by Bruce I. Jacobs and Kenneth N. Levy

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 clearer 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 alone 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.

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).[1] 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.[2] For instance, index funds tilted towards higher-yielding or smaller-capitalization stocks have become increasingly popular in the last few years.[3] 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.[4]

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 their 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 contravening 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.

1. Footnotes appear at end of article.

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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 really neglect that drives anomalous returns, with size and P/E being mere proxies for the underlying cause?[5] 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 anomaly interrelationships.[6] 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.[7] Some of these factors may also be anomalous in that they have

Table I Interrelationships of Equity Return Regularites: Some Previous Studies

Size and Price/Earnings Ratio
M. Reinganum, "Misspecification of Capital Asset Pricing: Empirical Anomalies Based on Earnings' Yields and Market Values," *Journal of Financial Economics*, March 1981, pp. 19–46
J. Peavy and D. Goodman, "A Further Inquiry Into the Market Value and Earnings Yield Anomalies" (SMU working paper #82-114, 1982)
S. Basu, "The Relationship Between Earnings Yield, Market Value and Return for NYSE Common Stocks: Further Evidence," *Journal of Financial Economics*, June 1983, pp. 129–156
T. Cook and M. Rozeff, "Size and Earnings/Price Ratio Anomalies: One Effect or Two?" *Journal of Financial and Quantitative Analysis*, December 1984, pp. 449–466
R. Banz and W. Breen, "Sample-Dependent Results Using Accounting and Market Data: Some Evidence," *Journal of Finance*, September 1986, pp. 779–793
D. Goodman and J. Peavy, "The Interaction of Firm Size and Price-Earnings Ratio on Portfolio Performance," *Financial Analysts Journal*, January/February 1986, pp. 9–12
Size and Neglect
A. Arbel and P. Strebel, "The Neglected and Small Firm Effects," *Financial Review*, November 1982, pp. 201–218
A. Arbel and P. Strebel, "Pay Attention to Neglected Firms," *Journal of Portfolio Management*, Winter 1983, pp. 37–42
A. Arbel, S. Carvell and P. Strebel, "Giraffes, Institutions and Neglected Firms," *Financial Analysts Journal*, May/June 1983, pp. 57–62.
Size and January
D. Keim, "Size-Related Anomalies and Stock Return Seasonality: Further Empirical Evidence," *Journal of Financial Economics*, June 1983, pp. 13–32
R. Roll, "Vas Ist Das? The Turn of the Year Effect and the Return Premia of Small Firms," *Journal of Portfolio Management*, Winter 1983, pp. 18–28
M. Reinganum, "The Anomalous Stock Market Behavior of Small Firms in January: Empirical Tests for Tax-Loss Selling Effects," *Journal of Financial Economics*, November 1983, pp. 89–104
M. Blume and R. Stambaugh, "Biases in Computed Returns: An Application to the Size Effect," *Journal of Financial Economics*, November 1983, pp. 387–404
D. Givoly and A. Ovadia, "Year-End Tax-Induced Sales and Stock Market Seasonality," *Journal of Finance*, March 1983, pp. 171–185
G. Constantinides, "Optimal Stock Trading with Personal Taxes: Implications for Prices and the Abnormal January Returns," *Journal of Financial Economics*, March 1984, pp. 65–90
J. Lakonishok and S. Smidt, "Volume and Turn-of-the-Year Behavior," *Journal of Financial Economics* 13 (1984), pp. 435–455
J. Lakonishok and S. Smidt, "Trading Bargains in Small Firms at Year-End," *Journal of Portfolio Management*, Spring 1986, pp. 24–29
P. Schultz, "Personal Income Taxes and the January Effect: Small Firm Stock Returns Before the War Revenue Act of 1917: A Note," *Journal of Finance*, March 1985, pp. 333–343
D. Keim and R. Stambaugh, "Predicting Returns in the Stock and Bond Markets," *Journal of Financial Economics* 17 (1986), pp. 357–390
R. Rogalski and S. Tinic, "The January Size Effect: Anomaly or Risk Mismeasurement?" *Financial Analysts Journal*, November/December 1986, pp. 63–70
Size and Residual Risk
S. Basu and S. Cheung, "Residual Risk, Firm Size, and Returns for NYSE Common Stocks: Some Empirical Evidence" (McMaster U. working paper, January 1982)
J. Lakonishok and A. Shapiro, "Stock Returns, Beta, Variance and Size: An Empirical Analysis," *Financial Analysts Journal*, July/August 1984, pp. 36–41
S. Tinic and R. West, "Risk, Return and Equilibrium: A Revisit," *Journal of Political Economy*," February 1986, pp. 127–147.
Size and Earnings Surprise
G. Foster, C. Olsen and T. Shevlin, "Earnings Releases, Anomalies and the Behavior of Security Returns," *The Accounting Review*, October 1984
R. Rendleman, C. Jones and H. Latané, "Further Insight into the S.U.E. Anomaly: Size and Serial Correlation Effects" (U North Carolina at Chapel Hill working paper, April 1986)
R. Freeman, "The Association Between Accounting Earnings and Security Returns for Large and Small Firms" (CRSP working paper #192, October 1986)
Size, Yield and Coskewness
T. Cook and M. Rozeff, "Size, Dividend Yield and Co-Skewness Effects on Stock Returns: Some Empirical Tests" (U. Iowa working paper #82-20, 1982)

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Table I continued

Size, January and Day-of-the-Week

R. Rogalski, "New Findings Regarding Day-of-the-Week Returns over Trading and Non-Trading Periods: A Note," *Journal of Finance*, December 1984, pp. 1603–1614

D. Keim, "Daily Returns and Size-Related Premiums: One More Time," *Journal of Portfolio Management*, Winter 1987, pp. 41–47

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

C. Barry and S. Brown, "Limited Information as a Source of Risk," *Journal of Portfolio Management*, Winter 1986, pp. 66–72

Size, January and Yield

D. Keim, "The Interrelation Between Dividend Yields, Equity Values and Stock Returns: Implications of Abnormal January Returns" (PhD. dissertation, U. of Chicago, 1983)

D. Keim, "Dividend Yields and Stocks Returns: Implications of Abnormal January Returns," *Journal of Financial Economics* 14 (1985), pp. 473–489

D. Keim, "Dividend Yields and the January Effect," *Journal of Portfolio Management*, Winter 1986, pp. 54–60

Size, Neglect and Price/Earnings Ratio

R. Dowen and S. Bauman, "The Relative Importance of Size, P/E and Neglect," *Journal of Portfolio Management*, Spring 1986, pp. 30–34

Size, Neglect, Price/Earnings Ratio and January

A. Arbel, "Generic Stocks: An Old Product in a New Package," *Journal of Portfolio Management*, Summer 1985, pp. 4–13

Price/Earnings Ratio and Residual Risk

D. Goodman and J. Peavy, "The Risk Universal Nature of the P/E Effect," *Journal of Portfolio Management*, Summer 1985, pp. 14–16

Price/Earnings Ratio, Controversy and Neglect

S. Carvell and P. Strebel, "A New Beta Incorporating Analysts' Forecasts," *Journal of Portfolio Management*, Fall 1984, pp. 81–85

Price/Earnings Ratio and Price/Sales Ratio

A. Senchack and J. Martin, "The Relative Performance of the PSR and PER Investment Strategies," *Financial Analysts Journal*, March/April 1987, pp. 46–56

Price/Earnings Ratio and Neglect

R. Dowen and S. Bauman, "A Test of the Relative Importance of Popularity and Price-Earnings Ratio in Determining Abnormal Returns," *Journal of the Midwest Finance Association* 13 (1984), pp. 34–47

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 #240, August 1981)

Day-of-the-Week and Time-of-the-Day

L. Harris, "A Transaction Data Study of Weekly and Intradaily Patterns in Stock Returns," *Journal of Financial Economics* 16 (1986), pp. 99–117

L. Harris, "How to Profit from Intradaily Stock Returns," *Journal of Portfolio Management*, Winter 1986, pp. 61–64

M. Smirlock and L. Starks, "Day-of-the-Week and Intraday Effects in Stock Returns," *Journal of Financial Economics* 17 (1986), pp. 197–210

Earnings Surprise and Trends in Analysts' Earnings Estimates

R. Arnott, "The Use and Misuse of Consensus Earnings," *Journal of Portfolio Management*, Spring 1985, pp. 18–27

G. Benesh and P. Peterson, "On the Relation Between Earnings Changes, Analysts' Forecasts and Stock Price Fluctuations," *Financial Analysts Journal*, November/December 1986, pp. 29–39

Residual Risk and January

M. Gultekin and B. Gultekin, "Stock Returns and the Tests of the APT," *Journal of Finance*, December 1987, pp. 1213-1224.

S. Tinic and R. West, "Risk, Return and Equilibrium: A Revisit," *Journal of Political Economy* 11 (1986), pp. 126–147 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.[9] 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.[10] Prior research has indicated, for example, that (1) much of the size effect occurs on Fridays,[11] (2) much of the size effect occurs in the first few trading days of January,[12] and (3) time-of-day and day-of-the-week effects interact.[13]

Some recent empirical work ties several seemingly unrelated anomalies to the human disposition to delay announcing bad news.[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 treated 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-divided-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 systematic (or undiversifiable) risk should be rewarded. But many studies have found an apparent compensation for unsystematic risk.[25] 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 Treasury-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 contrary to theory.[26] 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 Vasichek's Bayesian adjustment, in light of the well-known tendency of historical betas to regress over time towards the mean.[27]

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.[28] We calculated coskewness on a rolling 60-month basis as follows:

$$\frac{\Sigma(Ri-\overline{Ri}) \bullet (Rm-\overline{Rm})^2}{\Sigma(Rm-\overline{Rm})^3},$$

where Ri is stock excess return, Rm is the S&P 500 excess return, and $\overline{Ri}$ and $\overline{Rm}$ are rolling 60-month arithmetic averages.

