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1. Introduction.

Recent evidence has documented a predictable component in stock returns which is particularly large at low frequencies (see for example Fama and French [1988] and [1989]). Most previous studies have examined the predictability of bond portfolios, stock indices, size deciles and industry portfolios. A question which follows from these studies is the predictability of individual stock returns using the same information variables. Of particular concern is the stability of the predictive regresssion coefficients through time for individual stocks.

This study uses the NYSE/AMEX file of monthly returns to examine the period 1/68 to 12/89. Five information variables are employed: 1) a term spread variable; 2) the yield on a one month t-bill; 3) lagged return on a equal weighted stock index; 4) a dividend yield variable; and, 5) a January dummy. The coefficients are likely to be time-varying so a five year window is used for the individual stock predictive regressions.

A related question is the behavior of portfolios formed on the basis of the coefficients from the predictive regressions for individual stocks. More precisely, can the five year predictive regressions be used to form portfolios with desired coefficient values? Two types of portfolios are formed: 1) pairs of portfolios are formed with extreme coefficients on a given information variable; and, 2) portfolios with weights chosen such that the weighted average of the coefficients on a given information variables is maximized (minimized) subject to the constraint that the weighted average of the other coefficients is equal to the cross sectional average. For each year in the sample, rolling predictive regressions are run over the previous five years, portfolio weights are determined and post ranking returns are calculated for the next twelve months. The portfolio formation approach is analogous to that of Fama and French [1991]. The major result is that the first procedure produces pairs of portfolios with significantly different coefficients on the relevant information variables while the second procedure does not produce portfolios with equal coefficients on the other information variables.

Gibbons and Ferson [1985] proposed a test of asset pricing models which does not require the underlying risk factors to be specified. Instead, conditional risk premia are hypothesized to be linear in a set of information variables. Further, the conditional risk loadings are assumed to be constant (proportional)[1] implying that conditional expected return is linear in the set of information variables. The latent variables methodology can only detect more than one factor if the risk premia are time varying. Thus, the literature documenting return predictability (see for example Fama and French [1989]) has provided candidate information variables which can be used in latent variables tests.[2] A number of recent studies have employed Hansen's [1982] GMM methodology and these candidate information variables to determine the minimum number of factors which do not allow rejection of the restriction obtained under the proportional (constant) risk factor assumption. Generally, only proportional beta models with less than two factors are rejected by the data.[3]

One possible reason why these tests in general are unable to reject a two factor, constant beta model is a lack of power. There are considerably more securities on the CRSP tapes than the number of assets which can be handled computationally when implementing GMM. It may be possible to improve the power of the GMM test by forming stock portfolios on some criteria other than size or industry. Some evidence on this point is presented in this paper. Specifically, portfolios of the first type described above are used together with extreme size and market beta deciles to perform latent variables tests. A priori, using these portfolios would be expected to improve power relative to using size deciles since we are ranking on more than one dimension. In fact, the extreme portfolios detect

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[1] The weakest condition which gives the result is that the ratio of the risk loadings is constant. Hereafter, this condition will be referred to as the proportional risk loading condition.

[2] Variables found to have predictive ability include a term spread yield variable, a default spread yield variable and dividend yield (Fama and French [1989]), the one month T-bill rate (Campbell [1987] and Ferson [1989]) and a January dummy (Keim [1983]).

[3] Specifically, Ferson [1990] uses seven information variables (plus a constant) and quarterly return data for size quintiles and three bond portfolios to reject a one factor constant beta model but not a two factor version. Daily returns on the Dow Jones 30 common stocks are found by Ferson, Foerster and Keim (1991) to conform to a two factor model using two or three information variables plus a constant. In fact, their evidence against a one factor model is weak. Their GMM tests for monthly returns on size and industry portfolios which use five information variables plus a constant indicate that no more than two factors are needed to describe stock returns. Ferson, Foerster and Keim also test the restriction imposed by asset pricing models without the assumption that conditional expected return is linear in the information variables. Using GMM, they are able to reject a two factor model but not a three factor one. Also see Campbell [1987] and Ferson [1989] for monthly bond and stock data.

an extra factor relative to the size deciles. This result indicates that a greater number of factors may be needed to describe individual stock returns than has been suggested by the latent variables testing to date. Descriptive evidence is also provided on the relative power of GMM latent variable tests and principal component analysis of the predictable (using the information variables) component of returns.

Finally, all portfolio formation procedures and tests are performed on three data sets: 1) NYSE and AMEX combined; 2) NYSE only; and, 3) AMEX only. One motivation for this partitioning of the sample comes from Reinganum [1990] who compared the pricing of NYSE and NASDAQ securities. He found that small firms on NYSE earn higher risk adjusted returns than comparable firms on NASDAQ.[4] The implication is that the pricing of assets may vary across exchanges. Some very preliminary evidence on this issue is provided for the NYSE and AMEX exchanges by the latent variables testing performed in this paper. The number of factors needed to describe returns using a proportional risk loading model is reduced by at least one going from the combined sample to either the NYSE or AMEX samples.

The paper is organized as follows. The data and portfolio formation technique are described in Section 2 while Section 3 contains a discussion of latent variables testing and its implementation using GMM. Results are presented in Section 4 and Section 5 concludes.

2. Information Variables and Portfolio Formation Procedures.

Table 1 contains a brief description of the symbols used in the paper to represent the information variables and portfolios employed in the testing.

2.1. Information Variables.

Five variables plus a constant are used to explain variation in expected return. Each is discussed in turn.

Fama and French [1989] document that asset returns are predictable using dividend yield and

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[4] He then provided some evidence supporting the argument that the difference is due to different liquidity services across exchanges for small firms.

a term spread variable. Excluding market inefficiency as an explanation, the most likely explanation for their result is that these variables track expected returns. Dividend yield VDP(t-1) is defined to be VD(t-1)/VP(t-1) where VD(t-1) is the dividend paid on the value weighted index of NYSE over the twelve months prior to period t and VP(t-1) is the value of the index at the start of period t.[5] Variation in the term structure is measured by TRM(t-1) = YB5(t-1) - YBL(t-1) where YB5(t-1) and YBL(t-1) are respectively the nominal yields on a five year bond and a one month bill known at the end of t-1. The former is obtained from the CRSP riskfree rate files while the latter is extracted from the Fama-Bliss discount bond file.

It is well documented that returns are higher in January than in other months of the year and that this effect is greatest for small firms (Keim[1983]). So a January dummy JAN(t-1) is used to help explain expected return variation. A negative relationship has been documented between the nominal one month t-bill yield and real stock returns (see Ferson [1989]). For this reason, YBL(t-1) is used as an information variable. RCE(t-1) is the continuous real return on the NYSE equal weighted index provided by CRSP over the month prior to the start of period t. Conrad, Kaul and Nimalendran [1991] provide evidence that expected short horizon returns are autocorrelated and lagged index return may capture the common component of this autocorrelation.

So in this paper, the $\mathbf{Z}_{t-1}$ vector is defined to be [1, TRM(t-1), YBL(t-1), RCE(t-1), VDP(t-1), JAN(t)]'. All these variables have been used in prior latent variables studies (see Ferson, Foerster and Keim [1991], Campbell [1987] and Ferson and Foerster [1991]). Their correlations are reported in Table 1 and all but two are less than .5 in absolute value with none greater than 0.66. When a principal components analysis is performed the first component explains less than 40% of the variation. These results suggests that the information variables are not highly collinear.

