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Commonality in the determinants of expected stock returns

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Abstract

We find that the determinants of the cross-section of expected stock returns are stable in their identity and influence from period to period and from country to country. Out-of-sample predictions of expected return are strongly and consistently accurate. Two findings distinguish this paper from others in the contemporary literature: First, stocks with higher expected and realized rates of return are *unambiguously* lower in risk than stocks with lower returns. Second, the important determinants of expected stock returns are strikingly common to the major equity markets of the world. Overall, the results seem to reveal a major failure in the Efficient Markets Hypothesis.

Key words: Market efficiency; Cross-sectional prediction; International
JEL classification: G12; G14

1. Introduction

There is mounting evidence that relative stock returns can be predicted by factors that are inconsistent with the accepted paradigms of modern finance.

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DeBondt and Thaler (1985), Jegadeesh and Titman (1993), Chopra, Lakonishok, and Ritter (1992), and Jegadeesh (1990) show that the return history of a stock is useful in predicting relative returns. In addition, Fama and French (1992), Lakonishok, Shleifer, and Vishny (1994), and Davis (1994) show that future returns can be predicted by the relative sizes of (a) the current market price of a stock and (b) the current values of accounting numbers, such as book value or earnings per share.

The reaction to this evidence has been strong. Some believe it is flawed and results, at least in part, from bias. Kothari, Shanken, and Sloan (1995), Brown and Goetzmann (1995), and Brown, Goetzmann, and Ross (1995) cite survival bias as a problem that can exaggerate predictive power. Black (1993), Merton (1987), and Lo and MacKinlay (1990) suggest that the results represent some form of data snooping prior to testing.

Others take the view that while success in prediction may be somewhat exaggerated by the influence of various biases, the fundamental nature of the results still stands, and it deserves close attention. We can divide those who take this position into two groups. One group believes that the differences are related to relative risk, while the other attributes them to bias in the market's pricing.

The first group believes that the differentials in stock returns are expected and required by investors (see Fama and French, 1992, 1993; Ball, Kothari, and Shanken, 1995) and that the differentials are risk premiums. While they argue that the nature of the risk premiums seem inconsistent with the predictions of the capital asset pricing model (CAPM), they claim that the premiums could be consistent with other, multifactor models. Thus, while this group believes that the new results can lead to a rejection of the CAPM, their view of the efficient markets theory remains intact.

The second group believes that the differentials in predicted returns come as a surprise to investors. (see Chopra, Lakonishok, and Ritter, 1992; Lakonishok, Shleifer, and Vishny, 1994; Haugen, 1995). The differential returns could derive from market over- or underreactions to various events. Distortions in the patterns of realized returns, caused by bias in the pricing of stocks, can mask the true nature of the relation between expected return and risk, whatever its nature. This group sees the results as a major setback for the efficient markets hypothesis.

The tests of forecasting power conducted in this paper minimize the various sources of bias discussed in the literature. Given our procedures and the size of the predictable return differentials found, it seems unlikely that these differentials are merely artifacts of bias in methodology. Since the differences in realized returns are too large to be credibly called risk premiums and since the high return deciles are not relatively risky, our results also strongly favor the pricing bias hypothesis.

The determinants of differential stock returns are surprisingly stable over time, and the forecasting power of our expected return factor model is also surprisingly high. We also find high power in other countries: There seems to be a great deal of commonality across markets in firm characteristics that explain differences in expected returns. This is true in spite of the fact that the monthly payoffs to these characteristics are not significantly correlated across the five countries examined. Thus, the determinants of expected stock returns appear to be common across different time periods and different markets.

In Section 2 we identify the sources of bias that can distort the results of studies of predictive power in stock markets. Section 3 discusses the nature of the firm characteristics (factors) used to predict return. Sections 4 through 12 discuss our methodology, and Section 13 concludes.

2. Sources of bias in predicting stock returns

As noted above, some studies argue that success in predicting relative stock returns is flawed by several sources of bias. Our objective is to design a test, under which the effects of the problems discussed below are minimized, but we can still be confident that our results are real.

If a database systematically excludes significant numbers of firms that have become individually inactive, the data can be said to suffer from *survival bias*. To illustrate the bias, consider studies of mutual fund performance. Suppose all mutual funds have identical expected rates of return (equal to that of the market index), but different variability in return. Suppose also that if performance falls below some threshold, a fund goes inactive. Then the probability of reaching that threshold increases with the fund's risk. If we observe the performance of only those funds that remain active, we will probably find that the survivors' performance exceeds the market's. We may also find that performance increases with the level of variability in return. Thus, it will appear that we can predict performance on the basis of fund risk.

In studies of individual firms, the nature of the bias is less clear, since many firms can disappear by merger as well as failure. In either case, it is likely that nonsurvivors' overall returns will be abnormal.

If the factors used in prediction are somehow related to the probability of going inactive, failure to include inactive firms in the database results in misleading estimates of predictive power. Survival bias is exacerbated by the nature of firms that are backfilled in commercial databases. Providers tend to add companies that show significant market positions when their records are backfilled. Thus, given two firms of identical size five years prior to the backfill, the larger (and more successful) firm at the time of the backfill is more likely to be added to the database.

Look-ahead bias occurs when data items are used as predictive factors, the values of which were unknown when the predictions were made. Suppose, for example, that the earnings-to-price ratio (earnings yield) is used as the predictive factor. If the ratio is calculated with an earnings number that was not actually reported at the date of the prediction, the predictive power of the factor is exaggerated. This is because the set of firms with relatively high (low) earnings yields includes those with unexpectedly high (low) last quarter numbers. Market reaction to these numbers is likely to be positive (negative). Thus, high (low) earnings yields are associated with high (low) subsequent returns, even though there may be no true predictive information in the number.

A phenomenon called *bid–ask bounce* can also instill bias in tests of predictive power in equity markets. Stocks trade at the bid or ask prices, and returns are usually measured close-to-close. Assume that the underlying market value of a stock does not change during month t, but that the last trade of the month was at the bid. Assume also that the stock remains constant in price during month $t + 1$. There is roughly an even chance that it will close at the ask price at the end of $t - 1$ or $t + 1$. Thus, assuming no change in the bid–ask spread, the measured return will either be zero or negative for t and either zero or positive for $t + 1$. Thus, returns measured over closing prices can appear to be negatively autocorrelated, even when they are not. Thus, the existence of bid–ask bounce can lead to the false conclusion that last period's return has predictive power, even when successive stock returns are completely uncorrelated.

Bias associated with *data snooping* occurs when researchers (a) examine the properties of a database or the results of other studies of a database, (b) build predictive models employing promising factors based in the previous results, and then (c) test the power of their models on the same database. Since most researchers currently employ the same database of U.S. firms, and since they publish and discuss their results, this is both an important concern and a difficult problem to address. Nevertheless, the problem can be addressed by employing data from markets that have not been studied extensively, or predicting by using time periods that are new to analysis.

3. Firm characteristics (factors) that may induce differentials in expected returns

Factor models that employ firm characteristics to predict the *second moment* (the variance) of stock returns (or statistics related to the second moment, such as volatility relative to a benchmark portfolio, market beta, and residual variance) have been applied by practicing analysts for decades.[1] In this study, we employ such a model to predict the first moment (the expected value) of stock returns. Our model employs a variety of factors similar in number and nature to those used in second-moment factor models.

[1] The most commercially successful of these is the Barra model.

In more traditional tests, empiricists have chosen factors based on theoretical models of asset pricing (Fama and MacBeth, 1973) or variables that have power in explaining the covariances between stocks (Chen, 1983). If stock markets are perfectly liquid and highly efficient, differences in risk should be the sole determinant of differences in expected return.

However, if stocks are heterogeneous in their liquidity and if pricing is biased relative to the available information set, many nonrisk-related variables can be important in predicting the cross-section. In light of this possibility, our predictions of expected stock returns are based on five classes of factors: risk, liquidity, price level, growth potential, and price history.

Given the price reactions to unexpected changes in market risk reported in longitudinal studies (French, Schwert, and Stambaugh, 1987; Haugen, Talmor, and Torous, 1991), differences in the *risk* of stocks are likely to have predictive power in the cross-section. Accepted paradigms point to specific risk variables, such as the CAPM and arbitrage pricing theory (APT) betas, as theoretically appropriate variables for forecasting returns. However, as discussed by Haugen (1995), it is increasingly apparent that these models can have low power. In spite of this, we include the standard market-related beta[2] and betas related to macroeconomic variables. These include monthly percentage changes in industrial production and inflation and the rate of return on 30-day Treasury bills. They also include the differences in return between a 30-year Treasury bond and a 30-day T bill, and the Salomon Brothers composite corporate bond index: and a two-security portfolio of Treasury bonds with the same duration. In addition, we include a stock's own variance, its residual variance, the ratio of total debt to stockholders' equity, income available for the payment of interest relative to total interest charges, and the standard error of preceding five-year, time-trended, quarterly earnings per share scaled by average earnings per share over the trailing period. Collectively, we expect to find that the risk variable's payoff is positive.

Differences in the *liquidity* of stocks can also be important. In rebalancing their portfolios, traders must buy at the ask price and sell at the bid price. The bid–ask spread serves as part of the cost of trading. A trade's market impact is also important. Individual stocks have widely differing degrees of liquidity. To keep commensurate the expected rates of return, net of trading costs, stocks must have *gross* expected returns that reflect the relative cost of trading (see Stoll and Whaley, 1983; Amihud and Mendelson, 1986). Factors associated with liquidity include price per share, the annual average volume of daily trading relative to annual average total market capitalization (price per share times the total number of shares outstanding), the five-year time trend in this variable, and

[2]All market and APT betas are computed over trailing five-year periods using monthly data.

contemporary total market capitalization. Overall, an investor should expect negative payoffs for the various factors that represent differentials in liquidity, with the liquid stocks having the lower expected returns.

Factors related to *price level* indicate the level of current market price relative to various accounting numbers. These measures indicate whether a stock is selling cheap or dear. Factors representing cheapness in price include contemporary market price relative to earnings per share, cash flow per share, dividends per share, book value per share, and sales per share. The trailing five-year time trends and variability within these variables are also included as factors. We include the time trends to differentiate firms that are declining in their price level from those that are emerging or recovering. Recent research shows that stocks with low ratios of price to current cash flows have earned relatively high rates of return in recent decades. The source of these higher returns is the subject of much controversy.

Chan and Chen (1991) and Fama and French (1992) believe that value stocks are 'fallen angels' and are therefore more risky. They believe the premium returns to these stocks are expected and required. Therefore, factors indicating a cheap price actually belong in the risk category discussed above.

Chopra, Lakonishok, and Ritter (1992), Lakonishok, Shleifer, and Vishny (1994), and Haugen (1995) believe that the premium returns to value stocks are unexpected and systematically surprise investors, and that investors overreact to the past records of success and failure by firms. Proponents of overreactive markets believe that competition in a line of business quickly drives profits to normal levels. By projecting prolonged rapid growth, investors in growth stocks can drive prices too high. As the forces of competition affect growth stocks faster than these investors expect, they are apt to be disappointed by the earnings reports. There is a tendency for future dividends and capital gains on these stocks to be smaller than expected and returns to be relatively low. The opposite is usually true for value stocks.

Regardless of whether these payoffs result from risk or overreaction, they should be positive. The stocks that have the highest current cash flows in relation to market price should have the greatest expected rates of return.

