly positive in all countries, except Norway, Austria, Sweden, and Italy. The largest short-term returns are from the Netherlands, where our trading strategy generates a mean monthly return of 1.84%. The largest long-term returns are from Switzerland and Belgium, where the mean monthly returns are 0.84%. It is possible that institutional differences in banking and research, or legal and cultural differences across countries explain the neutral performance of our trading strategy in Northern Europe. Alternatively, it is possible that corporate governance mechanisms and earnings management vary across countries, as documented by Leuz, Dhananjay, and Wysocki (2004). Using a classification system developed by Leuz, Dhananjay, and Wysocki (2004) that ranks countries based on institutional features such as the level of investor protection, stock market development, and ownership concentration, we group the 13 European countries into three clusters. The U.K. and Norway reside in the first cluster, where investor protections are greatest and earnings management is lowest; Italy and Spain reside in the third cluster, where earnings management is greatest; the remaining countries reside in cluster 2. Within each cluster, we follow Leuz, Dhananjay, and Wysocki (2004) and order countries based on their aggregate earnings management score. If earnings management is driving our trading strategy's performance, we should expect to see greater performance in those countries toward the bottom of the table. In fact, we see positive performance in each cluster, with a preponderance of entries in the top half of the table.

We next sort country-level firms into five size quintiles, with the smallest firms placed in quintile S1 and the largest firms in quintile S5. Table 9 reports mean monthly returns for the trading strategy P5 − P1 for each country, for each of the five size quintiles. Only 1-month holding period returns are reported. Here we observe no simple relation between size and return at the country level. Hence, we can be fairly confident that we are not simply picking up a size effect within each country.

## V. POTENTIAL EXPLANATIONS

In this section we discuss possible reasons for the pattern of return continuation that we observe in our trading strategy based on forecast revisions. We begin with the assumption that analysts produce valuable information. The positive returns realized on the buy portfolio are large and persistent. Reversals do not appear over the 12-month holding period we examine. On the other hand, the sell portfolio

**Table 9. Portfolio Returns by Country: Forecast Revision Index by Size** Table 9 reports average monthly portfolio returns for the period May 1988 through November 2001 for all stocks representing 13 European countries, excluding those with a share price less than £1. First, we sort stocks by country; next, we sort stocks by size. Stocks in the S1 (S5) quintile are those with the lowest (highest) market capitalization values. Within each size quintile, stocks are ranked in ascending order based on the forecast revision index, which is defined as the difference between the number of upward revisions and the number of downward revisions by analysts since the last monthly production report, as provided by I/B/E/S. Stocks in portfolio P1 (P5) are those that contain the highest number of downward (upward) revisions. This table reports returns on the P5−P1 strategy. The portfolios are equally weighted at formation and held for 1 month. *T*-statistics are reported in parentheses and adjusted for autocorrelation.