2.2 Return Data and Portfolio Formation Techniques.

2.2.1 Return Data.

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[5] The VDP(t-1) series is obtained using the CRSP value-weighted index of NYSE stocks and calculated using a discrete return version of the algorithm described in Fama and French [1988b].

This study uses monthly return data for individual stocks obtained from the NYSE and AMEX file maintained by CRSP. Three samples of stocks are examined over the 22 year period 1/68 to 12/89:[6] NYSE and AMEX; NYSE only; and, AMEX only. For the combined NYSE and AMEX sample, all available returns on the file are used. For the other two samples, if portfolios are being formed for the year y, then for that year each stock is assigned to the exchange it belongs to at the start of that year.

The value weighted size deciles (S1 to S10) for each exchange or set of exchanges used in the tests are obtained from the CRSP monthly index series for the relevant exchange(s). The deciles are formed at the start of each calendar year on the basis of market capitalization at the end of the previous year. Let RSp(t) denote the real return on the pth size decile where the 10th decile contains the largest stocks. Two long term bond series are also used. RGB(t) denotes the real return on the long term government bond portfolio described above. The other bond series is a low grade bond portfolio whose real return is denoted RHY(t) and which consists of those bonds which are rated Baa or under in a random sample of 100 corporate bonds. Both bond series are obtained from Ibbotson and Associates.

All portfolio returns are discretely compounded,[7] and deflated by discretely compounded

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[6] When forming portfolios on the basis of a firm characteristic like size, it is important that the properties of the set of stocks used do not alter over time. Otherwise the characteristics of the ranking portfolios will also vary over time, making it easier to reject a given factor model in the testing. (To see why this is true, suppose a one factor constant beta model holds for individual stocks. Then form portfolios each consisting of two stocks with weights which vary through time. These porfolios will not have constant betas even though the individual assets do.) Consequently, the sample period could not start before 1/68 and still use AMEX stocks, since AMEX is not available on CRSP until 7/62 and a five year window is used in the monthly rolling regressions.

[7] If continuous compounding is used, portfolio return is no longer a linear combination of security returns. Thus, portfolio regression coefficients are no longer a weighted average of stock regression coefficients. Since this study forms extreme portfolios and deciles using coefficients from rolling regressions of asset returns on the information variables, discrete compounding is preferred. An analogous argument is made by Ferson and Korajczyk [1991] who also use discrete compounding.

inflation measured using the U.S consumer price index.[8] Excess real return on asset i is defined by ri(t) = Ri(t) - RTB(t) where Ri(t) is the real return on asset i, and RTB(t) is the discretely compounded holding period return over month t on the shortest maturity treasury bill maturing at or after the end of that month.

2.2.2 Portfolio Formation Techniques: Size Portfolios.

Although the value weighted size deciles (S1-S10) are just the relevant CRSP indices, the following size based portfolios used in this paper are constructed from the CRSP file of NYSE and AMEX stocks. Both the NYSE and AMEX samples were formed into portfolios (denoted A1-A10) using the combined NYSE and AMEX size decile break points. A portfolio Uj was formed from Sj (j=1,2,...,10) for the combined sample using the following procedure. For each firm in Sj for a year, a number q distributed Uniform [0,1] and independant of all other q's was drawn and if $q > 0.5$ that firm was omitted from the portfolio. On average, portfolio Uj will have half the firms of Sj.

2.2.3 Portfolio Formation Techniques: Extreme and Constrained Portfolios.

For each year in the sample period, real excess return is regressed on the five instruments plus a constant using the previous five years for all firms on the relevant exchange satisfying the following: 1) listed on the exchange over the five year period; and, 2) there are at least 30 usable returns over the previous five years. Portfolios of post ranking real excess returns are then formed using several construction procedures. For each information variable, the stocks are ranked on the basis of that variable's coefficient and the top and bottom 10% are used to form extreme portfolios over the sample year. For each month in the given year, an equal weighted portfolio is formed using those stocks in the top and bottom 10% with usable returns for that month. Repeating this for every year in the sample gives 5 pairs of portfolios of post ranking returns, a pair for each information variable (denoted "10% EXTREME" portfolios).

This technique is designed to form portfolios with extreme values for the coefficients on the

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[8] Since excess returns are used in the tests, the use of real as opposed to nominal returns should have little effect on the returns. If continuous compounding were used, the choice of deflator would have no effect on the results.

information variables. It will only be successful if these coefficients for individual stocks are stable over time and exhibit cross-section dispersion.

Also, the true coefficients are measured with error by the rolling regressions. Thus, a better spread on the ranking coefficient may be obtained by scaling each individual firm coefficient estimate by a measure of its precision. For this reason, five pairs of portfolios are formed in the following way and denoted "10% SCALED EXTREME" portfolios. For any given year, the procedure for obtaining a pair of portfolios is the same as for the extreme portfolios except firms are ranked using a scaled version of the relevant coefficient. Each individual firm coefficient is scaled by the estimated standard deviation obtained from the firm specific regression which produced the coefficient. Thus, the estimated standard deviation for a coefficient varies across firms and across years. Specifically, consider the following time series regression which is run for $i=1,\ldots,N_y$ over the five years prior to year y:

$$
\begin{aligned}
ri(t) &= \alpha_{y,1,i} + \alpha_{y,TRM,i}\,TRM(t-1) + \alpha_{y,YBL,i}\,YBL(t-1) \\
&+ \alpha_{y,RCE,i}\,RCE(t-1) + \alpha_{y,VDP,i}\,VDP(t-1) \\
&+ \alpha_{y,JAN,i}\,JAN(t-1) + \epsilon_{y,i}(t) \quad t=1,\ldots,T_{i,y}. \qquad (1)
\end{aligned}
$$

where $s_{y,j,i}$ is the standard deviation of $\alpha_{y,j,i}$ as estimated by the OLS regression, j=TRM,YBL,RCE,VDP,JAN. Define $\alpha_{y,j}$ to be the mean of $\alpha_{y,j,i}$; and, $\delta_{y,j,i}$ to be $(\alpha_{y,j,i} - \alpha_{y,j})/s_{y,j,i}$. Then the pair of portfolios for variable j and year y are obtained by ranking on $\delta_{y,j,i}$.

Pairs of portfolios (denoted "5% CONSTRAINED" portfolios) are also formed each year by choosing weights in the following manner. The weighted average of the rolling predictive regression coefficients on a given variable is maximized (minimized) subject to the constraint that the weighted average of the coefficients for the other variables is equal to the cross-sectional mean. Portfolio weights are constrained to be positive but less than 5%. The same procedure is also used to form pairs of portfolios using the scaled coefficients. These portfolios are denoted " 5% SCALED CONSTRAINED" portfolios. Using monthly real returns, the portfolio formation procedure described above is also utilized to form deciles (B1 to B10) ranked on the basis of Dimson [1979] market Beta.[9]

3. Methodological and Econometric Issues.

3.1 Portfolio Formation and Tests of Coefficient Stability.

For each of the three samples, the 5 year rolling regressions are performed using OLS on those stocks which satisfy the criteria for inclusion in the extreme and constrained portfolios. Average R^2's and error variances for size deciles are calculated by first averaging across firms in the decile in a given year and then averaging over time.[10] The size deciles are formed on the basis of capitalisation at the end of the five year window.[11]

The time series behavior of the predictive regression coefficients for individual stocks is also an issue. Evidence on this point can be obtained by performing hypothesis tests on the coefficients of the S1-S10 deciles and the EXTREME and CONSTRAINED portfolios.[12] These tests are performed using both a standard Wald test and a Wald statistic that employs White's [1980] heteroscedasticity consistent covariance estimator. If both statistics give the same conclusion, it is less likely that the result is being driven by small sample properties.

