Commonality In The Determinants Of Expected Stock Returns*

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Commonality in the Determinants of Expected Stock Returns

-- Abstract --

Evidence is presented 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. The determinants are related to risk, liquidity, price-level, growth potential, and stock price history. Out-of-sample predictions of expected return, using moving average values for the payoffs to these firm characteristics, are strongly and consistently accurate. Two findings, however, distinguish this paper from others in the contemporary literature. First, the stocks with higher expected and realized rates of return are *unambiguously* of lower risk than the stocks with lower returns. Second, we find that the important determinants of expected stock returns are strikingly common to the major equity markets of the world. Given the nature of the tests, it is highly unlikely that these results may be attributed to bias or data snooping. Consequently, the results seem to reveal a major failure in the Efficient Markets Hypothesis.

Commonality In The Determinants Of Expected Stock Returns

Evidence is mounting that relative stock returns can be predictable with factors that are inconsistent with the accepted paradigms of Modern Finance. DeBondt and Thaler (1985), Jegadeesh and Titman (1993), Chopra, Lakonishok and Ritter (1992), and Jegadeesh (1990) show that the return history of a stock contains useful information 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; three interpretations have been offered to explain the results.

Some believe that the evidence 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 (1988) and Lo and MacKinlay (1990) suggest that the results can be the result of snooping the data in some fashion prior to testing.

Others take the view that, while success in prediction may be exaggerated to some degree by the influence of various biases, the fundamental nature of the results still stands, and it deserves the close attention of the field. 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 pricing by the market.

Those in the first group believe that the differentials in expected stock returns are expected and required by investors. (See Fama and French, 1992 and 1993 and Ball, Kothari, and Shanken 1995.) They believe 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, they claim that they may be consistent with other, multi-factor models. Thus, while this group believes that the new results can lead to a rejection of the CAPM, in their view the efficient markets theory remains intact.

The second group, on the other hand, believes that the differentials in predicted returns come as a surprise to investors. (See Chopra, Lakonishok and Ritter (1992), Lakonishok, Shleifer, and Vishny (1994), and Haugen (1995)) The differential returns are said to derive from market over or under reactions 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, the 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. Interestingly, 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 across different markets.

In the next section we identify the sources of bias that can distort the results of studies of predictive power in stock markets. Following this discussion, we move to a discussion of the nature of the firm characteristics (factors) used to predict return. We then discuss our methodology, and finally we present our results.

1. Sources of bias in predicting stock returns

As discussed above, some have argued that reports of success in predicting relative stock returns are flawed by several sources of bias. Our objective is to design a test, where the effects of the problems discussed below are minimized to so that we are confident that our results are real.

If significant numbers of firms that have become individually inactive are systematically excluded from a data base, the data can be said to suffer from *survival bias*. To illustrate the bias, consider studies of the performance of mutual funds. For simplicity, suppose all mutual funds have identical expected rates of return (equal to that of the market index), but they have different variability in return. Assume also that, if performance falls below some threshold, a fund becomes inactive. Then the probability of reaching that threshold will increase with the risk of the fund. If we observe the performance of only those funds that remain active, we will tend to find that the performance of survivors exceeds the market's. We will also tend to find that performance increases with the level of variability in return. Thus, it will appear that one can predict performance on the basis of fund risk. For studies of portfolios of individual firms, the nature of the bias is less clear because many firms can disappear because of merger as well as failure. In either case, however, it is likely that the overall returns to nonsurvivors will be abnormal. This being the case, if factors used in prediction are somehow related to the probability of going inactive, failure to include inactive firms in the data base will result in misleading estimates of predictive power. Survival bias is exacerbated by the nature of firms that tend to be back filled in commercial data bases. Providers tend to add companies that have significant market positions when the records are back filled. Thus, given two firms of identical size five years prior to the back fill, the larger (and more successful) firm at the time of the back fill is more likely to be added to the data base.

Look ahead bias occurs when data items are used as predictive factors, the values of which were unknown when the predictions are assumed to be 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 reported as of the date of the prediction, the predictive power of the factor will be exaggerated. This is because the set of firms with relatively high (low) earnings yields will include those with unexpectedly high (low) last quarter numbers. Market reactions to these numbers are likely to be positive (negative). Thus, high (low) earnings yields will be associated with high (low) subsequent returns, even though there may be no true predictive information in the number whatsoever.

A phenomenon called *bid-asked bounce* can also instill bias in tests of predictive power in equity markets. Stocks trade at bid or asked prices, and returns are usually measured close-to-close. Suppose that the underlying market value of a stock does not change during a month, t, but that the last trade of the month was at the bid. Assume also that the stock continues to remain constant in price during month t+1. There is roughly an even chance that it will close at the asked price at the end of t-1 or t+1. Thus, assuming no change in the bid-asked 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 may appear to be negatively auto correlated, even when they are not. Thus, the existence of bid-asked bounce can lead a researcher to falsely conclude 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 data base or the results of other studies of a data base, then (b) build predictive models employing promising factors based in the previous results, and then (c) test the power of their models on the same data base. Since most researchers currently employ the same data base of U.S. firms and 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 by attempting to predict over time periods that are new to analysis.

2. 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.[2] In this study we shall employ such a model to predict the first moment (the expected value) of stock returns. Our model will employ a variety of factors similar in number and nature to those employed in second moment factor models.

In more traditional tests of the determinants of the cross-section of expected stock returns, 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

[2] The most commercially successful of these models is the Barra Model.

cross-section. In light of this possibility, our predictions of expected stock returns will be 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) and 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 CAPM and APT betas, that are theoretically appropriate variables for forecasting returns. However, as discussed by Haugen (1995), it is becoming increasingly apparent that these models can have low power. In spite of this, we include the standard market related beta[3] and betas related macro-economic variables. These include monthly percentage changes in industrial production and inflation, the rate of return on 30 day Treasury bills, as well as the differences in return between (a) a 30 year Treasury bond and a 30 day Treasury bill, and (b) the Salomon Brothers composite corporate bond index. and a two security portfolio of Treasury bonds with the same duration. In addition, we shall also 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 payoffs to the risk variables is positive.