Earnings controversy: Some maintain that stocks with more uncertainty about future prospects produce superior returns, perhaps as compensation for information deficiency or even as a proxy for systematic risk.[29] 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 proposition that stocks whose earnings estimates have been recently upgraded by analysts tend to produce abnormal returns.[30] Some possible explanations are imperfect information dissemination and the psychology of Wall Street analysts (notably, 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 experienced recent earnings surprises tend to produce abnormal returns.[31] 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 separately for each of the three most recent calendar months, calculated as the difference between the actual earnings announcement and the consensus 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 expected to have high future earnings growth may be more susceptible to negative surprises (or "torpedoes"); those with low expected earnings may be more likely to experience positive surprises. There is some empirical support for the proposition that low-expectation stocks on average outperform their high-expectation counterparts.[32] 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 studies support the investment merit of relative price strength, while finding perverse results for one-month relative strength and for January.[33] The measure we used is the alpha intercept from our rolling 60-month beta regression.

Residual reversal: As noted, near-term relative 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.[34] We examined the predictive 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.[35] Some have found investors' behavior to be irrational in light of traditional finance theory; others have sought novel explanations for the observed effects.[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.[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.[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).[39] It has been demonstrated, however, that results can be sensitive to the grouping procedure.[40] In any case, with a large number of anomalies studied simultaneously, grouping becomes intractable.[41]

We modeled the return regularities linearly and utilized cross-sectional regression analysis (as did the previously cited multifactor studies).[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 below. 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.[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.[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.[45] Also, by lagging price we avoided the accidental capture of bid/ask spreads in our estimates of anomaly payoffs.[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.[47]

We normalized each measure (including beta) by subtracting its capitalization-weighted average and dividing by its cross-sectional standard deviation, with outliers truncated.[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 attri-

Table II Monthly Average Returns to Anomalies

	Naive Anomaly		*Pure Anomaly*		*Differential (Pure−Naive)*	
Anomaly	*Monthly Average*	*t-Statistic*	*Monthly Average*	*t-Statistic*	*Monthly Average*	*t-Statistic*
Low P/E	0.59%	3.4**	0.46%	4.7**	−0.13%	−1.4
Small Size	0.15	2.3*	0.12	2.7**	−0.03	−0.7
Yield	−0.01	−0.1	0.03	0.5	0.04	0.4
Zero Yield	0.00	0.0	0.15	1.3	0.15	0.6
Neglect	0.14	1.9*	0.10	1.7*	−0.04	−0.7
Low Price	−0.01	−0.1	0.01	0.2	0.02	0.3
Book/Price	0.17	1.4	0.09	1.2	−0.08	−0.7
Sales/Price	0.17	3.1**	0.17	3.7**	−0.01	−0.2
Cash/Price	0.36	2.7**	0.04	0.6	−0.32	−2.3*
Sigma	0.16	0.6	0.07	0.6	−0.09	−0.4
Beta	−0.01	−0.0	0.04	0.3	0.05	0.4
Coskewness	0.09	0.6	0.04	0.7	−0.05	−0.3
Controversy	−0.33	−2.1*	−0.05	−0.8	0.27	2.0*
Trend in Estimates (−1)	0.48	4.8**	0.51	8.1**	0.03	0.3
Trend in Estimates (−2)	0.40	4.4**	0.28	4.9**	−0.12	−1.3
Trend in Estimates (−3)	0.29	3.0**	0.19	3.8**	−0.10	−1.3
Earn. Surprise (−1)	0.44	2.1*	0.48	3.7**	0.04	0.2
Earn. Surprise (−2)	0.47	1.8*	0.18	0.8	−0.28	−1.8*
Earn. Surprise (−3)	−0.03	−0.1	−0.21	−1.1	−0.18	−1.0
Earn. Torpedo	−0.00	−0.0	−0.10	−1.7*	−0.10	−1.2
Relative Strength	0.30	1.4	0.34	3.5**	0.04	0.3
Res. Reversal (−1)	−0.54	−4.9**	−1.08	−17.8**	−0.54	−7.3**
Res. Reversal (−2)	−0.13	−1.4	−0.37	−8.1**	−0.23	−3.3**
Short-Term Tax	−0.08	−0.4	−0.04	−0.4	0.04	0.3
Long-Term Tax	−0.29	-1.6	−0.00	−0.1	0.28	1.7*

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

butes return to its underlying sources.

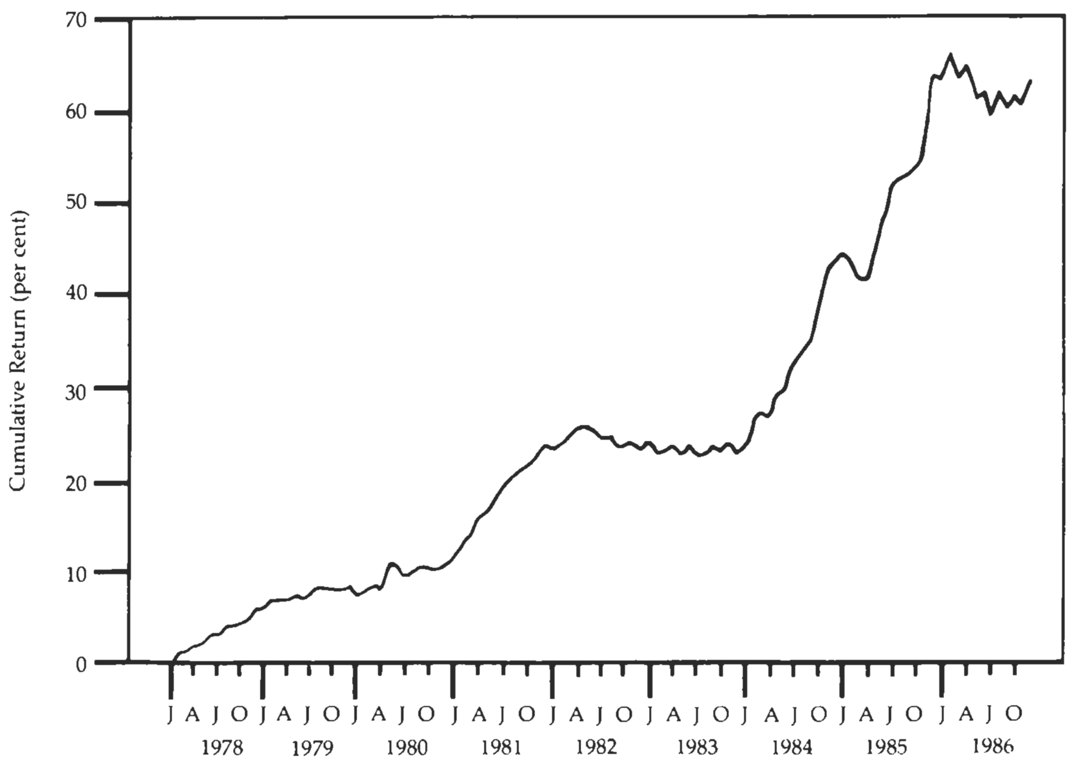
Table II presents summary statistics for the monthly cross-sectional regressions over the period January 1978 to December 1986. The average monthly return and associated t-statistic for each anomaly are shown in both naive and pure forms.[49] A paired t-test on the difference between naive and pure returns is also displayed.[50] 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.[51] 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."[52] 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



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]

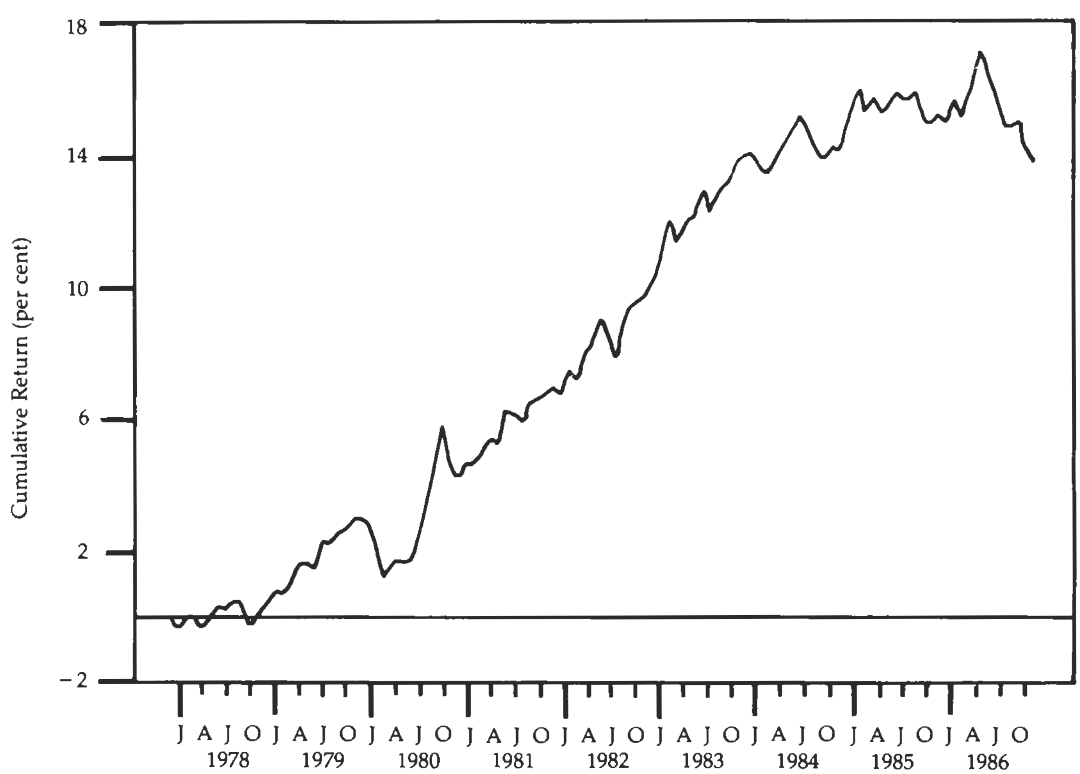
The small-size effect was also more significant on average in its pure than its naive form, albeit with a slightly lower average monthly return of 12 basis points, versus 15 for the naive effect. The existence of a size effect in its pure form demonstrates that small size is not just a proxy for some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



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 multifactor 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 decumulations 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.[58]

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 coskewness 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