Factors related to *growth potential* indicate the probability for faster(slower)-than-average future growth in a stock's earnings and dividends. Within the cross-section, relatively profitable firms tend to grow faster, at least until competitive entry into their lines of business forces profits to normal levels. Based on the assumption that currently profitable firms have greater potential for future growth, we use several measures of profitability as predictive factors. These measures include the ratios of net earnings to book equity, operating income to total assets, operating income to total sales, total sales to total assets, and the trailing, five-year time trends in these variables. We also include the trailing, five-year time trend in earnings per share, expressed as a percentage of average earnings over the five-year period.[3] Given the size of the factors that reflect the price level of a stock, the greater the growth potential for profits and dividends, the greater the expected future rate of return. If the market mistakenly assigns identical prices to stocks with differing growth potentials, we expect the growth potential factor payoffs to be collectively positive.

Technical factors describe the *price history* of a stock. Recent research shows three relations between the history of return and future expected return. First, there appear to be very short-term (one to two months) reversal patterns in returns. If a stock went up significantly in price last month, this could signal a reversal for the next month (see Jegadeesh, 1990). These short-term reversal patterns can be caused by price pressures induced by investors who are attempting to buy or sell large amounts of a particular stock quickly. Although a seller can drive the price of the stock below its fair value, the stock can be expected to return to fair value. As discussed above, it is also possible that short-term negative serial correlation can be induced by bid–ask bounce. Jegadeesh (1990) argues that this bias is likely to be small. He finds that trading strategies that try to exploit short-term reversals are successful even when returns for the previous month do not reflect the last day of trading. On the other hand, Ball, Kothari, and Wasley (1995) find that bid–ask problems can be very troublesome in simulations of short-term contrarian strategies that seek to exploit short-term reversal patterns. Bid–ask problems have little impact on the tests reported in this paper. The results remain fundamentally intact, with a one-month gap separating the point in time when our expected return deciles are formed and the period over which performance is measured. In addition, our deciles are not distinguished by the short-term performance of their stocks.

Second, there are intermediate-term inertia patterns in stock returns. Stocks that have done well (poorly) in the previous six to 12 months have good (poor) future prospects. These intermediate-term inertia patterns in stock returns can be due to the market's tendency to (a) exhibit lagged reactions to individual earnings reports and (b) to underreact to *initial* reports of unusually high or low rates of profitability by firms. An initial good (bad) quarterly earnings report tends to be followed by one or two more. If the market fails to recognize this, it underreacts to the first report, then completes its reaction as the next one or two reports are issued in the six months that follow (see Jegadeesh and Titman, 1993; Bernard and Thomas, 1990).

Finally, Jegadeesh and Titman (1993) show that there are long-term (three to five years) reversal patterns in stock returns. This can be due to the fact that the market overreacts to a *chain* of positive (negative) reports of good (bad) earnings numbers. Believing that the chain will continue into the future for an extended

[3]Firms with negative average earnings over the five-year period are assigned the population average factor exposure.

period, investors drive the price up (down) too high (low). Again, as competitive forces come into play, the stocks that have gone up or down in price in the past tend to reverse their performance in the future.

Proponents of efficient markets contend that these technical patterns are not the product of market under- or overreaction (see, for example, Chen, 1991). Instead they believe that risk premiums on stocks are time-varying. Risk-premiums in expected returns become larger (smaller) as the risk of stocks becomes larger/smaller or as investors' sensitivity to risk grows (declines). The levels of risk and risk aversion can both change with the business cycle. As we move into a recession, the risk of common stocks can increase; we also become poorer, so our risk aversion can become stronger. Given this, the expected returns to stocks can be higher in recessions and lower in booms. To the extent that changes in prosperity occur in somewhat regular time patterns, the systematic patterns that we see in the history of stock returns can be induced by time-varying risk premiums.

Given the patterns stemming from pricing bias, we expect the payoffs to be (a) negative, (b) positive, and (c) negative with respect to a stock's performance in the past (i) one to two months, (ii) six to 12 months, and (iii) two to five years, respectively. A comprehensive list of all the factors used in the model is provided in the appendix to this paper.

4. Estimating and projecting factor payoffs

In building an expected return factor model, we must estimate the tendency for stocks with differing exposures to different factors to produce differing returns. For a given month, we simultaneously estimate the monthly payoffs (cross-sectional regression coefficients) to the variety of factor characteristics, using an ordinary least squares (OLS), cross-sectional, multiple regression analysis:

$$r_{j,t} = \sum_i \hat{P}_{i,t} * F_{j,i,t-1} + u_{j,t}\,, \tag{1}$$

where

$r_{j,t}$ = rate of return to stock j in month t,
$\hat{P}_{i,t}$ = regression coefficient or payoff to factor i in month t,
$F_{j,i,t-1}$ = exposure (firm characteristics such as APT betas, size, measures of profitability, etc.) to factor i for stock j at the end of month $t-1$,[4]
$u_{j,t}$ = unexplained component of return for stock j in month t.

[4] In each month and for each factor, the cross-sectional distributions are normalized with a Box–Cox (1964) transformation function. Outliers, more than four standard deviations from the mean, are removed.

Eq. (1) is estimated over a sequence of months to obtain a history of the payoffs to the various factors.

We can use the information embodied in the payoff histories to make out-of-sample projections on the sizes of the future payoffs in later periods. The experiments reported here for U.S. stocks employ averages of the payoffs observed in the 12 months prior to the month for which expected return is estimated.[5] Expected return for month t is then projected as

$$E(r_{j,t}) = \sum_i E(\hat{P}_{i,t}) * F_{j,i,t-1}\,, \tag{2}$$

where

$E(r_{j,t})$ = expected rate of return to stock j in month t,
$E(P_{i,t})$ = expected payoff to factor i in month t (the arithmetic mean of the estimated payoff over the trailing 12 months),
$F_{j,i,t-1}$ = exposure to factor i for stock j based on information available at the end of month $t-1$.

As stated above, risk models similar to the one employed here are used by practicing portfolio analysts to predict long-term statistics related to the second moment of the return distribution for equity portfolios. These models coordinate the covariance matrix of factor payoffs with portfolio exposures (differential exposures from an index) to obtain estimates of portfolio volatility (or perhaps tracking error relative to an index).

5. Results of the monthly regressions

In fitting the factor model in each month, we begin with the actual (as of each date) monthly lists of the stocks in the Russell 3000 stock index. The indexes consist collectively of roughly the 3000 largest stocks in the United States. Subject to data availability,[6] the sample includes all stocks that were actually represented in the index, as it existed, from 1979 through 1993.[7] In addition, if a particular stock's record is incomplete (the data required to compute its exposure to a particular factor are unavailable in a given month), the stock

[5] We employ sector dummies as additional control factors. The sector dummies identify a stock's principal line of business. The sectors include durables, nondurables, utilities, energy, construction, business equipment, manufacturing, transportation, financial, and business services.

[6] Our data sources include Compustat, CRSP, Interactive Data Corporation, Value Line, and Global Vantage. We are able to find information for 98% of the stocks in the Russell 3000 and nearly 100% of the stocks in the Russell 1000 stock indexes.

[7] We are grateful to the Frank Russell Company for providing us with a history of stocks in their indexes.

remains in the sample and is assigned the population mean value for the exposure. This procedure can bias our results, because numbers unavailable in the current record might have been available at the time for which the forecasts are to be made. It is our opinion that filling the missing records with population average exposure numbers creates less of a bias than removing the stock from the population. We have nevertheless run the tests both ways, with little difference in the results.

We estimate the payoffs for all months from 1979 through 1993. We employ factors related to risk, liquidity, price level, growth potential, and the technical history of stock returns. For accounting numbers such as earnings per share, we assume a reporting lag of three months. However, beginning in 1988, the data files that were commercially available in the forecast month are used to calculate all factor exposures. Thus, look-ahead bias should not seriously affect our results prior to 1988, and it should have no impact whatsoever on the results after 1988.

For the period 1979 through 1993, we run 180 multiple regressions to explain the differential monthly return to the individual stocks in the Russell 3000 population. Fig. 1 shows the time series of multiple adjusted coefficients of

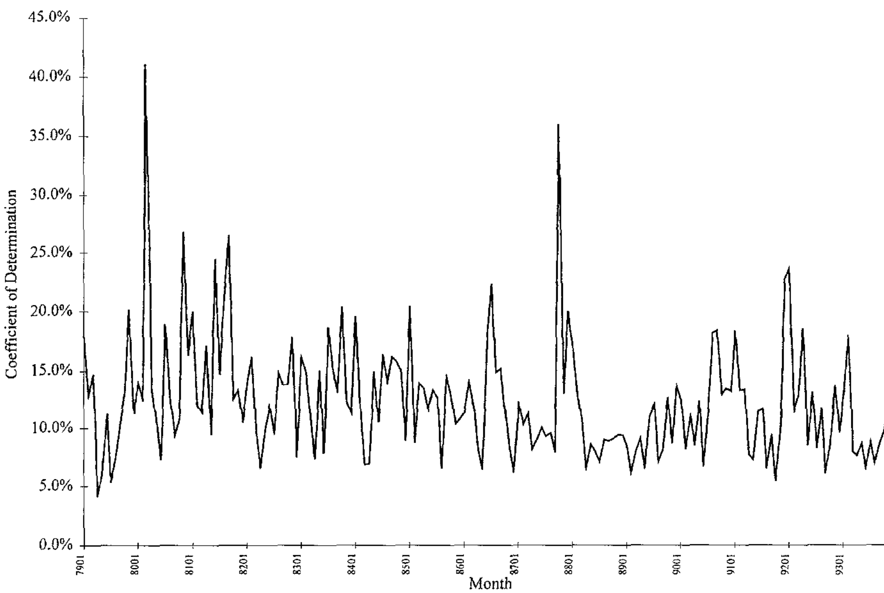

Fig. 1. Time series of adjusted R-squareds for the expected return factor model.

In each month, over the period 1979 through 1993, the cross-section of returns to the stocks in the Russell 3000 stock index are regressed (using OLS) on the cross-section of various firm characteristics related to risk, liquidity, price level, growth potential, and price history. The time series of the adjusted coefficients of determination for the individual monthly regressions are shown in the figure.

determination for these regressions. In interpreting the numbers, keep in mind that we are attempting to explain the monthly differentials in the returns to individual securities, not to well-diversified portfolios. In any given month, most return differentials result from unexpected information, which causes relative realized returns to deviate from expectations.

Across the 90 regressions for the first half of the overall period, we average the regression coefficients, or payoffs, associated with the various factors. The factors are then ranked on the basis of the absolute values for the t-statistics associated with the means across the first half. The Fama and MacBeth (1973) means and t-statistics for these factor payoffs are presented in the first panel of Table 1. In the second panel of Table 1, we present the mean coefficient values and t-statistics for the second half of the period for the 12 most important factors from the first half. Note that all the factors continue to have consistent signs, and the sizes of the mean payoffs are remarkably similar.

As do others, we find evidence of short-term reversal and intermediate-term inertia patterns in the technical history. We also find that the payoffs to the 'cheap price' variables (the ratios of book, earnings, and cash flow to price) are all positive and important in explaining the cross-section. It also appears that given the level of market price relative to current cash flows, the more profitable firms tend to have the greater expected returns. Liquidity also appears to be important, with stocks characterized by high, growing levels of trading volume selling at prices that produce lower levels of expected return. Since, the investor must buy now and sell later, the signs for the coefficients related to the current level and trend of trading volume are as expected.