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[9] The return on the equal weighted NYSE index and one lag are the two independent variables in the rolling regression. One lag is used by Fama and French [1991] when calculating Beta in an attempt to adjust for the effects of infrequent trading.

[10] No diagnostic checks are performed due to computational considerations. However, if the information variables are able to capture most of the time series variation in expected returns, then it is possible that the OLS errors are serially uncorrelated. At the same time, it unlikely that the constant variance assumption of OLS is satisfied. Even so, in the face of heterogeneity of unknown form, the OLS estimates are still consistent.

[11] The usual argument against using preranking variables is not applicable here since the aim of the exercise is to characterize the predictive regressions as a function of firm size.

[12] For example, consider a pair of extreme portfolios with respect to a given information variable. If there is a spread on that variable's coefficient across assets and this coefficient is stable through time, then the regression of post ranking returns for the pair of extreme portfolios on the information variables will produce coefficients for the given variable that are reliably different. Also, if the coefficient on a given information variable varies across size portfolios, then it can be concluded that there is some cross-sectional dispersion on that coefficient.

3.2. Latent Variable Testing.

This subsection provides a brief discussion of latent variables tests of asset pricing models and their implementation using GMM. The power of a latent variable test with a K factor null against a J>K factor model alternative is explicitly considered.

3.2.1. Latent Variables Restrictions.

Suppose returns conform to a conditional J factor model of asset pricing:

$$E[\mathbf{R}_t|\mathbf{I}^*_{t-1}] = \lambda^*_o(\mathbf{I}^*_{t-1})\, \mathbf{i}_M' + \lambda^*(\mathbf{I}^*_{t-1})\, \mathbf{B}(\mathbf{I}^*_{t-1}) \quad \text{for all t} \quad (2)$$

where

$\mathbf{R}_t$ is a 1xM vector whose mth element $R_{m,t}$ is the real returns on the mth asset over period t;

$\mathbf{I}^*_{t-1}$ is the available information at the start of period t;

$\lambda^*_o(\mathbf{I}^*_{t-1})$ is the return on an asset whose risk loading are all 0;

$\mathbf{i}_M$ is a Mx1 vector of 1s;

$\lambda^*(\mathbf{I}^*_{t-1})$ is a 1xJ vector of risk premia on the J factors; and

$\mathbf{B}(\mathbf{I}^*_{t-1})$ is a JxM matrix of risk loadings, the mth column $\mathbf{B}_m$ containing the J risk loadings for the mth asset.

Define an excess return vector $\mathbf{r}_t = \mathbf{R}_t - \mathbf{i}_M R_{M+1,t}$ where $R_{M+1,t}$ is the real return on an arbitrary asset which is not necessarily riskless. Further, assume $\mathbf{b}(\mathbf{I}^*_{t-1}) = \mathbf{b}\, c(\mathbf{I}^*_{t-1})$ where $c(\mathbf{I}^*_{t-1})$ is a scalar and $\mathbf{b}(\mathbf{I}^*_{t-1})$ is a JxM matrix whose mth column is $(\mathbf{B}_m(\mathbf{I}^*_{t-1}) - \mathbf{B}_{M+1}(\mathbf{I}^*_{t-1}))$. The law of iterated expectations implies:

$$E[\mathbf{r}_t|\mathbf{I}_{t-1}] = \lambda(\mathbf{I}_{t-1})\, \mathbf{b} \quad \text{for all t} \quad (3)$$

where $\mathbf{I}_{t-1}$ is a subset of $\mathbf{I}^*_{t-1}$; and, $\lambda(\mathbf{I}_{t-1}) = E[\lambda^*(\mathbf{I}^*_{t-1})\, c(\mathbf{I}^*_{t-1})|\mathbf{I}_{t-1}]$.

Suppose that the conditional risk premia in (3) are linear in a 1xL vector of information variables $\mathbf{Z}_{t-1}$ contained in the information set $\mathbf{I}_{t-1}$. Then for any N portfolios formed from the M assets using information contained in $\mathbf{I}_{t-1}$:

$$E[\mathbf{r}^p_t\, |\mathbf{I}_{t-1}] = \mathbf{Z}_{t-1}\, \boldsymbol{\phi}\, \mathbf{b}^p \quad \text{for all t} \quad (4b)$$

where

ϕ is a LxJ matrix such that ϕ_k is the kth column and $(\mathbf{Z}_{t-1}\ \phi_k) =$

$\lambda_k(\mathbf{I}_{t-1})$;

$\mathbf{X}$ is a MxN matrix of portfolio weights contained in contained in $\mathbf{I}_{t-1}$ with the nth column $\mathbf{X}_n$ containing the weights for the nth portfolio;

$\mathbf{r}^p_t = \mathbf{r}_t \mathbf{X}$ is a 1xN vector of returns on the N portfolios; and,

$\mathbf{b}^p = \mathbf{b}\ \mathbf{X}$ is a JxN matrix of portfolio risk loadings.

Now reorder and partition the N portfolios into J and (N-J) such that $\mathbf{b}^p_I$, the JxJ matrix of factor loadings for the first J assets is nonsingular. Consider the regression:

$$\mathbf{r}^p_t = \mathbf{Z}_{t-1}\ \alpha + \mathbf{u}^p_t \qquad (5a)$$

$$E[\mathbf{u}^p_t | \mathbf{I}_{t-1}] = \mathbf{0} \qquad \text{for all t} \qquad (5b)$$

where $\alpha = [\ \alpha_I \mid \alpha_{II}\ ]$; α_I is a LxJ matrix; and, α_{II} is a Jx(N-J) matrix. Gibbons and Ferson [1985] show that (4b) implies:

$$\alpha_I = \phi\ \mathbf{b}^p_I\ ;\ \text{and,}\ \alpha_{II} = \alpha_I\ (\mathbf{b}^p_I)^{-1}\ \mathbf{b}^p_{II}; \qquad (5c)$$

where $\mathbf{b}^p = [\ \mathbf{b}^p_I \mid \mathbf{b}^p_{II}\ ]$.