Differences in the *liquidity* of stocks are also potentially important. In rebalancing their portfolios, traders must buy at asked prices and sell at bid prices. The bid-asked spread serves as part of the cost of trading. The market impact of a trade is also important. Individual stocks have widely differing degrees of liquidity. To keep the expected rates of return, net of trading costs, commensurate, stocks must have *gross* expected returns that reflect the relative cost of trading (See Stoll and Whaley (1983) and 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 contemporary total market capitalization. Overall, an investor should expect the payoffs to the various factors that represent differentials in liquidity to be negative, 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 about trend in these variables are also included as factors. We include the time trends to differentiate firms that are declining in their profitability, from those that are emerging or recovering. Recent research has shown 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.

Some (Chan and Chen (1991) and Fama and French (1992)) believe that value stocks are "fallen angels" and therefore are more risky. They believe the premium returns to these stocks are

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

expected and required. Given that this is true, factors showing cheapness in price actually belong in the risk category discussed above.

Others (Chopra, Ritter and Lakonishok (1992), Lakonishok, Shleifer and Vishny (1994), and Haugen (1995)), believe that the premium returns to value stocks are unexpected and systematically surprise investors. They believe that investors over react to the past records of success and failure by firms. Proponents of over-reactive markets believe that the forces of competition in a line of business tend to quickly drive profits to normal levels. By projecting prolonged rapid growth, investors in growth stocks can drive prices too high. As the forces of competition come into play faster than these investors believe, they tend to be disappointed by the earnings reports of growth stocks. The future dividends and capital gains on these stocks tend to be smaller than expected and returns tend to be relatively low. The converse tends to be true of value stocks.

Irrespective of whether these payoffs spring from risk or over reaction, they should be positive, with the stocks having the highest current cash flows in relation to market price having the greatest expected rates of return.

Factors related to *growth potential* indicate the probability for faster (or slower) than average future growth in a stock's earnings and dividends. Within the cross-section, relatively profitable firms will tend to grow faster, at least until competitive entry into their lines of business forces profits to normal levels. Based on the assumption that firms that are currently relatively profitable have greater potential for future growth, we include several measures of profitability as predictive factors. They 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.[4] 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 potential, one would expect the payoffs to the growth potential factors 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 appears to be very short term (one to two months) reversal patterns in returns. If a stock went up significantly in price last month, this seems to signal a reversal for the next month (see Jegadeesh, (1990)). These short term reversal patterns can be caused by price pressure induced by investors actively attempting to buy or sell large amounts of a particular stock quickly. An investor attempting to sell can drive the price of the stock below its fair value. This being the case, the stock can be expected to recover and return to fair value shortly thereafter. As discussed above, it is also possible that short term negative serial correlation can be induced by "bid-asked bounce." Jegadeesh (1992) argues that this bias is likely to be small. He finds that trading strategies that attempt to exploit short term reversals remain successful even when returns for the previous

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

month do not reflect the last day of trading. On the other hand, Ball, Kothari, and Wasley (1995) find that bid-asked problems can be very troublesome in simulations of short term contrarian strategies that seek to exploit short term reversal patterns. Bid-asked 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, with stocks that have done well (poorly) in the previous six to 12 months having 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 under react 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. Failing to recognize this, the market under reacts to the first report and then completes its reaction as the next one or two are reported in the six months that follow (see Jegadeesh and Titman (1993) and 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 over reacts to a *chain* of positive (negative) reports of good (bad) earnings numbers. Believing that the chain will continue into the future for an extended period, investors drive the price up (down) too high (low). Consistent with the discussion above, as competitive forces come into play, the stocks that went 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 and over reaction (see, for example, Chen, (1991)). They believe, instead, that risk premiums on stocks are time varying. Risk premiums in expected returns become larger and smaller as the risk of stocks becomes larger or smaller, or as investors' sensitivity to risk grows or declines. Both the levels of risk and risk aversion can change with the business cycle. As we move into a recession, the risk of common stocks can increase; we also become poorer so our aversion to taking on risk 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 roughly 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 will expect the payoffs to be (a) negative, (b) positive, and (c) negative with respect to a stock's performance in the past (a) one to two months (b) six to 12 months, and (c) two to five years respectively. A comprehensive list of all the factors used in the model is provided in the Appendix to the paper.

3. Estimating and projecting factor payoffs

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

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

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,[5]

$u_{j,t}$ = unexplained component of return for stock j in month t.

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

One can use the information embodied in the payoff histories to make out-of-sample projections of the sizes of the future payoffs in future periods. The experiments reported in this paper for U.S. stocks employ simple averages of the payoffs observed in the 12 months prior to the month in which expected return is to be estimated.[6] Expected return for month t is then projected as:

$$E(r_{j,t}) = \sum_i E(P_{i,t}) * F_{j,i,t-1} \qquad (2)$$

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, models similar to the one employed here are used by practicing portfolio analysts to predict statistics related to the second moment of the return distribution for equity portfolios for decades. These risk models interface 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).

4. Results of the monthly regressions

[5] 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.

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

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,[7] the sample includes all stocks that were actually represented in the index, as it existed, from 1979 through 1993.[8] In addition, if a particular stock's record is incomplete, so that the set of data required to compute its exposure to a particular factor is unavailable in a given month, the stock 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 the forecasts are to be made. It is our opinion that filling the missing records with population average exposure numbers instills less of a bias than removing the stock from the population. We have run the tests both ways, however, with little difference in the results.

We estimate the payoffs in all months from 1979 through 1993. We employ factors related to (a) risk, (b) liquidity, (c) price-level, (d) growth potential, and (e) 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 set of data files that were actually 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.

Over the period 1979 through 1993, 180 multiple regressions are run to explain the differential monthly return to the individual stocks in the Russell 3000 population. The time series of multiple, adjusted coefficients of determination for these regressions is presented in figure 1. In interpreting the numbers, the reader should keep in mind that we are attempting to explain the monthly differentials in the returns to individual securities and not well diversified portfolios. In any given month, the great majority of the return differentials are caused by the receipt of unexpected information, causing relative realized returns to deviate from expectations.

