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Characteristics or Covariances?*

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Recent research has shown that small market capitalization and high book-to-market (value) stocks earn considerably higher average returns than the corresponding large stocks and low book-to-market (growth) stocks. Although there exist risk or factor-based explanations for this return differential, our empirical research instead supports a *characteristics model* in which expected returns are not linked to common variation in the returns. As we discuss in this paper, these empirical results have important implications for performance evaluation and portfolio management.

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1 Introduction

An investor's style is an important determinant of his or her portfolio performance. Over the past 35 years, value investors have generally outperformed growth investors and small cap investors have outperformed large cap investors. Explaining these return differences is a topic that is of interest to investors as well as academics.

The persistent performance advantage of value stocks over growth stocks can arise either because of fundamental risk differences between the styles - perhaps value stocks realize higher returns than growth stocks because they are riskier. However, the performance differential could also be a result of mispricing - perhaps value stocks outperform growth stocks because the market systematically underprices value stocks. These two theories have very different implications for how investment managers should form portfolios.[1]

If the return premium associated with value stocks arise because the stocks are fundamentally riskier, then we might expect these return premia to continue in the future. Investors who are not too concerned about the type of risk embodied in value portfolios may then continue to enjoy their high returns. If, however, the return premia arises because of mispricing, then we might expect the excess returns to be mitigated over time as investors become more knowledgeable.

In a series of papers, Fama and French [1992, 1993, 1995, 1996, 1997, 1998] argue that the observed pattern of stock returns supports the risk-based explanation. By pattern of returns we mean how the stock returns fluctuate from month to month – how much they move and the degree to which they move up an down in tandem with other stocks. Fama and French argue that the pattern of returns generated by high book to market (value) stocks are fundamentally different than the pattern of returns generated by low book to market (growth) stocks. Value stocks tend to move up and down together and growth stocks tend to move up and down together; however, after accounting for broad market moves, growth and value stocks generally do not move together. Value investors are therefore exposed to different risks than are growth investors and may thus require

[1] They also have very different implications for how corporations should finance their operations. See Stein [1996].

different return premia, or average returns, to compensate them for the risks associated with these stocks.

Up until recently, most academics would have concurred with the conclusions of the Fama and French analysis. However, the magnitude of the difference in risk premia between value and growth stocks appears to be implausibly large, which have led some individuals to question the risk-based explanation.[2] In our own research we have asked whether this value premium might be due to something captured by firm characteristics, but *unrelated to return patterns*.

Our analysis in Daniel and Titman [1997] suggests that the higher returns earned by the value stocks has little to do with the fact that their return patterns are generally somewhat different than the return patterns of growth stocks. Indeed, our results indicate that value stocks earn high returns whether their returns look like those of growth stocks, or like those of other value stocks. In other words, a stock's expected return seems to be determined more by its characteristics (*e.g.*, high versus low book to market) than by its return pattern, (*e.g.*, whether it covaries more with high or low book to market stocks). This evidence tends to support the mispricing over the risk-based explanation.

An investor would care about these results for at least three different reasons:

1. As mentioned above, a better understanding of the cause of past return differences may provide some clues about whether those return differences will persist in the future.

2. A better understanding of how returns were generated in the past will help us evaluate the past performance of professional money managers.

3. A better understanding of the return generating process allow us to build portfolios with higher expected returns for any given level of risk.

Since we know our limitations as forecasters, we will not comment about whether these return differences will persist in the future. However, we do have comments about

[2] Lakonishok, Shleifer and Vishny [1994] and MacKinlay [1995] discuss this point in detail.

how the past returns of a professionally managed portfolio should be evaluated. Indeed, we have recently published a study that uses our techniques to evaluate a sample of mutual funds.[3] In addition, we will summarize how to implement a portfolio strategy based on the idea that expected returns are determined by characteristics rather than by return patterns.

The paper is organized as follows: In Section 2 we provide a brief discussion of factor models, characteristic-based models, and the implications of each. In Section 3 we discuss our empirical tests, and show how we test for whether a factor model or a characteristics model better describes the cross-section of expected stock returns. Sections 4 and 5 discuss application of the characteristics model to two areas: performance measurement and portfolio theory. Section 6 concludes the paper.

2 Characteristics versus Factor Pricing

Rational asset pricing models form the basis of modern finance theory. These models generally have as a basis a set of rational investors who maximize utility, where utility is measured in terms of the investor's future consumption or wealth. In these models the reason that investors purchase financial assets like stocks, bonds or mutual funds is exclusively for the future cash flows that these assets will provide.

Finance theory concludes that capital assets should be priced to equal the discounted value of their future cash flows. In the case of riskless assets, investors must use the same factor to discount all cash flows that occur at the same point in time. This means that if there are two investments A and B, and A and B both pay $1000 in one year, then A's current price must equal B's, and their returns over time must be the same.