3.2.2 Power of a K Factor Test against a J>K Factor Alternative.

Under the J factor alternative, the return generating process conforms to (4) and (5). Using a null of a K<J factor model, the GMM procedure minimizes $\mathbf{g}_T'\ \mathbf{W}_T\ \mathbf{g}_T$ with $\mathbf{u}^p_t$ replaced by:

$$\mathbf{u}^\#_t = \mathbf{r}^p_t - \mathbf{Z}_{t-1}\ \alpha_I\ [\ \mathbf{I}_K : \gamma\ ]$$
$$= \mathbf{Z}_{t-1}\ \{\ \phi\ \mathbf{b}^p\ -\ \alpha_I\ [\ \mathbf{I}_K : \gamma\ ]\}\ + \mathbf{u}^p_t \qquad (6)$$

Now, $E[\mathbf{u}^\#_t \otimes \mathbf{Z}_{t-1}]$

$$= E[\ (\mathbf{Z}_{t-1}\ \{\ \phi\ \mathbf{b}^p\ -\ \alpha_I\ [\ \mathbf{I}_K : \gamma\ ]\}) \otimes \mathbf{Z}_{t-1}]$$
$$= E[\ (\mathbf{Z}_{t-1}\ \{\ \phi\ \mathbf{b}\ \mathbf{X} - \alpha_I\ [\ \mathbf{I}_K : \gamma\ ]\}) \otimes \mathbf{Z}_{t-1}] \qquad (7)$$

which in general will not be zero. The question is how to choose $\mathbf{X}$ to maximize the power of a K factor test against a J>K factor alternative.[13]

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[13] Intuition tells us that asymptotically the power of GMM will be increasing in the deviation of $E[\mathbf{u}^\#_t \otimes \mathbf{Z}_{t-1}]$ from zero and decreasing in the size of $E[(\mathbf{u}^\#_t \otimes \mathbf{Z}_{t-1})'(\mathbf{u}^\#_t \otimes \mathbf{Z}_{t-1})]$ (see Ferson and Foerster [1991]). As can be seen from (8), the deviation of $E[\mathbf{u}^\#_t \otimes \mathbf{Z}_{t-1}]$ from $\mathbf{0}$ depends on the size

While analytically, this problem seems highly intractable, intuition can provide some guidance. Appendix 1 contains a discussion of situations when the power of the latent variables test will be low. This discussion of power suggests that forming portfolios with extreme values for the factor loadings may produce a more powerful test than using just size or industry portfolios. Briefly, the latent variables test of a K factor model is essentially a test whether the rank of the coefficient matrix α is less than or equal to K. Using portfolios with extreme values on the factor loadings ensures that the coefficient matrix has rank J>K.

Treating the coefficients on the predictive regression as risk loading proxies provides a motivation for using the EXTREME portfolios in latent variables tests.[14] The same argument provides a rationale for including the extreme deciles for both size and market beta (i.e., S1, S10, B1 and B10) in the testing. Fama and French [1991] interpret their evidence by viewing size as a risk loading proxy while the arguments for market wealth as a priced factor are well known.

3.2.3. Implementing Latent Variables Testing Using GMM.

Equation (5) can be tested and estimated using Hansen's [1982] GMM[15] which exploits the fact that (5b) implies $E[\mathbf{u}^p_t \otimes \mathbf{Z}_{t-1}] = \mathbf{0}$ for all t. Define $\mathbf{g}_T(\alpha_I, \gamma) = (1/T) \Sigma^T_{t=1} (\mathbf{u}^p_t \otimes \mathbf{Z}_{t-1})'$, a (NL)x1 vector. Testing whether (5) is misspecifed against a general alternative involves minimizing the function $\mathbf{g}_T' \mathbf{W}_T \mathbf{g}_T$ where $\mathbf{W}_T$ is a weighing matrix. Given $\mathbf{W}_T \rightarrow_p \mathbf{W}_0$, the choice of $\mathbf{W}_0$ which minimizes the asymptotic covariance matrix of the coefficient estimators is given by

$$(E[(\mathbf{u}^p_t \otimes \mathbf{Z}_{t-1})'(\mathbf{u}^p_t \otimes \mathbf{Z}_{t-1})])^{-1}. \quad (8)$$

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of $\{\phi\, \mathbf{b}^p - \alpha_I [\, \mathbf{I}_K : \gamma \,]\}$.

[14] A similar argument could be used to motivate the use of the CONSTRAINED portfolios in latent variables tests. However, the inclusion of these portfolios leads to numerical problems when performing GMM.

[15] The advantage of using GMM over maximum likelihood (ML) techniques is that very general specifications of $\mathbf{u}^p_t$ can be handled with relative ease. GMM provides less efficient estimators than ML when the latter is not misspecified but requires less information about the processes and so is more robust.

Asymptotically under the null, the minimized value of ($T\, \mathbf{g}_T'\, \mathbf{W}_T\, \mathbf{g}_T$) is chi-share distributed with degrees of freedom equal to the number of restrictions imposed by (5): NL-JL-(N-J)J=(N-J)(L-J).

A consistent estimator of $\mathbf{W}_0$ in (8) is obtained by defining $\mathbf{W}_T$:

$$\{(1/T)\, \Sigma^{T}_{t=1}[(\mathbf{u}\hat{}_t \otimes \mathbf{Z}_{t-1})'(\mathbf{u}\hat{}_t \otimes \mathbf{Z}_{t-1})]\}^{-1}. \qquad (9)$$

where $\mathbf{u}\hat{}_t$ is obtained using the GMM parameter estimates and so $\mathbf{W}_T$ depends on the parameter estimates. A two step procedure for obtaining the GMM statistic has been proposed by Hansen and Singleton [1982]. First, $\mathbf{g}_T'\, \mathbf{W}_T\, \mathbf{g}_T$ is minimized with respect to the parameters after setting $\mathbf{W}_T$ equal to the NLxNL identity matrix. The estimated parameters are then used to form $\mathbf{W}_T$ according to (9). Second, $\mathbf{g}_T'\, \mathbf{W}_T\, \mathbf{g}_T$ is again minimized using the $\mathbf{W}_T$ formed from the previous step. The new parameter estimates are used to reform $\mathbf{W}_T$ and the value of the objective function from the second step is calculated using this new $\mathbf{W}_T$. An iterative procedure has also been proposed where this second step is repeated until the objective function converges or reaches a minimum. Asymptotically, these two methods are equivalent, but the bootstrap evidence of Ferson and Foerster [1991] indicates that the two step procedure rejects too frequently in small samples using the asymptotic null distribution of ($T\, \mathbf{g}_T'\, \mathbf{W}_T\, \mathbf{g}_T$). For this reason, the iterated procedure is employed in this paper.

3.3. Principal Components.

Principal components analysis is performed for all sets of assets used in the latent variables testing. The purpose is to assess the ability of the principal components technique to detect factors in a constant (proportional) risk loading model. Any latent variables test is a test of the rank of the coefficient matrix from regressing $\mathbf{r}^p_t$ on $\mathbf{Z}_{t-1}$. Thus, principal components may have some ability to detect additional factors. For each set of assets, principal components is performed on the predictable portion of returns which is obtained by regressing asset return on the five information variables plus a constant.

4. Results.

Table 3 reports some summary information from the 5 year rolling predictive regressions for individual stocks. The results of the portfolio predictive regressions run over the entire sample period (1/68 to 12/89) are contained in Tables 4 and 5 while Table 6 presents the latent variables and principal components results. In each of Tables 4 through 6, three panels of results are reported, each corresponding to a different sample. Panel A forms portfolios using both NYSE and AMEX stocks while the second and third panels use only NYSE and AMEX stocks respectively.

4.1. The Predictive Regressions.

Table 3 contains results for the rolling five year predictive regressions. Average regression R^2's and error variances are obtained for size deciles by first equally weighing across stocks in a decile and then averaging over time for each decile. Deciles are formed using market capitalization at the end of each 5 year window. The major finding is that both the average R^2 and average error variance are higher for the small firm deciles, irrespective of the sample being considered. For the combined NYSE and AMEX sample, the average R^2 range from 0.133 for the largest decile to 0.168 for the smallest. In comparison, the average R^2 of the smallest NYSE (AMEX) decile is 0.158 (0.174). Thus, the fact that AMEX has smaller firms than NYSE leads to a higher average R^2 for its smallest decile than for NYSE or the combined sample.

