Disentangling Equity Return Regularities: New Insights and Investment Opportunities

Stock market phenomena such as the January and low price/earnings ratio effects entice investors with prospects of extraordinary returns. Most previous stock market anomaly research has focused on one or two return regularities at a time. Multivariate regression, however, can provide a unified framework for disentangling and analyzing numerous return effects. By simultaneously controlling for other attributes, it 'purifies' the effect of each anomaly, affording a cleaner picture of which anomalies are 'real' and which are merely proxies for other effects.

While "pure" payoffs may be smaller than the naive payoffs (given the independent nature of the pure effects and the proxying behavior of the naive effects), their statistical significance is often greater. The residual reversal effect is an exception, emerging stronger in magnitude in its pure form than its naive form, primarily because the pure measure separates out related effects such as earnings surprise. Some effects, however, such as cash flow/price ratio disappear completely in their pure form. And both naive and pure returns to beta prove inconsequential in explaining cumulative returns.

The strength and persistence of returns to some of the anomaly measures, such as trends in analysts' earnings estimates, represent evidence against semi-strong market efficiency. Furthermore, the significant payoffs to other measures, such as residual reversal, suggest that past prices allow do matter—that is, the market is not even weak-form efficient.

Controlling for tax-loss selling and other attributes in a multivariate framework mitigates the January seasonals exhibited by many of the naive anomaly measures. For instance, the small size effect's January seasonal vanishes. The yield effect's January seasonal remains strong, however. Also, because long-term tax-loss selling is more powerful than short-term, investor behavior appears suboptimal. A negative January seasonal in pure returns to the relative-strength measure appears to arise from profit-taking associated with tax-gain deferral.

Returns to many attributes appear to have market-related components. For example, naive returns to low P/E behave defensively, while pure returns to low P/E are not market-related at all. Apparently naive returns to low P/E are proxies for related defensive effects such as the yield effect. Returns to beta, however, are strongly procyclical in both their naive and pure forms.

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OVER THE LAST decade, a growing body of literature has documented equity return regularities (or "anomalies") that seem contrary to the Capital Asset Pricing Model (CAPM), the Efficient Market Hypothesis (EMH) and even Arbitrage Pricing Theory (APT). While some of these effects appear to represent true pockets of stock market inefficiency, others, such as the small size effect, may be driven by the macroeconomy.

Nevertheless, a growing amount of assets has been targeted to the exploitation of various sectors of the stock market perceived to be inefficient. For instance, index funds tilted towards higher-yielding or smaller-capitalization stocks have become increasingly popular in the last few years. Many active managers are also riding the anomaly bandwagon, but often in an ad hoc fashion. For example, a recent survey revealed that 29.3 per cent of institutional equity managers regard low P/E as an integral part of their investment strategy.

Whether these equity return patterns represent true mispricing or are empirical regularities only in a broader macroeconomic framework, efficacious equity management requires that they be properly identified and measured. Unraveling the interrelationships is a critical part of the process. It has not yet been conclusively determined whether these effects are mere proxies for one another or whether they are independent and hence additive. This article focuses on these issues. We disentangle returns associated with 25 different anomaly measures and compare our results with earlier findings. Several interesting insights emerge. For example, previous research has generally been baffled by the presence of a January seasonal in the small size anomaly. We find that this seasonal effect vanishes once year-end tax-loss selling is properly controlled for.

We also present substantial evidence contra-vending market efficiency, document significant autocorrelations in the time series of equity return effects, and analyze the relationship of these return effects to stock market returns. The findings suggest some equity strategies based on empirical return regularities.

Previous Research
Recent articles examining the interrelationships of equity return regularities generally consider only two or three anomalies at once. Unfortunately, a study drawing conclusions based on only a few explanatory variables may yield highly misleading results. For example, if one wanted to study the determinants of a person's blood pressure, one would not arbitrarily limit the explanatory variables to marital status and years of education. Other factors, such as exercise, diet and income, are clearly important. Furthermore, many of these factors are highly correlated. A similar situation holds for stock market return regularities. Many studies have considered the interrelationship of the size and P/E effects to determine if one subsumes the other. Is it size that really matters, or P/E, or some combination of the two effects? Or, given the high correlation between both these attributes and a firm's degree of institutional neglect, is it these neglect that drives anomalous returns, with size and P/E being mere proxies for the underlying cause? Any effort to disentangle size and P/E without considering and controlling for other effects is incomplete and potentially confusing. This may partially account for the high frequency of conflicting results from previous studies.

Table I categorizes and provides references for empirical studies that have examined the interrelationships of equity return regularities. Their results will be discussed in light of our findings.

In addition to studies of equity return interrelationships in the U.S. stock market, a small but growing body of literature has considered foreign stock market anomalies. International studies are especially useful for gaining perspective on the January/size connection, because tax laws (hence optimal trading strategies) vary widely across countries.

Some major multifactor studies of the U.S. equity market consider multiple factors (such as industry affiliation or financial leverage) that have strong cross-sectional explanatory power for returns within a month. Some of these factors may also be anomalous in that they have
Table 1 Internships of Equity Return Regularities: Some Previous Studies

<table>
<thead>
<tr>
<th>Size and Price/Earnings Ratio</th>
</tr>
</thead>
</table>

Size and Neglect


Size and January


Size and Residual Risk


Size and Earnings Surprise

| R. Freeman, “The Association Between Accounting Earnings and Security Returns for Large and Small Firms” (CRSP working paper #192, October 1986). |

Size, Yield and Cookiness


Concluded on following page
Size, January and Day-of-the-Week

Size and Return Reversal
E. Fama and K. French, "Permanent and Temporary Components of Stock Prices" (CRSP working paper #178, February 1987)

Size, January and Neglect

Size, January and Yield

Size, Neglect and Price/Earnings Ratio

Size, Neglect, Price/Earnings Ratio and January

Price/Earnings Ratio and Residual Risk

Price/Earnings Ratio, Controversy and Neglect

Price/Earnings Ratio and Price/Sales Ratio

Price/Earnings Ratio and Neglect

Yield and Low Price
E. Elton, M. Gruber and J. Rentzler, "A Simple Examination of the Empirical Relationship Between Dividend Yields and Deviations From the CAPM.,” (NYU working paper #280, August 1981)

Day-of-the-Week and Time-of-the-Day
L. Harris, "How to Profit from Intraday Stock Returns.,” *Journal of Portfolio Management*, Winter 1986, pp. 61-64

Earnings Surprise and Trends in Analysts' Earnings Estimates

Residual Risk and January

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provided accumulating payoffs over time. The first of these models, developed by BARRA over a decade ago, is widely used in the investment community. 8 Two other multifactor models by Sharpe and Reid study a much longer time span, but lack data on accounting-based factors such as P/E. We present a comprehensive analysis of equity return regularities in the spirit of these multifactor studies.

Because our analysis is based on monthly returns, we do not consider "faster" time-related anomalies such as time-of-the-day, day-of-the-week and week-of-the-month effects, despite evidence of their interrelationships with anomalies we do consider. 9 Prior research has indicated, for example, that (1) much of the size effect occurs on Fridays, 10 (2) much of the size effect occurs in the first few trading days of January, 11 and (3) time-of-day and day-of-the-week effects interact. 12

Some recent empirical work ties several seemingly unrelated anomalies to the human disposition to delay announcing bad news. 13,14 This tendency may partially account for three anomalies. (1) The day-of-the-week effect may relate to management's disposition to delay reporting bad news until after the market closes, especially over the weekend. This bunching of negative news would help explain weak Friday-to-Monday returns. (2) The week-of-the-month effect may relate to management's proclivity for announcing good earnings reports quickly (generally during the first two weeks of a calendar month) and sitting on bad reports longer. (3) Because companies long overdue for an earnings announcement may be delaying the release of bad news, there might be a "late reporter" anomaly, whereby late announcements are often negative and cause a price decline.