| | **Firm Size** | | | | |
|---|---|---|---|---|---|
| Country | S1 | S2 | S3 | S4 | S5 |
| United Kingdom | 0.0175 | 0.0167 | 0.0183 | 0.0035 | 0.0064 |
| | (2.49) | (2.06) | (2.60) | (0.50) | (1.13) |
| Norway | 0.0003 | 0.0233 | 0.0086 | 0.0032 | −0.0030 |
| | (0.01) | (1.32) | (0.47) | (0.21) | (−0.16) |
| Austria | −0.0124 | 0.0253 | 0.0091 | 0.0402 | −0.0127 |
| | (−0.53) | (1.36) | (0.50) | (2.27) | (−0.76) |
| Switzerland | 0.0083 | 0.0272 | 0.0108 | 0.0151 | 0.0039 |
| | (0.77) | (1.67) | (1.08) | (1.94) | (0.50) |
| Germany | 0.0201 | 0.0291 | 0.0251 | 0.0132 | 0.0121 |
| | (2.05) | (3.47) | (2.75) | (1.61) | (1.56) |
| Belgium | 0.0118 | 0.0159 | 0.0214 | 0.0135 | −0.0059 |
| | (0.89) | (1.02) | (1.60) | (1.21) | (−0.50) |
| Netherlands | 0.0259 | 0.0309 | 0.0191 | 0.0228 | 0.0070 |
| | (3.11) | (3.60) | (2.40) | (2.52) | (0.97) |
| Denmark | 0.0232 | 0.0073 | 0.0749 | −0.0062 | 0.0156 |
| | (1.99) | (0.74) | (1.37) | (−0.50) | (1.78) |
| France | 0.0229 | 0.0056 | 0.0145 | 0.0111 | 0.0116 |
| | (2.12) | (0.67) | (1.93) | (1.51) | (1.67) |
| Finland | 0.0412 | 0.0200 | 0.0234 | −0.0018 | 0.0236 |
| | (1.78) | (1.01) | (1.40) | (−0.10) | (1.25) |
| Sweden | 0.0349 | −0.0568 | −0.0039 | 0.0066 | 0.0054 |
| | (1.67) | (−1.06) | (−0.30) | (0.58) | (0.49) |
| Italy | 0.0162 | 0.0141 | 0.0134 | 0.0198 | 0.0057 |
| | (0.97) | (0.87) | (0.84) | (1.21) | (0.38) |
| Spain | 0.0293 | 0.0068 | 0.0002 | 0.0171 | 0.0103 |
| | (1.90) | (0.53) | (0.01) | (1.70) | (0.98) |

generates a near zero return, which does not appear to vary over the holding period. So, one key observation is that the bad news was already impounded in the stock price, before we formed our portfolios. On the other hand, the good news diffused slowly. Why would we observe this pattern? Well, it is entirely possible if investors are aware of institutional biases inherent in equity research activities. These biases

may encourage analysts to report overly optimistic earnings, and investors may respond by being cynical and adopting a wait-and-see approach when it comes to good news.

Several recent papers provide support for such a story. Analysts are biased because of conflicts of interest introduced by underwriting relationships (Michaely and Womack, 1999). They are overoptimistic and have a tendency to herd, where herding is defined as "excessive agreement" among forecasts and recommendations (Welch, 2000; De Bondt and Forbes, 1999). Analysts are rewarded for being optimistic; they enjoy favorable job separations for issuing forecasts that are optimistic relative to consensus estimates (Hong and Kubik, 2003). Moreover, analysts collude with firms to play an "earnings guidance game," where optimistic forecasts are issued at the start of the year and then "walked down" to a level that firms can beat by the end of the year (Richardson, Teoh, and Wysocki, 2004; Brown, 2001; Matsumoto, 2002).

Bradshaw, Richardson, and Sloan (2003) provide strong evidence that sell-side analysts routinely produce overly optimistic stock research for firms that are issuing new securities. In fact, the predictability in future stock returns is directly related to predictable biases in analysts' earnings forecasts. Bradshaw, Richardson, and Sloan (2003) suggest that investors are systematically fooled by analyst hype. In contrast, our evidence supports the notion that investors are skeptical, but, ultimately, they learn that they can profit from the "hype."

It is not obvious why investors remain skeptical of good news when, on average, they would be rewarded for being more trusting. Perhaps this is a second-best equilibrium, and if investors were more trusting, analysts would alter their behavior to exploit investor gullibility. For example, effort-averse analysts might simply work less and produce poorer quality research. Or, analysts who earn compensation based on trade commissions might revise their forecasts more than their true sentiments would dictate. It is also possible that analysts employed by investment or commercial banks might issue bogus forecasts and attempt to profit from gullible investors by front-running trades.