For example, let's say that A is a newly issued one year riskless bond, and B is a two year riskless bond with one year remaining to maturity. Both have a face value of $1000, and have no remaining coupons.[4] Then these two bonds should have the same

[3] See Daniel, Grinblatt, Titman and Wermers [1997].

[4] It turns out that there may very well be slight discrepancies in the prices of these two bonds because of liquidity effects; on-the-run and off-the-run bonds have slightly different prices (see, for example, Warga [1992]). To make these really comparable, we'll have to say that you can't sell these bonds prior to the maturity date.

price.

Now let's say that we found that the price of A (the one-year bond) was consistently \$1 higher than that of asset B. When we investigate this further, we might find that investors have some fear about two-year bonds, so they discount the cash flow from B at a higher rate. Perhaps they find that they can't sleep well at night knowing that they are holding two year bonds, and holding one-year bonds lets them sleep well. If it is truly the case that the investors' fears are unfounded, then we might conclude that investors are in some sense irrational and appeal to a behavioral model to explain the prices.[5]

Of course, since most investments aren't risk-free, we can't usually make such easy comparisons. With risky investments we must account for the fact that different average returns may reflect different levels of risk. For example, the fact that stocks earn higher returns than T-bills reflects the fact that stocks are riskier. However, our argument that investments with comparable cash flows are priced the same can still be extended to include risky investments. If two investments have the same expected cash flows as well as the same expected patterns of future returns they should have the same price or equivalently the same expected return. Here, by expected pattern of future returns, we mean how the return of the investment covaries or moves with the returns of other investments that typical investors would hold. These covariances, or equivalently factor sensitivities, are important since they tell us how this investment contributes to the riskiness of a typical portfolio.

How does this affect the question of whether value stocks are properly priced? We know that value stocks have high average returns, or equivalently a low price for the future cash flows they produce. This might be because they are underpriced relative to growth stocks. Book-to-market ratios are related to salient features of a stock which might cause investors to misprice them.[6] High book-to-market stocks are generally "losers," stocks that have had poor earnings or cash flow performance and in other ways look unattractive. If the typical investor avoids these stocks because they are viewed as

[5] See for example Daniel, Hirshleifer and Subrahmanyam [1998].

[6] See, for example, Lakonishok, Shleifer and Vishny [1992] and Lakonishok et al. [1994].

unattractive, then they are likely to have low prices and commensurately high expected returns.

But they need not be mispriced: an alternative hypothesis is that investors rationally assign low prices to value stocks because value stocks are riskier than growth stocks. However, this can only be the case if there is something in the pattern of future cash flows of value stocks that investors dislike: if the book-to-market ratio is uninformative about the patterns of future cash flows, then we would have to conclude that investors are being irrational in the way that they price these investments. In technical language, the rationality hypothesis assumes that the book-to-market ratio must be *proxying* for the future return patterns of the investments.

Stocks with similar size and book-to-market characteristics do in fact have similar return patterns, meaning they tend to move up and down together. As a result, while small stocks and value stocks have generally done well, in some years they move down together. This means that even large, well diversified portfolios of these stocks will sometimes lose. For example, in the five years from 1969 through 1973, large market capitalization stocks rose 12%, while small-capitalization stocks fell 41%. Similarly, over the two year period from 89 through 90, value stocks fell by about 2%, while growth stocks rose by 17%.[7]

Fama and French [1993], noting how characteristics proxy for return patterns, proposed a factor model where the relevant factor portfolios consist of what they call an *HML* (High-Minus-Low) portfolio which is long high book-to-market stocks and short low book-to-market stocks, an *SMB* (Small-Minus-Big) portfolio which is long small cap stocks and short large cap stocks, and a *Mkt* portfolio which is long a value-weighted index of common stocks, and short the short-term riskfree asset. Those stocks with returns that are especially sensitive to these factors, or in other words which covary with these factor portfolios, contribute more to the variance of most typical well diversified portfolio and are thus deemed to be more risky. Fama and French [1993] find that the returns of value stocks covary strongly with the HML returns, as do small stock returns

[7] These returns are for the H, L, and S and B portfolios constructed by Fama and French [1993]. Our construction of these portfolios is also described in the appendix.

with the SMB portfolio returns. This demonstrates that the characteristic does indeed proxy for future return patterns, and appears to provide support for the risk-based explanation. However, as we discuss below, this evidence is not sufficient to rule out the characteristic based explanation.

The problem is a bit like that of trying to figure out the value of a college degree (the characteristic) for one's future earning power. We know that people with college degrees earn more. The question is why. One hypothesis (the "characteristic model") might be that getting a degree raises your earning power. However, an alternative hypothesis (the "factor model") is that the degree doesn't add anything; only IQ is valued. The reason that individuals with degrees earn more is that the degree proxies for their IQ.