Return Regularities We Consider

Below, we describe briefly each return regularity considered in this article. The method of constructing and normalizing each measure is explained more fully in the next section.

Low P/E: It has been well-documented that stocks with lower price/earnings ratios tend to outperform those with higher P/E ratios. 15 We used the reciprocal of P/E, E/P, measured as the trailing year's fully diluted earnings divided by price. This measure allowed us to accommodate negative and zero earnings in a continuous fashion.

Small size: Smaller size has a pronounced correlation with future performance. 16 We found, as did many previous researchers, that the effect is roughly linear in the log of size. Hence we used the negative of the natural log of market capitalization.

Dividend yield: Because U.S. tax law has logated capital gains more favorably than dividends, taxable investors may have demanded a higher pretax return on higher-yielding stocks to compensate for the increased tax liability. (Even under the Tax Reform Act of 1986, taxes on capital gains are not taxed until realized, although they no longer enjoy a preferential rate.) Alternatively, investors may have a psychological preference for cash dividends. 17 There are conflicting empirical studies on these propositions. 18 In addition, zero-yielding stocks have been shown to have unusually high returns, especially in January. 19 We used a dividend-dividend-by-price measure, as well as a binary indicator of zero yield, to model these relationships.

Neglect: Neglected stocks have tended to outperform the market. 20 Neglect has been modeled by measures of institutional ownership, the intensity of Wall Street security analyst coverage, and the extent of information availability. We used the negative of the natural log of one plus the number of analysts.

Low price: Some researchers have found low-priced stocks to produce extra rewards. 21 The measure we used is the negative of the natural log of price.

Book-price: Stocks with high book value in relation to price have outperformed the market. 22 We used common-equity-per-share divided by price to measure this effect.

Sales-price: Some have suggested that sales-price may be superior to E/P as an investment criterion. 23 We use the trailing year's sales-per-share divided by price, relative to the capitalization-weighted average sales-price for that stock's industry. This is the only variable we calculated as an industry relative, because of (1) the enormous disparity across industries for this particular measure and (2) the looser theoretical link between sales and value than between earnings or dividends and value across industries.

Cash flow/price: It can be argued that, because of disparate accounting practices, cash flow is superior to earnings as a measure of value. 24 The definition we used is trailing year's earnings plus depreciation and deferred taxes-
per-share divided by price.

Sigma: The CAPM maintains that only sys-

tematic (or undiversifiable) risk should be re-

warded. But many studies have found an ap-

parent compensation for unsystematic risk. 23

Such risk is often referred to as residual risk, or

sigma. We calculated sigma as the standard

error of estimate, or dispersion of error terms,

from a rolling historical 60-month regression of

excess stock return (i.e., return over the Trea-

sury-bill rate) on the S&P 500 excess return.

Beta: The finance literature is replete with

empirical tests of the CAPM. Many findings on

the reward to bearing systematic risk have been

counter to theory. 24 We included a historical

beta measure in our model, not merely for risk

adjustment, but also to explore the payoff to

beta when controlling for multiple anomalies.

We calculated beta for each security from the

rolling 60-month regression described above.

We then applied Vasicek’s Bayesian adjust-

ment, in light of the well-known tendency of

historical betas to regress over time towards

the mean. 25

Coskewness: Investors may prefer positive

skewness in their portfolios. Because the market

has positive skewness, investors might pay

more for securities having positive coskewness

with the market. 26 We calculated coskewness on

a rolling 60-month basis as follows:

\[
\frac{\sum (R_i - \bar{R}) \cdot (R_m - \bar{R})^2}{\sum (R_m - \bar{R})^3}
\]

where \(R_i\) is stock excess return, \(R_m\) is the S&P

500 excess return, and \(\bar{R}\) and \(\bar{R}_m\) are rolling

60-month arithmetic averages.

Earnings controversy: Some maintain that

stocks with more uncertainty about future pros-

pects produce superior returns, perhaps as

compensation for information deficiency or even

as a proxy for systematic risk. 27 We used

the standard deviation of next year’s analysts’

earnings estimates normalized by stock price.

Trends in analysts’ earnings estimates: There

is substantial empirical support for the pro-

position that stocks whose earnings estimates have

been recently upgraded by analysts tend to

produce abnormal returns. 28 Some possible ex-

planations are imperfect information dissemina-

tion and the psychology of Wall Street analysts

(possibly, their “herd instinct” and aversion to

substantial earnings-estimate revisions). We

measured the trend separately for each of the

three most recently completed months as the

change in next fiscal year’s consensus estimate

normalized as a percentage of stock price (rather

than normalized by earnings, to avoid problems

caused by near-zero or negative divisors). By

employing three distinct monthly lags, we

could observe the time decay in information

content.

Earnings surprise: Stocks that have experi-

enced recent earnings surprises tend to produce

abnormal returns. 29 Reasons advanced include

imperfect information propagation, a tendency

for surprises to repeat quarter-to-quarter, and

analysts’ inclination to be reactive to earnings

announcements. We measured surprises sepa-

rately for each of the three most recent calendar

months, calculated as the difference between the

actual earnings announcement and the con-

sensus estimate on that date, normalized by

stock price. Again, by using three monthly lags, we

could observe the time decay in information

content.

The “earnings torpedo” effect: Stocks expect-
ed to have high future earnings growth may be

more susceptible to negative surprises (or “tor-

pedoes”); those with low expected earnings

may be more likely to experience positive sur-

prises. There is some empirical support for the

proposition that low-expected stocks on aver-

age outperform their high-expected counter-

parts. 30 We used the change from the earnings-

per-share last reported to next year’s consensus

estimate and normalized by stock price.

Relative strength: Market technicians have

long claimed that the market is not efficient, even

in the “weak-form” sense (i.e., past prices alone

may have predictive content). Some recent stud-

ies support the investment merit of relative price

strength, while finding perverse results for one-

month relative strength and for January. 31 The

measure we used is the alpha intercept from our

rolling 60-month beta regression.

Residual reversal: As noted, near-term rela-

tive price strength tends to reverse. This effect is

not an artifact of pricing errors, bid/ask spreads

or infrequent trading, and it may persist for up

to two months. 32 We examined the pre-dictive

power of residuals (from our beta regression)

separately, for each of the previous two

months, to study the decay pattern.

January: From as early as 1942, studies have

documented the effects of year-end tax-loss

selling on January returns. 33 Some have found

investors’ behavior to be irrational in light of
traditional finance theory; others have sought novel explanations for the observed effects.\textsuperscript{36} In addition, recent studies have documented January seasonals in returns to small size, neglect, dividend yield, P/E and sigma, as listed in Table I. We utilized separate proprietary measures of potential long-term and short-term tax-loss selling pressure for each stock. These were designed to capture price rebounds in January after year-end tax-loss selling abates. We also examined the January versus rest-of-year behavior of all our measures in light of the substantial previous evidence.

**Methodology**

Two common methodologies have been applied in previous anomaly research. The first, which often implicitly assumes a stationary return generating process, usually groups stocks into portfolios based on a particular characteristic, such as firm size.\textsuperscript{37} Time-series regressions of each group's returns on the market are followed by an analysis of portfolios' regression intercepts to test for significant differences. If this approach is extended to cross-classification on two anomalies, however, care must be taken to randomize the experimental design.\textsuperscript{38} Such an approach becomes unwieldy as the number of anomalies to be studied increases.