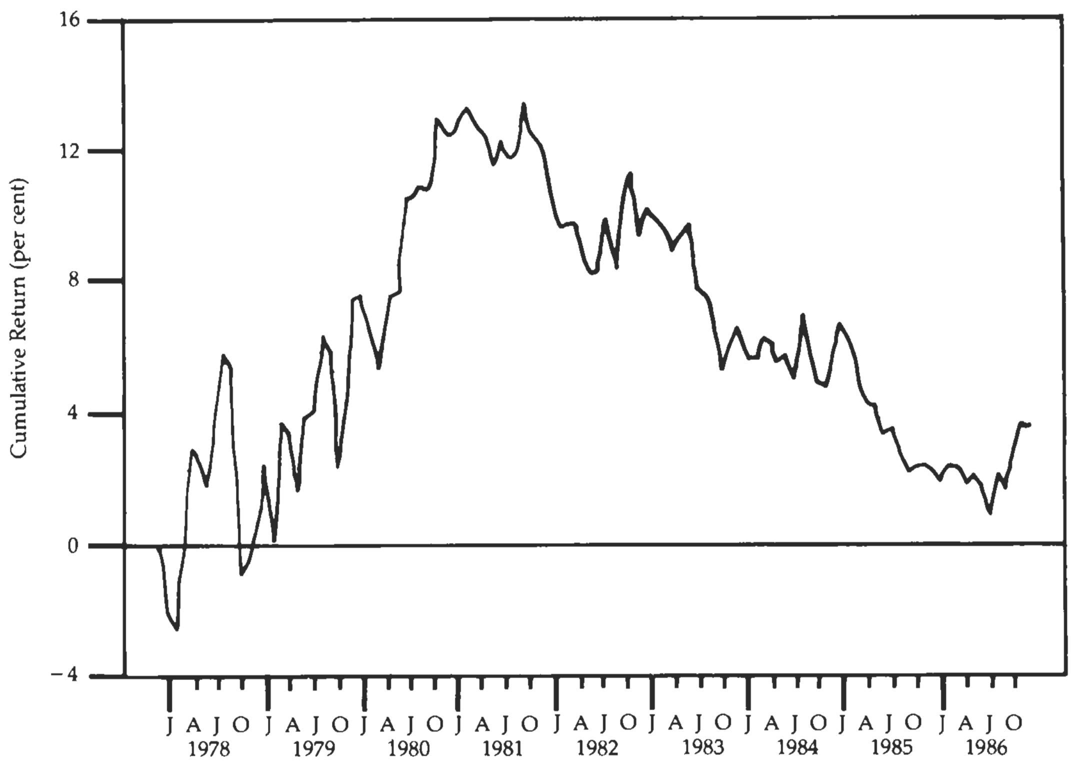
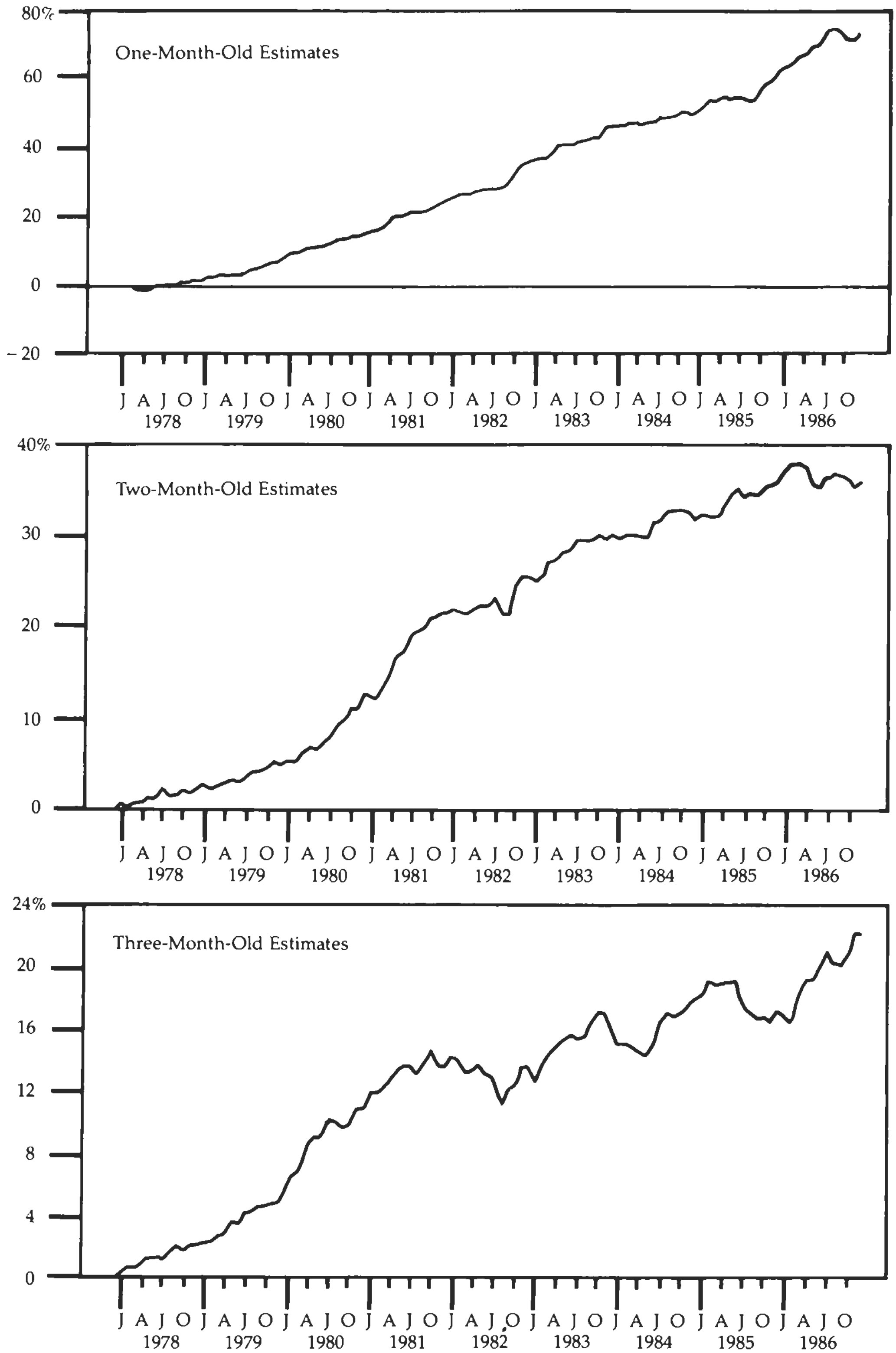


Figure D Cumulative Return to Trends in Earnings Estimates



history is especially interesting. While seemingly 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 negatively 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 insignificant results in a pure sense. This is inconsistent 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 *ex post* 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 tendency of analysts systematically to underestimate 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 significant in their pure form; by the time surprises were three months old, results were perverse. Naive returns to earnings surprise were significant for two monthly lags.

Our univariate regression provided no evidence 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 multivariate regression. Reid's multifactor model included a one-year relative-strength measure that was also quite powerful. Sharpe's multifactor relative-strength measure, a 60-month alpha similar to ours, had negative return attribution, perhaps because of the absence of related measures, such as residual reversal.

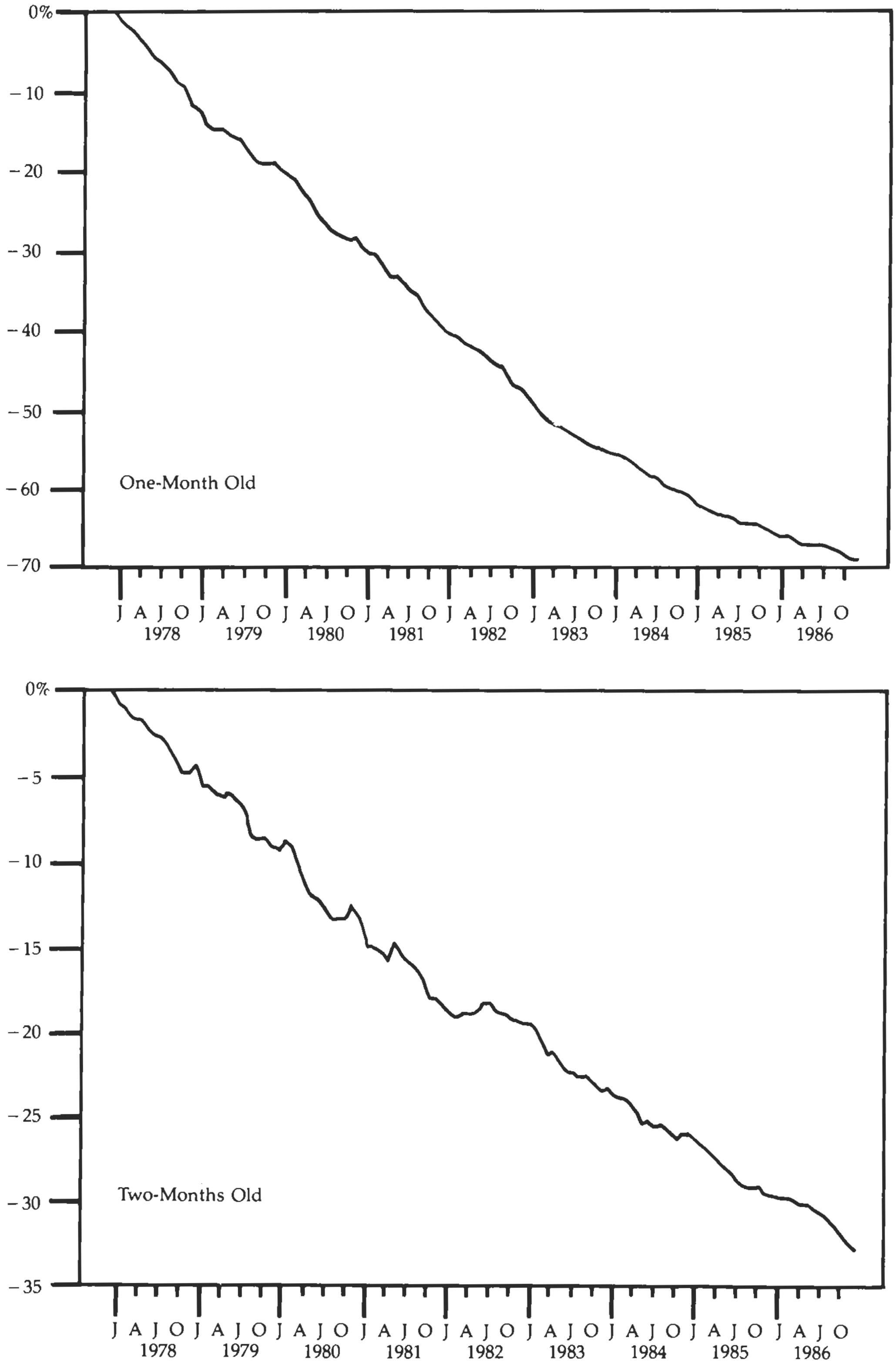
Residual reversal turned out to be by far the most powerful effect we found, especially in the multivariate regression. The t-statistic of –17.8 for one-month reversals is in line with the findings of previous researchers.[61] The paired t-test on differential returns showed a significant increase in the strength of pure versus naive residual reversal. Pure returns to residual reversal emerged more powerfully, because related effects such as earnings surprise were disentangled. Figure E illustrates cumulative returns to one and two-month-old residual returns. The negative payoffs demonstrate the strong tendency 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. Rosenberg and Rudd examined one and two-month-old reversals separately and found persistence 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 examine the January effect.