Results of running predictive regressions over the entire period for the two bond portfolios (GB and HY), the CRSP index file size deciles and post ranking portfolio returns are reported in Table 4. Thirty stock portfolio regressions are reported for each of the three samples used: S1 to S10; 10% SCALED EXTREME; and, 5% SCALED CONSTRAINED. For the combined NYSE and AMEX size deciles, the R^2 range from 0.097 for the top decile to 0.347 for the bottom. Comparing across exchanges, the smallest decile for NYSE (AMEX) alone has a lower (higher) R^2 than for the combined sample, reflecting the greater concentration of small firms in the AMEX exchange. Notice that irrespective of the exchange, the R^2's for the large (small) firm deciles are smaller (much larger) than the average R^2's reported in Table 3 for the rolling 5 year regressions. The implication for small stocks is that a large proportion of unpredictable variation is diversified away when they are formed into small firm deciles. The evidence suggests this implication does not hold for large stocks. Instead, time series variation in the coefficients is allowing the 5 year regressions to have greater predictive ability than the entire period regression. For TRM, 82/90 of the coefficients are negative but only 4 of those 82 are significantly different from zero at the 5%

level; the non-negative coefficients are in the combined and NYSE samples while the rejections are in the AMEX sample. The coefficient for YBL is significantly different from zero at 5% and negative for all 90 regressions.

Focusing on the size deciles, all 30 coefficients are positive on the RCE variable. Further, all are significantly different from zero at 5% for the AMEX sample while only the bottom eight (five) deciles are significant for the combined (NYSE) sample. Thus, the RCE coefficient is only significantly nonzero for sufficiently small firms. This result is consistent with the argument (described in more detail below) that infrequent trading is driving the predictive power of the RCE.

For VDP, all 90 coefficients are positive and significantly different from zero at 5%. Considering the size deciles, all 30 coefficients are positive on the JAN variable. While all but the top decile are significantly different from zero at 5% for the AMEX and combined samples, only the bottom 6 deciles are significant for the NYSE sample.

The implication is that the coefficient on the JAN and RCE variables can be used to proxy for size. Examining these coefficients for the five pairs of 10% SCALED EXTREME portfolios and the five pairs of 5% SCALED CONSTRAINED portfolios suggests that ranking on any of the other variables also leads to a ranking on size even when the remaining nonranking variables are being constrained.

The formal hypothesis testing reported in Table 5 provides additional evidence. For each variable, tests of the equality of that variable's coefficient across the other 4 pairs of 10% SCALED EXTREME portfolios can be rejected at 5% using either the usual or heteroscedasticity consistent Wald statistic, irrespective of the sample; the only exception is the heteroscedasticity consistent statistic for TRM in the NYSE sample. Identical tests for the 5% SCALED CONSTRAINED portfolios are unable to reject equality at the 5% level for TRM (both tests) and RCE (both tests) in the combined sample, for VDP (both) and TRM (heteroscedasticity consistent only) in the NYSE sample, and for TRM (both),YBL (heteroscedasticity consistent only) and RCE (both) in the AMEX sample.

For the pairs of 10% SCALED EXTREME portfolios, one-sided tests of coefficient equality on the ranking variable can be rejected in all the samples (with the exception of the YBL pair in the AMEX sample). The implication is that the portfolio formation procedure is producing pairs of portfolios with spread on the ranking coefficient.[16]

When identical tests are performed on the pairs of 5% SCALED CONSTRAINED portfolios, fewer rejections are observed at the 5% level. For all three samples, it is not possible to reject a one sided test on the YBL and VDP coefficients. The one sided test on the TRM coefficient is only rejected by both tests for the AMEX sample. Thus, the constraints on the other coefficients imposed when forming the 5% SCALED CONSTRAINED portfolio pairs is reducing the dispersion on the ranking coefficient, particularly for the YBL and VDP pairs.[17] What is puzzling is that the lack of dispersion on the ranking variables within each pair does not translate into a lack of dispersion for that coefficient across the other pairs (see the discussion of the relevant tests above).

Finally, the finding of spread on the ranking coefficient for pairs of 10% EXTREME and 10% SCALED EXTREME result offers hope that the latent variables tests performed using these portfolios may have greater power than using size deciles. The latent variables results are described in the next section.

4.2. Latent Variables Testing using GMM and Principal Components Analysis.

Table 6 presents the principal components evidence and the results from testing the latent variables restrictions using GMM. Four sets of portfolios are tested for each of the three monthly return samples. The first set consists of size deciles plus the two bond portfolios (denote this set "SIZE-S") while the third consists of the five pairs of 10% SCALED EXTREME portfolios, top and bottom size deciles, top and bottom market beta deciles plus the two bond portfolios (denote this set

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[16] Similar results (available on request) are obtained using pairs of 10% EXTREME portfolios.

[17] Similar results (available on request) are obtained when portfolios are formed using the unscaled coefficients. For the 5% CONSTRAINED portfolios, a one-sided test of ranking coefficient equality cannot be rejected for the VDP pair in all three samples nor for the TRM or YBL pairs in the combined or NYSE samples. The ability to obtain dispersion subject to constraints on the other variables is also largely unaffected by reducing the maximum portfolio weight from 5% to 1%. Wald statistics testing the hypothesis that the ranking coefficient for the maximum portfolio is greater than or equal to the ranking coefficient for the minimum portfolio are both insignificant at the 5% level for the VDP and YBL pairs in all three samples and for the TRM pair in the NYSE sample.

"S:EXTM-10"). The fourth set is the same as the third except that the five pairs of 10% SCALED EXTREME portfolios are replaced by the five pairs of 10% EXTREME portfolios (denote this set "U:EXTM-10"). For the NYSE and AMEX samples (Panels B and C respectively), the second set is the size portfolios formed using combined NYSE and AMEX breakpoints plus the two bond portfolios (denoted "SIZE-A"). For the combined NYSE and AMEX sample, the portfolios (U1 to U10) randomly formed from the size deciles constitute the third set, together with the two bond portfolios (denoted "SIZE-U"). To identify the sample of assets being referred to, the following suffixes will be employed:"NYSE","AMEX" and "COMBINED".

Using the SIZE-S COMBINED set of assets allows a two factor model to be rejected, while forming the size deciles using only NYSE (AMEX) stocks allows no (only one) factor to be rejected. Possible explanations include:

1) the combined NYSE and AMEX deciles have a greater spread on size than either the NYSE deciles or the AMEX deciles;

2) the latent variables test for the combined sample has greater power because the combined NYSE and AMEX deciles have a larger number of assets in each decile than the NYSE deciles or the AMEX deciles; or,

3) there are factors whose risk loadings vary across NYSE stocks but not AMEX stocks, and vice versa.

The three other sets of size portfolios described in Section 2.2.2 were used in the latent variables tests in an attempt to rule out the first two explanations. Since the result is found to persist when SIZE-S NYSE and SIZE-S AMEX are replaced by SIZE-A NYSE and SIZE-A AMEX, it seems that explanation 1) is not driving the greater number of factors in the combined sample. However, the SIZE-U COMBINED set of assets only rejects a one factor model suggesting that the tests performed on the combined sample may have greater power because of larger numbers of stocks in the portfolios.