Across the 90 regressions for the first half of the overall period, the regression coefficients, or payoffs, associated with the various factors, are averaged. 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. The mean coefficient values and “T” statistics for the second half of the period for the 12 most important factors of the first half are presented in the second panel of table 1. Note that all the factors continue to have consistent signs, and the sizes of the mean payoffs are remarkably similar.

As reported by others, we find evidence of short term reversal patterns and intermediate term inertia patterns in the technical history. We also find that the payoffs to the variables showing cheapness in price (the ratios of book, earnings and cash flow to price) all payoff positively and are 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

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

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

appears to be important, with stocks characterized by high and growing levels of trading volume selling at prices to produce lower levels of expected return. Since, to invest in these stocks, you must buy now and then sell in the future, the signs for the coefficients related to the current level of trading volume and its trend are as expected.

Interestingly, 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 be of 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 payoff to market beta, volatility of total return and residual variance is .01%, .03%, and .15% respectively.

Comparing the two periods, we see 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 the majority 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=.000). Thus, we conclude that the payoffs are jointly nonzero at an extremely high level of confidence.

5. 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 in 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 on the relative expected returns, and we form the stocks into ten equally weighted deciles, with decile one containing the stocks with the lowest expected rates of return.

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

The results are shown in table 2. Over the entire period, the spread between decile ten and decile one 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; they 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 one to decile ten, the realized return tends to become larger, and the spreads are surprisingly large.[9]

To test for the potential effect of the "bid-asked bounce," we reran the tests, where we attempted to predict returns in month t+2 on the basis of information available at t. The effect of separating the forecasts from the exposures by a month is to slightly reduce the overall slope of table 2, while slightly increasing 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-asked 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 simultaneously employs a variety of predictive variables, rather a than one or two at a time. Second, and importantly, the deciles of table 2 are reformed monthly rather than annually as in other studies. 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 market behaviors reported previously by others, we ran the tests excluding all but selected factors. First, we replicated 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 cheapness in price are the primary drivers, we reran 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 with 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.[10]

In interpreting the table 2, it is important to realize that each stock has a *term structure* of expected return, with some components of expected return more persistent than others. For example, the exposures of a particular stock to factors relating to recent stock performance can be expected to 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

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[9] Ball, Kothari, and Shanken (1995) argue that the results of tests of the relative performance of winners and losers 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 re-run the analysis, initiating it separately in each of the 12 months of the year. The results are not significantly related to the starting month.

[10] Our results appear to have an interesting sensitivity 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 is extended from 24 to 60 months might be consistent with the presence of time-varying components in the expected values of the payoffs.

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 have done 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 3.0% with an R^2 of 91.7%.

At the bottom of table 2 we report the annualized volatilities of the monthly rates of return to the deciles. Note that volatility tends to decrease as we move from decile one to decile ten. This provides us with initial evidence that investors might not regard the stocks in decile ten as being highly risky. Figure 2 plots the frequency distributions of monthly returns for deciles one and ten. Once again, there is nothing apparently alarming in the nature of the distribution of returns for decile ten relative to decile one that might induce investors to expect and require a large differential in expected return. Of course it is possible that the returns to the deciles have highly differing sensitivities to macroeconomic variables that are of great concern to portfolio investors. 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 of data snooping on tests of the predictive accuracy of stock forecasting models. When this particular test was conducted, the authors were unaware of any results extending past 1990. Thus, the post 1990 period was not "premined". Nevertheless, the results for the period 1991 to 1993 do not differ materially from the preceding periods. We will more fully address the data snooping issue later, when we take the model to other, international markets.

6. 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 taken over the 1979 to 1993 period. The results are rather striking. As we move from decile one (low return) to decile ten (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 considered (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 ten. Decile ten 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-asked problems, we provide some additional results related to the distributions of price and size within the deciles. The median values for price for Deciles one and ten are \$12.21 and \$26.94 respectively. The median values for market capitalization are \$167.85M and \$439.66M respectively. We also computed the mean value for the highest and lowest 10% of the stocks within each decile. For price, in decile one, the values are \$36.81 and \$3.35. For price in decile ten the values are \$65.53 and \$11.33. For size in decile one, the values are \$1,925.25M and \$34.26M. For size in decile ten, the values are \$3,793.51M and \$69.30M. Thus, there doesn't appear to be anything unusual about the distributions for either price or market capitalization. Decile ten stocks have also exhibited good relative performance during the past year. It is interesting to 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. It is also interesting to 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 tend to 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 tend to be 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 seems extremely difficult to make a case for the notion that the stocks of decile ten, with relatively high expected returns, are distressed companies that are perceived to be more risky relative to the stocks of decile one. *Indeed, the very opposite is almost certainly true.* It would also be difficult to make a case for the notion that the relatively high returns of decile ten stocks are an artifact of survivorship bias, given the fact that (a) our coverage of the Russell 3000 populations is very high and (b) that the attrition rate for the type of stocks that populate decile ten is likely to be very low.

In spite of the rather impressive fundamental characteristics of the high expected return stocks, table 3 shows that they tend to sell at inexpensive prices relative to their earnings, cash flow, and dividends-per-share. This result seems counter intuitive in the context of an 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 type of stocks that resemble those that collectively appear to populate decile ten. These are called GARP stocks (Growth At a Reasonable Price). Actually, the stocks of decile ten might be better named GAIP stocks (Growth At an Inexpensive Price), in light of their relatively high earnings, cash flow, and dividend yields.

It is important to note that, while of decile ten stocks collectively have the characteristics reported in table 3, individual members of the decile do not have the complete profile. Individually, by construction, their expected returns will always be relatively high, but they will be high 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, desired characteristics, they should have a difficult time screening into the type of stocks that populate our decile ten. Indeed, if you were to screen, requiring each to have decile ten characteristics, you might well find an empty set, with no stocks at once exhibiting, low risk, high liquidity, low price-level, and high profitability.

7. Risk-adjusting the realized returns

Fama and French (1993) claim that they can explain the cross-section of expected stock returns on the basis of the loadings of stocks with respect to three factors: (a) the excess return to the capweighted market index, (b) the difference between the rates of return to small stocks 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 on the three factors, they 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 shall employ a similar three factor model. In our model the factors are defined as follows:

MKTPREM: The monthly excess return to the capweighted Russell 3000 stock index (using the monthly return to 90 day Treasury bills).