The second methodology involves cross-sectional regressions of returns on predetermined attributes. Here, a stationary generating process need not be presumed. The return observations can be either on a stock-by-stock basis or on a portfolio basis. Grouping reduces dimensionality, which may permit application of Zellner's seemingly unrelated regression model (SURM).\textsuperscript{39} It has been demonstrated, however, that results can be sensitive to the grouping procedure.\textsuperscript{40} In any case, with a large number of anomalies studied simultaneously, grouping becomes intractable.\textsuperscript{41}

We modeled the return regularities linearly and utilized cross-sectional regression analysis (as did the previously cited multifactor studies).\textsuperscript{42} For each month from January 1978 through December 1986, we ran a generalized-least-squares (GLS) regression for our universe of the 1500 largest capitalization stocks. The dependent variable was excess return for each security; the independent variables were its anomaly exposures, normalized as described before. We calculated the GLS weights, updated monthly, as the squared reciprocal of each stock's residual risk, as measured by sigma; each stock's weight was limited to a maximum of 10 times and a minimum of one-tenth the average GLS weight.

The use of GLS produces more statistically efficient estimates than ordinary-least-squares regression in the presence of heteroscedasticity.\textsuperscript{43} Intuitively, stocks that exhibit relatively lower residual risk have a higher percentage of their returns explained by anomalies, hence greater estimation accuracy is achieved by placing more weight on them. Because higher residual risk is correlated with small size, GLS weights generally lie between capitalization and equal weights.

Data errors, especially in historical prices, can cause severe problems.\textsuperscript{44} Our data were examined for extreme outliers. A normalization and truncation process, described below, diminished this concern. Additionally, we lagged the price used to calculate anomalies such as P/E by one month. By lagging price, we controlled for spurious returns to low-P/E stocks that would otherwise result if a price were incorrect one month and correct the next.\textsuperscript{45} Also, by lagging price we avoided the accidental capture of bid-ask spreads in our estimates of anomaly payoffs.\textsuperscript{46} Lagging price does induce a slightly conservative bias to the payoffs of price-related anomalies, because the price used to construct each is slightly "stale."

We also controlled for "survivorship" bias. If the population is defined retrospectively as those companies that survived and prospered, then bankrupt, merged and shrinking firms are omitted from the analysis. This can severely bias the results. Additionally, we controlled for "look-ahead" bias. If one constructs P/E using earnings that were as yet unknown, because of announcement lags, a positive return bias is induced for low P/E stocks. To control for this bias, we lagged all accounting variables three months. Thus the P/E for IBM as of 12/31/80 was calculated using its price as of 11/30/80 and its earnings as of 9/30/80. Another deficiency that several anomaly studies suffer from is the arbitrary restriction to companies with December fiscal years. Such a constraint, imposed for computational simplicity, may induce industry and other biases.\textsuperscript{47}

We normalized each measure (including beta) by subtracting its capitalization-weighted average and dividing by its cross-sectional standard deviation, with outliers truncated.\textsuperscript{48} The payoff
coefficients to each anomaly were thus scaled consistently. Each coefficient, or return attribution, represents the marginal return to a stock with an exposure to that factor of one cross-sectional standard deviation. For example, if the distribution of book/price across stocks in a particular month has a capitalization-weighted average of 1.1 and a standard deviation of 0.2, then an attribution of –0.15 implies that a stock with a book/price ratio of 1.3 (i.e., a book/price ratio one standard deviation higher than the capitalization-weighted average of book/price) would have underperformed the market by 15 basis points that month. This analysis assumes neutral (or average market) exposures to all other anomalies.

In addition to normalized anomaly measures, we included a zero-yield indicator in the form of a binary dummy variable. In total, we have 25 anomaly measures. We also used binary variables to assign each company to one of 38 industries, based on SIC code. The binary industry variables were utilized to purify anomaly return attributions from the impact of industry return comovement. (As noted, industry assignments were also used to calculate industry relative sales/price ratios.) Payoffs to the binary variables have the simple interpretation of being the marginal return arising from that attribute.

The Results on Return Regularities

We ran two sets of GLS cross-sectional regressions of excess stock return on normalized anomaly measures for the 108-month period from January 1978 to December 1986. The first set consisted of 25 univariate cross-sectional regressions each month, treating each of our measures individually. The second set consisted of one multivariate cross-sectional regression each month, treating all 25 anomaly and 38 industry variables simultaneously.

The multivariate regressions measure all anomaly and industry effects jointly, thereby “purifying” each effect so that it is independent of other effects. We refer to the multivariate return attributions as “pure” returns and to the univariate attributions as “naive” returns. The univariate regressions naively measure only one anomaly at a time, with no effort to control for other related effects. A single anomaly will often be a proxy for several related effects; a multivariate anomaly framework properly attrib-

Table II: Monthly Average Returns to Anomalies

<table>
<thead>
<tr>
<th>Anomaly</th>
<th>Naive Anomaly</th>
<th>Pure Anomaly</th>
<th>Differential (Pure–Naive)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Monthly Average</td>
<td>t-Statistic</td>
<td>Monthly Average</td>
</tr>
<tr>
<td>Low P/E</td>
<td>0.59%</td>
<td>0.01</td>
<td>0.46%</td>
</tr>
<tr>
<td>Small Size</td>
<td>0.15</td>
<td>2.7**</td>
<td>0.12</td>
</tr>
<tr>
<td>Yield</td>
<td>-0.01</td>
<td>0.04</td>
<td>0.03</td>
</tr>
<tr>
<td>Zero Yield</td>
<td>0.00</td>
<td>1.3</td>
<td>0.13</td>
</tr>
<tr>
<td>Neglect</td>
<td>0.14</td>
<td>1.7**</td>
<td>0.10</td>
</tr>
<tr>
<td>Low Price</td>
<td>-0.01</td>
<td>0.2</td>
<td>0.01</td>
</tr>
<tr>
<td>Book/Price</td>
<td>0.17</td>
<td>1.2</td>
<td>0.09</td>
</tr>
<tr>
<td>Sales/Price</td>
<td>0.17</td>
<td>3.1**</td>
<td>0.17</td>
</tr>
<tr>
<td>Cash/Price</td>
<td>1.36</td>
<td>0.6</td>
<td>0.36</td>
</tr>
<tr>
<td>Sigma</td>
<td>0.36</td>
<td>0.6</td>
<td>0.07</td>
</tr>
<tr>
<td>Beta</td>
<td>-0.00</td>
<td>0.0</td>
<td>0.04</td>
</tr>
<tr>
<td>Cooksiness</td>
<td>0.09</td>
<td>0.6</td>
<td>0.04</td>
</tr>
<tr>
<td>Controversy</td>
<td>-0.33</td>
<td>2.1</td>
<td>-0.35</td>
</tr>
<tr>
<td>Trend in Estimates (-1)</td>
<td>0.48</td>
<td>4.8**</td>
<td>0.51</td>
</tr>
<tr>
<td>Trend in Estimates (-2)</td>
<td>0.40</td>
<td>4.4**</td>
<td>0.28</td>
</tr>
<tr>
<td>Trend in Estimates (-3)</td>
<td>0.29</td>
<td>3.0**</td>
<td>0.19</td>
</tr>
<tr>
<td>Earn. Surprise (-1)</td>
<td>0.44</td>
<td>2.1*</td>
<td>0.48</td>
</tr>
<tr>
<td>Earn. Surprise (-2)</td>
<td>0.47</td>
<td>1.8*</td>
<td>0.18</td>
</tr>
<tr>
<td>Earn. Surprise (-3)</td>
<td>-0.03</td>
<td>0.1</td>
<td>-0.21</td>
</tr>
<tr>
<td>Earn. Torpedo</td>
<td>-0.00</td>
<td>0.0</td>
<td>-0.10</td>
</tr>
<tr>
<td>Relative Strength</td>
<td>0.30</td>
<td>1.4</td>
<td>0.34</td>
</tr>
<tr>
<td>Res. Reversal (-1)</td>
<td>-0.54</td>
<td>4.9**</td>
<td>-1.08</td>
</tr>
<tr>
<td>Res. Reversal (-2)</td>
<td>-0.13</td>
<td>1.4</td>
<td>-0.37</td>
</tr>
<tr>
<td>Short-Term Tax</td>
<td>-0.08</td>
<td>0.4</td>
<td>-0.04</td>
</tr>
<tr>
<td>Long-Term Tax</td>
<td>-0.29</td>
<td>1.6</td>
<td>-0.00</td>
</tr>
</tbody>
</table>

*Significant at the 10 per cent level.
**Significant at the 1 per cent level.