If it is the case that, on average, individuals with high IQs get college degrees than don't (*i.e.*, if the characteristic and the factor loading are correlated), then finding that the average salary of graduates is higher than the average salary of non-graduates really tells us nothing about the value of either IQ or the degree on their own. Similarly, finding that high IQ individuals earn more than low IQ individuals again doesn't allow us to separate out the effect of IQ and education – it might just be the case that only the degree is valued, but more of the high IQ people have degrees. The only way we can determine which variable is driving salaries is by finding high IQ individuals without degrees, or alternatively low IQ individuals with degrees.

The equivalent problem, which we addressed our study [Daniel and Titman 1997], was to identify value stocks that have future return patterns like those of growth stocks, and growth stocks with return patterns like those of value stocks. In the next section we discuss how we do this.

3 Empirical Tests: Characteristic-Balanced and Factor-Balanced Portfolios

As we mentioned in the last section, the purpose of our research was to determine whether expected stock returns are related to book-to-market ratios because this characteristic proxies for the return pattern, or whether it is the characteristic itself that determines the expected returns. Distinguishing between these two hypotheses is difficult because, as we just mentioned, book-to-market is indeed a good proxy for the return patterns.

If we are to distinguish between these alternative hypotheses we must be able to construct portfolios of stocks that have similar return patterns but different characteristics, and other portfolios of stocks with similar characteristics but different return patterns. If it is the return patterns that determine expected returns then the first set of portfolios should have equal returns and the second set should have different returns. In contrast, if characteristics rather than return patterns determine expected returns, then the first set of portfolios should have different expected returns and the second set should have the same expected returns.

The following set of figures graphically illustrate our empirical design. Figure 1 illustrates the two alternative models: the Factor Model on the left and the Characteristics Model on the right. The Factor Model says that the only thing that determines expected returns is the factor sensitivity (β_{HML}, labeled 'beta-HML'). Consider **A** and **B**, two common stock portfolios with the same average book-to-market ratios (BM's), but with different β_{HML}'s. The left panel of this figure shows that if the factor model is true these two portfolios must have different expected returns. A's high β_{HML} means that A behaves like a value stock portfolio and therefore must have a high expected return; its BM ratio doesn't matter once you have taken account of its factor sensitivity. Portfolio C has a higher BM ratio than B, but no higher β_{HML}, so its expected return is the same. However, the right panel shows that, if the characteristics model is correct, A and B should have the same expected return, but portfolio C, because of its high BM, will have a higher return even though its factor sensitivity is the same as B's.

Note that to illustrate the differences between the factor model and the characteristics model, we had to use portfolios A and C for which the betas and the book-to-market ratios were not perfectly correlated. If they had been perfectly correlated it might have been impossible to distinguish between the two theories.[8] For example, the portfolios

[8]Relating this to the example of the previous section, A and B are like non-degreed people, but A is high IQ and B is low IQ. C is degreed, with a low IQ.

indicated by the five asterisks ($*$'s) on the diagonals of the two panels have betas and characteristics which are perfectly correlated, and for these portfolios the expected returns predicted by the two models are exactly the same (the height of the portfolios is the same in the two panels). To show this more clearly, in Figure 2 we combine the left and right panels of Figure 1.

When would we expect the characteristics and factor loadings of our test portfolios to be very highly correlated? If there is any correlation between the characteristics and the factor loading of the individual firms, than the answer is almost any time when we form portfolios along only one dimension.

Figure 3 illustrates this. Each + in this plot represents a firm's common stock, where its location on the y-axis is determined by its book-to-market ratio and its location on the x-axis is determined by its β_{HML}.[9]

Now imagine that we form portfolios from these stocks by sorting into portfolios on the basis of the BM ratio. It is clear that the higher BM portfolios will also have higher HML factor loadings, and that we will end up with characteristics and βs which are very highly correlated. Thus, it might seem like we could sort into portfolios based on some other variable which forecasts the factor loading; but this will also yield perfectly correlation between the characteristics and the factor loadings. Relative to the example in the last section, this would be like either sorting on education level alone, or like sorting on IQ alone; neither one will separate out the data in the way we need. So, just as in the education example, what we need to do here is a sort along multiple dimensions. We need to find value stocks that behave like growth stocks, and vice-versa.[10]

The high correlation between the characteristics and the factor sensitivities makes it difficult but not impossible to do this. Our method is relatively straightforward. Characteristics are directly observable, so we first sort directly into portfolios based on

[9]This plot is illustrative only. However, it reflects our empirical results which show that B/M and β_{HML} are highly correlated, but not perfectly correlated.