SML: The 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 return between the smallest and largest quintile.

HML: Assuming a six month reporting lag, the Russell 3000 stock 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.

For each of the deciles of table 2, the monthly excess return is regressed on the three factors over the period 1979 through 1993. The results of these regressions are presented in table 4. Note that the intercepts for the low expected return 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*.

The patterns in the factor loadings are also interesting. 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 there is no tendency for the high return deciles to contain stocks with high ratios of book-to-price, they do contain stocks with strong growth characteristics (stocks that are highly profitable and stocks with rapid trailing rates of growth 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 that there is no tendency for book to price to become larger in moving from decile one to decile ten. However, profitability tends to increase significantly for the upper deciles. This accounts for the smaller loadings on HML. We note that if Fama and French believe that value stocks, that have high loadings on SML and HML are more risky than average, then, presumably, they must also believe that the high expected return stocks found here (with low loadings on SML and HML) are below average in their risk.

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

There is considerable turnover of names within these 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 depicted in table 2. To get a more accurate picture of attainable performance, we now move to 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 employ a Markowitz optimization on the largest 1000 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 at the beginning of each quarter. Estimates of portfolio volatility are based on the full covariance matrix of returns to the 1000 stocks in the previous 24 months. Estimates of expected returns to the 1000 stocks are based on the factor model discussed above. 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 0% (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 to be 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 in the optimization toward higher expected return.

These constraints are designed to merely keep the portfolios diversified. Reasonable changes in the constraints do not affect the results materially. Numerical search procedures are used 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 vs. risk to different degrees. We shall 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, $\sigma^2 - \lambda E(r)$. 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 in 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. A conservative (for the 1 thousand largest U.S. stocks) 2% round trip transactions cost is assumed.

The results are shown in figure 3. Note that the global minimum variance portfolio has both lower risk and higher return than the capweighted Russell 1000 stock index. This result is consistent with the evidence provided in Haugen (1995), as well as with the results, presented in table 6 of this paper, showing 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 also both dominate the capweighted Russell 1000 stock index. The H portfolio has approximately four hundred basis points greater return than the index, while achieving the same overall level of volatility.[11] The portfolio denoted by an L in the graph is built with the opposite signed λ from the H portfolio. In the case of the L portfolio, transactions costs are added to the returns because investors would presumably be short selling this portfolio in which case the cost of raising the funds would be the returns of the stocks plus the costs of trading the portfolio. Note that the spread between L and H is nearly nine hundred basis points. Thus, the return differentials of table 2 appear to be realizable to an 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 following results:

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

Portfolio	**a**	**T-stat**	**s**	**T-stat**	**h**	**T-stat**	**m**	**T-stat**	**R^2**
H	.0041	3.923	-.0508	-2.608	-.0546	-1.728	.9558	39.35	.921
L	-.0060	-5.006	.0508	2.283	.2129	5.914	1.111	40.13	.910

Note that H and L have statistically significant positive and negative intercepts respectively, with H loading negatively (but insignificantly) on HML and L loading positively. The annualized, risk adjusted spread between H and L is approximately 12%.

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

Bias associated with data snooping is a very difficult problem. As stated previously, we gain some comfort in the fact that the model holds up over a period (1991 through 1993) that had not

[11] Some can argue that it is unfair to compare the performance of managed portfolios like G, I and H with a passive, capweighted market index. However, it should be noted that there is turnover in the capitalization-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 "G" portfolio. Moreover, we gain added comfort by noting that while no transactions costs are charged to the index, we have assumed a 2% round-trip transactions cost for the managed portfolios. We have re-run the optimization with constraints designed to give the same turnover as the cap-weighted index. These constraints only slightly weaken our results.

been snooped as of the date of our tests. In this section we shall attempt to gain additional comfort by taking the same procedure to four other countries.

Tests with the same set of factors discussed above are run over a total of 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 employ their research data base, that includes inactive companies. A reporting lag for accounting variables of three months is again assumed. Global Vantage does not include quarterly accounting numbers, so that 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 is presumed to be zero in the first month of 1985; in 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 the projected expected returns, the firms are again formed into deciles within each country, and the actual monthly returns for the deciles are then observed. 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 the four panels of table 5. Once again, the factor model proves to be very powerful. Note that in nearly all cases, the slopes, relating realized return to decile ranking, are positive and the coefficients of determination continue to be high.

As in the U.S., an examination of the annualized volatility of return at the bottom of each panel shows no evidence of an increase in risk as we move from decile one (low return) to decile ten (high return) in any of the countries examined.

10. Simulation of investment performance for global markets

The same optimization constraints are employed as in 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 portfolios are again constructed in the optimization process: the global minimum variance portfolio (G), an intermediate return portfolio (I), and a high return portfolio (H). Following the optimization, the subsequent quarter’s returns are observed and linked. A 2% round trip transaction cost is assumed.

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

Also in figure 4, we show the results of a combined optimization across the largest two thousand stocks in the five largest countries (including the U.S.), where returns are denominated in U.S. dollars. Since the factor models project relative expected returns within markets only, the country weightings were constrained to approximate the capitalization weightings of each country. Note that, through international diversification, one is able to appreciably lower volatility, while enhancing the spread in realized return, relative to the capitalization weighted FTA five country equity index.

11. 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 6. There is a surprising degree of commonality in the important factors. Note that the signs of the average payoffs are identical in all of the countries. We can also report that, within the top 15 factors, there is but one sign inconsistency. The same basic forces seem to be affecting 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 ($p = .000$), 3.38 for Germany ($p = .000$), 4.77 for Japan ($p = .000$), 3.86 for the U.K. ($p = .000$), and 9.34 for the U.S. ($p = .000$). Hotelling-T^2 tests are also performed on each of the 12 most important factors of table 6 to determine whether the average payoffs were 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.