The time-series of returns to our 38 industries exhibited nothing unusual. Seven industries had average returns that were significantly different 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

Figure E Cumulative Return to Residual Reversal



analysis of returns to industries revealed expected patterns, such as the existence of an interest-rate-sensitive financial sector.[63] Furthermore, the industry return 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.[64] (Adjusted 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.[65]

To summarize, there is strong evidence that the stock market was rife with return regularities during the period from 1978 to 1986. Our evidence documents several statistically significant 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 examined 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, however, able to reject narrower definitions of efficiency, which is even more indicative of market inefficiency. Consider, for instance, the predictive 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* evidence 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 represent independent evidence of inefficiency, because 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 features of the stock market and the quirks of human nature, are slow to change.[66] 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 approximation, market impact is a function of a stock's market capitalization, while commission (expressed 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 payoffs to other anomalies, such as low P/E, represent the return to a low-P/E stock that has average market size and price. In other words, our return attribution to low P/E can be captured on average by trading stocks of average price and size, implying approximately average transaction costs.

The various return regularities studied obviously require differing amounts of trading to maintain a given portfolio exposure. At one extreme, heavy monthly trading would be necessary 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 substantial evidence that "anomaly capture strategies" have the potential to generate above-market returns (net of transaction costs) that are both economically and statistically significant.[67] These strategies are designed to utilize Stein-James estimators, which are superior to historical averages as estimates of true payoffs to anomalies. This estimation technique, sometimes referred to as Empirical Bayes, is applicable when the number of measures to be estimated exceeds two, and works better the larger the number of measures.[68] Such diversified anomaly exploitation strategies can also benefit from the January effect, discussed below.

January Versus Rest-of-Year Returns

As mentioned earlier, several studies have

Table III Monthly Average Returns to Anomalies: January versus Non-January

	Naive Anomaly					*Pure Anomaly*				
Anomaly	*Average January*	*t-Stat.*	*Average Non-Jan.*	*t-Stat.*	*t-Stat. of Difference*	*Average January*	*t-Stat.*	*Average Non-Jan.*	*t-Stat.*	*t-Stat. of Difference*
Low P/E	0.19%	0.3	0.63%	4.0**	−0.9	0.09%	0.5	0.49%	4.7**	−1.1
Small Size	0.57	2.5*	0.11	1.7*	1.9*	0.14	1.3	0.12	2.5*	0.2
Yield	0.25	0.4	−0.03	−0.2	0.5	0.67	3.4**	−0.03	−0.4	2.9**
Zero Yield	1.42	1.5	−0.13	−0.5	1.6	1.00	1.9*	0.08	0.6	2.1*
Neglect	0.53	2.3*	0.10	1.4	1.6	0.36	1.8*	0.08	1.3	1.3
Low Price	0.94	2.5*	−0.10	−1.1	3.1**	0.38	2.0*	−0.02	−0.4	2.1*
Book/Price	0.97	2.0*	0.10	0.8	2.0*	0.51	2.4*	0.05	0.7	1.9*
Sales/Price	0.71	3.2*	0.13	2.3*	2.9**	0.05	0.2	0.18	4.1**	−0.8
Cash/Price	0.28	0.6	0.37	2.6*	−0.2	−0.15	−2.0*	0.05	0.8	−1.0
Sigma	1.32	1.3	0.06	0.2	1.3	0.62	2.1*	0.02	0.2	1.4
Beta	0.15	0.2	−0.02	−0.1	0.3	−0.05	−0.1	0.05	0.4	−0.2
Coskewness	0.34	0.6	0.07	0.4	0.5	0.10	0.5	0.04	0.6	0.3
Controversy	0.89	2.5*	−0.44	−2.7**	2.4*	−0.01	−0.1	−0.06	−0.8	0.2
Trend in Earnings (−1)	0.25	0.9	0.50	4.7**	−0.7	0.60	3.8**	0.50	7.5**	0.5
Trend in Earnings (−2)	0.15	0.5	0.42	4.4**	−0.8	0.25	1.6	0.29	4.7**	−0.2
Trend in Earnings (−3)	−0.18	−0.4	0.33	3.5**	−1.5	0.13	0.6	0.19	3.8**	−0.4
Earn. Surprise (−1)	0.18	0.2	0.46	2.0*	−0.3	1.36	1.6	0.42	3.4**	1.8*
Earn. Surprise (−2)	−0.48	−0.6	0.53	2.0*	−1.0	0.14	2.0	0.18	0.7	−0.1
Earn. Surprise (−3)	−0.39	−0.3	−0.01	0.0	−0.3	−0.01	0.0	−0.22	−1.1	0.3
Earn. Torpedo	0.15	0.5	−0.02	−0.2	0.5	0.08	0.3	−0.12	−1.9*	0.9
Relative Strength	−0.66	−0.6	0.39	1.9*	−1.4	−0.13	−0.2	0.39	4.0**	−1.4
Res. Reversal (−1)	−0.51	−1.7	−0.83	−4.6**	−0.8	−1.38	−6.0**	−1.06	−16.8**	−1.5
Res. Reversal (−2)	−0.64	−1.5	−0.09	−0.9	−1.6	−0.56	−2.5*	−0.35	−7.7**	−1.3
Short-Term Tax	1.06	1.3	−0.19	−0.8	1.6*	0.38	1.8*	−0.08	−0.7	1.2
Long-Term Tax	1.43	2.9*	−0.44	−2.5*	2.9**	0.78	3.2**	−0.07	−1.2	3.6**

*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 months.[69]

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.[70] 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.[71] 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.[72]

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.[73] 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 seasonals for low price and book/price are attenuated in magnitude compared with their naive counterparts, while the pure January seasonals for small size, sales/price and earnings controversy vanish completely. Perhaps the most striking result in Table III relates to small size. While the naive January return to smallness of 57 basis points is significantly different from the non-January naive return of 11 basis points, the pure returns to smallness exhibit no discernible seasonality. Apparently, the January size seasonal 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.[74] Furthermore, irrational investor behavior may offer a potential explanation; investors are often more averse to admitting recent mistakes than to admitting older ones.[75] 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,

Table IV Autocorrelation of Anomaly Returns

	Naive Anomaly					*Pure Anomaly*				
Anomaly	*Autocorr. Lag of 1 Month*	*t-Stat.*	*Autocorr. Lag of 2 Months*	*t-Stat.*	*Q-Stat.*	*Autocorr. Lag of 1 Month*	*t-Stat.*	*Autocorr. Lag of 2 Months*	*t-Stat.*	*Q-Stat.*
Low P/E	0.16	1.7*	−0.01	−0.1	61.2**	0.06	0.6	0.25	2.6**	45.1*
Small Size	0.03	0.3	0.08	0.8	31.3	0.09	0.9	−0.06	−0.6	30.5
Yield	0.23	2.4*	−0.05	−0.5	35.0	0.22	2.3*	0.04	0.4	22.8
Zero Yield	0.19	2.0*	0.06	0.6	48.6*	0.07	0.7	0.03	0.3	29.2
Neglect	−0.20	−2.1*	0.10	1.0	29.7	−0.12	−1.2	−0.05	−0.5	18.0
Low Price	0.14	1.5	−0.03	−0.3	40.7*	0.21	2.2*	0.16	1.7*	32.0
Book/Price	0.14	1.5	−0.01	−0.1	24.0	0.06	0.6	0.09	0.9	32.9
Sales/Price	0.14	1.5	−0.06	−0.6	32.2	0.07	0.7	−0.03	−0.3	21.9
Cash/Price	0.13	1.4	−0.03	−0.3	39.1	0.13	1.4	0.06	0.6	43.1*
Sigma	0.20	2.1*	0.02	0.2	34.8	0.21	2.2*	0.16	1.7*	74.2**
Beta	0.14	1.5	−0.09	−0.9	25.7	−0.10	−1.0	−0.22	−2.3*	42.1*
Coskewness	0.23	2.4*	0.00	0.0	20.2	0.02	0.2	0.03	0.3	26.7
Controversy	0.00	0.0	−0.11	−1.1	24.8	−0.18	−1.9*	−0.13	−1.4	30.2
Trend in Earnings (−1)	0.02	0.2	−0.11	−1.1	36.4	0.13	1.4	−0.01	−0.1	24.4
Trend in Earnings (−2)	0.07	0.7	−0.26	−2.7**	46.5*	0.07	0.7	−0.08	−0.8	20.6
Trend in Earnings (−3)	0.05	0.5	−0.25	−2.6**	50.9**	0.13	1.4	−0.08	−0.8	32.9
Earn. Surprise (−1)	0.14	0.8	−0.01	−0.1	13.6	0.03	0.2	0.17	1.0	15.2
Earn. Surprise (−2)	−0.04	−0.2	0.03	0.2	31.7*	−0.02	−0.1	−0.03	−0.2	24.8
Earn. Surprise (−3)	0.14	0.8	−0.02	−0.1	37.6**	−0.02	−0.1	−0.09	−0.5	37.5**
Earn. Torpedo	0.29	3.0**	0.17	1.8*	47.6*	0.18	1.9*	0.25	2.6**	46.8*
Relative Strength	0.24	2.5*	−0.04	−0.4	17.4	0.39	4.1**	0.12	1.2	39.4
Res. Reversal (−1)	−0.03	−0.3	−0.06	−0.6	31.7	0.08	0.8	0.01	0.1	30.1
Res. Reversal (−2)	0.05	0.5	−0.07	−0.7	30.5	0.02	0.2	−0.13	−1.4	35.3
Short-Term Tax	0.01	0.1	−0.10	−1.0	37.5	−0.03	−0.3	−0.07	−0.7	28.5
Long-Term Tax	0.21	2.2*	0.02	0.2	28.2	0.15	1.6	−0.17	−1.8*	36.7
Average Anomaly	0.11	4.9**	−0.03	−1.8*		0.07	3.1**	0.01	0.4	