[10]If the characteristics and factor-loadings were perfectly correlated, then it might be impossible to discriminate between the two models, as we could not construct portfolios which were not off the diagonal of Figure 2. However, as Figure 3 illustrates, book-to-market ratios and HML factor sensitivities are highly correlated but are not perfectly correlated.

on size and book-to-market ratios.[11] Then, as a proxy for the future factor loadings we look at how the stocks behaved in the past. If the returns of a stock with a high book-to-market ratio hadn't covaried strongly with the returns of the current group of high book-to-market stocks in the past 3 years, then we assumed that they wouldn't covary as strongly in the future. We tested this assumption, and discovered that it is correct: past covariances do forecast future covariances. Based on this, we then sorted each of the stocks in these characteristic sorted portfolios, each with roughly the same book-to-market ratio, into five sub-portfolios based on their past covariance with the past HML returns.

With this sorting procedure we now have a set of sub-portfolios which are "off of the diagonal," which allows us to distinguish between the factor model and the characteristics model. We illustrate this in Figure 4.[12] Now each portfolio has been separated into five sub-portfolios. Since these sub-portfolios lie off of the diagonal, there is some distance between the two surfaces, we can now test whether average returns are determined by the factor or characteristics model.

We have placed the asterisks in Figure 4 where they should be if the characteristics model holds, and indeed this is what the data tell us: we find that a value stock that behaves like a growth stock has an average return that is still high. The average return appears to reflect components of the stock's book-to-market ratios that are unrelated to its future covariances with other value stocks. We'll now go into more detail on exactly how we test this. For those who want the technical details, we have provided them in the Appendix.

To determine which model better represents the data, we constructed two portfolios, a *factor-balanced* (FB) and a *characteristic-balanced* (CB) portfolio. Both portfolios are long-short or zero net-investment portfolios, meaning the long side and the short side are of equal value, so that the proceeds from the short sales could in theory finance the stock purchases. The FB portfolio has a factor loading of zero on each of the three factors, so it is "balanced" in its factor loadings, but it is "unbalanced" in the characteristic

[11] We sort on size also because we need to find variation in factor loadings that is unrealted to *any* of the characteristics.

[12] We have made a cutout in the factor-model surface to allow viewing of the portfolios.

dimension: is long high BM stocks and is short low BM stocks. The CB portfolio buys and sells equal amounts of high BM stocks, so it is characteristic-balanced, but it has a high loading on the HML factor.

These portfolios are important for our testing method because they are designed to behave very differently depending on whether the factor model or the characteristics model better describes returns. If the factor-model is correct, than the FB portfolio should have a zero average return and the CB portfolio a high positive average return. In contrast, if the characteristics model is correct, then the opposite should be true: the CB portfolio should have a zero average return and the FB portfolio a high positive average return.

The way we build our FB portfolio is to buy a portfolio of high book-to-market stocks that have a low β_{HML}, and then to sell a portfolio of relatively low book-to-market stocks that have exactly the same β_{HML}. In this way we create a portfolio which covaries neither with growth nor with value stocks, even though it is tilted towards value stocks. To relate this to Figure 1, we would get a FB portfolio by buying portfolio C and selling portfolio B. According to the factor-model, this portfolio should have an expected return of zero. However, the characteristic-model indicates that this portfolio should have a high return because it is tilted towards stocks with characteristics that tend to be associated with high returns.

The CB portfolio buys and sells portfolios which have equal characteristics. Again, if you were to buy Portfolio A and sell Portfolio B in Figure 1 you would have a CB portfolio. Note that the CB portfolio has a positive β_{HML}, and would therefore have a positive expected return if the factor model were correct. However, as is clear from Figure 1, if the characteristics model is correct, its average return should be zero.

Figure 5 shows the dollar value of these two portfolios as a function of time. It is clear from this plot that, counter to the predictions of the factor model, the FB portfolio has a high average return over the 1973-1993 period (our statistical tests confirm that this high performance is unlikely to be due to chance). Moreover, this high return is consistent with the characteristics interpretation of the data. On the other hand, the CB portfolio, which should have a high average return if the factor model is correct, instead has an average return of approximately zero, consistent with the characteristics model. Again, our statistical tests indicate that this is the case.[13]

4 Using the Characteristics Approach to Evaluate Mutual Funds

Our paper, Daniel et al. [1997], details our approach for evaluating the performance of active portfolio managers when expected returns are determined by characteristics rather than by factor sensitivities. The approach evaluates the performance of investors by comparing the performance of each stock held by the fund against a benchmark consisting of a portfolio of stocks with similar characteristics.[14]

The difference between the performance of a fund, (the weighted average performance of the stocks held in the portfolio), and the weighted average performance of the benchmarks provides what we call the Characteristics-Based Selectivity Measure. This measure can be calculated with the following equation:

$$CS_t = \sum_{j=1}^{N} \tilde{w}_{j,t-1}(\tilde{R}_{j,t} - \tilde{R}_t^{b_{j,t-1}}), \tag{1}$$

where $\tilde{w}_{j,t-1}$ is the portfolio weight on stock j at month $t-1$, $\tilde{R}_{j,t}$ is the month t return of stock j, and $\tilde{R}_t^{b_{j,t-1}}$ is the month t return of the characteristic-based benchmark portfolio that is matched to stock j during month $t-1$. The time-series average, over all months that a fund exists, gives the Characteristic Selectivity measure (CS) for that fund.[15]

For example, if Fidelity Magellan held IBM stock on March 31, 1993, we would subtract from IBM's April, 1993 return the April return of the portfolio that best matched IBM in terms of prior-year return, book-to-market ratio, and size. Subtracting the relevant portfolio return from IBM's stock return gives IBM's benchmark-adjusted return. We multiply IBM's benchmark-adjusted return by its weight in the Magellan portfolio. Repeating this procedure for each stock held by Magellan that month and summing

[13] The appendix describes exactly how these portfolios and returns were generated.