Some can argue that commonality in the important factors results from high correlation in factor payoffs. It may be argued 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 payoffs 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 with 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 across the five countries and the 12 most important factors, is equal to 0.105. The low values for the correlation coefficients deserve 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. 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 would increase, 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, some 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 activity, we would 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 would at least expect this across the three closely linked European countries. In these countries there may be meaningful linkages between cash flows and payoffs. However, as we see in table 7, 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, of course, 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, then will be equal to the true covariance between the underlying payoffs plus the covariance between the errors themselves. Given this, our estimate of the true correlation between the payoffs must be downward biased, with the size of the bias related to the signal-to-noise ratio. However, that, given the strong consistency and predictive power of the payoffs, it seems unlikely that the variance of the estimation errors is overwhelming.

12. 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, employing a factor model to estimate expected return, dominate the capitalization weighted market index for each of the countries, as well as the aggregate capweighted 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 more likely that the predictive accuracy can be attributed, instead, to bias in market pricing.

Interestingly, there exists a surprising degree of commonality in the factors that are most important in determining the relative expected returns between different stocks. While the signs of the mean values for the monthly payoffs are all the same for the twelve most important factors, the correlation between the monthly payoffs is quite 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 who exhibit forms of investment behavior that result 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, of the factors related to sensitivities to macro economic variables, none appear to be as relatively 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 about 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 (5-year quarterly time trend in year over year times interest earned)
- Yield Variability (5-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 4-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 4-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 4-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 5-year quarterly time trend in year over year profit margin)
- Capital Turnover (total sales to total assets)
- Capital turnover Trend (trailing 5-year quarterly time trend in year over year capital turnover)
- Return on Assets (net operating income to total assets)
- Return on Assets Trend (trailing 5-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 5-year quarterly time trend in year over year return on equity)
- Earnings Growth (trailing 5-year quarterly time trend in year over year earnings per share divided by the training 5-year average earnings per share)

5. Technical factors

- Excess Return (relative to the S&P 500) in Previous 1 Month
- Excess Return (relative to the S&P 500) in Previous 2 Months
- Excess Return (relative to the S&P 500) in Previous 3 Months
- Excess Return (relative to the S&P 500) in Previous 6 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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Table 1

The mean and “T” statistics for the most important factors of 1979/01 through 1986/06

Factor	1979/01 through 1986/06		1986/07 through 1993/12	
	Mean	“T”-stat	Mean	“T” stat
One month excess return	-.97%	-17.04	-.72%	-11.04
Twelve months excess return	.52%	7.09	.52%	7.09
Trading volume/market cap	-.35%	-5.28	-.20%	-2.33
Two months excess return	-.20%	-4.97	-.11%	-2.37
Earnings to price	.27%	4.56	.26%	4.42
Return on equity	.24%	4.34	.13%	2.06
Book to price	.35%	3.90	.39%	6.72
Trading volume trend	-.10%	-3.17	-.09%	-2.58
Six months excess return	.24%	3.01	.19%	2.55
Cash flow to price	.13%	2.64	.26%	4.42
Variability in cash flow to price	-.11%	-2.55	-.15%	-3.38

In each month, over the period 1979/1 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 then 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 may 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.

Table 2
U. S. Realized annualized returns across deciles
formed by ranking on expected return

Deciles	1	2	3	4	5	6	7	8	9	10	Slope	R-squared
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%	.446
1980	17.4%	26.2%	25.4%	27.2%	25.8%	41.3%	42.6%	45.3%	55.6%	68.4%	5.0%	.897
1981	-15.6%	-14.2%	-7.9%	-4.6%	2.1%	5.6%	0.4%	6.3%	9.7%	16.2%	3.3%	.931
1982	3.2%	15.5%	21.8%	24.6%	24.0%	25.9%	32.1%	34.6%	39.5%	49.7%	4.1%	.929
1983	11.8%	18.0%	23.4%	29.5%	28.8%	39.3%	37.8%	46.1%	45.1%	54.5%	4.4%	.962
1984	-30.9%	-20.7%	-13.4%	-9.1%	-6.5%	1.0%	2.8%	12.8%	15.4%	22.4%	5.5%	.986
1985	4.3%	18.4%	26.6%	37.8%	34.9%	37.8%	34.9%	41.2%	43.4%	45.7%	3.7%	.776
1986	-15.2%	-7.1%	1.9%	9.2%	12.1%	15.1%	19.9%	23.2%	23.0%	30.9%	4.7%	.925
1987	-23.8%	-12.3%	-5.0%	-6.8%	0.0%	1.6%	-3.4%	-2.0%	1.2%	-5.1%	1.8%	.486
1988	1.5%	10.4%	18.5%	24.0%	22.2%	28.8%	26.9%	25.9%	29.7%	27.0%	2.5%	.714
1989	-3.0%	8.2%	9.7%	16.8%	18.7%	21.5%	28.5%	29.8%	32.4%	28.7%	3.6%	.893
1990	-46.9%	-36.2%	-27.5%	-21.7%	-15.5%	-12.7%	-10.2%	-9.9%	-2.9%	1.3%	4.8%	.937
1991	23.9%	29.3%	36.5%	42.0%	45.2%	45.7%	51.1%	46.6%	46.9%	57.4%	3.1%	.817
1992	2.5%	7.5%	16.3%	20.3%	17.8%	15.7%	17.1%	18.9%	21.1%	24.5%	1.8%	.619
1993	6.4%	9.2%	18.2%	18.5%	19.9%	20.1%	20.0%	20.7%	24.2%	22.2%	1.6%	.738
Average returns												
1979-1993	-4.5%	3.7%	10.3%	15.1%	16.5%	22.3%	21.6%	24.0%	27.1%	30.9%	3.5%	.932
Annualized risk												
1979-1993	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.