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

the average January return is negative while the average non-January return is significantly positive. 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 designed 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.[76] 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 characteristics for autocorrelation. If returns between adjacent months are correlated (first-order autocorrelation), then an optimal prediction for next month's return uses the product of the correlation coefficient and the past month's return. Past prices alone would have predictive content. 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 (macroeconomic) shocks, (2) nonsynchronous response of individual assets to a factor, and (3) changing risk premiums for various stock attributes.[78] We extended their approach. First, we calculated results for both naive and pure anomalies. Second, rather than aggregating anomalies up to the individual stock level, we analyzed 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 autocorrelation, with several being statistically significant.[79] A t-test of the hypothesis that the average 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 average not significantly different from zero (consistent 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 anomalies acting as proxies for one another. For example, P/E, book/price, cash/price, sales/price and yield are all closely related. In the naive analysis, the returns (hence autocorrelations) 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 estimates have negative second-order autocorrelations 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-randomness in the time-series of returns to each attribute.[80] The autocorrelations at many different monthly lags (including and beyond the two shown) are strong enough that returns to several 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 further evidence of departures from randomness.

As mentioned above, significant autocorrelations can arise from changing risk premiums—that is, from time-varying expected returns to equity characteristics. Risk premiums may fluctuate because of macroeconomic events. Because risk premiums are likely to evolve slowly over 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 forces, 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.[81] A more rigorous approach, taken here, is a time-series regression of monthly anomaly returns on monthly market excess returns.[82] 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 V Regressions of Anomaly Returns on Market Returns

	Naive Anomaly				*Pure Anomaly*			
	Intercept	*t-stat.*	*Slope*	*t-stat.*	*Intercept*	*t-stat.*	*Slope*	*t-stat.*
Low P/E	0.66%	4.4**	−0.11	−2.8**	0.46%	4.6**	0.00	0.2
Small Size	0.16	2.4*	−0.01	−0.4	0.12	2.7**	−0.00	−0.2
Yield	0.13	1.1	−0.23	−8.4**	0.06	1.0	−0.05	−3.5**
Zero Yield	−0.17	−0.7	0.27	4.9**	0.15	1.2	0.01	0.2
Neglect	0.18	2.6**	−0.07	−4.1**	0.13	2.3*	−0.05	−3.7**
Low Price	0.02	0.2	−0.05	−2.5*	−0.00	−0.1	0.03	2.1*
Book/Price	0.25	2.4*	−0.13	−5.5**	0.08	1.1	0.02	0.9
Sales/Price	0.15	2.7**	0.05	3.8**	0.15	3.4**	0.02	2.2*
Cash/Price	0.44	3.5**	−0.13	−4.5**	0.04	0.7	−0.01	−0.4
Sigma	−0.07	−0.3	0.38	7.2**	0.05	0.4	0.05	1.7*
Beta	−0.21	−1.6	0.33	10.7**	−0.09	−0.9	0.21	9.7**
Coskewness	−0.02	−0.2	0.13	5.3**	0.04	0.6	0.00	0.2
Controversy	−0.38	−2.4*	0.07	2.2*	−0.07	−1.0	0.03	1.7*
Trend in Earnings (−1)	0.49	4.9**	−0.02	−0.8	0.49	7.9**	0.02	1.6
Trend in Earnings (−2)	0.40	4.3**	−0.00	−0.0	0.28	4.8**	0.01	0.4
Trend in Earnings (−3)	0.27	2.8**	0.03	1.2	0.18	3.6**	0.01	0.9
Earn. Surprise (−1)	0.11	1.6	−0.01	−0.4	0.52	3.5**	−0.01	−0.1
Earn. Surprise (−2)	0.16	1.8*	−0.02	−0.8	0.17	0.6	−0.01	−0.2
Earn. Surprise (−3)	−0.06	−0.6	−0.00	−0.2	−0.21	−1.0	−0.04	−0.8
Earn. Torpedo	−0.02	−0.2	0.03	1.3	−0.10	−1.6	−0.00	−0.3
Relative Strength	0.15	0.8	0.17	4.9**	0.28	3.1**	0.09	4.5**
Res. Reversal (−1)	−0.53	−4.7**	−0.01	−0.6	−1.08	−17.5**	−0.01	−0.7
Res. Reversal (−2)	−0.16	−1.7*	0.05	2.3*	−0.37	−8.2**	0.02	1.5
Short-Term Tax	−0.15	−0.8	0.12	2.6**	−0.09	−0.8	0.06	2.6*
Long-Term Tax	−0.25	−1.8	0.04	1.3	0.02	0.3	−0.02	−1.0

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

well in bull than in bear markets. However, it would take a one-month excess market return of 6 per cent ($-0.11 \times 6\% = -0.66\%$) to offset fully the 0.66 per cent advantage of (a one-cross-sectional standard deviation exposure to) low 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 prediction of a stock's beta.[83] For example, because the pure returns to low yield and neglect are negatively 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 Vasichek-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 component 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 unsuitable 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 example, 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 difference between January and non-January returns to be in the expected direction, but not statistically 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 contention that negative pure returns to relative strength in January arise from profit-taking associated with tax-gain deferral.

As we indicated earlier, the presence of equity return regularities calls into question the EMH and current asset pricing models, including 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 validity of a multifactor CAPM.[84]

Conclusion

Anomalies such as residual reversal and trends in analysts' earnings estimates appear to be true pockets of stock market inefficiency. Other effects, 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 uncovering new return regularities, as better databases (such as real-time pricing) and greater computer power are brought to task. At the same time, 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

1. For a review of the anomaly literature, see D. Keim, "The CAPM and Equity Return Regularities," *Financial Analysts Journal*, May/June 1986, pp. 19–34. See E. Fama, *Foundations of Finance* (New York: Basic Books, 1976), for a discussion of the CAPM and tests of market efficiency.

   While still controversial, some recent research finds anomalies even in an APT framework. See M. Reinganum, "The Arbitrage Pricing Theory: Some Empirical Results," *Journal of Finance*, May 1981, pp. 313–321; B. Lehmann and D. Modest, "The Empirical Foundations of the Arbitrage Pricing Theory I: The Empirical Tests" (Columbia U. Business School working paper, August 1985); G. Conner and R. Korajczyk, "Risk and Return in an Equilibrium APT" (Kellogg Graduate School of Management working paper #9, April 1987); and N. Chen, T. Copeland and D. Mayers, "A Comparison of Single and Multifactor Portfolio Performance Methodologies" (UCLA working paper, February 1987).

   While the Lehmann and Modest paper shows the size-related rejection of APT is not an artifact of infrequent trading or solely due to the month of January, they also find that the dividend-yield and own-variance effects are not anomalous in their APT framework (while they are CAPM anomalies). Conner and Korajczyk find APT performs better in explaining the January seasonality in 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 enigma are not explained by an APT framework. Value Line uses a composite of several measures, such as earnings surprise, and price and earnings momentum.

   M. Gultekin and B. Gultekin ("Stock Return Anomalies and the Tests of the APT," *Journal of Finance*, December 1987, pp. 1213-1224) find that APT cannot explain January, size or sigma return regularities.
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-based strategies is justified." (Also see B. Jacobs and K. Levy, "Investment Management: Opportunities in Anomalies?" *Pension World*, February 1987, pp. 46–47, for thoughts on the philosophy of anomaly investing. For a recent view from Wall Street, see S. Einhorn, P. Shangkuan and R. Jones, "A Multifactor 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 R. Dornbusch, eds., *Macroeconomics and Finance: Essays in Honor of Franco Modigliani* (Cambridge: MIT Press, 1987)) 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 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.
4. *Pensions & Investment Age*, 11/10/86, p. 92.
5. A. Arbel, "Generic Stocks: An Old Product in a New Package," *Journal of Portfolio Management*, Summer 1985, pp. 4–13.
6. For the January/size connection in Australia, see P. Brown, D. Keim, A. Kleidon and T. Marsh, "Stock Return Seasonalities and the Tax-Loss Selling Hypothesis: Analysis of the Arguments and Australian Evidence," *Journal of Financial Economics* 12 (1983), pp. 105–127; in Canada, see S. Tinic, G. Barone-Adesi and R. West, "Seasonality in Canadian Stock Prices: A Test of the 'Tax-Loss-Selling' Hypothesis," *Journal of Financial and Quantitative Analysis*, March 1987, pp. 51–63; in Japan, see N. Terada and T. Nakamura, "The Size Effect and Seasonality in Japanese Stock Returns," presented at the Institute for Quantitative Research in Finance, May 1984, and K. Kato and J. Schallheim, "Seasonal and Size Anomalies in the Japanese Stock Market," *Journal of Financial and Quantitative Analysis*, June 1985, pp. 243–260; in the U.K., see S. Beckers, B. Rosenberg and A. Rudd, "The January or April Effect: Seasonal Evidence from the United Kingdom," in *Proceedings of the Second Symposium on Money, Banking and Insurance* (U. of Karlsruhe, West Germany, December 1982), H. Goppi and R. Henn, eds. (Atheneum, 1982), pp. 537–550.
7. For a comparison of multifactor models with the CAPM and Ross' Arbitrage Pricing Theory, see W. Sharpe, "Factor Models, CAPM, and the APT," *Journal of Portfolio Management*, Fall 1984. For a demonstration that multifactor models may explain stock returns better than APT models, see M. Blume, M. Gultekin and B. Gultekin, "On the Assessment of Return Generating Models" (U. of Pa. Rodney White working paper #13, 1986).
8. See B. Rosenberg and V. Marathe, "Common Factors in Security Returns: Microeconomic Determinants and Macroeconomic Correlates," *Proceedings of the Seminar on the Analysis of Security Prices* (U. of Chicago, May 1976, pp. 61–115) and A. Rudd and H. Clasing, *Modern Portfolio Theory: The Principles of Investment Management* (Homewood, Il.: Dow Jones-Irwin, 1982). The original BARRA model, termed "E1," consists of six composite risk factors—market variability, earnings variability, low valuation and unsuccess, immaturity and smallness, growth orientation, and financial risk—and 39 industry classifications. The second generation BARRA model, "E2," consists of 13 composite risk factors—variability