Only one of the 12 most important factors (variability in ratio of cash flow to market price) seems to be related to risk in the distributions of monthly returns, and its payoff seems to carry the wrong sign. We report that none of the market- or APT-related beta coefficients have significant t-scores. Ironically, much of the previous work in explaining the cross-section has concentrated exclusively on these variables. The average payoffs to market beta, volatility of total return, and residual variance are 0.01%, 0.01%, and $-$ 0.02%, respectively.

Comparing the two periods shows a high degree of commonality in the signs and sizes of the coefficients. All the important factors maintain their signs, and the sizes of the coefficients are remarkably similar.

To test the null hypothesis that the mean payoffs to all the factors across the entire period are all zero, we run a Hotelling-T^2 test of the joint significance of the mean values of the payoffs to all of the factors except those relating to sector. Since most of our factors are not statistical estimates and are measured without error, we do not adjust the Hoteling-T^2 for errors in variables. The value for the unadjusted Hotelling-T^2 is 8.206 ($p = 0.000$). Thus, we conclude that the payoffs are jointly nonzero at an extremely high level of confidence.

Table 1
The mean and t-statistics for the most important factors of 1979/01 through 1986/06

	1979/01 through 1986/06		1986/07 through 1993/12	
Factor	Mean	t-stat.	Mean	t-stat.
One-month excess return	−0.97%	−17.04	−0.72%	−11.04
Twelve-month excess return	0.52%	7.09	0.52%	7.09
Trading volume/market cap	−0.35%	−5.28	−0.20%	−2.33
Two-month excess return	−0.20%	−4.97	−0.11%	−2.37
Earnings to price	0.27%	4.56	0.26%	4.42
Return on equity	0.24%	4.34	0.13%	2.06
Book to price	0.35%	3.90	0.39%	6.72
Trading volume trend	−0.10%	−3.17	−0.09%	−2.58
Six-month excess return	0.24%	3.01	0.19%	2.55
Cash flow to price	0.13%	2.64	0.26%	4.42
Variability in cash flow to price	−0.11%	−2.55	−0.15%	−3.38

In each month, over the period 1979/01 through 1986/06, the returns to the stocks in the Russell 3000 stock index are regressed (using OLS) on various firm characteristics related to risk, liquidity, price level, growth potential, and price history. The coefficients are averaged over the 90 regressions. The factors are then ranked, based on the absolute value of the t-statistics for the means. The 12 highest ranking factors in this period are presented in the table. The mean values for the regression coefficients on these factors, as well as the t-statistics for the means, are shown in the second part of the table for the second period 1986/07 through 1993/12. The coefficients can be interpreted a the change in a stock's monthly expected return associated with a one-standard-deviation change in the stock's exposure to a factor in the cross-section. Trading volume is computed as the total dollar amount of trading in the stock over the trailing month as a percent of total market capitalization. Market capitalization is computed as the product of market price per share at the end of the trailing month times the most recently reported number of shares outstanding. Earnings to price, cash flow to price, and book to price are computed as the most recently reported ratio of the trailing 12 months earnings per share, earnings per share plus depreciation per share, and book value per share to price per share as of the end of the trailing month. Profit margin is the most recently reported ratio of net operating income to total sales. Return on equity is the most recently reported ratio of earnings per share to book value per share. Trend numbers are computed as the trailing five-year time trends divided by the five-year average values for each number. Prior to 1988, a three-month reporting lag is assumed. After 1988, the actual contemporary data files available at the end of each month are used for computations. Excess returns are computed as the difference between the trailing total rate of return to the stock and the trailing total return to the S&P 500 stock index. Variability in cash flow yield is computed as the variability in the monthly values for the yield about a five-year time trend.

6. A test of the out-of-sample accuracy of the predictions of expected returns

To test the accuracy of our predictions, we first estimate the payoffs to the factors for the 12 months prior to 1979. The payoffs are then averaged, and these mean values are used as projections for the first month of 1979. We employ a 12-month trailing mean to take advantage of the possibility that the expected values of the payoffs are time varying. Given the exposures of each stock (based on information available at the end of the previous month) and the projected factor payoffs for the next month, we can calculate each stock's relative expected rate of return. We then rank by the relative expected returns. We form the stocks into ten equally weighted deciles, with decile 1 containing the stocks with the lowest expected rates of return.

The process is repeated through December 1993. The 12-month trailing period, over which the payoffs are observed and averaged, moves with the process. We then calculate the actual linked, realized rates of return to the ranked deciles.

The results appear in Table 2. Over the entire period, the spread between decile 10 and decile 1 is approximately 35%. The slopes reported in Table 2 are derived from a regression of realized annual return on decile ranking. They can be interpreted as the expected increase in realized return when moving from one decile to the next. The coefficients of determination are also reported and are surprisingly high. To test for the reliability of the factor model, we also separate the realized returns by year in Table 2. In each year, as we go from decile 1 to decile 10, the realized returns tend to become larger, and the spreads are surprisingly large.[8]

To test for the potential effect of the bid–ask bounce, we reran the tests, in which we attempted to predict returns in month $t+2$ on the basis of information available at t. Separating the forecasts from the exposures by a month slightly reduces the overall slope of Table 2 and slightly increases the coefficient of determination. This effect seems consistent with staleness in the factor exposure estimates, and we conclude that our principle results are largely unaffected by bid–ask problems.

The results of Table 2 are dramatically different from those reported by others. Two differences in methodology account for the improvement in predictive power. First, the model employs a variety of predictive variables simultaneously, rather than one or two at a time. Second, unlike other studies, we re-form the Table 2 deciles monthly rather than annually. Many of the factor exposures, such as excess return in the previous month or quarter, tend to mean-revert rather quickly. As a result, their power in predicting return is much greater over a one-month horizon than over a one-year horizon.

To determine whether the results reported in Table 2 are primarily driven by the market behaviors reported previously by others, we run the tests excluding

[8]Ball, Kothari, and Shanken (1995) argue that the results of tests of winners and losers relative performance of are significantly affected by the starting month over which subsequent performance is measured. To determine the extent to which this is true for our tests, we rerun the analysis, initiating it separately in each of the 12 months of the year. The results are not significantly related to the starting month.

Table 2
U.S. realized annualized returns across deciles 1 to 10 formed by ranking on expected return

	Dec. 1	Dec. 2	Dec. 3	Dec. 4	Dec. 5	Dec. 6	Dec. 7	Dec. 8	Dec. 9	Dec. 10	Slope	R^2
Annual return												
1979	33.5%	32.6%	33.9%	43.1%	35.2%	36.3%	47.3%	40.1%	39.3%	43.4%	1.1%	0.446
1980	17.4%	26.2%	25.4%	27.2%	25.8%	41.3%	42.6%	45.3%	55.6%	68.4%	5.0%	0.897
1981	−15.6%	−14.2%	−7.9%	−4.6%	2.1%	5.6%	0.4%	6.3%	9.7%	16.2%	3.3%	0.931
1982	3.2%	15.5%	21.8%	24.6%	24.0%	25.9%	32.1%	34.6%	39.5%	49.7%	4.1%	0.929
1983	11.8%	18.0%	23.4%	29.5%	28.8%	39.3%	37.8%	46.1%	45.1%	54.5%	4.4%	0.962
1984	−30.9%	−20.7%	−13.4%	−9.1%	−6.5%	1.0%	2.8%	12.8%	15.4%	22.4%	5.5%	0.986
1985	4.3%	18.4%	26.6%	37.8%	34.9%	37.8%	34.9%	41.2%	43.4%	45.7%	3.7%	0.776
1986	−15.2%	−7.1%	1.9%	9.2%	12.1%	15.1%	19.9%	23.2%	23.0%	30.9%	4.7%	0.925
1987	−23.8%	−12.3%	−5.0%	−6.8%	0.0%	1.6%	−3.4%	−2.0%	1.2%	−5.1%	1.8%	0.486
1988	1.5%	10.4%	18.5%	24.0%	22.2%	28.8%	26.9%	25.9%	29.7%	27.0%	2.5%	0.714
1989	−3.0%	8.2%	9.7%	16.8%	18.7%	21.5%	28.5%	29.8%	32.4%	28.7%	3.6%	0.893
1990	−46.9%	−36.2%	−27.5%	−21.7%	−15.5%	−12.7%	−10.2%	−9.9%	−2.9%	1.3%	4.8%	0.937
1991	23.9%	29.3%	36.5%	42.0%	45.2%	45.7%	51.1%	46.6%	46.9%	57.4%	3.1%	0.817
1992	2.5%	7.5%	16.3%	20.3%	17.8%	15.7%	17.1%	18.9%	21.1%	24.5%	1.8%	0.619
1993	6.4%	9.2%	18.2%	18.5%	19.9%	20.1%	20.0%	20.7%	24.2%	22.2%	1.6%	0.738
Average returns												
1979–93	−4.5%	3.7%	10.3%	15.1%	16.5%	22.3%	21.6%	24.0%	27.1%	30.9%	3.5%	0.932
Annualized risk												
1979–93	22.62%	20.59%	19.28%	19.21%	18.19%	18.10%	17.83%	17.95%	17.45%	18.50%		

The 3000 stocks in the Russell 3000 stock index are ranked and formed into equally weighted deciles on the basis of their relative expected monthly returns. At the beginning of each month, the expected returns are computed by summing the products of (a) the individual factor exposures for each stock and (b) the average of the individual factor payoffs over the previous 12 months. The factor exposures are based on firm characteristics related to risk, liquidity, price level, growth potential, and price history. The deciles are re-formed monthly. The realized monthly returns to the deciles are then linked, and the annual returns and the averages of annual returns are reported in the table. The slopes and coefficients of determinations are obtained by regressing the yearly and average realized returns on the decile rankings. The volatilities are the annualized standard deviations of the monthly rates of return for each decile.

all but selected factors. First, we replicate the tests using factors related only to the intermediate momentum patterns in stock returns. We include only excess returns measured over the previous three, six, and 12 months. Using only these factors, we find a significant deterioration in predictive power. The overall spread drops from 35% to 15%, and we find negative slopes relating predicted return to decile number in four of the 15 years. To determine whether variables related to cheap price are the primary drivers, we rerun the tests using book to price and earnings to price as lone factors. The spread drops to 12% for book to price, and we find four years with negative slopes. The spread drops to 14% for earnings to price and there are three negative slope years. We conclude that it is the collective power of many of the factors in the group that accounts for the high level of accuracy in the predictions of return.[9]

In interpreting Table 2, we note each stock has a *term structure* of expected return, and some components of expected return are more persistent than others. For example, we can expect that if a particular stock is exposed to factors relating to recent stock performance it will mean-revert very quickly. Exposure to size, on the other hand, mean-reverts very slowly for small firms and shows little or no tendency to mean-revert for large firms. Thus, the numbers in Table 2 actually reflect *annualized* differences in the rates of return between the deciles for the first month following projection. [As an aside, we performed the analysis based on monthly arithmetic mean returns across the deciles (which is consistent with an assumed one-month investor horizon). The result over the 1979 to 1983 interval shows a slope of 3% with an R^2 of 91.7%.]