It is possible that our measure of forecast revisions captures behavioral factors that might influence asset prices. Our forecast revision index conveys the weight of analyst sentiment. So, for example, if 7 of the 20 analysts who cover British Petroleum revise earnings higher, this carries more weight with investors than if one of the two analysts who cover Desire Petroleum revises earnings higher. Investors may weigh the former information more heavily than the latter if the former receives more media coverage, or if their habits make them more inclined to buy and sell actively covered stocks, or if arbitrage constraints or other trading costs steer them away from low coverage stocks. (See, for example, Huberman, 1997; De Bondt and Forbes, 1999.) Alternatively, investors may respond to real-time trading pressures by selectively thinking about some information and voluntarily or involuntarily ignoring other information. (See, for example, Simon, 1955; Kahneman and Tversky, 1974; Conlisk, 1996.)

To the extent that our forecast revision index captures behavioral factors, our results are consistent with the investor conservatism model of Barberis, Shleifer,

and Vishny (1998). This model, motivated by psychological evidence, especially arguments from Griffin and Tversky (1992), assumes that in making forecasts, individuals pay too much attention to the strength of evidence and too little attention to its statistical weight.[6] Barberis, Shleifer, and Vishny (1998) cite corporate earnings news as an example of information with low strength and high weight. Their model predicts that investors will underreact to such information. Note that our measure of forecast revisions neatly fits the definition of information with low strength and high weight if we assume that analysts are conducting thorough research, and in their discussions with management and their analysis activities, they are generating heretofore private information. Consistent with Barberis, Shleifer, and Vishny (1998), we find that investors underreact to forecast revisions, especially, upward revisions. The return continuation pattern we observe is statistically significant and persists over a 12-month holding period.

On the other hand, our results are not consistent with Hong and Stein (1999). This model considers the role of private, firm-specific information in generating momentum. Because investors are unable to extract each other's private information from prices, momentum occurs. We postulate that revisions to earnings estimates by equity analysts might also be associated with private information flows. Hence it is reasonable to assume that our measure of forecast revisions also captures the rate of firm-specific, private information generation. Similarly, Hong, Lim, and Stein (2000) use residual analyst coverage as a proxy for the rate of private information flow. Whereas Hong, Lim, and Stein (2000) find that momentum profits are mostly generated by small firms with low analyst coverage, we find that a trading strategy based on forecast revisions produces very large returns for mid-size firms with high analyst coverage. Moreover, the cross section of European stock returns is positively related to residual analyst coverage. In general, our evidence is at odds with arguments that high transaction costs are the drivers of return continuation.

Our trading strategy may be profitable for other reasons. The simplest explanation—that European equity markets are not efficient with respect to equity analysts' forecasts—is far from palatable. An alternative explanation is that the forecast revision index proxies for changing risk premia or captures industry- or firm-specific effects that are not reflected in the other factors we examine. Jegadeesh, Kim, Krische, and Lee (2004) suggest that changes in recommendation values might capture "qualitative aspects of a firm's operations (e.g., managerial abilities, strategic alliances, intangible assets, or other growth opportunities) that do not appear in the quantitative signals" they examine. Perhaps our forecast revision index captures these same qualitative effects.

## VI. SUMMARY AND CONCLUSIONS

We analyze the role of earnings forecast revisions by equity analysts in predicting the cross section of European stock returns. We find that stocks with the greatest

[6] To illustrate the differences between strength and weight, Griffin and Tversky (1992) use a letter of recommendation as an example. The letter's "strength" refers to its warmth and degree of positive content. The letter's "weight" measures the stature and credibility of the letter writer.

number of upward revisions in earnings, net of downward revisions, earn significantly higher returns than otherwise similar stocks. In particular, a portfolio of stocks in the highest quintile of net upward revisions outperforms a portfolio of stocks in the lowest quintile of net upward revisions by more than 16% per year. This effect is not concentrated in small stocks, stocks with low analyst coverage, or stocks with low book-to-market ratios. The effect is statistically significant in seven out of the 13 European countries we analyze. Our results likely understate the performance of a trading strategy based on forecast revisions. Although we ignore transaction costs, we evaluate and sort stocks on a monthly basis, acting on forecast revisions data that, on average, have been public for more than several days.