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

9. W. Sharpe, "Factors in NYSE Exchange Security Returns, 1931–1979," *Journal of Portfolio Management*, Summer 1982, pp. 5–19, examines five attributes—beta, yield, size, bond beta (or interest rate sensitivity) and alpha—and six broad industry classifications; K. Reid, "Factors in the Pricing of Common Equity" (PhD Dissertation, U.C. Berkeley, 1982) examines the following attributes—cumulative stock price range, coskewness, beta, price, sigma, relative strength, and several measures each of size, yield and residual return—and eight broad industry classifications.
10. See B. Jacobs and K. Levy, "Calendar Anomalies," *Financial Analysts Journal*, forthcoming, and Jacobs and Levy, "Trading Tactics in an Inefficient Market," in W. Wagner, ed., *A Complete Guide to Securities Transactions: Controlling Costs and Enhancing Performance* (New York: John Wiley, 1988).
11. Keim, "Daily Returns and Size-Related Premiums: One More Time," cited in Table I.
12. Keim, "Size-Related Anomalies and Stock Return Seasonality," in Table I and Roll, "Vas Ist Das?" in Table I.
13. See Harris, "A Transaction Data Study of Weekly and Intradaily Patterns in Stock Returns," and "How to Profit From Intradaily Stock Returns," and Smirlock and Starks, "Day-of-the-Week and Intraday Effects in Stock Returns," all cited in Table I.
14. S. Penman, "The Distribution of Earnings News Over Time and Seasonalities in Aggregate Stock Returns," *Journal of Financial Economics*, March 1987, pp. 161–174.
15. Early studies include W. Breen, "Low Price-Earnings Ratios and Industry Relatives," *Financial Analysts Journal*, July/August 1968, pp. 125–127; W. Breen and J. Savage, "Portfolio Distributions and Tests of Security Selection Models," *Journal of Finance*, December 1968, pp. 805–819; J. McWilliams, "Prices, Earnings and P. E. Ratios," *Financial Analysts Journal*, May–June 1966, pp. 137–142; P. Miller and E. Widmann, "Price Performance Outlook for High & Low P/E Stocks," *Commercial & Financial Chronicle*, September 29, 1966, pp. 26–28; and F. Nicholson, "Price Ratios in Relation to Investment Results," *Financial Analysts Journal*, January/February 1968, pp. 105–109.

    The first to test carefully in a CAPM framework was S. Basu, "Investment Performance of Common Stocks in Relation to their Price-Earnings Ratios: A Test of the Efficient Market Hypothesis," *Journal of Finance*, June 1977, pp. 663–682. For an updated study of industry-relative P/E ratios, see D. Goodman and J. Peavy, "Industry Relative Price-Earnings Ratios as Indicators of Investment Returns," *Financial Analysts Journal*, July/ August 1983, pp. 60–66. For a test that circumvents potential CAPM pitfalls, see H. Levy and Z. Lerman, "Testing P/E Ratio Filters With Stochastic Dominance," *Journal of Portfolio Management*, Winter 1985, pp. 31–40. For a practitioner's view, see D. Dreman, *The New Contrarian Investment Strategy* (New York: Random House, 1982).
16. For evidence on the size effect, see R. Banz, "The Relationship Between Return and Market Value of Common Stocks," *Journal of Financial Economics*, March 1981, pp. 3–18; P. Brown, A. Kleidon and T. Marsh, "New Evidence on the Nature of Size-Related Anomalies in Stock Prices," *Journal of Financial Economics*, June 1983, pp. 33–56; and M. Reinganum, "Portfolio Strategies Based on Market Capitalization," *Journal of Portfolio Management*, Winter 1983, pp. 29–36. For an overview of some size-related anomaly issues, see W. Schwert, "Size and Stock Returns, and Other Empirical Regularities," *Journal of Financial Economics*, June 1983, pp. 3–12.

    For a discussion of transaction costs as a potential explanation, see H. Stoll and R. Whaley, "Transaction Costs and the Small Firm Effect," *Journal of Financial Economics*, June 1983, pp. 57–79, and P. Schultz, "Transaction Costs and the Small Firm Effect: A Comment," *Journal of Financial Economics*, June 1983, pp. 81–88. For evidence that the size anomaly is not a proxy for industry effects, see W. Carleton and J. Lakonishok, "The Size Anomaly: Does Industry Group Matter?" *Journal of Portfolio Management*, Spring 1986, pp. 36–40.

    For a discussion of deficient risk-adjustment, see R. Roll, "A Possible Explanation of the Small Firm Effect," *Journal of Finance*, September 1981, pp. 879–888; M. Reinganum, "A Direct Test of Roll's Conjecture on the Firm Size Effect," *Journal of Finance* 37 (1982), pp. 27–35; J. Booth and R. Smith, "The Application of Errors-in-Variables Methodology to Capital Market Research: Evidence on the Small-Firm Effect," *Journal of Financial and Quantitative Analysis*, December 1985, pp. 501–515; K. Chan and N. Chen, "Estimation Error of Stock Betas and the Role of Firm Size as an Instrumental Variable for Risk" (CRSP working paper #179, June 1986); W. Ferson, S. Kandel and R. Stambaugh, "Tests of Asset Pricing With Time-Varying Expected Risk Premiums and Market Betas," *Journal of Finance*, June 1987, pp. 201–220; and P. Hunda, S. Kothari and C. Wasley, "Bias in Estimation of Systematic Risk and its Implications for Tests of the CAPM" (N.Y.U. working paper #404, January 1987).

    R. Roll ("On Computing Mean Returns and the Small Firm Premium," *Journal of Financial Economics*, November 1983, pp. 371–386) and M. Blume and R. Stambaugh ("Biases in Computed Returns," in Table I) find the size effect halved in magnitude when the bid/ask bias in daily pricing is controlled for, while Y. Ahimud and H. Mendelson ("Asset Pricing and the Bid-Ask Spread," *Journal of Financial Economics* 17 (1983), pp. 223–249) find it totally subsumed.

    For a discussion of the size effect in an APT framework, see footnote 1.
17. See H. Shefrin and M. Statman ("Explaining Investor Preference for Cash Dividends," *Journal of Financial Economics* 13 (1984), pp. 253–282) articulate theories of choice behavior that lead to results contrary to standard financial theory.
18. F. Black and M. Scholes ("The Effects of Dividend Yield and Dividend Policy on Common Stock Prices and Returns," *Journal of Financial Economics* 1 (1974), pp. 1–22) and M. Miller and M. Scholes ("Dividends and Taxes: Some Empirical Evidence," *Journal of Political Economy* 90 (1982), pp. 1118–1141) find an effect not significantly different from zero. R. Litzenberger and K. Ramaswamy ("The Effect of Personal Taxes and Dividends on Capital Asset Prices: Theory and Empirical Evidence," *Journal of Financial Economics* 7 (1979), pp.

163–195) report a significant and positive relationship between yield and return. M. Blume ("Stock Returns and Dividend Yields: Some More Evidence," *Review of Economics and Statistics*, November 1980, pp. 567–577) finds a discontinuity, with zero-yielding stocks earning an abnormally high return.

19. Keim ("Dividend Yields and Stock Returns" Table I) shows the entire non-linear yield anomaly to occur in the month of January.
20. For example, see Arbel, "Generic Stocks," cited in Table I. For a theoretical model of the neglect effect, see R. Merton, "A Simple Model of Capital Market Equilibrium With Incomplete Information," *op.cit.*
21. See M. Blume and F. Husic, "Price, Beta and Exchange Listing," *Journal of Finance*, May 1973, pp. 283–299; B. Bachrach and D. Galai, "The Risk Return Relationship and Stock Prices," *Journal of Financial and Quantitative Analysis*, June 1979, pp. 421–441; and R. Edminster and J. Greene, "Performance of Super-Low-Price Stocks," *Journal of Portfolio Management*, Fall 1980, pp. 36–41. Stoll and Whaley ("Transaction Costs and the Small Firm Effect," *op. cit.*) report the low-price effect to be almost as powerful as the small-size effect.
22. B. Rosenberg, K. Reid and R. Lanstein, "Persuasive Evidence of Market Inefficiency," *Journal of Portfolio Management*, Spring 1985, pp. 9–16.
23. A. R. Senchack and J. Martin ("The Relative Performance of the PSR and PER Investment Strategies," cited in Table I) test this claim and find earnings/price superior. It was reported that sales/price is significant in a multifactor framework at the BARRA Research Seminar, June 1986, Berkeley, California.
24. BARRA has tested this measure contemporaneously with E/P, sales/price and book/price, and finds it significant; reported at the BARRA Research Seminar, June 1986, Berkeley California.
25. If investors do not hold well-diversified portfolios, they may demand compensation for bearing residual risk—see H. Levy, "Equilibrium in an Imperfect Market: A Constraint on the Number of Securities in the Portfolio," *American Economic Review*, September 1978, pp. 643–658, and J. Mayshar, "Transaction Costs and the Pricing of Assets," *Journal of Finance*, June 1981, pp. 583–597. However, price volatility confers on the taxable investor a valuable timing option for recognizing losses short-term and deferring gains (as per Constantinides, "Optimal Stock Trading With Personal Taxes," in Table I), which could cause a lower required return for higher sigma. Also, G. Benston and R. Hagerman ("Determinants of Bid-Asked Spreads in the Over-the-Counter Market," *Journal of Financial Economics* 1 (1974), pp. 353–364) found sigma to be strongly and positively related to the bid/ask spread. This raises the issue of whether a significant excess return can be achieved from high-sigma stocks net of transaction costs.