[14] The procedure of comparing returns to the returns of stocks with similar size and book-to-market has been employed by Ikenberry, Lakonishok and Vermaelen [1995] in an event-study context.

[15] Test statistics are also based on time-series methods.

gives Magellan's benchmark-adjusted performance for the month. Averaging over all months gives Magellan's overall selectivity ability.

To implement our approach we constructed a set of 125 benchmark portfolios with similar stock characteristics; the stocks in each benchmark have similar market capitalizations, book-to-market ratios and its prior-year returns. Once we form these 125 passive portfolios, calculating the Characteristic Selectivity measure is straightforward. Each stock, in each quarter, is assigned to a passive portfolio according to its size, book-to-market, and momentum rank. The excess return of a particular stock is then calculated by subtracting the passive portfolio's return from the stock's return. These differenced returns are then multiplied by the portfolio weights of the different funds to obtain the abnormal or benchmark-adjusted returns for each of the funds for each month.

In addition to selectivity, we consider the possibility that investors realize excess returns by successfully timing the characteristics. They may, for example, switch from growth stocks to value stocks just prior to a runup in the price of value stocks. These investors will be rewarded with a high Characteristics Timing Measure specified below:

The month t component of this measure is

$$CT_t = \sum_{j=1}^{N} (\tilde{w}_{j,t-1} \tilde{R}_t^{b_{j,t-1}} - \tilde{w}_{j,t-13} \tilde{R}_t^{b_{j,t-13}}). \tag{2}$$

Note that the portfolio weight of stock j at month $t-13$ is multiplied by $\tilde{R}_t^{b_{j,t-13}}$, the month t return of the characteristic-based benchmark portfolio that is matched to stock j during month $t-13$. Thus, if the Magellan fund, for example, increased its weight in high book-to-market stocks at the beginning of a month in which the book-to-market effect was unusually strong, then the Magellan fund would have a positive CT component for that month. Again, the average over all months that Magellan existed is the CT measure for Magellan.

The results of our mutual fund study were quite intuitive. We found that the typical mutual fund manager shows some selectivity ability but not enough to earn back more than their fees and expenses. In the first 10 years of our sample, 1975-1985, when the industry was less competitive, selectivity ability was more prevalent than in the latter,1985-1995, more competitive period. In addition, we found that the aggressive growth and growth funds exhibited more selectivity ability than other funds. However, since these funds generate the highest turnover and the highest expenses and fees, we do not believe that they offer their investors better returns than can be achieved with buy and hold strategies. Our study found no evidence of style timing performance.

5 Using the Characteristics Approach to Build Efficient Portfolios

What are the implications of a characteristic-based model for portfolio management? If the patterns that we have observed in the past persist into the future, our work suggests that investors should be able to construct portfolios with considerably higher Sharpe ratios than what is suggested by the factor model proposed in Fama and French [1993].

If expected returns are consistent with the Fama and French factor model, investors can do no better than holding a combination of their three factor portfolios.[16] Any deviation from this combination increases the portfolio's variance without increasing its expected return. Portfolio selection using a factor model is thus quite straightforward and does not require estimates of the expected returns, variances and covariances of individual stocks. In the Fama and French model, like all traditional finance models, covariances are appropriately priced so that there is little to be gained from better covariance estimates.

In contrast, since our model suggests that covariances are not directly linked to expected returns, better covariance estimates are quite useful and can be used to lower the portfolio's return variance in ways that may not penalize the portfolio's expected return. Indeed the characteristics model suggests that investors can realize high returns with relatively modest variances with a strategy of buying a "factor-balanced" portfolio, one that has a loading or beta of zero on each of the factors, yet is still long small stocks and value stocks, and which is short big stocks and growth stocks. Theoretically, all of the factor risk and most of the residual risk of such a portfolio could be eliminated, yet

[16] The equilibrium version of this model in Merton [1973] suggests that all investors will hold only combinations of the factor portfolios.

it would still have a large expected return. In practice, however, there are limits to how well the individual stock covariances can be estimated which means that, in reality, not all of the factor risk can be eliminated.[17]

We are currently experimenting with ways to form optimized portfolios that account for characteristics as well as covariances. Our basic approach is to develop an empirical model based on past history to estimate the expected returns of each stock as a function of their characteristics. This vector of expected returns, along with an estimated covariance matrix, are then used as inputs into a mean variance optimizer to obtain the optimal portfolio weights.