Table 3

The values for selected average firm characteristics by decile

	Decile	1 (low expected return)	2	3	4	5	6	7	8	9	10 (high expected return)
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	.95	.89	.87	.85	.83	.83	.82	.85	.85
	debt to equity growth	.27%	.12%	.08%	.05%	.05%	.06%	.05%	.02%	.04%	-.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	-.64%	-.31%	-.19%	-.10%	-.12%	-.11%	-.09%	-.05%	-.05%	-.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	.81	.77	.74	.73	.74	.74	.74	.74	.76	.80
Growth Potential	asset turnover	84%	98%	106%	112%	115%	116%	118%	119%	118%	115%
	asset turnover growth	-.13%	-.11%	-.09%	-.08%	-.08%	-.07%	-.05%	-.03%	-.01%	.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	-.95%	-.46%	-.27%	-.16%	-.10%	-.06%	-.02%	.03%	.04%	.07%
	return on assets	-1.51%	2.26%	3.98%	4.92%	5.36%	5.66%	5.94%	6.10%	6.24%	6.50%
	return on assets growth	-1.11%	-.62%	-.40%	-.28%	-.20%	-.15%	-.09%	-.03%	.01%	.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%	-.68%	-.45%	-.32%	-.23%	-.16%	-.10%	-.03%	.02%	.07%
	earnings growth	-.41%	.28%	.53%	.67%	.75%	.79%	.83%	.87%	.91%	.95%
Technical (excess returns)	one month	.09%	-.27%	-.12%	-.08%	.03%	.07%	.14%	.18%	.09%	-.14%
	two months	-1.80%	-1.03%	-.70%	-.55%	-.32%	-.14%	.03%	.30%	.58%	1.21%
	three months	-6.89%	-2.93%	-.49%	1.11%	2.37%	3.52%	4.53%	5.63%	6.83%	8.83%
	six months	-12.14%	-4.39%	-.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 3000 stocks of the Russell 3000 stock index are ranked and formed into equally weighted deciles on the basis of their 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 reformed 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 5-year time trends divided by the 5-year average values for each number. Prior to 1988 a 3-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.

Table 4

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

$$r_{j,t} - r_{f,t} = a + sSML_t + hHML_t + mMKTPREM_t + e_t$$

Decile	a(monthly)	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	-.87%	-5.094	0.3128	9.798	0.1368	2.646	1.1669	29.340	0.8604
4	-.42%	-2.937	0.2845	10.722	0.1102	2.563	1.1692	35.362	0.8997
5	-.22%	-1.559	0.2478	9.540	0.1029	2.446	1.1171	34.522	0.8945
6	.07%	0.564	0.2305	10.671	0.0997	2.851	1.1191	41.584	0.9245
7	.32%	2.502	0.2287	9.628	0.0838	2.178	1.1168	37.731	0.9105
8	.47%	3.871	0.2292	10.064	-0.0384	-1.041	1.0623	37.430	0.9160
9	.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: The monthly excess return to the cap-weighted Russell 3000 stock index (using the monthly return to 90 day Treasury bills).

SML: The 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 6-month reporting lag, the Russell 3000 stock 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 3000 stocks of the Russell 3000 stock index 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 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 reformed 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 .479% and a monthly standard deviation of 5.190%; SML had a mean of .672% and a standard deviation of 3.590%.

Table 5

Realized returns to expected return decile portfolios in four countries

Japan (715 stocks)

Deciles	Low 1	2	3	4	5	6	7	8	9	High 10	Slope	R-squared
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%	4.4%	-1.6%	7.4%	11.5%	10.7%	14.9%	22.0%	2.5%	84.7%
'85 - '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%		

France (208 stocks)

Deciles	Low 1	2	3	4	5	6	7	8	9	High 10	Slope	R-squared
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%
'85 - '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%		

Germany (195 stocks)

Deciles	Low 1	2	3	4	5	6	7	8	9	High 10	Slope	R-squared
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%
'85 - '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%		

Great Britain (406 stocks)

Deciles	Low 1	2	3	4	5	6	7	8	9	High 10	Slope	R-squared
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%
'85 - '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%		

In 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, 195 stocks in Germany, 406 stocks in Great Britain, and 715 stocks in Japan, as well as the stocks of the Russell 1000 index.

Table 6

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 1985/1 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 may be interpreted as the change in monthly expected return associated with a 1 standard deviation increase in the factor exposure. Our sample includes 208 stocks in France, 195 stocks in Germany, 406 stocks in Great Britain, and 715 stocks in Japan, as well as the stocks of the Russell 1000 index.