Turning to the sets of assets which include extreme portfolios, up to a three (one) factor model can be rejected for the S:EXTM-10 COMBINED (NYSE) set of assets. For both these samples, the U:EXTM-10 set is only able to reject the same number of factors as the SIZE-S set.

When the AMEX sample is used, both the S:EXTM-10 and U:EXTM-10 sets of assets can reject an extra factor relative to the SIZE-S set which could only reject one. So using scaled rather than unscaled coefficients to form the extreme portfolios provides greater power in the latent variables tests for the combined and NYSE samples.

To summarize, the pairs of extreme portfolios formed using scaled coefficients provide greater power than size deciles for all three samples. Possible reasons for the improved power of the S:EXTM-10 sets of assets are as follows: 1) Inclusion of the top and bottom market Beta deciles may capture a risk dimension in addition to the one captured by size; 2) The variation in the predictive regression coefficients on the ranking variable exhibited by the pairs of SCALED EXTREME portfolios may capture an additional risk dimension; and, 3) A greater number of portfolios (16 versus 12) are contained in the extreme portfolios and the small sample properties of GMM may depend on the number of assets in the test (see Ferson and Foerster [1991]).

The other main result is that the minimum number of factors which can not be rejected varies across samples. The caveat is that the result may be driven by different sample sizes. In the discussion to follow, the results for each of the S:EXTM-10 set of assets will be taken as characterizing the return generating process for stocks in each of the three samples. While up to a three factor constant beta model can be rejected for the COMBINED sample, no more than one (two) factors can be rejected for the NYSE (AMEX) sample. The ability to reject a K but not a (K+1) factor model for a set of assets implies that at least (K+1) factors must be employed to price all the assets in the set: 1) conditioning on at least the information variables used in the testing; and, 2) using conditional risk loadings that are proportional through time. Possible explanations for the subsamples needing a smaller minimum number of factors are:

1) A four factor model is needed for the COMBINED sample but for all stocks in the NYSE, the factor loadings on the other two of the factors are the same linear combination of the factor loadings on the first two factors. For all stocks in the AMEX sample, the factor loading on one of the first two factors is the same linear combination of the factor loadings of the other three variables.
2) The two markets are segmented.

The challenge presented by these preliminary results is to identify economically meaningful factors whose factor loadings would be expected to have the properties described in the first explanation.

One problem associated with including AMEX stocks in the samples is that a larger proportion of individual stock returns are contaminated by infrequent trading. The use of information variables which involves stock index price at the start of the period (RCE and VDP) means that ability of these variables to predict return could be due to infrequent trading effects and not the predictability of expected return. As discussed above, the RCE coefficients from the entire period predictive regressions using S1 to S10 provide support for this argument. Thus, the ability of a latent variables tests on portfolios from either the combined or AMEX samples to reject a higher factor model than for the NYSE sample could be due to the spurious effect of infrequent trading on observed returns. This possibility is an important qualification to the results for the combined sample.

The second section of each panel contains the results of principal components analysis performed on the sets of portfolio returns used in the latent variables tests. The cumulative proportion of the total variation explained by the first five principal components is reported for the predictable portion of returns. The predictable portion is obtained by regressing portfolio return on the information variables plus a constant. In each sample, the cumulative proportions explained by the first two principal components are larger for the two sets of assets which include EXTREME portfolios. The cumulative proportion explained by any number of principal components greater than two is similar across the four sets of assets irrespective of the sample. So the principal components evidence is ambiguous and not susceptible to a clear interpretation. It seems that principal components is unable to discriminate between different pricing models and fails to provide any useful incremental information relative to the GMM results.

5. Conclusions.

This study presents summary statistics obtained from running 5 year rolling predictive regressions for monthly returns on individual stocks listed on NYSE and AMEX. Five information variables plus a constant are used: 1) a term spread variable; 2) the yield on a one month t-bill; 3) lagged return on a equal weighted stock index; 4) a dividend yield variable; and, 5) a January dummy. Three samples are considered: 1) combined NYSE and AMEX; 2) NYSE; and, 3) AMEX. The major finding (which holds for all three samples) is that the R^2 of these regressions for firms in the top (bottom) size decile is greater (much smaller) than the R^2 for the predictive regression run over the entire period for the largest (smallest) firm decile. Both the average individual stock R^2 and the portfolio R^2 increase going from the large to the small firm deciles. At the same time, average error volatility increases going from the large to small deciles.

There is also some evidence that the coefficients from these individual stock predictive regressions are time varying. The major supporting evidence is the inability to form portfolios with equal coefficient values using the results of the individual stock regressions. Further research is needed to fully characterize the time series behavior of these coefficients.

An attempt is made to perform latent variables tests which have greater power than previous testing. The suggested strategy for improving power is to form extreme portfolios on the basis of factor loading proxies. Size, market beta and predictive regression coefficients are used as proxies in this paper. If size deciles and two bond portfolios conform to a K factor constant Beta model, then at least one of the sets of extreme portfolios formed using the stated proxies does not conform to a K factor model: in all three samples, one extra factor is needed. The important message is that the use of portfolios in the testing may mask factors which are needed to price individual stocks using a constant (proportional) Beta model.

Fama and French [1991] recently reported that the ratio (Book Equity/Market Equity) has ability to explain the cross section of returns which is distinct from the size effect. A suggestion for future research is to form extreme portfolios on the basis of Book to Market and include them in latent variable tests.

The paper also presents some evidence of different pricing structures across the NYSE and AMEX exchanges. Fewer factors are needed in a proportional (constant) factor loading model to describe returns for sets of assets formed from NYSE or AMEX stocks alone than is needed to describe returns for a set of assets formed using both NYSE and AMEX stocks. This intriguing result suggests that a fruitful avenue for future research may be to better characterize the asset pricing structures across the domestic U.S. stock exchanges. This type of research would be analogous to the work reported in a number of recent papers examining pricing differences across countries (see De Santis [1991]).

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Table 1

The information variables used are described in detail in Section 3.1 while the portfolio formation procedures are discussed in Section 3.2.

Symbol Descriptions

Information Variables

YBL(t-1): the nominal yield on a one month bill known at the end of t-1;
TRM(t-1): YB5(t-1) - YBL(t-1) where YB5(t-1) is the nominal yield on a five year bond known at the end of t-1.
RCE(t-1): the continuous real return on the NYSE equal weighted index provided by CRSP over the month prior to the start of period t;
VDP(t-1): VD(t-1)/VP(t-1) where VD(t-1) is the dividend paid on the value weighted index of NYSE over the twelve months prior to period t and VP(t-1) is the value of the index at the start of period t;
JAN(t-1): a January dummy set equal to 1 if t=January;

Portfolios

Sj: jth value weighted size decile for the given exchange(s), j=1, 2, ..., 10 (1=small);
Aj: jth value weighted size portfolio using NYSE and AMEX breakpoints;
Uj: For each firm in Sj in a year, a number q distributed U[0,1] is drawn and if q > 0.5 that firm is omitted from the portfolio;
Bj: jth equal weighted Beta decile formed for the given exchange(s), j=1, 2, ..., 10 (1=small);
s:j10 & s:j1: the top and bottom 10% SCALED EXTREME portfolios for information variable j, j=TRM, YBL, RCE, VDP, JAN;
s:jmn & s:jmx: the minimizing and maximizing 5% SCALED CONSTRAINED portfolios for information variable j, j=TRM, YBL, RCE, VDP, JAN;
u:j10 & s:j1: the top and bottom 10% EXTREME portfolios for information variable j, j=TRM, YBL, RCE, VDP, JAN;
GB: long term government bond portfolio; and,
HY: low grade corporate bond portfolio.