At the bottom of Table 2, we report the annualized volatilities of the monthly rates of return in each decile. Note that volatility decreases as we move from decile 1 to decile 10. This provides the initial evidence that investors might not regard the stocks in decile 10 as being highly risky. Fig. 2 plots the frequency distributions of monthly returns for deciles 1 and 10. Once again, there is nothing odd in the distribution of returns for decile 10 relative to decile 1 that might induce investors to require a large differential in expected return. It is possible that the returns in the deciles have highly differing sensitivities to macroeconomic variables that concern portfolio investors. However, this seems unlikely, because none of the APT betas surface as important determinants of expected return.

Table 2 also gives some important initial information on the influence that data snooping has on tests of the predictive accuracy of stock forecasting

[9]Our results appear to be sensitive to the length of the trailing period over which the payoffs are averaged. At the suggestion of the referee, we tried two other moving windows – 24 and 60 months. The 24-month window produces a 34% spread with a 90% coefficient of determination. The 60-month window, on the other hand, produces a 25% spread with a 87% coefficient of determination. The significant reduction in spread as the window between 24 and 60 months might be consistent with the presence of time-varying components in the expected values of the payoffs.

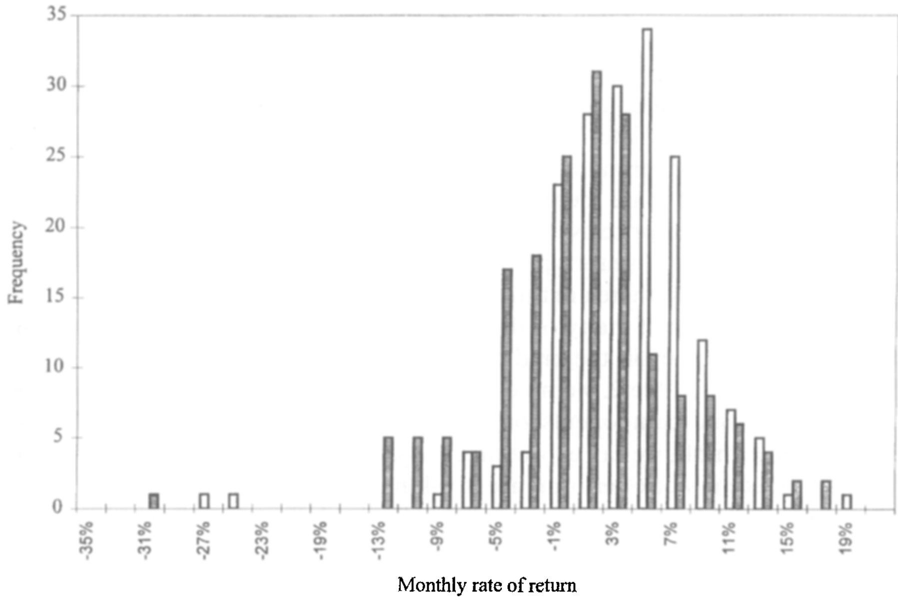

Fig. 2. Frequency distribution of monthly return for deciles 1 and 10.

Stocks are ranked and formed into equally weighted deciles on the basis of their relative expected monthly returns, computed by summing the products of (a) the individual factor exposures for each stock to characteristics related to risk, liquidity, price level, growth potential, and price history, and (b) the average of the factor payoffs over the previous 12 months. Factor payoffs are estimated as OLS cross-sectional regression coefficients relating realized monthly return to the stock characteristics. Deciles are re-formed monthly. The plot shows the frequency distribution of the post-ranking monthly rates of return to deciles 1 and 10. Decile 1 is represented by the shaded bars and decile 10 is represented by the white bars.

models. When we conducted this particular test, we were unaware of any results extending past 1990. Thus, the post-1990 period was not data snooped. Nevertheless, the results for the period 1991 to 1993 do not differ materially from the preceding periods.

7. Average characteristics of the stocks within the deciles

Table 3 shows selected (equally weighted) average fundamental characteristics of the stocks within each decile. The numbers are averages from the 1979 to 1993 period. The results are striking. As we move from decile 1 (low return) to decile 10 (high return), the stocks exhibit lower degrees of financial leverage, higher levels of interest coverage, lower market betas, lower volatility of total return, higher rates of earnings growth, and higher rates of profitability in all dimensions (profit margin, asset turnover, return on assets and equity, and on trailing rates of growth in earnings per share). Moreover, the trailing upward trend in the profitability numbers becomes more pronounced as we move toward decile 10. Decile 10 stocks also tend to be larger companies, selling at higher levels of price per share. To assure that these results are not driven by small firms and bid–ask problems, we provide some additional results related to the distributions of price and size within the deciles. The median values for price for deciles 1 and 10 are \$12.21 and \$26.94, respectively. The median values for market capitalization are \$167.85M and \$439.66M, respectively. We also compute the mean value for the highest and lowest 10% of the stocks within each decile. In decile 1, the price values are \$36.81 and \$3.35. In decile 10 the price values are \$65.53 and \$11.33. The decile 1 size values are \$1,925.25M and \$34.26M, and the decile 10 size values are \$3,793.51M and \$69.30M. Thus, there does not appear to be anything unusual about the distributions for either price or market capitalization.

Decile 10 stocks also exhibit good relative past-year performance. We note that the high-return deciles contain more liquid stocks, even though the payoff to liquidity is negative. This is because liquidity is positively correlated with profitability, and the negative payoff to liquidity is overwhelmed by the collective positive payoffs to the profitability factors, resulting in the inclusion of liquid stocks in the high return deciles. The profitability factors (profit margin, asset turnover, return on assets, return on equity, and trailing growth in earnings per share) have a collective average payoff of 1.57% over the 1979 to 1983 period. Note that the deciles do not distinguish themselves in terms of last month's excess return, in spite of the fact that this is the single most powerful factor. This is because exposures to this particular factor can be uncorrelated in the cross-section with exposures to other factors. In this regard, last month's excess return is different from exposures to the momentum factors, which are reinforced by their positive correlation with exposures to the profitability factors.

Based on these characteristics and the nature of the distributions of monthly returns, it is extremely difficult to make a case for the notion that the stocks of decile 10, which have relatively high expected returns, are distressed companies that are perceived to be more risky relative to the stocks of decile 1. Indeed, the very opposite is almost certainly true. It is equally difficult to think that the relatively high returns of decile 10 stocks are an artifact of survivorship bias, given the fact that our coverage of the Russell 3000 populations is very high and that the attrition rate for the stocks that populate decile 10 is likely to be very low.

In spite of the fundamental characteristics of the high-expected-return stocks, Table 3 shows that they can sell cheap relative to their earnings, cash flow, and dividends per share. This result seems counterintuitive in the context of an

Table 3
The values for selected average firm characteristics by decile (1 = low expected return, 10 = high expected return)

	Dec. 1	Dec. 2	Dec. 3	Dec. 4	Dec. 5	Dec. 6	Dec. 7	Dec. 8	Dec. 9	Dec. 10
Risk										
Market beta	1.21	1.16	1.13	1.11	1.09	1.07	1.05	1.03	1.02	1.00
Volatility (total return)	41.42%	38.42%	36.99%	36.00%	35.16%	34.29%	33.59%	32.86%	32.50%	33.22%
Debt to equity	1.03	0.95	0.89	0.87	0.85	0.83	0.83	0.82	0.85	0.85
Debt to equity growth	0.27%	0.12%	0.08%	0.05%	0.05%	0.06%	0.05%	0.02%	0.04%	−0.03%
Interest coverage	1.76	4.63	5.74	6.36	6.48	6.66	6.98	6.98	6.98	6.63
Interest coverage growth	−0.64%	−0.31%	−0.19%	−0.10%	−0.12%	−0.11%	−0.09%	−0.05%	−0.05%	−0.02%
Liquidity										
Trading volume (millions/month)	$42.42	$42.42	$47.19	$42.74	$65.23	$51.79	$56.02	$51.73	$60.94	$60.89
Market capitalization (millions)	$470	$513	$564	$593	$635	$680	$755	$843	$931	$1011
Price per share	$14.93	$18.03	19.91	$21.21	$22.58	$24.01	$25/58	$27.62	$29.31	$30.21
Price level										
Earnings yield	−1.55%	3.10%	5.25%	6.42%	7.26%	7.83%	8.31%	8.71%	9.19%	10.00%
Cash flow yield	6%	10%	12%	13%	14%	14%	15%	15%	15%	17%
Dividend yield	2.19%	2.33%	2.41%	2.48%	2.59%	2.72%	2.90%	3.05%	3.19%	3.69%
Sales to price	2.07	2.07	2.01	2.04	2.05	2.06	2.07	2.10	2.13	2.14
Book to price	0.81	0.77	0.74	0.73	0.74	0.74	0.74	0.74	0.76	0.80
Growth potential										
Asset turnover	84%	98%	106%	112%	115%	116%	118%	119%	118%	115%
Asset turnover growth	−0.13%	−0.11%	−0.09%	−0.08%	−0.08%	−0.07%	−0.05%	−0.03%	−0.01%	0.05%

Profit margin	−1.16%	3.31%	5.08%	6.01%	6.48%	6.73%	7.02%	7.15%	7.41%	7.86%
Profit margin growth	−0.95%	−0.46%	−0.27%	−0.16%	−0.10%	−0.06%	−0.02%	0.03%	0.04%	0.07%
Return on assets	−1.51%	2.26%	3.98%	4.92%	5.36%	55.66%	5.94%	6.10%	6.24%	6.50%
Return on assets growth	−1.11%	−0.62%	−0.40%	−0.28%	−0.20%	−0.15%	−0.09%	−0.03%	0.01%	0.08%
Return on equity	−2.14%	5.10%	8.75%	10.93%	12.19%	13.02%	13.69%	14.13%	14.61%	15.39%
Return on equity growth	−1.18%	−0.68%	−0.45%	−0.32%	−0.23%	−0.16%	−0.10%	−0.03%	0.02%	0.07%
Earnings growth	−0.41%	0.28%	0.53%	0.67%	0.75%	0.79%	0.83%	0.87%	0.91%	0.95%
Technical (excess returns)										
One month	0.09%	−0.27%	−0.12%	−0.08%	0.03%	0.07%	0.14%	0.18%	0.09%	−0.14%
Two months	−1.80%	−1.03%	−0.70%	−0.55%	−0.32%	−0.14%	0.03%	0.30%	0.58%	1.21%
Three months	−6.89%	−2.93%	−0.49%	1.11%	2.37%	3.52%	4.53%	5.63%	6.83%	8.83%
Six months	−12.14%	−4.39%	−0.02%	2.69%	4.90%	6.98%	8.87%	10.81%	12.92%	16.60%
Twelve months	−15.74%	−2.34%	4.73%	8.59%	12.08%	14.95%	18.00%	20.72%	24.44%	30.01%

The population of the Russell 3000 stock index is ranked and formed into equally weighted deciles on the basis of relative expected monthly returns, computed by summing the products of the factor exposures for each stock and the average of the factor payoffs over the previous 12 months. Deciles are re-formed monthly. Selected firm characteristics are computed for each firm and the arithmetic mean of these characteristics is computed across the 180 months and across the 300 stocks of each decile. Market beta and the variance of total return are computed over a trailing 60-month period. Debt to equity is computed as the ratio of the book value of total debt to the book value of equity, based on the most recently reported annual numbers as of the month. Trading volume is computed as the total dollar amount of trading in the stock over the trailing month. Market capitalization is computed as the product of market price per share at the end of the trailing month times the most recently reported number of shares outstanding. Price per share is as of the end of the trailing month. Earnings yield, cash flow yield, and book to price are computed as the ratio of the trailing 12-months earnings per share, earnings per share plus depreciation per share, and book value per share to price per share as of the end of the trailing month. Asset turnover is the most recently reported ratio of total sales to total assets. Profit margin is the most recently reported ratio of net operating income to total sales. Return on assets is the most recently reported ratio of net operating income to total assets. Return on equity is the most recently reported ratio of earnings per share to book value per share. Trend numbers are computed as the trailing five-year time trends divided by the five-year average values for each number. Prior to 1988, a three-month reporting lag is assumed. After 1988, the actual contemporary data files available at the end of each month are used for computations. Excess returns are computed as the difference between the trailing total rate of return to the stock and the trailing total return to the S&P 500 stock index.

efficient market. However, in a market characterized by serious biases and inefficiencies, is it really surprising that we can to build a 'high-quality' portfolio at a 'bargain' price? There is, in fact, an acronym in the investment business for the types of stocks that resemble those that collectively appear to populate decile 10: They are called GARP stocks (growth at a reasonable price). Actually, the stocks of decile 10 might be better named GAIP stocks (growth at an inexpensive price), in light of their relatively high earnings, cash flow, and dividend yields.