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but es return to its underlying sources.

Table II presents summary statistics for the monthly cross-sectional regressions over the period January 1978 to December 1986. The average monthly return and associated t-statistic for each anomaly are shown in both naive and pure forms. A paired t-test on the difference between naive and pure returns is also displayed. In several instances (notably residual reversals), the difference in returns is significant. These differences are due to the substantial proxying that muddies the waters in simple univariate regressions because of omitted-variable bias. A regression of return on just cash flow/price, for example, may unintentionally pick up part of the low P/E effect, as the average correlation between a stock’s cash flow/price and earnings/price ratios is 0.65 for our sample.

The use of multivariate regression to disentangle highly correlated effects may, however, raise the specter of multicollinearity. Does our use of so many closely related regressors somehow cause inefficiency, or are potential problems obviated by our large sample size? One simple diagnostic test is a comparison of the time series standard deviation of payoffs to each naive versus pure anomaly. Because "both strategies have the same standardized exposure . . . a reduction in time series variability can occur only if the risk reduction from immunizing the effects of other common factors has exceeded the risk increase due to higher specific variance." In fact, the time-series risk of all 25 anomalies is lower in the multivariate regression, often by over 50 per cent. Thus multicollinearity is not a serious problem.

P/E and Size Effects

The results displayed in Table II reveal significant return regularities during the period studied. First, low P/E paid off handsomely, on average, from 1978 to 1986. The naive return attribution averaged 59 basis points per month, while the pure return attribution averaged 46 basis points. The naive return to low P/E was confounded by other related effects such as sales/price. Because the payoff to sales/price was positive for this period, part of it, and other related effects, were unintentionally picked up by the naive low-P/E anomaly.

Figure A
Cumulative Return to Low Price/Earnings

<table>
<thead>
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<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Return</td>
<td>0</td>
<td>10</td>
<td>20</td>
<td>30</td>
<td>40</td>
<td>50</td>
<td>60</td>
<td>70</td>
<td></td>
</tr>
</tbody>
</table>

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Despite the lower average return of the pure low-P/E series, its t-statistic of 4.7 was higher than the 3.4 of the naive series; this can be attributed to its greater consistency. While the pure return was positive in 76 out of 108 months, or 70.4 per cent of the time, the naive return was positive in only 70 months, or 64.8 per cent of the time. Also, the volatility of the pure low-P/E series, as measured by standard deviation, was 1.01 per cent, while that of the naive series was 1.82 per cent.

Because t-statistics this large would be expected to occur by chance alone much less than 1/100th of the time if P/E truly did not matter, we conclude that low P/E is a statistically significant effect at the 1 per cent confidence level. The significance of the pure return to low P/E, furthermore, refutes the assertion that low P/E is merely a surrogate for some other effect, such as size or neglect.53

While pure returns to low P/E were significant on average over the period studied, there were, nonetheless, stretches when these pure returns were negative. For instance, Figure A, which illustrates the cumulative pure payoff to low P/E, shows negative returns from mid-1982 to early 1984. It appears that the low-P/E effect has been unstable.54

The small-size effect was also more significant on average in its pure than its naive form, albeit with a slightly lower average monthly return of 12 basis points, versus 15 for the naive effect. The existence of a size effect in its pure form demonstrates that small size is not just a proxy for some other underlying effect.55

While pure returns to small size peaked in 1984, as illustrated in Figure B, naive returns to size peaked earlier, in 1983. This divergence may be caused by naive returns to size picking up some of the low-price effect, which also peaked in 1983 (as discussed below). Additionally, the lack of persistence in returns to small size may be evidence of nonstationarity.56 Furthermore, the size effect and other return regularities may be related to macroeconomic events.57

Yield, Neglect, Price and Risk

Yield and zero-yield on average were not statistically significant over this period. How-

Figure B Cumulative Return to Small Size

![Graph showing cumulative return to small size from 1978 to 1986.](https://example.com/graph.png)
ever, a clearer picture emerges when January seasonals are examined (as discussed below).

Neglect was a significant effect both in its naive form, where it added an average of 14 basis points per month, and in its pure form, where it added 10. Because the neglect effect survives the purification process, it appears to exist independently of the low-P/E and small-size anomalies.

We found no significant accumulation of returns to low price over the period. This is in contrast to previous research on naive returns to low price, as well as Reid’s finding of a significant effect in his multivariate model. The difference is due primarily to our use of a more recent sample period. We observed significant naive and pure return accumulations from this effect until mid-1983, but deaccumulations thereafter. Another reason may be our practice of lagging price one month, which abstracts return attributions from pricing errors and bid/ask-spread biases. The low-price measure is especially sensitive to such problems.

Both naive and pure returns to book/price had the expected positive sign, but did not achieve statistical significance. While this might appear surprising in view of the research by Rosenberg, Reid and Lanstein, which highlighted the power of book/price, it is consistent with the BARRA finding that the introduction of sales/price and cash flow/price measures significantly weakens the return attribution to book/price.

Sales/price experienced a strong payoff. Both naive and pure returns averaged 17 basis points monthly, significant at the 1 per cent confidence level. Conversely, the 36-basis-point naive return to cash flow/price dissipated in the multivariate anomaly setting (as evidenced by the significant differential-returns t-test), indicating that it acted as a surrogate for other factors, primarily low P/E, in the univariate regression.

Sigma, beta and skewness all had negligible average monthly payoffs. While these measures do not accumulate over time, they generally have statistically significant cross-sectional explanatory power within a month, thereby further purifying return attributions to other effects. The lack of any cumulative return to beta during one of the most extended bull markets in

Figure C  Cumulative Return to Beta

![Cumulative Return to Beta](image)

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history is especially interesting. While seeming-
ly inconsistent with the CAPM (which is
couched, however, in expectational terms), it is
not inconsistent with other empirical findings.59
Figure C illustrates the cumulative pure payoff
to beta. These returns appear unstable, as they
cumulate positively in the early years and nega-
tively in the latter years. This change in trend
may be evidence of nonstationarity.60

Stocks with controversial earnings prospects
did poorly in a naive sense and produced insig-
nificant results in a pure sense. This is inconsis-
tent with the previous research on controversy,
which demonstrated a positive naive payoff. It is,
however, another illustration that for the
period we considered, there was an absence of
expected compensation for bearing many forms of
risk.

Trends and Reversals

Trends in analysts’ estimates for individual
stocks emerge as powerfully in their pure form
as in their naive form. Thus it is not true, for
example, that this anomaly is due to any ten-
dency of analysts systematically to underesti-
mate and then upgrade estimates on low-P/E
stocks (in which case it might merely be a proxy
for low P/E). Figure D plots cumulative pure
payoffs to analyst revisions made one, two and
three months previously. While there is a
marked decay in the value of this measure over
time (as evidenced by the t-statistics, which
decline from 8.1 to 4.9 to 3.8), even three-
month-old data are significant at the 1 per cent
level.

Returns to earnings surprise exhibit a quicker
decay than do returns to analyst revisions. Only
one-month-old surprises were statistically sig-
nificant in their pure form; by the time surprises
were three months old, results were perverse.
Naive returns to earnings surprise were signifi-
cant for two monthly lags.

Our univariate regression provided no evi-
dence of a torpedo stock effect. The pure effect
was present, however, and with the predicted
sign. There was a statistically significant and
negative pure average monthly payoff of 10
basis points to higher predicted earnings
growth.