Table 7

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

One Month Excess Return

	GERMANY	*FRANCE*
GERMANY		
FRANCE	0.264	
GREAT BRITIAN	0.017	0.143

Book to Price

	GERMANY	*FRANCE*
GERMANY		
FRANCE	0.169	
GREAT BRITIAN	0.141	0.030

Twelve Month Excess Return

	GERMANY	*FRANCE*
GERMANY		
FRANCE	0.267	
GREAT BRITIAN	0.096	0.124

Cash Flow to Price

	GERMANY	*FRANCE*
GERMANY		
FRANCE	-0.130	
GREAT BRITIAN	-0.038	0.152

Earnings to Price

	GERMANY	*FRANCE*
GERMANY		
FRANCE	0.032	
GREAT BRITIAN	0.112	0.153

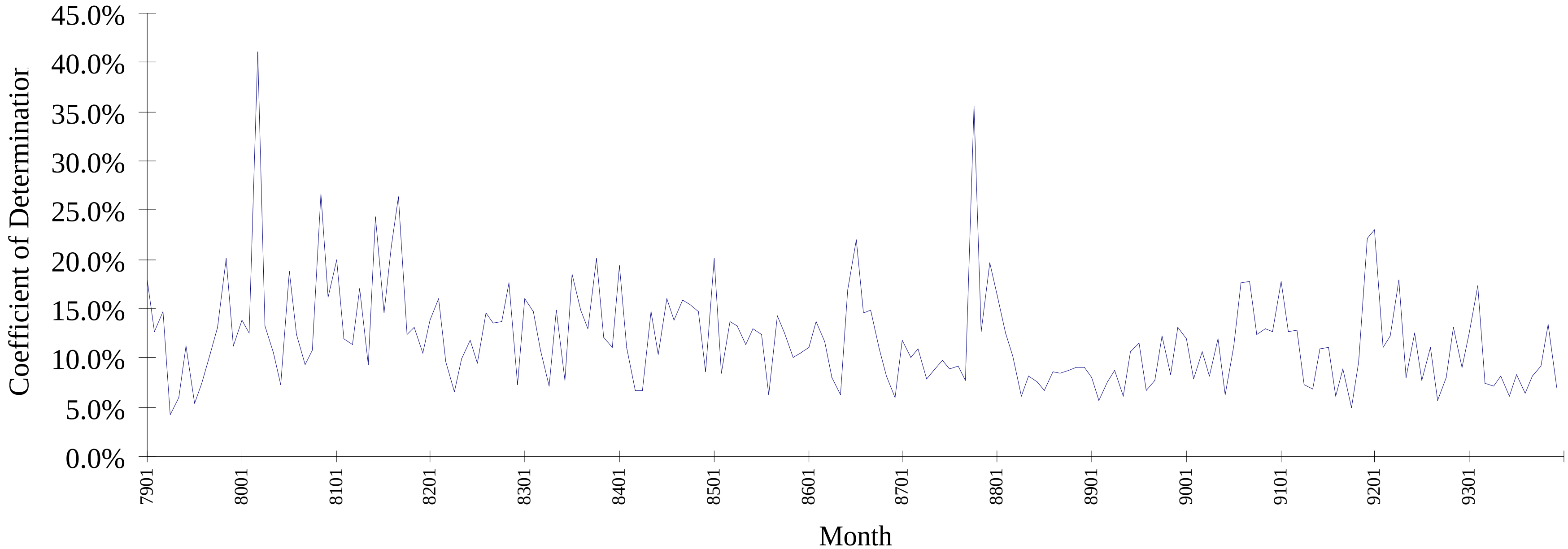
Sales to Price

	GERMANY	*FRANCE*
GERMANY		
FRANCE	-0.032	
GREAT BRITIAN	0.057	0.203

In each month, over the period 1985/1 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 Great Britain, and 208 stocks in France.