Using our measure of forecast revisions, we examine whether good and bad information are processed symmetrically by investors. We find differences in the return continuation patterns for stocks with net upward versus downward forecast revisions. In contrast to Hong, Lim, and Stein (2000), we find that bad news travels quickly, but good news travels slowly. This result is consistent with investors' attaching great significance to poor earnings forecasts, but adopting a wait-and-see approach to good news. This cynicism on the part of investors is perfectly rational, if analysts are biased toward issuing overly optimistic earnings forecasts.

Our study provides an opportunity to assess some of the explanations offered for momentum. We find general support for Barberis, Shleifer, and Vishny (1998). In particular, investors underreact to forecast revisions, especially upward revisions. The return continuation pattern we observe is statistically significant, and persists over a 12-month holding period. On the other hand, our results conflict with Hong and Stein (1999), Hong, Lim, and Stein (2000), and Diether, Malloy, and Scherbina (2002). We find that our trading strategy generates the largest returns for mid-size firms with high analyst coverage, where short-sale costs are likely to be low. Moreover, the cross section of European stock returns is positively related to residual analyst coverage. In general, our results are at odds with arguments that high transaction costs are the drivers of return continuation.

We show that European stock returns are positively related to our measure of forecast revisions. When one analyst upgrades a firm, that firm enjoys a 7-basis point increase in its return over the subsequent month. In contrast, we find that neither the mean consensus recommendation nor changes in that metric are significant in explaining the cross section of European stock returns.

## VII. REFERENCES

Barber, B., R. Lehavy, M. McNichols, and B. Trueman. 2001. "Can Investors Profit from the Prophets? Security Analyst Recommendations and Stock Returns." *Journal of Finance* 56:531–563.

Barber, B., R. Lehavy, M. McNichols, and B. Trueman. 2003. "Reassessing the Returns to Analysts' Stock Recommendations." *Financial Analysts Journal* 59:88–96.

Barberis, N., A. Shleifer, and R. Vishny. 1998. "A Model of Investor Sentiment." *Journal of Financial Economics* 49:307–343.

Bhushan, R. 1989. "Firm Characteristics and Analyst Following." *Journal of Accounting and Economics* 11:255–274.

Bradshaw, M., S. Richardson, and R. Sloan. 2003. "Pump and Dump: An Empirical Analysis of the Relation Between Corporate Financing Activities and Sell-Side Analyst Research." Unpublished paper, University of Michigan.

Brennen, M. and P. Hughes. 1991. "Stock Prices and the Supply of Information." *Journal of Finance* 46:1665–1691.

Brown, L. 2001. "A Temporal Analysis of Earnings Surprises: Profits and Losses." *Journal of Accounting Research* 39:221–241.

Chan, K. C. L., N. Jegadeesh, and J. Lakonishok. 1996. "Momentum Strategies." *Journal of Finance* 51:1681–1713.

Conlisk, J. 1996. "Why Bounded Rationality?" *Journal of Economic Literature* 34:669–700.

Conrad, J. and G. Kaul. 1998. "An Anatomy of Trading Strategies." *Review of Financial Studies* 11:489–519.

De Bondt, W. and W. Forbes. 1999. "Herding in Analyst Earnings Forecasts: Evidence from the United Kingdom." *European Financial Management* 5:143–163.

Diether, K., C. Malloy, and A. Scherbina. 2002. "Differences of Opinion and the Cross Section of Stock Returns." *Journal of Finance* 58:2113–2141.

Fama, E. F. and K. French. 1992. "The Cross-Section of Expected Stock Returns." *Journal of Finance* 47:427–465.

Fama, E. F. and K. French. 1996. "Multifactor Explanations of Asset Pricing Anomalies." *Journal of Finance* 51:55–84.

Graham, J. 1999. "Herding Among Investment Newsletters: Theory and Evidence." *Journal of Finance* 54:237–268.