Table 2

Sample correlations of the information variables over the period 1/68 - 12/89 (264 observations). Symbols are defined in Table 1 while the information variables are described in detail in Section 3.2.

Principal components analysis for the information variables is contained in the second section. The proportion of the total variation explained by the first five principal components is reported.

Information Variables

Correlation	TRM	YBL	RCE	VDP	JAN
TRM	1.0				
YBL	-.4740	1.0			
RCE	.1227	-.1080	1.0		
VDP	.0303	.6359	-.0330	1.0	
JAN	.0659	-.0601	.0320	.0028	1.0
Princ. Comp.	1st	2nd	3rd	4th	5th
Z	.3625	.2221	.1943	.1828	.0384

Table 3

Summary statistics for the 5 year rolling individual stock predictive regressions run using the five information variables (plus a constant) defined in Section 2.1. and monthly returns. The five year window starts with 1/63-12/67 and ends with 1/85-12/89. There are three samples of stocks: the combined NYSE and AMEX sample; NYSE alone; and, AMEX alone. The criteria that a stock must satisfy for inclusion in a sample are discussed in Section 2.2.3.

For each sample, average R^2 and error standard deviations are reported by size decile for the following rolling 5 year OLS regression (symbols are as defined in Table 1):

$$ri(t) = \alpha_{y,1,i} + \alpha_{y,2,i}\, UTS(t\text{-}1) + \alpha_{y,3,i}\, ECI(t\text{-}1) + \alpha_{y,4,i}\, RCE(t\text{-}1) + \alpha_{y,5,i}\, VDP(t\text{-}1) + \alpha_{y,6,i}\, JAN(t\text{-}1) + \epsilon_{y,i}(t) \quad y=1,\ldots,Y.$$

For each five year window, stocks are formed into deciles on the basis of capitalization at the end of the five years, and decile average R^2 and error standard deviations are calculated using equal weights. These cross-sectional averages are then averaged over time to obtain the figures reported in the table.

	Panel A: NYSE & AMEX		Panel B: NYSE		Panel C: AMEX	
Size Decile	Av R^2	Av STD ERR	Av R^2	Av STD ERR	Av R^2	Av STD ERR
1	0.168	0.153	0.158	0.125	0.174	0.162
2	0.162	0.135	0.156	0.111	0.168	0.150
3	0.155	0.125	0.154	0.106	0.163	0.145
4	0.158	0.117	0.151	0.102	0.163	0.137
5	0.153	0.111	0.147	0.097	0.161	0.134
6	0.149	0.105	0.142	0.093	0.156	0.132
7	0.143	0.096	0.138	0.090	0.154	0.130
8	0.138	0.092	0.131	0.084	0.156	0.126
9	0.131	0.083	0.130	0.079	0.148	0.127
10	0.133	0.075	0.133	0.073	0.138	0.112

Table 4

Results of running the following OLS regression using monthly post ranking returns over the period 1/68 - 12/89 (264 observations):

$$rp(t) = \alpha_{1,p} + \alpha_{2,p}\,TRM(t\text{-}1) + \alpha_{3,p}\,YBL(t\text{-}1) + \alpha_{4,p}\,RCE(t\text{-}1) + \alpha_{5,p}\,VDP(t\text{-}1) + \alpha_{6,p}\,JAN(t\text{-}1) + \epsilon_p(t)$$

for p =

i. a long term government bond portfolio (GB) and a low grade bond portfolio (HY);
ii. the value weighted size deciles (S1-S10);
iii. the five pairs of 10% SCALED EXTREME portfolios (s:TRM1,s:TRM10,...,s:JAN10); and,
iv. the five pairs of 5% SCALED CONSTRAINED portfolios (s:TRMmn,s:TRMmx,...,s:JANmx).

Descriptions of the symbols are contained in Table 1. All portfolios are described in detail in Section 2.2 with the five information variables as defined in Section 2.1. Briefly, the SIZE deciles are obtained from the CRSP index series. The 10% SCALED EXTREME portfolios consist of five pairs of weighted extreme portfolios formed in the following manner. Each firm's coefficients for a given 5 year regression are scaled by their standard deviations as estimated by that regression. Each year, the scaled coefficients for each information variable are ranked and the top and bottom 10% are used to obtain a pair of weighted extreme portfolios for the next 12 months. Portfolio 1 has the 10% of stocks with the smallest coefficients. To obtained a pair of 5% SCALED CONSTRAINED portfolios for a given information variable, portfolio weights are chosen each year to maximize (minimis) the portfolio's scaled coefficient for the relevant information variable subject to the following constraints:

1) all weights are non-negative but less than 0.05; and
2) the portfolio's scaled coefficient for each of the other information variables equals the cross-sectional average.

Each firm's coefficients for a given 5 year regression are scaled by their standard deviations as estimated by that regression. Each year, the scaled coefficients for each information variable are ranked and the top and bottom 10% are used to obtain a pair of weighted extreme portfolios for the next 12 months. Portfolio 1 has the 10% of stocks with the smallest coefficients.

Starred (*) coefficients are more than 1.96 standard errors from zero using White's [1980] heteroscedasticity consistent covariance estimator. Hypothesis test results are reported in Table 2.

Monthly Returns, Bond and Bill Portfolios, 1/68 - 12/89 (T=264,Y=22)

	CONST	TRM	YBL	RCE	VDP	JAN	R^2
GB	-0.022*	0.003	-0.001	0.003	0.722*	0.015*	0.106
HY	-0.011*	0.002*	0.000	-0.044	0.164	-0.000	0.055

Table 4 cont

Panel A: Monthly Returns, NYSE & AMEX, 1/68 - 12/89 (T=264,Y=22)