    Empirically, a positive payoff to sigma was found by G. Douglas, "Risk in the Equity Markets: An Empirical Appraisal of Market Efficiency," *Yale Economic Essays*, Spring 1969, pp. 3–45. His methodology was criticized by M. Miller and M. Scholes, "Rates of Return in Relation to Risk: A Re-Examination of Some Recent Findings," in M. Jensen, ed., *Studies in the Theory of Capital Markets* (New York: Praeger, 1972). E. Fama and J. MacBeth ("Risk, Return and Equilibrium: Empirical Tests," *Journal of Political Economy*, May/June 1973, pp. 607–636) found sigma to be positively but insignificantly related to risk-adjusted return. Later, I. Friend, R. Westerfield and M. Granito ("New Evidence on the Capital Asset Pricing Model," *Journal of Finance*, June 1978, pp. 903–920) found sigma significant. Finally, Tinic and West ("Risk, Return and Equilibrium: A Revisit," cited in Table I) replicated the Fama-MacBeth study on a longer time period and found sigma to be significant and to subsume beta, especially in January.
26. See Tinic and West, "Risk, Return and Equilibrium," cited in Table I, for recent evidence.
27. For a discussion of Vasichek and other beta adjustment procedures, see R. Klemkosky and J. Martin, "The Adjustment of Beta Forecasts," *Journal of Finance*, September 1975, pp. 1123–28.
28. See A. Kraus and R. Litzenberger, "Skewness Preference and the Valuation of Risk Assets," *Journal of Finance*, September 1976, pp. 1085–1100; I. Friend and R. Westerfield, "Co-Skewness and Capital Asset Pricing," *Journal of Finance*, September 1980, pp. 897–913; and G. Barone-Adesi, "Arbitrage Equilibrium With Skewed Asset Returns," *Journal of Financial and Quantitative Analysis*, 1985, pp. 299–313, for support of this proposition. C. Singleton and J. Wingender ("Skewness Persistence in Common Stock Returns," *Journal of Financial and Quantitative Analysis*, September 1986, pp. 335–341), however, find that individual stock skewness is not persistent and thus conclude that one should not bet on historical skewness.
29. J. Cragg and B. Malkiel, *Expectations and the Structure of Share Prices* (Chicago: U. of Chicago Press, 1982); R. Arnott, "What Hath MPT Wrought: Which Risks Reap Rewards?" *Journal of Portfolio Management*, Fall 1983, pp. 5–11; and S. Carvell and P. Strebel, "A New Beta Incorporating Analysts' Forecasts," cited in Table I.
30. See T. Kerrigan, "When Forecasting Earnings, It Pays to Watch Forecasts," *Journal of Portfolio Management*, Summer 1984; E. Hawkins, S. Chamberlin and W. Daniel, "Earnings Expectations and Security Prices," *Financial Analysts Journal*, September/October 1984, pp. 24–38; R. Arnott, "The Use and Misuse of Consensus Earnings," in Table I; and G. Benesh and P. Peterson, "On the Relation Between Earnings Changes, Analysts' Forecasts and Stock Price Fluctuations," cited in Table I.
31. For an early literature review, see R. Ball, "Anomalies in Relationships Between Securities' Yields and Yield-Surrogates," *Journal of Financial Economics* 6 (1978), pp. 103–126. For more recent results, see C. Jones, R. Rendleman and H. Latané, "Stock Returns and SUEs During the 1970's," *Journal of Portfolio Management*, Winter 1984, pp. 18–22; C. Jones, R. Rendleman and H. Latané, "Earnings Announcements: Pre-and-post Responses," *Journal of Portfolio Management*, Spring 1985, pp. 28–32; and R. Rendleman, C. Jones and H. Latané, "Further Insight into the SUE Anomaly," cited in Table I.
32. H. Rainville, "Earnings Momentum in Equities" (Paper presented at the Institute for Quantitative Research in Finance, Spring 1983); R. Hagin, "An Examination of the Torpedo Effect" (Paper presented at the Institute for Quantitative Research in Finance, Fall 1984); and Benesh and Peterson, "On the Relation Between Earnings Changes, Analysts' Forecasts and Stock Price Fluctuations" (cited in Table I), especially their Table V.

33. A recent paper noting these results is J. Brush, "Eight Relative Strength Models Compared," *Journal of Portfolio Management*, Fall 1986, pp. 21–28. Earlier studies include M. Greene and B. Fielitz, "Long-Term Dependence in Common Stock Returns," *Journal of Financial Economics*, May 1977, pp. 339–349; R. Arnott, "Relative Strength Revisited," *Journal of Portfolio Management*, Spring 1979, pp. 19–23; J. Bohan, "Relative Strength: Further Positive Evidence," *Journal of Portfolio Management*, Fall 1981, pp. 36–39; and J. Brush and K. Boles, "The Predictive Power in Relative Strength and CAPM," *Journal of Portfolio Management*, Summer 1983, pp. 20–23.
34. R. Schwartz and D. Whitcomb, "Evidence on the Presence and Causes of Serial Correlation in Market Model Residuals," *Journal of Financial and Quantitative Analysis*, June 1977, pp. 291–313; B. Rosenberg and A. Rudd, "Factor-Related and Specific Returns of Common Stocks: Serial Correlation and Market Inefficiency," *Journal of Finance*, May 1982, pp. 543–554; B. Rosenberg, K. Reid and R. Lanstein, "Persuasive Evidence of Market Inefficiency," *op. cit.*; J. Howe, "Evidence on Stock Market Overreaction," *Financial Analysts Journal*, July/August 1986, pp. 74–77. A longer cycle (three to five-year) return reversal is documented in Fama and French, "Permanent and Temporary Components of Stock Prices," cited in Table I.
35. S. Wachtel, "Certain Observations in Seasonal Movements in Stock Prices," *Journal of Business*, July 1942, pp. 184–193; M. Rozeff and W. Kinney, "Capital Market Seasonality: The Case of Stock Returns," *Journal of Financial Economics* 3 (1976), pp. 379–402; R. McEnally, "Stock Price Changes Induced by Tax Switching," *Journal of Business*, Fall 1976, pp. 47–54; E. Dyl, "Capital Gains Taxation and Year-End Stock Market Behavior," *Journal of Finance*, March 1977, pp. 165–175; B. Branch, "A Tax Loss Trading Rule," *Journal of Business*, April 1977, pp. 198–207; and C. Jones, D. Pearce and J. Wilson, "Can Tax-Loss Selling Explain the January Effect? A Note," *Journal of Finance*, June 1987, pp. 453–461. In addition, see the January/size studies referenced in Table I.
36. Constantinides ("Optimal Stock Trading With Personal Taxes," in Table I) demonstrates that the observed tax-trading pattern is irrational; J. Lakonishok and S. Smidt ("Volume for Winners and Losers: Taxation and Other Motives for Stock Trading," *Journal of Finance*, September 1986, pp. 951–974) show trading volume to be inconsistent with rational tax trading; and K. Chan ("Can Tax-Loss Selling Explain the January Seasonal in Stock Returns?" *Journal of Finance*, December 1986, pp. 1115–1128) finds the January effect as strong for long-term losses as for short-term, contrary to optimal tax trading.

    W. DeBondt and R. Thaler ("Does the Stock Market Overreact?" *Journal of Finance*, July 1985, pp. 793–805 and "Further Evidence on Investor Overreaction and Stock Market Seasonality," *Journal of Finance*, July 1987, pp. 557–581) suggest that investor "overreaction," in violation of Bayes' rule, may explain anomalies such as the January effect. H. Shefrin and M. Statman ("The Disposition to Sell Winners Too Early and Ride Losers Too Long: Theory and Evidence," *Journal of Finance*, July 1985, pp. 777–790) develop Kahneman and Tversky's prospect theory, as well as notions of mental accounting, regret aversion and self-control, to explain investors' observed January tax-loss behavior.
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 Basu, "The Relationship Between Earnings Yield, Market Vaue and Return For NYSE Common Stocks," in Table I.
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 G. Maddala, *Econometrics* (New York: McGraw Hill, 1977), p. 331). 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 Shapiro (in "Stock Returns, Beta, Variance and Size," referenced in Table I) cite this as a reason their results contradict Fama-MacBeth. Also see Litzenberger and Ramaswamy, "The Effect of Personal Taxes and Dividends on Capital Asset Prices," *op. cit.*, and A. Warga, "Experimental Design in Tests of Linear Factor Models" (Columbia U. Business School working paper, January 1987) for other arguments against grouping stocks.
41. To partition simultaneously into quintiles on the basis of our 25 anomalies results in 5^{25}, or 310^{17}, separate classifications. Using monthly returns on our 1500 stocks, it would take over 16.6 trillion years to generate just one observation per cell.
42. See. R. Grinold, "Multiple Factor Risk Models and Exact Factor Pricing" (U.C. Berkeley working paper #166, February 1987) for a discussion of the appropriateness of modeling expected returns linearly in equity characteristics.
43. See H. Theil, *Principles of Econometrics* (New York: John Wiley, 1971), Chapter 6.
44. See R. McElreath and D. Wiggins, "Using the Compustat Tapes in Financial Research: Problems and Solutions," *Financial Analysts Journal*, January/February 1984, pp. 71–76 for an overview of potential methodological pitfalls.
45. As suggested by Rosenberg, Reid and Lanstein, "Persuasive Evidence of Market Inefficiency," *op. cit.*
46. Blume and Stambaugh ("Biases in Computed Returns," Table I) 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 I) provide a comprehensive discussion of methodological problems and a stark example of the potential for survivorship and look-ahead biases to confound the disentangling of the size and P/E effects.
48. This type of normalization belongs to the general class of "Winsorised M-Estimators" discussed in G. Judge et al., *The Theory and Practice of Econometrics*, 2nd ed. (New York: John Wiley, 1985), pp. 829–834. This concept was

first applied in common stock research by BARRA in their E1 Model (see footnote 8).