6 Conclusions and Caveats

Our research suggests that after controlling for stock characteristics, factor sensitivities provide no information about a stock's expected rate of return. This suggests that investors can build superior portfolios with mean-variance optimizers that use characteristics to generate the expected return inputs along with covariance estimates either calculated with historical data or provided by a vendor such as BARRA. Such a strategy would have done exceptionally well in the past.

Before concluding, we must offer the following caveats. First, the past success of a particular investment strategy is not necessarily an indicator of its future success. For example, in the early 1980s, the small firm effect received a lot of attention because of the high returns generated by small firms in the previous decades. Because of this attention, a number of small cap funds were started which bid up the price, and bid down the returns, of these small cap stocks. Similarly, the relatively high returns of value stocks could be bid down as these stocks attract more attention.

A second caveat has to do with our assertion that a factor balanced portfolio tilted toward small cap and high book-to-market stocks would have very limited risk. Figure 5

[17] In the original arbitrage pricing theory [Ross 1976] if the factor model does not hold then arbitrage opportunities will exist. This is not the case here for several reasons. In the Ross economy perfect diversification is theoretically possible, and all factor loadings are known by market participants. Here arbitrage opportunities cannot be fully taken advantage of both because we are in a finite economy and because factor loadings cannot be precisely estimated.

shows that such a portfolio does quite well in almost all time periods; the portfolios performed well during the 1974 recession, the 1987 crash, and the 1991 recession. However, the portfolio did very poorly during the 1982 recession which was the deepest recession since the 1930s. Perhaps, the riskiness of this portfolio is revealed only during very deep recessions.

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A Appendix: Portfolio Construction Details

The construction of the book-to-market and size portfolios follows Fama and French [1993]. Using the merged CRSP/COMPUSTAT files maintained by CRSP we form portfolios of common shares based on the ratio of the book-equity to market equity (book-to-market) and on market equity (ME). Book equity is defined to be stockholder's equity plus any deferred taxes and any investment tax credit, minus the value of any preferred stock, all from COMPUSTAT. To determine the value of preferred stock we use redemption value if this is available, otherwise we use liquidating value if it is available, and if not we use carrying value. In calculating book-to-market, we use the book equity from any point in year $t-1$, and the market equity on the last trading day in year $t-1$, where the market equity, from CRSP, is defined as the number of shares outstanding times the share price. The ME used in forming the size portfolios is the market equity on the last trading day of June of year t. We only include firms in our analysis which have been listed on COMPUSTAT for at least two years and which have prices available on CRSP in both December of $t-1$ and June of year t. The book-to-market ratios, and ME's of the firms thus determined are then used to form the portfolios from July of t through June of year $t+1$. As discussed in Fama and French [1993], the end of June is used as the portfolio formation date because the annual report containing the book-equity value for the preceding year is virtually certain to be public information by that time.

To form our portfolios, we first exclude from the sample all firms with book values less than zero. We take all NYSE stocks in the sample and rank them on their book-to-market and size as described above. Based on these rankings, we calculate breakpoints for book-to-market and size. To form the H, L, S and B portfolios, we follow Fama and French [1993] and use 30% and 70% breakpoints for book-to-market and a 50% breakpoint for size. To form the nine BM/size portfolios used in our empirical analysis, we use 33 1/3 % and 66 2/3 % breakpoints for both size and BM (see our paper Daniel and Titman [1997] for more detail on this).

We create the factor-balanced (FB) and characteristic-balanced (CB) portfolios using the portfolios we used to test the factor-model, as described in section 3. Recall that our test portfolios consisted set of nine portfolios formed by sorting common stocks into groups based on their size and book-to-market. We then sorted each of these nine portfolios into five sub-portfolios based on their expected future loadings on the HML factor (for a total of 45 sub-portfolios)

Both the FB and CB portfolios are zero-investment portfolios, meaning that the dollar amount invested is equal to the dollar amount shorted. To create the CB portfolio, for each OF our test portfolios we buy the two sub-portfolios with the highest factor loadings on the HML factor, and sell the two with the lowest forecast future loading. This results in a zero investment portfolio where we buy an sell equal amounts of stocks with the same characteristics, but with different loadings on the HML factor. When we measure the loadings of the CB portfolio on the HML, SMB and Mkt factors, we find that the β's are 0.724, 0.134 and 0.110 respectively; this suggests that the returns of this portfolio look very much like those of the HML portfolio (which has loadings of 1, 0 and 0.)