While decile 10 stocks collectively have the characteristics reported in Table 3, individual stocks in the decile do not have the complete profile. Individually, by construction, their expected returns will always be relatively high, but that will be because the stocks are outstanding in terms of selected characteristics. Since managers typically screen stocks individually to form 'buy lists' populated by stocks with homogeneous, desirable characteristics, they should have a difficult time screening in the type of stocks that populate our decile 10. Indeed, if we were to screen by requiring each stock to have decile 10 characteristics, we might well find an empty set, with no stocks simultaneously exhibiting low risk, high liquidity, low price level, and high profitability.

8. Risk-adjusting the realized returns

Fama and French (1993) claim that they can explain the cross-section of expected stock returns based on loading according to three factors: (a) the excess return to the capitalization-weighted market index, (b) the difference between the rates of return to small and large stocks, and (c) the difference between the rates of return to stocks with high book-to-price ratios and stocks with low book-to-price ratios. After regressing the monthly returns to ranked groupings of stocks according to these three factors, Fama and French find that the intercepts of their regressions are generally not significantly different from zero. They conclude from this that the cross-section can be explained by differences in relative risk, as given by differences in the factor loadings.

To see if this same result holds for our deciles, we employ a similar three-factor model. In our model, the factors are defined as follows:

$MKTPREM$ = monthly excess return to the cap-weighted Russell 3000 stock index (using the monthly return to 90-day T bills),

SML = Russell 3000 population is ranked monthly (in accord with the procedures used to create the decile returns) on the basis of market capitalization; we form equally weighted quintiles; SML is the monthly difference in return between the smallest and largest quintiles,

HML = assuming a six-month reporting lag, the Russell 3000 population is ranked monthly on the basis of the ratio of the most recently reported book value per share to market price per share; we form equally weighted quintiles; *HML* is the difference in monthly return between the highest and lowest quintile.

For each of the deciles of Table 2, the monthly excess return is regressed on the three factors for the period 1979 through 1993. We present results of these regressions in Table 4. Note that the intercepts for the low-expected-return

Table 4

The results of regressions of risk premiums to decile portfolios on three factors: 1979 through 1993

$r_{j,t} - r_{f,t} = a + s\ SML_t + h\ HML_t + m\ MKTPREM_t + e_t$

Decile	a[a]	t-stat.	s	t-stat.	h	t-stat.	m	t-stat.	R^2
1	−2.42%	−9.091	0.4323	8.715	0.2933	3.651	1.2488	20.206	0.7414
2	−1.59%	−8.078	0.3587	9.730	0.1674	2.804	1.2219	26.601	0.8355
3	−0.87%	−5.094	0.3128	9.798	0.1368	2.646	1.1669	29.340	0.8604
4	−0.42%	−2.937	0.2845	10.722	0.1102	2.563	1.1692	35.362	0.8997
5	−0.22%	−1.559	0.2478	9.540	0.1029	2.446	1.1171	34.522	0.8945
6	0.07%	0.564	0.2305	10.671	0.0997	2.851	1.1191	41.584	0.9245
7	0.32%	2.502	0.2287	9.628	0.0838	2.178	1.1168	37.731	0.9105
8	0.47%	3.871	0.2292	10.064	−0.0384	−1.041	1.0623	37.430	0.9160
9	0.79%	6.058	0.2010	8.290	−0.0652	−1.660	1.0259	33.955	0.9009
10	1.14%	6.314	0.1891	5.605	−0.1795	−3.286	0.9802	23.319	0.8251

In the regression, the factors are defined as follows:

MKTPREM = monthly excess return to the cap-weighted Russell 3000 stock index (using the monthly return to 90-day T bills),

SML = Russell 3000 stock population is ranked monthly (in accord with the procedures used to create the decile returns) on the basis of market capitalization; equally weighted quintiles are formed; *SML* is the monthly difference in total return between the smallest and largest quintile,

HML = assuming a six-month reporting lag, the Russell 3000 population is ranked monthly on the basis of the ratio of the most recently reported book value per share to market price per share; equally weighted quintiles are formed; *HML* is the difference in monthly return between the highest and lowest quintile.

The population of the Russell 3000 stock index is ranked and formed into equally weighted deciles on the basis of relative expected monthly returns, computed by summing the products of (a) the factor exposures for each stock to firm characteristics related to risk, liquidity, price level, growth potential, and price history and (b) the average of the factor payoffs over the previous 12 months. Deciles are re-formed monthly. For each of the deciles, the monthly excess return is regressed on the three factors over the period 1979 through 1993. The results of these regressions are presented in the table. For the total period, *HML* had a mean monthly return of 0.479% and a monthly standard deviation of 5.190% and *SML* had a mean of 0.672% and a standard deviation of 3.590%.

[a]Monthly.

deciles are negative and highly significant; the intercepts for the high-expected-return deciles are positive and also highly significant. In fact, when annualized, the differences between the risk-adjusted intercepts are larger than the differences between the raw realized returns of Table 2. This is because risk tends to *decrease* across the deciles even as raw returns *increase*.

Note that the loadings on *SML* for the high-expected-return deciles are smaller, because these deciles are populated by large-cap stocks. The loadings on *HML* are also smaller for these deciles. While the high-return deciles don't usually contain stocks with high book-to-price ratios, they do include stocks with strong growth characteristics (both highly profitable stocks and stocks with rapid trailing growth rates in earnings per share). The high-return deciles also have smaller loadings on *MKTPREM*, reflecting their lower levels of (market-related) risk. Note in Table 3, book-to-price does not become larger in moving from decile 1 to decile 10. However, profitability increases significantly for the upper deciles. This accounts for the smaller loadings on *HML*. We note that if Fama and French believe that value stocks with high loadings on *SML* and *HML* are more risky than average, then presumably they also believe that the high-expected-return stocks found here (with low loadings on *SML* and *HML*) are below-average.

9. Simulating the investment performance of the expected return factor model

There is considerable turnover within the deciles as stocks migrate from one decile to another. Given the costs of trading these stocks, the return differentials actually experienced relative to a buy-and-hold strategy will be considerably less than those shown in Table 2. For a more accurate picture of attainable performance, we use a simulation in which the factor model is employed to import expected returns to a Markowitz-type optimization. In the simulation trading is controlled and transaction costs are accounted for.

To minimize any residual survival bias, we use a Markowitz optimization on the largest 1,000 stocks in the population at the beginning of each quarter from 1979(q1) to 1993(q4). The simulation is based on the Russell 1000 stock index as it existed in the Frank Russell Company's records for the beginning of each quarter. Estimates of portfolio volatility are based on the full covariance matrix of returns to the 1,000 stocks in the previous 24 months. Estimates of expected returns to the 1,000 stocks are based on the factor model discussed earlier. The following constraints are applied to portfolio weights for each quarterly optimization:

(1) The maximum weight in a portfolio that can be assigned to a single stock is limited to 5%. The minimum is zero. (Short-selling is not permitted.)

(2) No more than three times its percentage of the Russell 1000 total market capitalization can be invested in any one stock in the portfolio.
(3) The portfolio industry weight is restricted within 3% of the market capitalization weight of that industry (based on the two-digit SIC code).
(4) Turnover in the portfolio is constrained from 20% to 40% annually, depending on the emphasis on higher expected return.

These constraints are designed to keep the portfolios diversified. Reasonable changes in the constraints do not materially affect the results. We use numerical search procedures to find the lowest volatility portfolio, given expected return. Thus, we do not have to invert the covariance matrix. Given the constraints imposed on the optimization, exact unique solutions to the problems exist.

In each quarterly optimization, three portfolios are constructed. One is designed to have the lowest possible volatility, irrespective of expected rate of return. This is the global minimum-variance portfolio (G), or the portfolio at the nose of the set of constrained, minimum-variance portfolios. The other two portfolios are designed to emphasize return versus risk to different degrees. We call them the intermediate-return portfolio (I) and the high-return portfolio (H). To show the spread in achievable returns within the cross-section of the Russell 1000 population, we also construct a low-return portfolio (L), that can be taken to be the converse of the H portfolio.

In the optimization, we minimize the function, $\sigma^2 - \lambda \mathrm{E}(r)$. For portfolio G, λ takes a value of zero. The coefficient λ is assigned progressively higher values for the I and H portfolios. The value for λ for the L portfolio is the negative of the value used for the H portfolio. For all simulations in both the U.S. and other countries, the values for λ are identical over countries and constant over time for all portfolios. The returns of these four portfolios are then observed, on a buy-and-hold basis, over each quarter following the quarterly optimization. We assume a conservative (for the 1,000 largest U.S. stocks) 2% round-trip transaction cost.

The results appear in Fig. 3. Note that the global minimum-variance portfolio has lower risk and higher return than the cap-weighted Russell 1000 stock index. This result is consistent with the evidence provided in Haugen (1995) and with the results presented in Table 6 of this paper, which show that the average payoff to volatility of return is negative in each of the five largest markets of the world. The I and H portfolios both dominate the cap-weighted Russell 1000 stock index. The H portfolio has an approximately 400 basis points greater return than the index, while achieving the same overall level of volatility.[10] The

[10] We can argue that it is unfair to compare the performance of managed portfolios like G, I, and H with a passive, cap-weighted market index. However, we note that there is turnover in the cap-weighted Russell 1000 resulting from sales and repurchases of stocks by firms, mergers, spin-offs, and bankruptcies. All these activities result in slightly less turnover in the index than we have in our

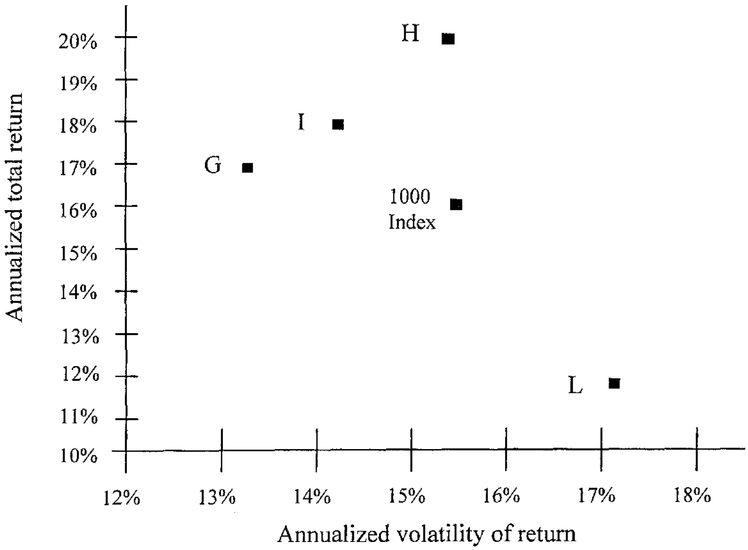

Fig. 3. Optimized portfolios in the Russell 1000 population; 1979–1993.