Relative strength paid off handsomely. Its
pure return of 34 basis points per month was
strongly significant statistically in the multi-
variate regression. Reid’s multifactor model includ-
ed a one-year relative-strength measure that
was also quite powerful. Sharpe’s multifactor
relative-strength measure, a one-month alpha
similar to ours, had negative return attribution,
perhaps because of the absence of related mea-
ures, such as residual reversal.

Residual reversal turned out to be by far the
most powerful effect we found, especially in the
multivariate regression. The t-statistic of −17.8
for one-month reversals is in line with the
findings of previous researchers.61 The paired t-
test on differential returns showed a significant
increase in the strength of pure versus naive
residual reversal. Pure returns to residual rever-
sal emerged more powerfully, because related
effects such as earnings surprise were disentan-
gled. Figure E illustrates cumulative returns to
one and two-month-old residual returns. The
negative payoffs demonstrate the strong ten-
dency for these residuals to reverse partially
over the next two months. The relative stability
of returns to these measures over time is in
marked contrast to the less regular patterns
noted in some of the earlier figures.

Reid’s multifactor model considered one-
month and one-quarter returns subsequent to a
one-month-old residual and found a roughly
equal reversal after either holding period.
Ro-
senberg and Rudd examined one- and two-
month-old reversals separately and found per-
sistence from two months ago to be about 26 per
cent as strong as that from one month ago.62 We
found reversal persistence from two months
ago to be about 34 per cent as strong as that
from one month ago. We can reconcile our
results and those of Rosenberg-Rudd with
Reid’s as follows: We found that the three-
month-old residual had a payoff about equal in
magnitude and opposite in sign to the two-
month-old residual; thus the total one-quarter
return examined by Reid should be of roughly
the same magnitude as his one-month return,
as months two and three cancel each other out.

Finally, on average there was no significant
payoff to our tax measures. A clearer picture of
tax effects emerges, however, when we exam-
ine the January effect.

The time-series of returns to our 38 industries
exhibited nothing unusual. Seven industries
had average returns that were significantly dif-
ferent from zero at the 10 per cent level, versus
four that would be expected by chance alone.
Only one (media) was significant at the 1 per
cent level, perhaps because of the recent wave
of takeovers in that industry. Also, a cluster

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analysis of returns to industries revealed expect-
ed patterns such as the existence of an interest-
rate-sensitive financial sector.43 Furthermore, the industry returns series appear to be related
to macroeconomic events. For example, returns to
the most volatile industry, precious metals,
were closely related to gold prices.

Some Implications
How much explanatory power does our
multivariate anomaly framework possess? The
average R-squared from our 108 monthly cross-
sectional regressions was 39 per cent.44 (Adjust-
ed for degrees of freedom used up by all our
measures, the variance explained was 36 per
cent.) This corresponds very favorably with the
R-squared of 10 per cent achieved by Sharpe’s
model.45

To summarize, there is strong evidence that
the stock market was rife with return regulari-
ties during the period from 1978 to 1986. Our
evidence documents several statistically signifi-
cant and independent return regularities, which
often differed substantially from their naive
manifestations. The failure of beta to be priced
is further evidence that conventional theory is
unable to explain observed stock returns.

The EMH is strongly contradicted. We ex-
amined only publicly available information. Thus
we do not test directly the contention that the
market is “strong-form” efficient—that is, that
prices fully reflect all information (including
private or “insider” information). We are, how-
ever, able to reject narrower definitions of effi-
ciency, which is even more indicative of market
inefficiency. Consider, for instance, the predic-
tive power of the measure of trends in analysts’
earnings estimates, which documents “semi-
strong” inefficiency; that is, prices do not fully
and instantaneously reflect all publicly available
information. The ability of residual reversal, which
is derived solely from past returns, to explain
future returns represents prima facie evi-
dence that the stock market is “weak-form”
inefficient: Past prices alone have predictive
power.

The significant return accumulations to our
purified anomalies independently add to the
weight of evidence contravening the EMH. The
same cannot be said of previous studies. For
instance, separate studies of trends in analysts’
estimates and earnings surprise do not repre-
sent independent evidence of inefficiency, be-
cause these effects are closely related and may
proxy for one another.

While some anomalies provided consistent
excess performance, month-by-month, others
were less stable in nature. The stationarity of
some return effects is questionable. Granted,
many of these return regularities have been
exhibited as far back as data are available. Also,
the underlying causes, such as institutional fea-
tures of the stock market and the quirks of
human nature, are slow to change.46 An issue of
vital concern to investors is whether the returns
to anomalies were of sufficient magnitude and
stability to have been exploitable for profit, net
of transaction costs.

The costs of trading consist of both market
impact and commissions. As a first approxima-
tion, market impact is a function of a stock’s
market capitalization, while commission (ex-
pressed in percentage terms) is a function of
stock price. Recall that capitalization and price
are two of the factors we control for in our
multivariate regression. Hence payouts to other
anomalies, such as low P/E, represent the re-
turn to a low-P/E stock that has average market
size and price. In other words, our return attri-
butation to low P/E can be captured on average by
trading stocks of average price and size, imply-
ing approximately average transaction costs.

The various return regularities studied obvi-
ously require differing amounts of trading to
maintain a given portfolio exposure. At one
extreme, heavy monthly trading would be nec-
sary to maintain a big portfolio bet on residual
reversal. Conversely, relatively little trading
would be needed to maintain a more stable
characteristic, such as small size.

Although not reported here, there is substan-
tial evidence that “anomaly capture strategies”
have the potential to generate above-market
returns (net of transaction costs) that are both
economically and statistically significant.47 These
strategies are designed to utilize Stein-
James estimators, which are superior to histori-
cal averages as estimates of true payoffs to
anomalies. This estimation technique, some-
times referred to as Empirical Bayes, is applica-
tible when the number of measures to be estimat-
ed exceeds two, and works better the larger the
number of measures.48 Such diversified anoma-
ly exploitation strategies can also benefit from
the January effect, discussed below.

January Versus Rest-of-Year Returns
As mentioned earlier, several studies have

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<table>
<thead>
<tr>
<th>Anomaly</th>
<th>Naive Anomaly</th>
<th>Pure Anomaly</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low P/E</td>
<td>0.19%</td>
<td>0.3</td>
</tr>
<tr>
<td>Small Size</td>
<td>0.57%</td>
<td>2.5**</td>
</tr>
<tr>
<td>Yield</td>
<td>0.25</td>
<td>0.4</td>
</tr>
<tr>
<td>Zero Yield</td>
<td>1.42</td>
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</tr>
<tr>
<td>Neglect</td>
<td>0.53</td>
<td>2.3**</td>
</tr>
<tr>
<td>Low Price</td>
<td>0.94</td>
<td>2.5**</td>
</tr>
<tr>
<td>Book/Price</td>
<td>0.97</td>
<td>2.5**</td>
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<td>Sales/Price</td>
<td>0.71</td>
<td>3.2**</td>
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<td>Cash/Price</td>
<td>0.28</td>
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</tr>
<tr>
<td>Sigma</td>
<td>1.32</td>
<td>1.3</td>
</tr>
<tr>
<td>Beta</td>
<td>0.15</td>
<td>0.2</td>
</tr>
<tr>
<td>CoKwesnity</td>
<td>0.34</td>
<td>0.6</td>
</tr>
<tr>
<td>Controversy</td>
<td>0.89</td>
<td>2.5**</td>
</tr>
</tbody>
</table>

*Significant at the 10 per cent level.
**Significant at the 1 per cent level.

found significant January seasonals in the returns to anomalies. Our findings transcend much of the previous work because of our substantial purification and our careful abstraction from both potential long-term and short-term tax-loss selling pressure.

Table III displays the average monthly returns and associated t-statistics for each attribute, in both naive and pure form, for January and non-January months. Also shown is a difference-of-means test for January versus non-January month.