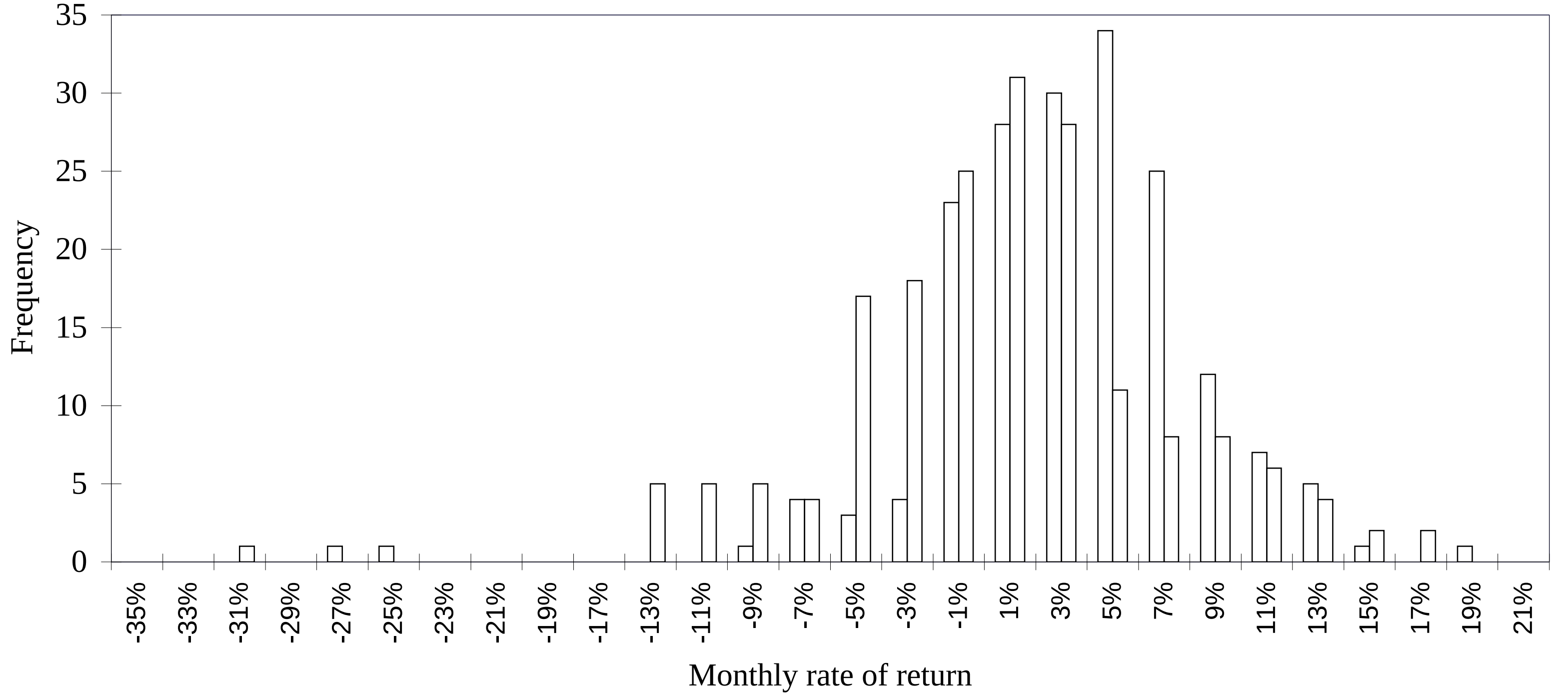
Figure 1

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



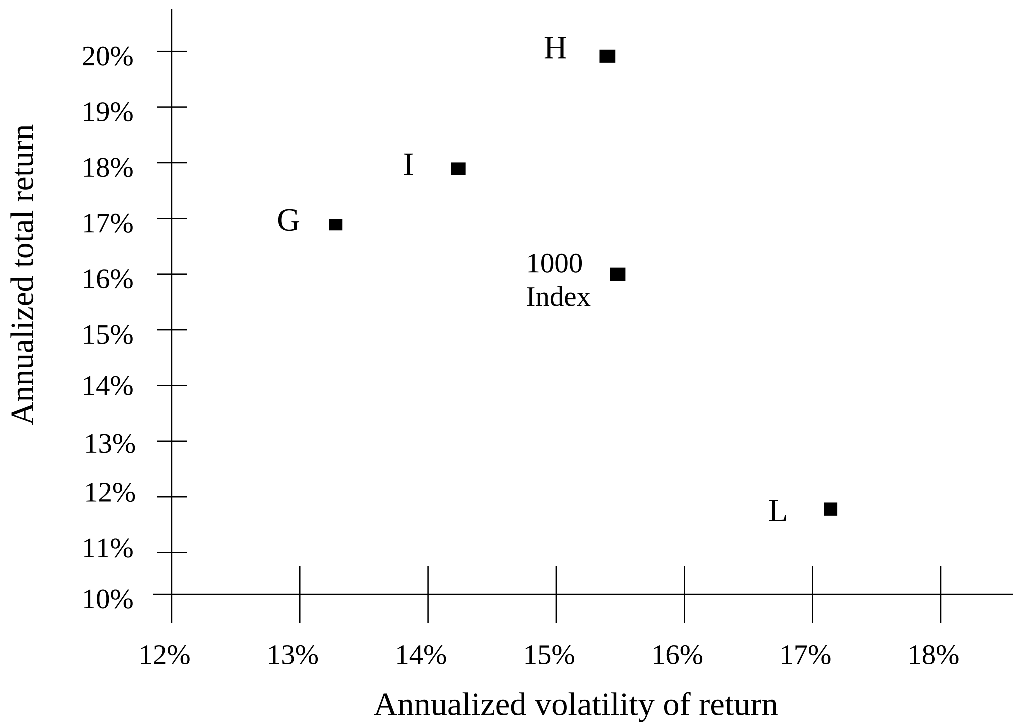
In each month, over the period 1979 through 1993, the cross section of returns to the stocks in the Russell 3000 Stock Index are regressed (using OLS) on the cross section of various firm characteristics related to risk, liquidity, price-level, growth potential, and price history. The time-series of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

Figure 2
Frequency distribution of monthly return for deciles one and ten



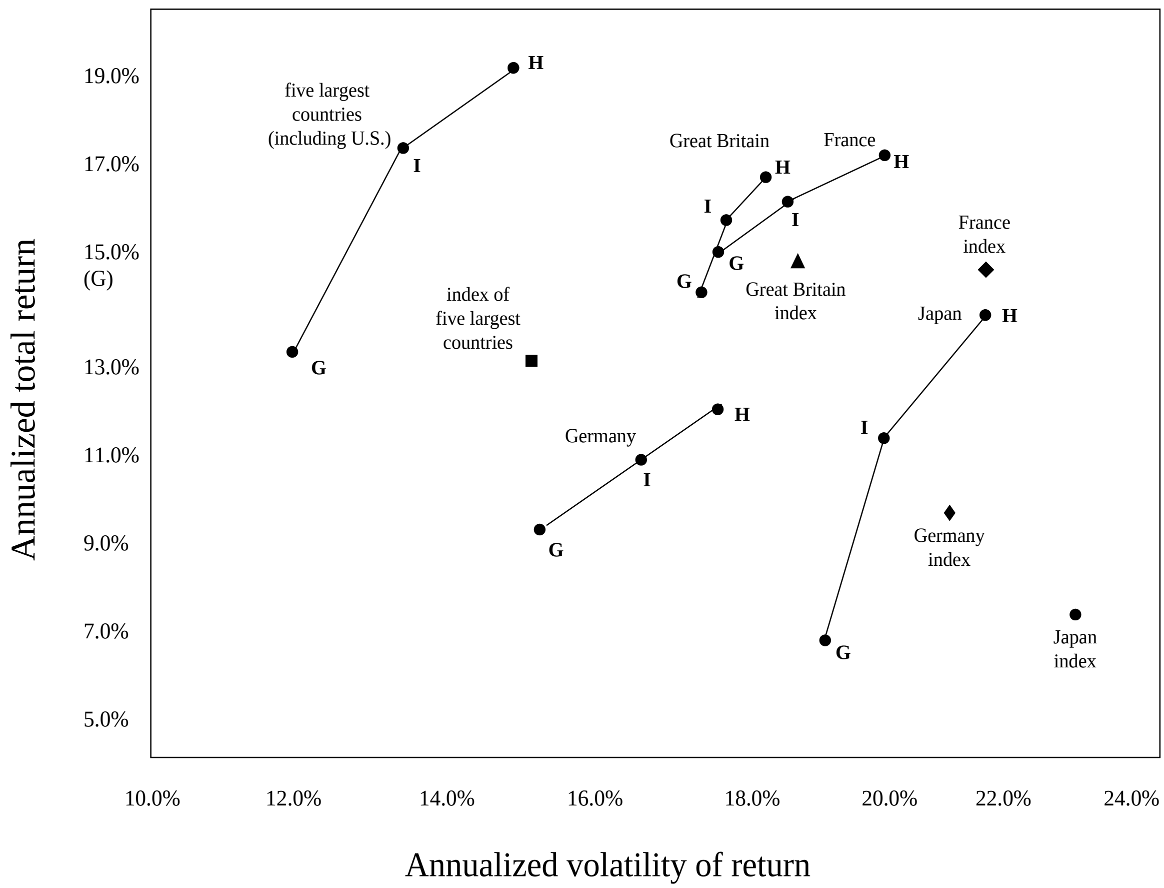
Stocks are ranked and formed into equally weighted deciles on the basis of their relative expected monthly returns, computed by summing the products of (a) the individual factor exposures for each stock to characteristics related to risk, liquidity, price-level, growth potential and price history and (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 reformed monthly. The plot shows the frequency distribution of the post ranking monthly rates of return to deciles one and ten. Decile one is represented by the shaded bars and decile ten is represented by the white bars.

Figure 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-sectionof 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 then 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 portfolio and added to the returns to the L portfolio.

Figure 4
Optimization in France, Germany, Great Britain, Japan
and across the five largest countries. 1985-1994



In each of the five countries an identical set of factors are used to obtain monthly factor payoffs using multiple regressions. Our sample includes 208 stocks in France, 195 stocks in Germany, 406 stocks in Great Britain, 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. For each of the four countries returns are in local currency. For the collective optimization over all five countries, the returns are denominated in U.S. dollars.