49. J. Ratcliffe ("The Effects on the T-Distribution of Nonnormality in the Sampled Population," *Applied Statistics* 17 (1968), pp. 42–48) 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.
50. For a description of paired t-tests, see G. Snedecor and W. Cochran, *Statistical Methods*, 6th ed. (Ames, Iowa: Iowa State Press, 1967), pp. 91–100.
51. See J. Kmenta, *Elements of Econometrics* (New York: Macmillan, 1971), pp. 392–395.
52. Rosenberg, Reid and Lanstein, "Persuasive Evidence of Market Inefficiency," *op. cit.*, p. 14. Also, for a general discussion of multicollinearity, see Kmenta, *Elements of Econometrics, op. cit.*, pp. 380–391.
53. For example, Arbel ("Generic Stocks," in Table I) suggested that P/E might be a proxy for neglect; Reinganum ("Misspecification of Capital Asset Pricing," Table I) and Banz and Breen ("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 Dowen and Bauman, "The Relative Importance of Size, P/E and Neglect," and Cook and Rozeff, "Size and Earnings Price Ratio 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) pure return variances across time for eight of our 25 anomaly measures, and significantly different pure 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 subperiods for each attribute. A difference-of-means test was then performed using the stricter 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 indicate a significant 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 deleterious to returns.
57. See K. Chan, N. Chen and D. Hsieh, "An Exploratory Investigation of the Firm Size Effect," *Journal of Financial Economics* 14 (1985), pp. 451–471, for an analysis of linkages between the size effect and macroeconomic measures. See Keim and Stambaugh, "Predicting Returns in the Stock and Bond Markets," in Table I for linkages to several *ex ante* risk premiums.

    For analyses of various univariate return effects and their macroeconomic correlates see R. Arnott and W. Copeland, "The Business Cycle and Security Selection," *Financial Analysts Journal*, March/April 1985, pp. 26–32; for an analysis with multivariate factors, see V. Marathe, "Elements of Covariance in Security Returns and their Macroeconomic Determinants" (U.C. Berkeley PhD. dissertation, 1979).
58. Rosenberg, Reid and Lanstein, "Persuasive Evidence of Market Inefficiency," *op. cit.*; BARRA Research Seminar, June 1986, *op. cit.*
59. Lakonishok and Shapiro ("Stock Returns, Beta, Variance and Size," in Table I) find that the size effect subsumes returns to both beta and sigma. Tinic 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.

    Sharpe's multifactor beta did accumulate significantly over time; Reid's multifactor beta also had a positive total payoff, but a t-statistic test that was not quite significant. In addition, Reid's model included coskewness and sigma factors. His coskewness factor had a significantly positive accumulation; sigma had a marginally significant negative payoff.
60. Nonstationarity of returns to systematic risk has been demonstrated by Tinic and West, "Risk, Return and Equilibrium," in Table I.
61. Rosenberg, Lanstein and Reid (RLR) ("Persuasive Evidence 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-return attributions) while ours and Reid's are residual of the beta-adjusted market return. As Reid noted, the two approaches produce reversals of similar magnitude. Note also that it is impossible to abstract from pricing errors and bid/ask spreads by lagging price in constructing this measure. However, RLR do some diagnostics that indicate the measure is robust with respect to such concerns. Furthermore, the observed second-month reversal persistence is by construction free from any pricing concerns.
62. "Factor Related and Specific Returns of Common Stocks," *op. cit.*
63. For an early application of cluster analysis to finance, see J. Farrell, "Analyzing Covariance of Returns to Determine Homogeneous Stock Groupings," *Journal of Business*, April 1974, pp. 186–207.
64. The explanatory power was generally much higher in months with unusual market returns. This stems from the increased cross-sectional variation of returns explained by beta in such months. See the discussion of beta in Table V for quantification of its market sensitivity.
65. See Sharpe, "Factors in New York Stock Exchange Security Returns, 1931–1979," *op. cit.*, p. 9. Sharpe's model has a time-series R^2 of 40 per cent versus a cross-sectional R^2 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.
66. For example, the salient features of tax laws and their effects on optimal trading strategies are usually relatively constant. Human nature is even less fluid; hence

observed "irrational" behavior (inconsistent with the CAPM and EMH) need not become rational in the future. For a discussion of human irrationality and security markets, see K. Arrow, "Risk Perception in Psychology and Economics," *Economic Inquiry*, January 1982, pp. 1–9.

67. See B. Jacobs and K. Levy, "Anomaly Capture Strategies" (Paper presented at the Berkeley Program in Finance, September 1986).
68. When the number of means to be estimated jointly exceeds two, using each historical average individually is "inadmissible." An estimator is inadmissible if there is another that has smaller risk (in terms of mean square error) independent of the true unknown mean. Stein-James estimators shrink all individual historical averages toward the grand average. The shrinking factor for each historical average varies inversely with its standard deviation. The shrinking factor is thus positively correlated with the degree of randomness or uncertainty in each measure. See W. James and C. Stein, "Estimation With Quadratic Loss," *Proceedings of the 4th Berkeley Symposium on Probability and Statistics* (Berkeley: U. of Ca. Press, 1961), pp. 361–379.
69. Before applying the difference-of-means test, we used an F-test to check for equality of variances in January and non-January months for each attribute. Equality of variances could only be rejected in three cases, and the subsequent difference-of-means tests were robust to the stricter Cochran criteria in all three cases. Hence the t-tests shown for January versus non-January differences are based on a pooled estimate of January and non-January return variance. These tests were two-sided with the exception of the tax-loss measures. Because theory predicted positive January tax measure coefficients, one-sided tests were used. (See footnote 54.)
70. For example, on size see Keim, "Size-Related Anomalies and Stock Return Seasonality," in Table I; on controversy, see R. Arnott and W. Copeland, "The Business Cycle and Security Selection," *op. cit.*; on tax measures, see Reinganum, "The Anomalous Stock Market Behavior of Small Firms in January," in Table I.
71. Compare this with Arbel, "Generic Stocks," listed in Table I.
72. For example, on yield see Keim, "Dividend Yields and the January Effect"; on sigma see Tinic and West, "Risk Return and Equilibrium"; on relative strength see Brush, "Eight Relative Strength Models Compared," *op. cit.* These authors focus on fewer anomalies than we do, thereby facilitating a longer sample period and hence greater statistical power. Their findings are consistent with ours, but are also statistically significant.
73. For example, see Cook and Rozeff, "Size and Earnings/Price Ratio Anomalies," in Table I.
74. Chan ("Can Tax Loss Selling Explain the January Seasonal in Stock Returns?" *op. cit.*) reports that a loss from two calendar years prior has about as much January impact as a loss from the most recent calendar year. As our long-term measure is broader than Chan's, an even larger impact from long-term losses is not unexpected.
75. See Shefrin and Statman, "The Disposition to Sell Winners Too Early and Ride Losers Too Long," *op. cit.*
76. Arbel ("Generic Stocks," in Table I) cites year-end release of information as a potential explanation of a neglect seasonal. However, V. Chari, R. Jagannathan and A. Ofer ("Fiscal Year End and the January Effect" (Kellogg Graduate School of Management working paper #20, July 1986)) find no excess returns at fiscal year-end for non-December fiscal year reporters, casting doubt on Arbel's thesis.

    Kato and Schallheim ("Seasonal and Size Anomalies in the Japanese Stock Market," *op. cit.*) suggest additional liquidity in the economy as a possible explanation for the Japanese January/June seasonals and the U.S. January/size anomaly. However, our finding that the January/size seasonal is subsumed after properly controlling for tax-loss selling appears to belie this rationale.
77. J. Grant, "Long-Term Dependence in Small Firm Returns" (Boston College working paper #84-10, March 1984); Fama and French, "Permanent and Temporary Components of Stock Prices," *op. cit.*; A. Morgan and I. Morgan, "Measurement of Abnormal Returns From Small Firms," *Journal of Business and Economic Statistics*, January 1987, pp. 121–129; and A. Lo and C. MacKinlay, "Stock Market Prices Do Not Follow Random Walks: Evidence From a Simple Specification Test" (National Bureau of Economic Research, working paper #2168, February 1987) document periodicity in naive returns to the size effect.
78. Rosenberg and Rudd, "Factor Related and Specific Returns of Common Stocks," *op. cit.* The concept of changing expected risk premiums inducing autocorrelation in return was discussed earlier by Fama in *Foundations of Finance, op. cit.*, p. 149.
79. The t-statistic for each attribute is calculated using the Bartlett approximation. See G. Box and G. Jenkins, *Time Series Analysis: Forecasting and Control*, revised ed. (Holden-Day, 1976), pp. 34–36.
80. The metric we use is the portmanteau statistic Q given in G. Ljung and G. Box, "On a Measure of Lack of Fit in Time Series Models," *Biometrika* 65 (1978), pp. 297–303. The first 31 autocorrelation lags for each attribute were tested for nonstationarity (18 lags for earnings surprise).
81. Such an approach is taken by Lakonishok and Shapiro, "Stock Returns, Beta, Variance and Size," in Table I.
82. Specifically, the independent variable is monthly S&P 500 excess (over Treasury bills) return. This type of analysis is also implemented in the multifactor works of Sharpe and Reid.
83. This approach was pioneered by B. Rosenberg and W. McKibben, "The Prediction of Systematic Risk in Common Stocks," *Journal of Financial and Quantitative Analysis*, March 1973, pp. 317–333.
84. See Sharpe, "Factors in New York Stock Exchange Security Returns, 1931–1979," *op. cit.*, pp. 17–18. Fluctuations in risk premiums could induce significant intercepts, which would not contravene a multifactor CAPM. But as noted earlier, our autocorrelation results are not generally supportive of changing anomaly risk premiums.

    In fact, it is doubtful that any meaningful definition of risk is as transient as some of our return effects. Furthermore, fleeting return effects, such as residual return reversal, should be immune to Roll's CAPM critique, because they are likely robust to any reasonable definition of the market portfolio. See R. Roll, "A Critique of the Asset Pricing Theory's Tests, Part I: On Past and Potential Testability of the Theory," *Journal of Financial Economics*, March 1977, pp. 129–176.