Our findings of significantly different January versus non-January naive returns to small size, low price, book/price, sales/price, earnings controversy and tax measures agree with earlier anomaly studies. For neglect, however, while the difference-of-means test showed no January seasonal at even a 10 per cent significance level, the average January return of 53 basis points is significantly non-zero. Our results for naive returns to yield (including zero yield), sigma and relative strength, although not statistically significant, are in accord with earlier reported results.

Of all the naive anomaly results displayed in Table III, only low P/E is at variance with some of the previous studies, which found low P/E to be more powerful in January than in other months. This difference may arise from our use of a more recent time period than those used in previous studies.

Purifying anomalies and controlling for potential tax-loss selling in our multivariate regressions reveal several noteworthy features. The January yield effect, including zero yield, remains powerful and strongly non-linear in our multivariate framework. Interestingly, the significant January return attributable to zero-yield stocks is not subsumed by sigma, small size,
low price or other related attributes.

The pure January seasonal for low price and book price are attenuated in magnitude compared with their naïve counterparts, while the pure January seasonal for small size, sales price and earnings controversy vanish completely. Perhaps the most striking result in Table III relates to small size. While the naïve January return to smallness of 57 basis points is significantly different from the non-January naïve return of 11 basis points, the pure returns to smallness exhibit no discernible seasonality. Apparently, the January size season observed by the researchers cited in Table I is merely a proxy for tax-related effects.

While both pure tax-effect measures are significant in January, the long-term tax-loss measure has a rebound effect of 78 basis points, about twice the magnitude of the short-term measure. This is somewhat surprising, in view of the lower tax rate on long-term versus short-term capital gains during the period studied. Greater short-term loss-taking might be expected, because it shelters more income. However, our results are consistent with other empirical findings. 24 Furthermore, irrational investor behavior may offer a potential explanation; investors are often more averse to admitting recent mistakes than to admitting older ones. 25 The attenuation of non-January returns to our tax-loss measures in their pure forms provides further evidence that they are sensibly constructed.

Although the difference between January and non-January returns is not quite statistically significant for our relative-strength measure,
the average January return is negative while the average non-January return is significantly posi-
tive. The negative returns in January likely arise from increased profit-taking among stocks with
positive relative strength, motivated by a desire to defer gain recognition until the following tax
year. Our tax measures, in contrast, are de-
signed only to capture rebounds from year-end
tax-loss taking.

There is no solid theoretical explanation for a
January seasonal to yield, size or any other
security characteristic other than to tax-related
measures.70 Thus, while our results showing a
January seasonal in yield remain a puzzle, the
dissipation of pure January seasonals for other
anomalies such as small size is gratifying.

**Autocorrelation of Return Regularities**

Earlier, we asserted that the evidence presented
strongly contradicts both the weak and semi-
strong forms of the EMH. A more subtle test of
weak-form efficiency entails an examination of the
time-series of returns to equity characteris-
tics for autocorrelation. If returns between adja-
cent months are correlated (first-order autocor-
relation), then an optimal prediction for next
month’s return uses the product of the correla-
tion coefficient and the past month’s return. Past
prices alone would have predictive con-
tent. The sequence of first and higher-order
autocorrelations can be used to measure the
“memory” of the return-generating process and
may be useful in forecasting.

We examined the time-series properties of the
returns to each anomaly. There is some prior
evidence of patterns in these series, with most
previous work having focused on naive returns to
stock characteristics.77

Rosenberg and Rudd, using a multifactor
framework, reported significantly positive
monthly first-order, and negligible second-
order, autocorrelation in the total factor-related
return component of each stock. They discussed
various possible explanations—(1) under-
response of the market to exogenous (macro-
economic) shocks, (2) nonsynchronous re-
sponse of individual assets to a factor, and (3)
changing risk premiums for various stock attri-
butes.78 We extended their approach. First, we
calculated results for both naive and pure anom-
aliies. Second, rather than aggregating anom-
aliies up to the individual stock level, we ana-
lyzed the autocorrelations of the return series to
each pure anomaly separately. Third, we tested
each return effect’s overall autocorrelation
structure for significance. Table IV reports the
results.

Note that most anomalies, both naive and
pure, exhibit positive first-order autocorrela-
tion, with several being statistically signifi-
cant.79 A test of the hypothesis that the aver-
age anomaly’s lag-one-month autocorrelation is
zero is strongly rejected, with a t-statistic of 4.9
for the naive and 3.1 for the pure case. Pure
anomaly autocorrelations of lag-two are on av-
erage not significantly different from zero (con-
sistent with Rosenberg-Rudd).

The naive autocorrelations for lag-one are
stronger than the pure anomaly results, and the
naive lag-two results are significantly negative.
One explanation for these differences with the
pure results is the impact of related naive anom-
aliies acting as proxies for one another. For
example, P/E, book/value, cash/value, sales/
price and yield are all closely related. In the
naive analysis, the returns (hence autocorrela-
tions) to any one of them contains information
from all the other related effects. The positive
first-order autocorrelations in each of these pure
series are thus partially additive for each naive
anomaly. Similarly, past trends in analyst esti-
mates have negative second-order autocorrela-
tions and are also highly correlated; hence the
negative second-order autocorrelation in any
one naive series is stronger than that in the
associated pure anomaly.

Table IV also displays a test for non-random-
ness in the time-series of returns to each attri-
bute.80 The autocorrelations at many different
monthly lags (including and beyond the two
shown) are strong enough that returns to sever-
al naive and pure anomalies are statistically
non-random, as shown by their significant Q-
statistics. We leave it to the interested reader to
compare results for anomalies in their naive and
pure forms. We simply want to point to this
demonstration of meaningful patterns in the
returns to various anomalies over time as fur-
ther evidence of departures from randomness.

As mentioned above, significant autocorrela-
tions can arise from changing risk premiums—
that is, from time-varying expected returns to
equity characteristics. Risk premiums may fluc-
tuate because of macroeconomic events. Be-
cause risk premiums are likely to evolve slowly
time, autocorrelation patterns consistent with
such variation would exhibit persistence over
many lags, and thus need not contravene
weak-form efficiency. Careful examination of the lag structures of our measures reveals persistence for some. For the majority of anomalies, however, no such persistence is observed.

We thus have further evidence of weak-form inefficiency. Irrespective of the issue of market efficiency, the presence of autocorrelation suggests that time-series modeling of the individual return effects might have investment merit.

Return Regularities and Their Macroeconomic Linkages

We have suggested that exogenous factors, such as macroeconomic events, might play a role in driving returns to various equity characteristics. A full investigation of such linkages is beyond the scope of this article. However, we note some possible connections below.

One special macroeconomic measure is the return to the stock market. At the economy-wide level, this measure is useful, as indicated by its inclusion in the Index of Leading Indicators. It may also have explanatory power for returns to stock market attributes. In fact, market folklore maintains that low-P/E and high-yield stocks are generally “defensive” in nature. One might thus suppose that their payoffs are dependent on the direction of the stock market.

A simple method of testing this possibility would be to examine anomaly returns in up and down markets separately. A more rigorous approach, taken here, is a time-series regression of monthly anomaly returns on monthly market excess returns. Table V displays the results of these time series regressions for both naive and pure anomalies. The intercept refers to each anomaly’s payoff in a flat market month (that is, a month providing no market excess return). The slope, or market sensitivity, refers to the incremental return to an anomaly above (below) the intercept, given a 1 per cent market excess return.