Monthly sets of contemporary firm characteristics representing risk, liquidity, price level, growth potential, and price history are regressed on the cross-section of realized monthly returns to obtain factor payoffs. The payoffs are then projected for the next month on the basis of their average values over the trailing 12 months. The projections are interfaced with each stock's contemporary characteristics to obtain the estimates of expected returns used in the optimizations. The optimizations are based on the Russell 1000 population as it existed in each quarter. The G (global minimum-variance portfolio), I (intermediate emphasis on return), H (high emphasis on return), and L (high emphasis on low return) portfolios are optimized quarterly, based on expected return projections from the factor model and full covariance, volatility projections based on the trailing 24 monthly rates of return. Following each quarterly optimization, the subsequent quarterly return is observed. The quarterly returns are then linked, and the annualized, realized returns and volatilities are plotted in the diagram. An assumed 2% round-trip transactions cost is subtracted from the returns to G, I, and H portfolios and added to the returns to the L portfolio.

portfolio denoted by an L in the graph is built with the opposite signed λ from the H portfolio. For the L portfolio, transaction costs are added to the returns because investors presumably short-sell this portfolio, in which case the cost of raising the funds is the return of the stocks plus the cost of trading the portfolio. Note that the spread between L and H is nearly 900 basis points. Thus, the return differentials of Table 2 appear to be realizable to an

G portfolio. Moreover, we note that while no transaction costs are charged to the index, we have assumed a 2% round-trip transactions cost for the managed portfolios. We have rerun the optimization with constraints designed the same turnover as the cap-weighted index. These constraints only slightly weaken our results.

Table 5
Risk-adjusted monthly returns on the high- and low-return portfolios
$r_{j,t} - r_{f,t} = a + s\,SML_t + h\,HML_t + m\,MKTPREM_t + e_t$

Portfolio	a	t-stat.	s	t-stat.	h	t-stat.	m	t-stat.	R^2
H	0.0041	3.923	−0.0508	−2.608	−0.0546	−1.728	0.9558	39.35	0.921
L	−0.0060	−5.006	0.0508	2.283	0.2129	5.914	1.111	40.13	0.910

Monthly sets of contemporary firm characteristics representing risk, liquidity, price level, growth potential, and price history are regressed on the cross-section of realized monthly returns to obtain factor payoffs. The payoffs are then projected for the next month on the basis of their average values over the trailing 12 months. The projections are interfaced with each stock's contemporary characteristics to obtain the estimates of expected returns used in the optimization process to construct a high-return portfolio (H) and a low-return portfolio (L). The optimizations are based on the Russell 1000 population as it existed in each quarter. Portfolios are optimized quarterly, based on expected return projections from the factor model and full covariance, volatility projections based on the trailing 24 monthly rates of return. Following each quarterly optimization, the subsequent monthly returns are observed for the next quarter. An assumed 2% round-trip transactions cost is subtracted from the returns to the H portfolio and added to the returns to the L portfolio. The monthly returns on the H and L portfolios are then regressed on a Fama–French three-factor model in order to risk-adjust the returns. In the regression, the factors are defined as follows: $MKTPREM$: monthly excess return to the cap-weighted Russell 3000 stock index (using the monthly return to 90-day T bills). SML: Russell 3000 stock population is ranked monthly (in accord with the procedures used to create the decile returns) on the basis of market capitalization; equally weighted quintiles are formed; SML is the monthly difference in total return between the smallest and largest quintile. HML: Assuming a six-month reporting lag, the Russell 3000 population is ranked monthly on the basis of the ratio of the most recently reported book value per share to market price per share; equally weighted quintiles are formed; HML is the difference in monthly return between the highest and lowest quintile. Deciles are re-formed monthly. The results of these regressions are presented in the table. For the total period, HML had a mean monthly return of 0.479% and a monthly standard deviation of 5.190% and SML had a mean of 0.672% and a standard deviation of 3.590%.

economically meaningful degree, even to an investor who must bear significant trading costs.

As with the deciles, we regress the excess returns on H and L on the market's excess return, SML, and HML over the period 1979 through 1993. The regression yields the results shown in Table 5. Note that H and L have statistically significant positive and negative intercepts, respectively. H loads negatively (but insignificantly) on HML and L loads positively. The annualized, risk-adjusted spread between H and L is approximately 12%.

10. The accuracy of factor models in other countries: A test of the size of the data snooping bias in the U.S. results

Data snooping bias is a very difficult problem. As stated previously, our model holds up over a period (1991–1993) that had not been snooped as of the date of our tests. In this section, we take the same procedure to four other countries.

Tests with the same set of factors discussed above are run for 208 stocks in France, 195 in Germany, 715 in Japan, and 406 in the United Kingdom. Because of limitations in coverage associated with commercially available data files, the tests must be run over the period 1985 through midyear 1994. Our data is taken from Compustat's Global Vantage, and we use their research database, which includes inactive companies. Again, we assume a three-month reporting lag for accounting variables. Global Vantage does not include quarterly accounting numbers, thus the assumed reporting lag can be as long as 15 months. In the tests, payoffs are projected, based on the basis of their trailing average values. We stress that these payoffs are estimated individually across each country. To economize on data, the payoff to all factors set at zero in the first month of 1985. For the second month of 1985 the projected payoffs are assumed to take on the values for January of 1985. Payoffs in subsequent months are then based on the available trailing histories, up to a limit of 12 months. All returns are in local currency. Based on our projections for expected returns, the firms are re-formed into deciles within each country, and we then observe the actual monthly returns for the deciles. The process is repeated for all months of the year, and the monthly decile returns are then linked. The results for each country are shown in Tables 6a–6d. Once again, the factor model proves to be very powerful. Note that in nearly all cases, the slopes that relate realized return to decile ranking are positive, and the coefficients of determination continue to be high.

In all the countries examined, we find that the annualized volatility of return at the bottom of each panel shows no evidence of an increase in risk as we move from decile 1 (low return) to decile 10 (high return).

11. Simulation of investment performance for global markets

The same optimization constraints are employed as for the U.S., except in those cases where a few stocks dominate a country's total market capitalization. In this case, the maximum weight assigned to each stock is the lowest of (a) three times the stock's market capitalization weight, (b) its capitalization weight plus 2%, or (c) 10%.

As in the U.S. simulation, the portfolios are reoptimized quarterly. Portfolio volatility is again estimated on the basis of the full covariance matrix of the 24 monthly returns trailing each quarter. Three similar portfolios (G, I, and H) are again constructed in the optimization process. Following the optimization, we observe and link the subsequent quarter's returns. A 2% round-trip transaction cost is assumed.

The results of the simulations are presented in Fig. 4. Note that in every country, realized returns as well as volatilities increase monotonically as we go

Table 6a
Realized returns to expected return decile portfolios in Japan (715 stocks)

	Dec. 1	Dec. 2	Dec. 3	Dec. 4	Dec. 5	Dec. 6	Dec. 7	Dec. 8	Dec. 9	Dec. 10	Slope	R^2
Return												
1985	3.6%	7.6%	10.3%	16.1%	14.3%	22.5%	24.1%	33.7%	31.3%	50.3%	4.5%	91.0%
1986	48.5%	36.7%	44.3%	39.5%	36.5%	32.1%	29.4%	46.6%	42.5%	25.5%	−1.2%	21.3%
1987	−2.5%	−2.0%	10.0%	8.5%	28.3%	40.5%	43.7%	45.7%	65.8%	56.5%	7.9%	93.9%
1988	24.2%	23.6%	19.2%	37.6%	33.9%	45.2%	54.7%	55.9%	59.3%	82.0%	6.2%	89.4%
1989	39.1%	27.8%	31.6%	33.2%	59.4%	44.4%	43.1%	58.0%	65.6%	69.1%	4.1%	70.7%
1990	−37.0%	−35.5%	−36.3%	−38.2%	−36.4%	−40.0%	−38.3%	−35.5%	−36.4%	−37.1%	0.0%	0.8%
1991	−1.8%	−6.3%	−3.7%	−2.1%	3.5%	4.5%	2.1%	1.7%	8.0%	15.0%	1.8%	74.5%
1992	−24.0%	−30.0%	−24.1%	−25.6%	−24.8%	−25.2%	−25.2%	−21.4%	−18.8%	−10.7%	1.3%	56.3%
1993	−3.6%	1.8%	−0.9%	14.4%	−1.6%	7.4%	11.5%	10.7%	14.9%	22.0%	2.5%	84.7%
1985–93 returns	2%	0%	3%	5%	9%	10%	12%	17%	20%	24%	2.7%	90.2%
Std. dev.	26.0%	23.7%	24.8%	24.7%	24.8%	24.9%	25.8%	25.5%	26.7%	27.6%		

For each of the four countries, an *identical* (*to the* U.S.) set of factors is used to obtain monthly factor payoffs using OLS multiple regression. Each country is modeled individually. Stocks in each of the four countries are ranked and formed into equally weighted deciles on the basis of their expected monthly returns, computed by summing the products of the individual factor exposures to firm characteristics related to risk, liquidity, price level, growth potential and price history with their projected payoffs. For the first month of 1985, the projected payoff for all factors is assumed to be zero. For February of 1985, the payoffs are projected to be those of January of 1985. For March, the payoffs are projected to be the average of January and February, and so on until a history of 12 payoffs is obtained. From this point on, the payoffs are projected as a 12-month moving average. Portfolios are re-formed monthly. After formation, the realized returns to the deciles are linked, and the annual returns are reported in the table. The slopes and coefficients of determinations are obtained by regressing the realized returns on the decile rankings. The volatilities are the annualized standard deviations of the monthly rates of return for each decile. Our sample includes 715 stocks in Japan.