Grinblatt, M., S. Titman, and R. Wermers. 1995. "Momentum Investment Strategies, Portfolio Performance, and Herding: A Study of Mutual Fund Behavior." *American Economic Review* 85:1088–1105.

Hong, H. and J. Kubik. 2003. "Analyzing the Analysts: Career Concerns and Biased Earnings Forecasts." *Journal of Finance* 58:312–351.

Hong, H., T. Lim, and J. Stein. 2000. "Bad News Travels Slowly: Size, Analyst Coverage, and the Profitability of Momentum Strategies." *Journal of Finance* 55:265–295.

Hong, H. and J. Stein. 1999. "A Unified Theory of Underreaction, Momentum Trading and Overreaction in Asset Markets." *Journal of Finance* 54:2143–2184.

Huberman, G. 1997. "Familiarity Breeds Investment." Unpublished paper, Columbia University.

Jegadeesh, N., J. Kim, S. Krische, and C. Lee. 2004. "Analyzing the Analysts: When Do Recommendations Add Value?" *Journal of Finance* 59:1083–1124.

Jegadeesh, N. and S. Titman. 1993. "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency." *Journal of Finance* 48:65–91.

Jegadeesh, N. and S. Titman. 2001. "Profitability of Momentum Strategies: An Evaluation of Alternative Explanations." *Journal of Finance* 56:699–720.

Kahnemann, D. and A. Tversky. 1974. "Judgment Under Uncertainty: Heuristics and Biases." *Science* 185:1124–1131.

Keim, D. 2003. "The Cost of Trend Chasing and the Illusion of Momentum Profits." Unpublished paper, University of Pennsylvania.

Lesmond, D., M. Schill, and C. Zhou. 2004. "The Illusory Nature of Momentum Profits." *Journal of Financial Economics* 71:349–380.

Leuz, C., N. Dhananjay, and P. Wysocki. 2004. "Earnings Management and Investor Protection: An International Comparison." *Journal of Financial Economics* 69:505–527.

Matsumoto, D. 2002. "Management's Incentives to Influence Analysts' Forecasts." *Accounting Review* 77:483–514.

Michaely, R. and K. Womack. 1999. "Conflict of Interest and the Credibility of Underwriter Analyst Recommendations." *Review of Financial Studies* 12:653–686.

Miller, E. 1977. "Risk, Uncertainty, and Divergence of Opinion." *Journal of Finance* 32:1151–1168.

Richardson, S., S. Teoh, and P. Wysocki. 2004. "The Walkdown to Beatable Analyst Forecasts: The Roles of Equity Issuance and Insider Trading Incentives." *Contemporary Accounting Research* 21:885–924.

Rowenhorst, G. 1998. "International Momentum Strategies." *Journal of Finance* 53:267–284.

Simon, H. 1955. "A Behavioral Model of Rational Choice." *Quarterly Journal of Economics* 69:99–118.

Welch, I. 2000. "Herding Among Security Analysts." *Journal of Financial Economics* 58:369–396.

## VIII. NOTES ON CONTRIBUTORS/ACKNOWLEDGMENTS

**Phillip J. McKnight** is Assistant Professor of Finance at the University of St. Andrews (Scotland, UK). His research interests include asset pricing and corporate governance. Dr. McKnight has published papers in several journals, including *European Financial Management* and the *British Journal of Industrial Relations*.

**Steven K. Todd** is Associate Professor of Finance at Loyola University, Chicago. His research interests include financial institutions, asset pricing, and corporate finance. Dr. Todd has published papers in several journals, including the *Journal of Business*, *Journal of Corporate Finance*, and *Real Estate Economics*.

We thank Lu Hong, Marcin Kacperczyk, Tom Nohel, and seminar participants at Washington University in Saint Louis for helpful comments and suggestions. We are grateful for financial support provided by The Leverhulme Trust. We thank Thomson Financial for providing earnings per share forecast data through the Institutional Brokers Estimate System, I/B/E/S, as part of a broad academic program to encourage research in earnings expectations.