Conventional wisdom holds that low-P/E stocks are defensive; indeed, the significantly negative slope coefficient shown in Table V indicates that low-P/E stocks do relatively less

<table>
<thead>
<tr>
<th>Table V</th>
<th>Regressions of Anomaly Returns on Market Returns</th>
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<tbody>
<tr>
<td></td>
<td>Naive Anomaly</td>
</tr>
<tr>
<td>Low-P/E</td>
<td>0.66%</td>
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<td>Small Size</td>
<td>0.16</td>
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<td>Yield</td>
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<td>Beta</td>
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</tr>
<tr>
<td>Conk *</td>
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<td>Controversy</td>
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Trend in Earnings
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<tr>
<th>Intercept</th>
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<tr>
<td>Low-P/E</td>
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<td>4.0**</td>
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<tr>
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<td>0.40</td>
<td>4.7**</td>
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<td>Yield</td>
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<td>2.8**</td>
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<tr>
<td>Zero Yield</td>
<td>0.11</td>
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<tr>
<td>Neglect</td>
<td>0.16</td>
<td>1.8*</td>
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<tr>
<td>Conk *</td>
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<tr>
<td>Controversy</td>
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<td>-2.4*</td>
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Relative Strength
<table>
<thead>
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<th>Intercept</th>
<th>t-stat.</th>
<th>Slope</th>
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</thead>
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<td>Low-P/E</td>
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<td>4.7**</td>
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<tr>
<td>Small Size</td>
<td>-0.16</td>
<td>-3.7*</td>
</tr>
<tr>
<td>Yield</td>
<td>-0.15</td>
<td>-0.8</td>
</tr>
<tr>
<td>Zero Yield</td>
<td>-0.25</td>
<td>-1.8</td>
</tr>
</tbody>
</table>

Significant at the 10 per cent level.
**Significant at the 1 per cent level.

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well in bull than in bear markets. However, it would take a one-month excess market return of 6 per cent (−0.11 × 6% = −0.66%) to offset fully the 0.66 per cent advantage of (a one-cross-
sectional standard deviation exposure to) various P/E stocks. This defensiveness does not carry over to the pure low-P/E anomaly, which has a zero slope coefficient. In other words, the pure return to the low-P/E anomaly is not affected by the direction of the market. A glance at Figure A confirms this: While pure low P/E did not add value in the mid-1982 to mid-1983 roaring bull market, it did add value during other up market periods, such as mid-1984 to late-1985.

Conventional wisdom is confirmed for the yield attribute: Returns to higher yield have a strong negative slope in both naive and pure regressions, indicating that their relative payoffs move inversely with the market’s direction. Other attributes, however, are strongly procyclical. For example, monthly naive and pure returns to historical beta are intimately and positively tied to excess market returns. Also, a significant positive relationship exists between market movements and returns to earnings controversy and to relative strength.

These fitted time-series relations represent a simple mechanism for making forecasts of returns to equity characteristics conditional on market returns. Also, the significant market-related components highlight the power of various prespecified attributes in forming a predic-
tion of a stock’s beta.48 For example, because the pure returns to low yield and neglect are nega-
tively related to market action (both having slopes of −0.05), individual stocks with these attributes will tend to exhibit lower systematic risk than otherwise. Note that our analysis controls for historical beta in deriving each pure anomaly return series. Not unexpectedly, our Vasicek-adjusted historical beta in the pure case is the dominant contributor to predictive beta, having a slope coefficient of 0.21 with a t-
statistic of 9.7. The reader may wonder why this slope coefficient differs so much from one; the answer lies in our use of a normalized historical beta measure, which is scaled differently from the predictive, raw-form beta.

We noted above that the purification of the low-P/E effect caused its market-related compo-
nent to dissipate. Similar diminution occurred for the market sensitivity of zero yield, cash/ price and coskewness. The market sensitivity of the low-price and book-price measures actually reverses sign when purified. Unlike their pure counterparts, naive anomalies are clearly un-
suitable for beta prediction, because they serve as proxies for each other and their market sensitivities are not additive.

A comparison of the naive and pure anomaly intercepts in Table V with the average monthly anomaly returns in Table II indicates that the statistically significant anomalies are generally robust to market-return adjustment. For exam-
ple, the pure sales/price intercept is 15 basis points, with a t-statistic of 3.4, while the naive monthly average return is 17 basis points, with a t-statistic of 3.7. This similarity holds despite the statistically significant slope coefficient for pure sales/price.

Also, our earlier findings on the pure January seasonality of various anomalies are robust to market-return adjustment. In fact, our results become more conclusive for the relative-
strength measure. Earlier, we found the differ-
ence between January and non-January returns to be in the expected direction, but not statisti-
cally significant. However, once we adjust for the average excess market return in January of 2.3 per cent, the difference between January and non-January intercepts is significant at the 1 per cent level. This further supports our conten-
tion that negative pure returns to relative strength in January arise from profit-taking asso-
ciated with tax-gain deferral.

As we indicated earlier, the presence of equi-
ity return regularities calls into question the EMH and current asset pricing models, includ-
ing the CAPM and APT. Also, the existence of significant pure anomaly intercepts, in the time-
series regressions of anomaly returns on excess market returns, raises questions about the valid-
ity of a multifactor CAPM.49

Conclusion
Anomalies such as residual reversal and trends in analysts’ earnings estimates appear to be true pockets of stock market inefficiency. Other ef-
flicts, such as low P/E and small size, appear nonstationary; they may be anomalous, or they might represent empirical return regularities only in a broader macroeconomic framework. The future holds open the potential of uncover-
ning new return regularities, as better databases (such as real-time pricing) and greater computer power are brought to task. At the same time,

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however, as we develop better ways of measuring risk and newer asset pricing models, new theories will undoubtedly arise to fit the observed facts. In will be exciting to observe the progress on both fronts.

Footnotes


While the Lehman and Modern paper shows the size-related rejection of APT is not an artifact of infrequent trading or safety due to the month of January, they also find that the dividend-yield and own-variance effects are not anomalies in their APT framework (while they are CAPM anomalies). Connor and Korajczyk find APT performs better in explaining the January seasonality returns to small size, but no better than CAPM in non-January months. Chen, Copeland and Mayers show that the size effect and Value Line engine are not explained by an APT framework. Value Line uses a composite of several measures, such as earnings surprise, and price and earnings momentum.


2. There are contrary opinions as to the advisability of doing so. One one hand, O. Joy and C. Jones ("Should We Believe the Tests of Market Efficiency?" Journal of Portfolio Management, Summer 1986, pp. 49-54) concluded that "until we have incontrovertible knowledge of the true state of market efficiency, adoption of the anomalies as guidelines is justified." (Also see B. Jacobs and K. Levy, "Investment Management: Opportunities in Anomalies?" Pensions World, February 1987, pp. 64-67, for thoughts on the philosophy of anomaly investing. For a recent view from Wall Street, see S. Einhorn and F. Liebman, "A Multi-factor Model," Goldman Sachs Portfolio Strategy, 4/10/87. On the other hand, R. Merton ("On the Current State of the Stock Market Rationality Hypothesis," in S. Fischer and J. Dornbusch, eds., Macroeconomics and Finance: Essays in Honor of Milton Friedman (Cambridge: MIT Press, 1982) suggests that since all researchers are essentially analyzing the same data set and since only interesting anomaly articles get published, it "creates a fertile environment for both unintended selection bias and for attaching greater significance to otherwise unbiased estimates than is justified." Nevertheless, Merton constructs a theoretical model positing the existence of multiple anomalies (including the neglected firm size and size effects) and discusses some investment implications in a "Simple Model of Capital Market Equilibrium With Incomplete Information." Journal of Finance, July 1987, pp. 483-510.

3. F. Hawthorne, "When is an Index Fund Not an Index Fund?" Institutional Investor, May 1984, pp. 73-81.


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in markets, success, size, trading activity, earnings price, book price, earnings variance, financial leverage, foreign income, labor turnover, yield, and a low-capitalization indicator—and 55 industry classifications.


12. Keim, "Size-Related Anomalies and Stock Return Seasonality," in Table 1 and Roll, "Van Ilst Desk," in Table 1.


19. Keitm ("Dividend Yields and Stock Returns" Table I) shows the entire non-linear pattern actually to occur in the month of January.

20. For example, see Artell, "Genetic Stocks," cited in Table I. For a theoretical model of the neglect effect, see R. Menton, "A Simple Model of Capital Market Equilibrium With Incomplete Information," op. cit.