Table 6b
Realized returns to expected return decile portfolios in France (208 stocks)

	Dec. 1	Dec. 2	Dec. 3	Dec. 4	Dec. 5	Dec. 6	Dec. 7	Dec. 8	Dec. 9	Dec. 10	Slope	R^2
Return												
1985	41.9%	50.1%	38.1%	70.4%	66.1%	60.4%	73.6%	46.5%	92.3%	95.3%	5.0%	57.1%
1986	11.7%	47.9%	36.1%	60.5%	72.2%	54.1%	59.0%	78.4%	87.9%	57.4%	5.3%	55.3%
1987	−30.9%	−31.7%	−30.4%	−30.9%	−22.8%	−27.5%	−12.9%	−19.8%	−25.6%	−10.0%	2.0%	61.4%
1988	55.9%	58.8%	97.1%	43.6%	58.1%	56.6%	45.7%	53.9%	68.0%	90.3%	1.0%	2.8%
1989	31.2%	29.5%	50.7%	25.6%	59.1%	36.2%	48.6%	48.3%	48.0%	66.2%	2.9%	43.5%
1990	−42.9%	−30.3%	−30.6%	−26.4%	−18.4%	−24.6%	−23.7%	−14.8%	−18.5%	−9.7%	2.8%	81.2%
1991	23.4%	10.5%	16.7%	27.3%	−0.9%	5.5%	5.6%	18.7%	7.0%	16.9%	−0.8%	7.2%
1992	−28.4%	−9.4%	−1.3%	16.2%	4.8%	4.4%	6.1%	4.4%	5.7%	6.2%	2.5%	39.4%
1993	51.4%	24.4%	45.5%	40.0%	60.2%	46.3%	49.5%	39.2%	45.9%	37.7%	0.1%	0.0%
1985–93												
returns	6%	12%	18%	20%	25%	19%	23%	24%	28%	34%	2.4%	69.7%
Std. dev.	26.4%	21.2%	23.3%	22.1%	22.0%	22.0%	21.8%	23.8%	23.2%	25.1%		

For each of the four countries, an identical (to the U.S.) set of factors is used to obtain monthly factor payoffs using OLS multiple regression. Each country is modeled individually. Stocks in each of the four countries are ranked and formed into equally weighted deciles on the basis of their expected monthly returns, computed by summing the products of the individual factor exposures to firm characteristics related to risk, liquidity, price level, growth potential and price history with their projected payoffs. For the first month of 1985, the projected payoff for all factors is assumed to be zero. For February of 1985, the payoffs are projected to be those of January of 1985. For March, the payoffs are projected to be the average of January and February, and so on until a history of 12 payoffs is obtained. From this point on, the payoffs are projected as a 12-month moving average. Portfolios are re-formed monthly. After formation, the realized returns to the deciles are linked, and the annual returns are reported in the table. The slopes and coefficients of determinations are obtained by regressing the realized returns on the decile rankings. The volatilities are the annualized standard deviations of the monthly rates of return for each decile. Our sample includes 208 stocks in France.

Table 6c
Realized returns to expected return decile portfolios in U.K. (406 stocks)

	Dec. 1	Dec. 2	Dec. 3	Dec. 4	Dec. 5	Dec. 6	Dec. 7	Dec. 8	Dec. 9	Dec. 10	Slope	R^2
Return												
1985	21.2%	17.5%	25.5%	36.3%	41.5%	47.1%	39.2%	38.3%	37.2%	57.1%	3.3%	68.5%
1986	18.9%	24.5%	34.8%	33.1%	38.1%	34.8%	39.5%	46.0%	55.0%	89.8%	5.6%	73.6%
1987	4.2%	4.5%	7.9%	17.0%	32.9%	25.7%	24.9%	23.7%	42.3%	61.0%	5.3%	80.3%
1988	5.8%	9.4%	11.9%	10.3%	15.4%	18.8%	19.9%	20.2%	30.4%	34.2%	2.9%	91.6%
1989	17.7%	18.6%	18.5%	22.3%	27.6%	23.3%	23.4%	28.4%	27.9%	34.5%	1.6%	81.7%
1990	−34.9%	−24.5%	−20.4%	−15.0%	−13.2%	−9.6%	−12.7%	−13.5%	−9.1%	−14.4%	2.0%	61.5%
1991	−7.7%	3.0%	12.0%	19.3%	20.0%	30.4%	32.6%	27.2%	28.0%	22.7%	3.5%	67.0%
1992	−5.6%	−4.5%	1.8%	13.0%	20.2%	15.4%	16.6%	15.7%	24.4%	19.8%	3.1%	76.6%
1993	25.8%	25.3%	37.1%	33.6%	40.7%	34.3%	38.5%	46.6%	53.2%	76.4%	4.3%	74.4%
1985–93												
returns	3%	7%	13%	18%	24%	23%	24%	24%	31%	39%	3.4%	86.0%
Std. dev.	26.9%	21.8%	21.9%	20.0%	19.4%	19.3%	18.4%	19.0%	19.1%	20.2%		

For each of the four countries, an identical (to the U.S.) set of factors is used to obtain monthly factor payoffs using OLS multiple regression. Each country is modeled individually. Stocks in each of the four countries are ranked and formed into equally weighted deciles on the basis of their expected monthly returns, computed by summing the products of the individual factor exposures to firm characteristics related to *risk*, *liquidity*, *price level*, *growth potential* and price history with their projected payoffs. For the first month of 1985, the projected payoff for all factors is assumed to be zero. For February of 1985, the payoffs are projected to be those of January of 1985. For March, the payoffs are projected to be the average of January and February, and so on until a history of 12 payoffs is obtained. From this point on, the payoffs are projected as a 12-month moving average. Portfolios are re-formed monthly. After formation, the realized returns to the deciles are linked, and the annual returns are reported in the table. The slopes and coefficients of determinations are obtained by regressing the realized returns on the decile rankings. The volatilities are the annualized standard deviations of the monthly rates of return for each decile. Our sample includes 406 stocks in the U.K.

Table 6d
Realized returns to expected return decile portfolios in Germany (195 stocks)

	Dec. 1	Dec. 2	Dec. 3	Dec. 4	Dec. 5	Dec. 6	Dec. 7	Dec. 8	Dec. 9	Dec. 10	Slope	R^2
Return												
1985	31.6%	39.6%	67.8%	50.2%	38.6%	39.7%	67.3%	41.4%	60.4%	45.5%	1.2%	7.6%
1986	14.4%	24.4%	24.3%	18.8%	15.3%	33.8%	12.5%	14.0%	8.9%	13.8%	−1.0%	16.6%
1987	−39.6%	−26.5%	−25.4%	−26.4%	−18.0%	−22.4%	−12.9%	−11.3%	−8.9%	−0.5%	3.5%	90.8%
1988	23.0%	29.6%	27.7%	46.3%	45.2%	44.1%	41.0%	33.9%	40.2%	56.5%	2.4%	49.4%
1989	33.6%	60.2%	36.2%	68.8%	53.7%	39.8%	44.6%	58.3%	67.8%	55.0%	1.6%	15.2%
1990	−9.6%	3.1%	1.6%	−3.2%	−3.2%	4.2%	−3.4%	4.9%	0.1%	−1.2%	0.5%	10.5%
1991	2.3%	−1.9%	5.6%	−2.2%	−7.1%	−2.9%	−1.1%	−0.1%	−2.3%	5.3%	0.0%	0.0%
1992	−24.7%	−16.7%	−18.3%	−16.7%	−11.4%	−5.9%	−3.0%	3.4%	−1.7%	7.4%	3.3%	93.3%
1993	32.4%	35.3%	38.5%	35.7%	29.2%	22.3%	39.5%	44.6%	33.4%	47.4%	1.0%	15.7%
1985–93 returns	4%	13%	14%	15%	13%	15%	18%	19%	19%	23%	1.5%	62.3%
Std. dev.	20.4%	18.5%	19.1%	17.7%	17.6%	16.5%	16.3%	15.0%	15.8%	15.7%		

For each of the four countries, an identical (to the U.S.) set of factors is used to obtain monthly factor payoffs using OLS multiple regression. Each country is modeled individually. Stocks in each of the four countries are ranked and formed into equally weighted deciles on the basis of their expected monthly returns, computed by summing the products of the individual factor exposures to firm characteristics related to risk, liquidity, price level, growth potential and price history with their projected payoffs. For the first month of 1985, the projected payoff for all factors is assumed to be zero. For February of 1985, the payoffs are projected to be those of January of 1985. For March, the payoffs are projected to be the average of January and February, and so on until a history of 12 payoffs is obtained. From this point on, the payoffs are projected as a 12-month moving average. Portfolios are re-formed monthly. After formation, the realized returns to the deciles are linked, and the annual returns are reported in the table. The slopes and coefficients of determinations are obtained by regressing the realized returns on the decile rankings. The volatilities are the annualized standard deviations of the monthly rates of return for each decile. Our sample includes 195 stocks in Germany.

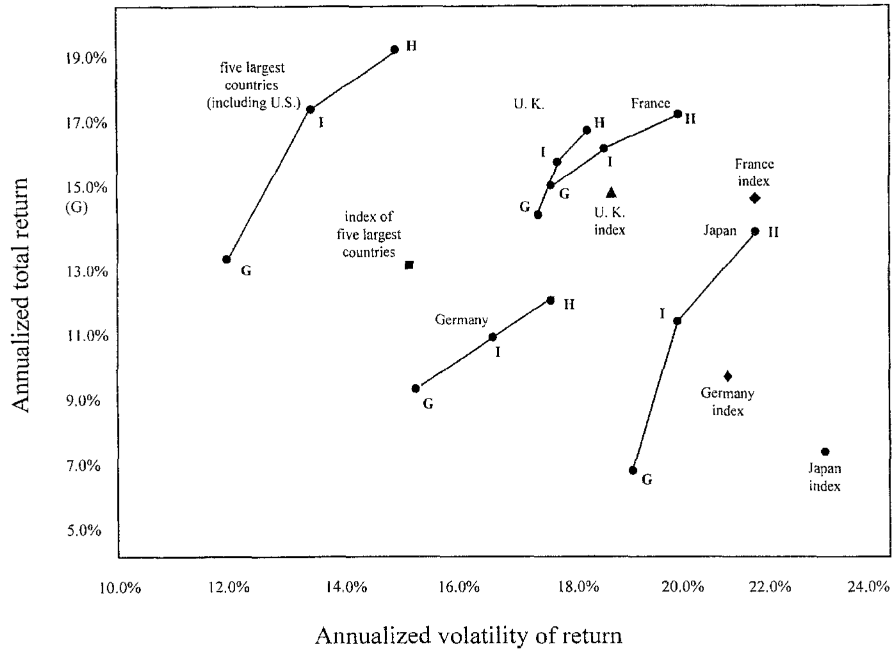

Fig. 4. Optimization in France, Germany, U.K., and Japan, and across the five largest countries; 1985–1993.

In each of the five countries, an identical set of factors is used to obtain monthly factor payoffs using multiple regressions. Our sample includes 208 stocks in France, 195 stocks in Germany, 406 stocks in U.K., 715 stocks in Japan, and the stocks of the Russell 1000. For the first month of 1985, the projected payoff for all factors is assumed to be zero. For February of 1985, the payoffs are projected to be those of January 1985. For March, the payoffs are projected to be the average of January and February, and so on until a history of 12 payoffs is obtained. From this point on, the payoffs are projected as a 12-month moving average. Relative expected returns are the sum of the products of (a) each stock's contemporary factor exposures and (b) the projected payoffs for the month. The country indexes are the Financial Times Actuarial Indexes. The G (global minimum-variance portfolio), I (intermediate emphasis on return), and H (high emphasis on return) portfolios are optimized quarterly, based on expected return projections from the factor model, and full covariance volatility projections based on the trailing 24 monthly rates of return. An assumed 2% round-trip transactions cost is subtracted from the returns to the portfolios. Following these quarterly optimizations, the quarterly returns are linked, and the realized returns and volatilities are plotted in the diagram. Returns are in local currency for each of the four countries. For the collective optimization over all five countries, the returns are denominated in U.S. dollars.

from the global minimum-variance portfolio to the high-return portfolio. In addition, the intermediate- and high-return portfolios dominate the capitalization-weighted FTA equity index for every country.

Fig. 4 also shows the results of a combined optimization across the largest 2000 stocks in the five largest countries (including the U.S.). Returns are denominated in U.S. dollars. Since the factor models project relative expected returns within markets only, the country weightings are constrained to approximate the capitalization weightings of each country. Note that through international diversification, we are able to appreciably lower volatility, while enhancing the spread in realized return, relative to the cap-weighted FTA five-country equity index.