To create the FB (factor balanced) portfolio, what we do is to buy 0.724, 0.134 and 0.11 units of the HML, SMB and Mkt. portfolio, respectively, and sell the CB portfolio. This means that the factor loadings of our FB portfolio are all zero. However, this portfolio is not characteristic-balanced: in buying so much of the HML portfolio we end up with a portfolio which is long high B/M stocks and short low B/M stocks.

Figures

Figure 1: The Factor Model and the Characteristic Alternative

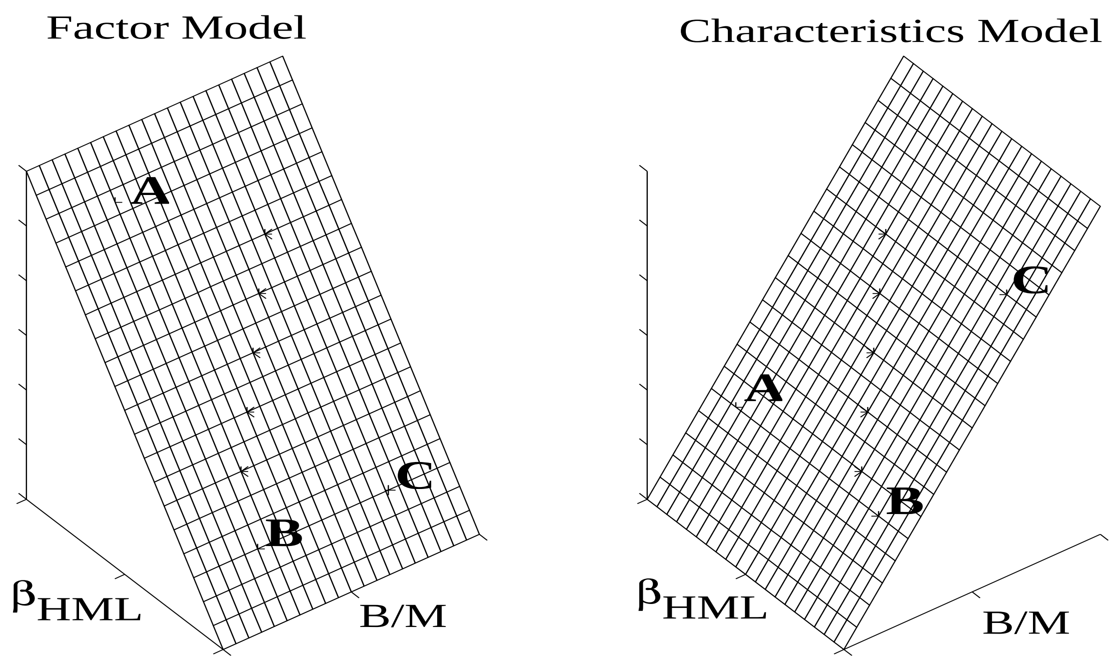

Figure 2: The Factor Model and the Characteristic Alternative

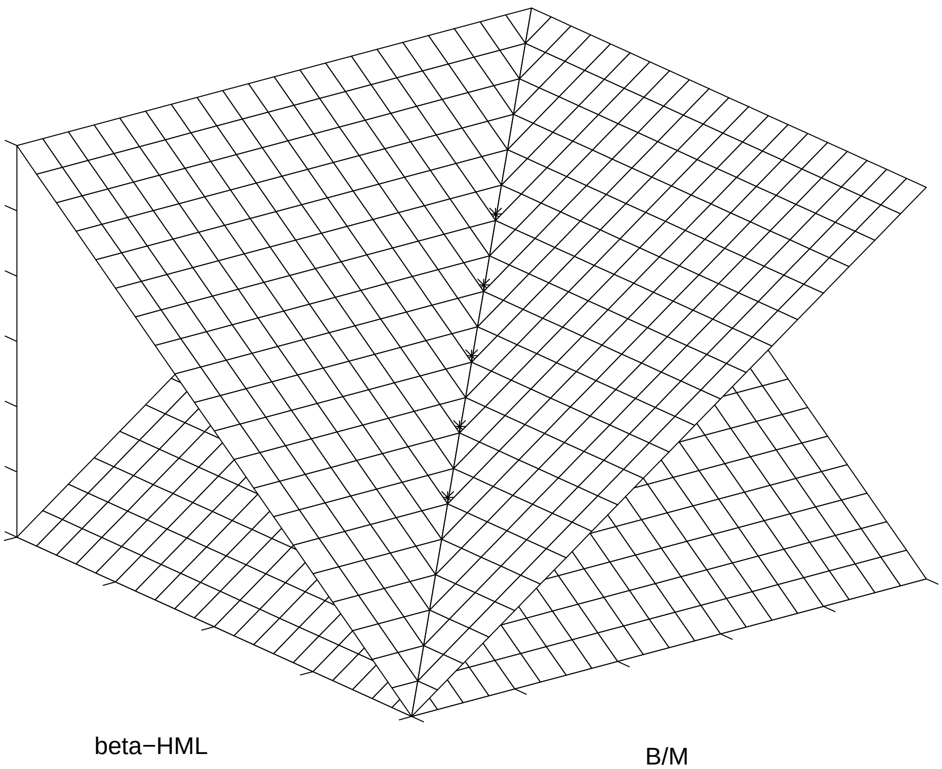

Figure 3: The Distribution of Characteristics and Factor Sensitivities

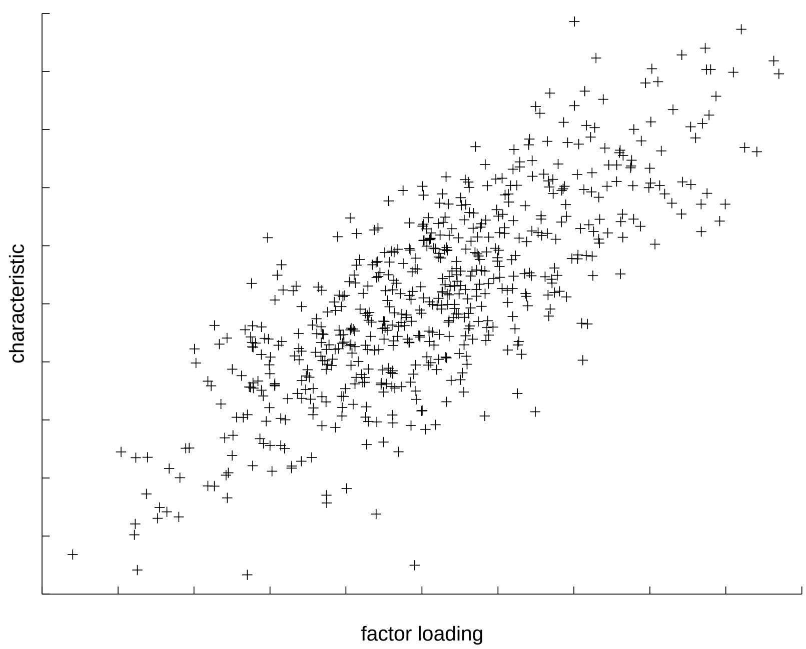

Figure 4: Portfolio Locations Overlayed on Plots of the Factor Model and the Characteristic Model

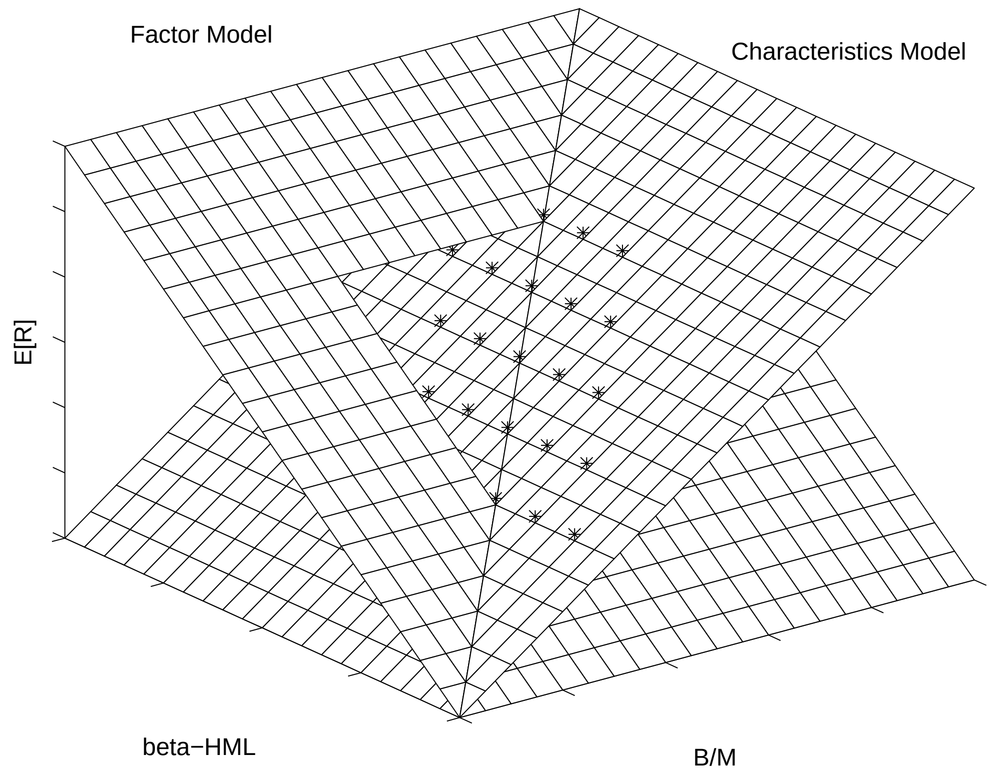

Figure 5: Cumulative Returns on Characteristic and Factor Balanced Portfolios