23. A. R. Serfack and J. Martin, "The Relative Performance of the PSR and PET Investment Strategies," cited in Table I, test this claim and find earnings-price superiority. It was reported that sales-price is significant in a multifactor framework at the BARRA Research Seminar, June 1980, Berkeley, California.

24. BARRA has tested this measure contemporaneously with E/P, mae/price and book/price, and finds it significant; reported at the BARRA Research Seminar, June 1986, Berkeley, California.


26. See Tzin and West, "Risk, Return and Equilibrium," cited in Table I, for recent evidence.


32. H. Rainville, "Earnings Momentum in Equities" (Paper presented at the Institute for Quantitative Research in Finance, Spring 1980); R. Hagin, "An Examination of the Torpedo Effect" (Paper presented at the Institute for Quantitative Research in Finance, Fall 1980); and Ben-son and Peterson, "On the Relation Between Earnings Changes, Analysts' Forecasts and Stock Price Fluctua- tions" (cited in Table I, especially their Table V.

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37. Portfolio grouping helps to resolve the econometric problem of measurement error. See Fama and MacBeth, "Risk, Return and Equilibrium," op. cit.

38. For example, see Bass, "The Relationship Between Earnings Yield, Market Value and Return For NYSE Common Stocks," in Table 1.

39. See Brown, Kleidon and Marsh, "New Evidence on the Nature of Size-Related Anomalies in Stock Prices," op. cit., for an application of SURM to the size effect. While SURM is more efficient asymptotically, it is only feasible if the number of assets (stocks or portfolios) is small in relation to the number of time periods (see C. Maddala, Econometrics (New York: McGraw Hill, 1977, p. 381)). Since we cannot compact our stocks into portfolios because of the large number of attributes studied simultaneously, this approach is inapplicable here. We also consider it inappropriate for another reason—we take the perspective of an investor seeking to exploit anomalies, and thus could not have claimed ex ante knowledge of the future error covariance structure.

40. For example, Lakonishok and Shaprio (in "Stock Returns,贝克, Variance, and Size," referenced in Table 1) cite this as a reason their results contradict Fama-MacBeth. Also see Litterberger and Ramaswamy, "The Effect of Personal Taxes and Dividends on Capital Asset Prices," op. cit., and A. Weag, "Experimental Design in Tests of Linear Factor Models" (Columbia University, Business School working paper, January 1987) for other arguments against grouping stocks.

41. To partition simultaneously into quintiles on the basis of our 25 size anomalies results in 5th, or 25th, separate classifications. Using monthly returns on our 500 stocks, it would take over 6.6 trillion years to generate just one observation per cell.

42. See R. Gitold, "Multiple Factor Risk Models and Exact Factor Pricing" (L. C. Berkley working paper #166, February 1987) for a discussion of the empirical appropriateness of modeling expected returns linearly in equity characteristics.


45. As suggested by Rosenberg, Reid and Lanestine, "Per- sonal Evidence of Market Inefficiency," op. cit.

46. Blume and Stambaugh, "Computed Returns," Table 1) demonstrate this problem in the context of the small-size and low-price effects.

47. Banz and Breen, "Sample-Dependent Results Using Accounting and Market Data," in Table 1) provides a comprehensive discussion of methodological problems and a stark example of the potential for survivorship and look-ahead biases to confound the disentanglement of the size and P/B effects.

48. This type of normalization belongs to the general class of "Varonized M-Estimators" discussed in G. Judge et al, The Theory and Practice of Econometrics, 2nd ed. (New York: John Wiley, 1985), pp. 524–504. This concept was
first applied in common stock research by BARRA in their E1 Model (see footnote 8).

49. J. Ratchef ("The Effects on the T-Distribution of Nonnormality in the Sampled Population," Applied Statistics 17 (1968), pp. 43-48) demonstrates this test to be robust in samples of over 80 observations. Because of data availability constraints, our earnings surprise series commence in 1984. Significance levels shown for this anomaly reflect the lesser degrees of freedom.


53. For example, Arbit ("Generic Stocks," in Table I) suggested that P/E might be a proxy for neglect; Rein- garn ("Nonspecification of Capital Asset Pricing," Table I) and Blau and Breun ("Sample Dependent Results Using Accounting and Market Data," Table I) found the size effect to subsume P/E. Our results are more consistent with those of Downes and Baumer, "The Relative Importance of Size, P/E and Neglect," and Cook and Rozell, "Size and Earnings Prior to Positive Anomalies," who identify an independent P/E effect.

54. In fact, an arbitrary split of the sample period into two subperiods of equal length reveals significantly different (at the 1 per cent level) price return variances across time for eight of our 25 anomaly measures, and significantly different price average monthly returns for three of our measures. These frequencies of rejecting equality are, of course, much greater than expected from chance alone at the 1 per cent level if the series were truly stationary. An F-test was used to check for equality of variances across time in price returns. A difference-of-means test was then performed using the strictest Cochran criteria in those cases where equality of variances was rejected. These tests were two-sided. For a discussion of these tests, see G. Snedecor and W. Cochran, Statistical Methods, op. cit., pp. 104-116.

55. This contradicts Basu, "The Relationship Between Earnings Yield, Market Value and Return for NYSE Common Stocks," in Table I, who found the P/E effect to subsume the size effect. Consistent with our findings, however, all three previously cited multifactor models stipulate a size effect.

56. Brown, Kleidon and Marsh ("New Evidence on the Nature of Size-Related Anomalies in Stock Prices," op. cit.) document major time periods when small size was determinant to returns.


60. Lakonishok and Shoven ("Stock Returns, Beta, Vari- ance and Size," in Table I) find that the size effect subsumes returns to both beta and sigma. Tintic and West ("Risk, Return and Equilibrium") report that the interaction of returns to beta, sigma and size depends on whether or not the month is January. We will examine January separately later.

61. Sharpe's multifactor beta did accumulate significantly over time; Reid's multifactor beta also had a positive total payoff, but a t-statistic that was not quite significant. In addition, Reid's model included cashflow- ness and sigma factors. His cashflow factor had a significantly positive accumulation; sigma had a margin- ally significant negative payoff.

62. Nonstationarity of returns to systematic risk has been demonstrated by Tintic and West, "Risk, Return and Equilibrium," in Table I.

63. Rosenberg, Lanstein and Reid (LRB) ("Pervasive Evi- dence of Market Inefficiency," op. cit.) report a t-statistic of -13.8 and Reid's multifactor residual reversal achieves -15.0; our -17.8 is slightly stronger; despite our shorter time period, RLR report a consistency rate of 91.3 per cent, while 103 out of 108 of our monthly payoffs were negative, for a consistency of 95.4 per cent.

Note, however, that the RLR measure is specific return (net of factor-returns) attribution while ours and Reid's are residual of the beta- and market returns. As Reid noted, the two approaches provide reversals of similar magnitude. Note also that it is impossible to abstract from pricing errors and bid/ask spreads by lagging price in constructing the RLR. RLR do some diagnostics that indicate the measure is robust with respect to such concerns. Furthermore, the observed second-month reversal persistence is by con- struction free from any pricing concern.

64. See Related and Specific Returns of Common Stocks," op. cit.


66. The explanatory power is generally much higher in months with unusual market returns. This stems from the increased cross-sectional variation of returns ex- plained by beta in such months. The discussion of beta in Table V for quantification of its market sensitivi-

67. See Sharpe, "Factors in New York Stock Exchange Security Returns, 1933-1974," op. cit., p. 9. Sharpe's model has a time-series R² of 40 per cent versus a cross- sectional R² of 10 per cent. The former is an average across stocks (regressed over time); the latter is an average across months (regressed over stocks). Sharpe discusses the difference between the two measures.

68. For example, the salient features of tax laws and their effects on optimal trading strategies are usually relative- ly constant. Human nature is even less fluid; hence