12. Commonality in the primary factors for the five countries

Over the period 1985 through June of 1994, the factor payoffs for the five countries (including the U.S.) are averaged individually by country, and the factors are ranked by the average absolute values of the t-statistics for the means. The mean values and the t-statistics for the 12 highest ranking factors (based on absolute t-scores averaged across the five countries) are reported in Table 7. There is a surprising degree of commonality in the important factors. Note that the signs of the average payoffs are identical in all five countries. We can also report that within the top 15 factors there is only one sign inconsistency. The same basic forces seem to affect expected returns in all five countries. Hotelling-T^2 tests of the joint significance of all the factors except those relating to sector are conducted in each country. The T^2-statistics are 3.57 for France ($p = 0.000$), 3.38 for Germany ($p = 0.000$), 4.77 for Japan ($p = 0.000$), 3.86 for the U.K. ($p = 0.000$), and 9.34 for the U.S. ($p = 0.000$). We also perform Hotelling-T^2 tests on each of the 12 most important factors of Table 7 to determine whether the average payoffs are jointly different from zero. For all of the factors, we are able to reject the hypothesis that they are equal to zero at extremely high levels of probability.

We can argue that commonality in the important factors results from high correlation in factor payoffs. We can also argue that these are simply the ones that were the most important during this particular period. For example, suppose that the true, underlying expected value of the payoff to a particular factor is zero in all countries. Suppose also that the month-to-month payoffs happen to be highly positively correlated. Under these conditions, if the average realized payoff in one country is significantly nonzero, it will tend to be nonzero in other countries, and it will have the same sign. On the other hand, if payoffs are uncorrelated, commonality in realized averages signals nonzero expected values of the same sign.

As it turns out, however, the monthly values of the payoffs are *not* highly correlated. The average absolute correlation coefficient between the payoffs is equal to 0.105 across all five countries and all 12 most important factors. The low values for the correlation coefficients warrant some additional commentary. Some of the factors (for example, the previous month's residual return) need not be correlated, even if the five international stock markets are fully integrated.

Table 7
Mean payoffs and t-statistics in for the twelve most important factors in five countries (1985–93)

	United States		Germany		France		United Kingdom		Japan	
	Mean	t-stat.	Mean	t-stat.	Mean	t-stat.	Mean	t-stat.	Mean	t-stat.
One-month excess return	−0.32%	−10.8	−0.26%	−8.8	−0.33%	−11.3	−0.22%	−7.6	−0.39%	−13.3
Book to price	0.14%	4.7	0.16%	5.3	0.18%	6.1	0.12%	4.2	0.12%	4.2
Twelve-month excess return	0.23%	7.8	0.08%	2.8	0.12%	4.2	0.21%	7.3	0.04%	1.5
Cash flow to price	0.18%	6.2	0.08%	2.7	0.15%	5.1	0.09%	3.1	0.05%	1.7
Earnings to price	0.16%	5.5	0.04%	1.4	0.13%	4.4	0.08%	2.7	0.05%	1.9
Sales to price	0.08%	2.7	0.10%	3.3	0.05%	5.1	0.05%	1.7	0.13%	4.5
Three-month excess return	−0.01%	−0.5	−0.14%	−4.7	−0.08%	−2.6	−0.08%	−2.6	−0.26%	−8.7
Debt to equity	−0.06%	−2.1	−0.06%	−2.1	−0.09%	−3.1	−0.10%	−3.4	−0.01%	−0.4
Variance of total return	−0.06%	−1.9	−0.04%	−1.4	−0.12%	−4.1	−0.01%	−0.5	−0.11%	−3.8
Residual variance	−0.08%	−2.6	−0.04%	−1.3	−0.09%	−3.1	−0.03%	−1.2	0.00%	−0.1
Five-year excess return	−0.01%	−0.4	−0.02%	−0.7	−0.06%	−1.9	−0.06%	−2.1	−0.07%	−2.3
Return on equity	0.11%	3.9	0.01%	0.4	0.10%	3.5	0.04%	1.3	0.05%	1.8

In each month, over the period 1985/01 through 1993/12, the returns to the stocks in each individual country are regressed (using OLS) on an identical set of firm characteristics related to risk, liquidity, price level, growth potential, and price history. Monthly payoffs based on the cross-sectional regression coefficients for all of the factors (except those related to sector) are averaged individually, in each country. Then the factors are ranked on the basis of the absolute value for their (Fama–MacBeth) t-values, averaged over the five countries. The mean payoffs and t-values for the top 12 factors are reported in the table. The coefficients can be interpreted as the change in monthly expected return associated with a one-standard-deviation increase in the factor exposure. Our sample includes 208 stocks in France, 195 stocks in Germany, 406 stocks in the U.K., and 715 stocks in Japan, as well as the stocks of the Russell 1000 index.

Suppose that the negative payoff related to the previous month's residual return is related to price pressure. The size of the payoff to this factor increases in absolute value with the fraction of the returns attributable to price pressure (as opposed to the fraction attributable to permanent changes in equilibrium values) in the previous month. This fraction need not be correlated across countries, even if the various markets are fully integrated. However, we might expect that the payoffs associated with factors relating to price level (such as earnings yield, cash flow yield, and book to price) should be correlated to a significant degree. If there is strong correlation in the level of economic

Table 8
The correlations between the payoffs to the top six factors in Europe

	Germany	France
One-month excess return		
Germany		
France	0.264	
U.K.	0.017	0.143
Book to price		
Germany		
France	0.169	
U.K.	0.141	0.030
Twelve-month excess return		
Germany		
France	0.267	
U.K.	0.096	0.124
Cash flow to price		
Germany		
France	−0.130	
U.K.	−0.038	0.152
Earnings to price		
Germany		
France	0.032	
U.K.	0.112	0.153
Sales to price		
Germany		
France	−0.032	
U.K.	0.057	0.203

In each month, over the period 1985/01 through 1993/12, the returns to the stocks in each individual country are regressed (using OLS) on an identical set of firm characteristics related to risk, liquidity, price level, growth potential, and price history. The correlations reported are between the payoffs for the six highest ranking factors based on the absolute values of their Fama–MacBeth t-scores averaged across the five countries. The reported correlations are those between the monthly payoffs for each factor for each of the three European countries over the period 1985 through 1993. Our sample includes 195 stocks in Germany, 406 stocks in the U.K., and 208 stocks in France.

activity, we can expect correlation in the size of these payoffs, as changes the level of economic activity induce simultaneous deviations in the payoffs from their expected values.

We at least expect this across the three closely linked European countries. In these countries, there could be meaningful linkages between cash flows and payoffs. However, as we see in Table 8, which reports the correlations for the six most important factors, the values for the correlation coefficients for the payoffs in these countries are also quite low.

It is possible that the low values for the correlation coefficients are induced by errors made in estimating the factor payoffs. The covariance between any two estimated payoffs will then be equal to the true covariance between the underlying payoffs plus the covariance among the errors themselves. Given this, our estimate of the true correlation between the payoffs may be biased, with the size of the bias related to the signal-to-noise ratio. However, given the strong consistency and predictive power of the payoffs, it seems unlikely that the variance of the estimation errors is overwhelming.

13. Summary

After minimizing various sources of bias that have been attributed to previous tests of the predictability of stock returns, this paper shows that expected return factor models are surprisingly accurate in forecasting future relative returns to stocks in the five major countries of the world. Optimized portfolios, which use a factor model to estimate expected return, dominate the capitalization-weighted market index for each of the countries, as well as the aggregate cap-weighted index for all five countries.

There is no evidence from differences in firm fundamental characteristics, or in the nature of the distributions of return between our high- and low-return deciles, that the realized return differences are risk-related. Rather, it appears likely that the predictive accuracy can be attributed to bias in market pricing.

There exists a surprising degree of commonality in the factors that are most important in determining the relative expected returns among different stocks. While the signs of the mean values for the monthly payoffs are the same for the 12 most important factors, the correlation between the monthly payoffs is low. This can be attributed to the fact that the nature of investment behavior is common to the various investors of the world.

Our results appear to be consistent with the hypothesis that the markets are populated by investors whose investment behavior results in highly similar determinants of differences in expected return. The most plausible explanation for the predictive power of the factor model seems to be its exploitation of important forms of bias in pricing in the five markets. Finally, it is noteworthy that none of the factors related to sensitivities to macroeconomic variables seem to be important determinants of expected stock returns.

Appendix: Factors used in the analysis

1. Risk factors

- Market beta (trailing 60-month regression of monthly excess returns)
- APT betas (trailing 60-month regressions on T bill returns, percentage changes in industrial production, the rate of inflation, the difference in the returns to long- and short-term government bonds, and the difference in the returns to corporate and government bonds)
- Volatility of total return (trailing 60 months)
- Residual variance (non-market-related risk over trailing 60 months)
- Earnings risk (standard error of year over year earnings per share around time trend)
- Debt to equity (most recently available book value of total debt to book value of common equity)
- Debt to equity trend (five-year trailing time trend in debt to equity)
- Times interest earned (net operating income to total interest charges)
- Times interest earned trend (five-year quarterly time trend in year over year times interest earned)
- Yield variability (five-year trailing volatility in earnings, dividend, and cash flow yield)

2. Liquidity factors

- Market capitalization (current market price times the most recently available number of shares outstanding)
- Market price per share
- Trading volume/market capitalization (trailing 12-month average monthly trading volume to market capitalization)
- Trading volume trend (five-year time trend in monthly trading volume)

3. Factors indicating price level

- Earnings to price (most recently available four quarters, earnings to current market price)
- Earnings to price trend (five-year monthly time trend in earnings to price)
- Book to price (most recently available book value to current market price)
- Book to price trend (five-year monthly time trend in book to price)

- Dividend to price (most recently available four quarters, dividend to current market price)
- Dividend to price trend (five-year monthly time trend in dividend to price)
- Cash flow to price (most recently available ratio of earnings plus depreciation per share to current market price)
- Cash flow to price trend (five-year monthly time trend in cash flow to price)
- Sales to price (most recently available four-quarters, total sales per share to current market price)
- Sales to price trend (five-year monthly time trend in sales to price)

4. Factors indicating growth potential

- Profit margin (net operating income to total sales)
- Profit margin trend (trailing five-year quarterly time trend in year over year profit margin)
- Capital turnover (total sales to total assets)
- Capital turnover trend (trailing five-year quarterly time trend in year over year capital turnover)
- Return on assets (net operating income to total assets)
- Return on assets trend (trailing five-year quarterly time trend in year over year return on assets)
- Return on equity (net income to total book value of total equity capital)
- Return on equity trend (trailing five-year quarterly time trend in year over year return on equity)
- Earnings growth (trailing five-year quarterly time trend in year over year earnings per share divided by the trailing five-year average earnings per share)

5. Technical factors

- Excess return (relative to the S&P 500) in previous one month
- Excess return (relative to the S&P 500) in previous two months
- Excess return (relative to the S&P 500) in previous three months
- Excess return (relative to the S&P 500) in previous six months
- Excess return (relative to the S&P 500) in previous 12 months
- Excess return (relative to the S&P 500) in previous 24 months
- Excess return (relative to the S&P 500) in previous 60 months

6. Sector variables

- Zero/one dummy variables reflecting firm's principal line of business (durables, nondurables, utilities, energy, construction, business equipment, manufacturing, transportation, financial, and business services)

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