	CONST	TRM	YBL	RCE	VDP	JAN	R^2
			Post-Ranking Size Decile Returns: Regression Coefficients				
S1	-0.061*	-0.009	-0.012*	0.348*	3.844*	0.146*	0.347
S2	-0.067*	-0.007	-0.011*	0.289*	3.786*	0.098*	0.270
S3	-0.071*	-0.005	-0.011*	0.214*	3.777*	0.075*	0.231
S4	-0.069*	-0.005	-0.011*	0.175*	3.715*	0.066*	0.214
S5	-0.067*	-0.005	-0.011*	0.168*	3.653*	0.053*	0.191
S6	-0.065*	-0.004	-0.011*	0.158*	3.623*	0.040*	0.184
S7	-0.057*	-0.003	-0.009*	0.124*	3.207*	0.033*	0.163
S8	-0.053*	-0.002	-0.009*	0.103*	2.967*	0.023*	0.149
S9	-0.048*	-0.002	-0.008*	0.059	2.714*	0.017*	0.124
S10	-0.033*	0.001	-0.006*	0.044	1.825*	0.006	0.097
			Post-Ranking 10% SCALED EXTREME Port. Returns: Reg. Coefficients				
TRM1	-0.065*	**-0.007**	-0.010*	0.197*	3.627*	0.064*	0.225
TRM10	-0.053*	**-0.001**	-0.008*	0.145*	2.898*	0.037*	0.173
YBL1	-0.068*	-0.007	**-0.012***	0.235*	3.991*	0.066*	0.222
YBL10	-0.044*	-0.001	**-0.008***	0.082	2.563*	0.034*	0.162
RCE1	-0.043*	-0.000	-0.005*	**0.021**	2.101*	0.026*	0.130
RCE10	-0.072*	-0.005	-0.011*	**0.286***	3.750*	0.087*	0.270
VDP1	-0.039*	-0.003	-0.006*	0.090	**2.178***	0.047*	0.167
VDP10	-0.071*	-0.004	-0.011*	0.208*	**3.881***	0.052*	0.199
JAN1	-0.042*	-0.000	-0.006*	0.063	2.155*	**0.017**	0.119
JAN10	-0.064*	-0.006	-0.012*	0.279*	3.752*	**0.112***	0.297
			Post-Ranking 5% SCALED CONSTRAINED Port. Returns: Reg. Coefficients				
TRMmn	-0.039	**-0.006**	-0.010*	0.176*	2.864*	0.099*	0.217
TRMmx	-0.063*	**-0.002**	-0.013*	0.161*	3.931*	0.018	0.166
YBLmn	-0.049*	-0.006	**-0.013***	0.252*	3.559*	0.121*	0.255
YBLmx	-0.053*	-0.001	**-0.009***	0.153*	3.013*	0.008	0.123
RCEmn	-0.050*	0.002	-0.005*	**0.088**	2.231*	0.032*	0.140
RCEmx	-0.082*	-0.003	-0.009*	**0.296***	3.721*	0.087*	0.230
VDPmn	-0.054*	-0.007	-0.013*	0.245*	**3.760***	0.126*	0.267
VDPmx	-0.058*	-0.000	-0.010*	0.185*	**3.177***	0.005	0.132
JANmn	-0.039*	-0.002	-0.007*	0.097*	2.430*	**0.025**	0.111
JANmx	-0.060*	-0.005	-0.009*	0.194*	3.142*	**0.085***	0.186

Table 4 cont

Panel B: Monthly Returns, NYSE Only, 1/68 - 12/89 (T=264,Y=22)

	CONST	TRM	YBL	RCE	VDP	JAN	R^2
			Post-Ranking Size Decile Returns: Regression Coefficients				
S1	-0.064*	-0.006	-0.011*	0.168*	3.714*	0.092*	0.220
S2	-0.071*	-0.005	-0.011*	0.135*	3.787*	0.068*	0.213
S3	-0.065*	-0.004	-0.010*	0.148*	3.484*	0.053*	0.194
S4	-0.063*	-0.004	-0.010*	0.130*	3.519*	0.040*	0.183
S5	-0.057*	-0.003	-0.009*	0.120*	3.180*	0.036*	0.169
S6	-0.056*	-0.002	-0.009*	0.097	3.051*	0.030*	0.157
S7	-0.054*	-0.002	-0.009*	0.098	2.957*	0.018	0.143
S8	-0.047*	-0.002	-0.008*	0.049	2.744*	0.018	0.124
S9	-0.046*	-0.000	-0.007*	0.051	2.430*	0.012	0.115
S10	-0.031*	0.001	-0.005*	0.040	1.735*	0.005	0.094
			Post-Ranking 10% SCALED EXTREME Port. Returns: Reg. Coefficients				
TRM1	-0.067*	**-0.005**	-0.010*	0.145*	3.554*	0.049*	0.184
TRM10	-0.052*	**-0.000**	-0.008*	0.077	2.762*	0.021	0.150
YBL1	-0.068*	-0.006	**-0.012***	0.183*	3.965*	0.052*	0.188
YBL10	-0.051*	0.000	**-0.007***	0.025	2.529*	0.024	0.149
RCE1	-0.044*	0.000	-0.005*	**-0.001**	2.038*	0.024*	0.118
RCE10	-0.062*	-0.004	-0.011*	**0.178***	3.554*	0.048*	0.190
VDP1	-0.041*	-0.001	-0.005*	0.026	**2.037***	0.035*	0.134
VDP10	-0.066*	-0.003	-0.011*	0.172*	**3.689***	0.039*	0.169
JAN1	-0.043*	-0.000	-0.006*	0.071	2.210*	**0.014**	0.113
JAN10	-0.056*	-0.004	-0.011*	0.162*	3.475*	**0.067***	0.211
			Post-Ranking 5% SCALED CONSTRAINED Port. Returns: Reg. Coefficients				
TRMmn	-0.045*	**-0.006**	-0.011*	0.151*	3.164*	0.093*	0.214
TRMmx	-0.047*	**-0.001**	-0.010*	0.151*	3.119*	0.004	0.129
YBLmn	-0.046*	-0.006	**-0.012***	0.181*	3.391*	0.112*	0.236
YBLmx	-0.055*	0.001	**-0.008***	0.117	2.835*	-0.004	0.110
RCEmn	-0.056*	0.001	-0.005*	**0.023**	2.375*	0.029*	0.136
RCEmx	-0.060*	-0.004	-0.011*	**0.182***	3.608*	0.044*	0.174
VDPmn	-0.042	-0.006	-0.011*	0.172*	**3.183***	0.112*	0.224
VDPmx	-0.058*	0.001	-0.008*	0.146*	**2.901***	-0.008	0.111
JANmn	-0.039*	-0.002	-0.008*	0.067	2.513*	**0.026**	0.113
JANmx	-0.045*	-0.004	-0.010*	0.185*	2.977*	**0.045***	0.167

Table 4 cont

Panel C: Monthly Returns, AMEX Only, 1/68 - 12/89 (T=264,Y=22)

	CONST	TRM	YBL	RCE	VDP	JAN	R^2
			Post-Ranking Size Decile Returns: Regression Coefficients				
S1	-0.063*	-0.009	-0.013*	0.391*	4.020*	0.180*	0.384
S2	-0.063*	-0.009	-0.012*	0.314*	3.869*	0.140*	0.335
S3	-0.072*	-0.007	-0.011*	0.325*	3.758*	0.110*	0.295
S4	-0.062*	-0.006	-0.011*	0.299*	3.528*	0.093*	0.267
S5	-0.072*	-0.007	-0.012*	0.255*	4.053*	0.085*	0.241
S6	-0.072*	-0.005	-0.011*	0.254*	3.729*	0.070*	0.243
S7	-0.067*	-0.005	-0.011*	0.199*	3.725*	0.059*	0.207
S8	-0.068*	-0.006	-0.011*	0.236*	3.754*	0.050*	0.194
S9	-0.065*	-0.006	-0.012*	0.203*	3.839*	0.032*	0.158
S10	-0.040*	-0.006	-0.010*	0.150*	2.970*	0.019	0.114
			Post-Ranking 10% SCALED EXTREME Port. Returns: Reg. Coefficients				
TRM1	-0.058*	**-0.009***	-0.011*	0.292*	3.630*	0.085*	0.274
TRM10	-0.062*	**-0.003**	-0.010*	0.259*	3.371*	0.066*	0.221
YBL1	-0.061*	-0.009*	**-0.012***	0.328*	3.807*	0.084*	0.258
YBL10	-0.045*	-0.003	**-0.010***	0.240*	2.964*	0.066*	0.223
RCE1	-0.049*	-0.005	-0.010*	**0.183***	3.176*	0.060*	0.224
RCE10	-0.079*	-0.005	-0.011*	**0.347***	4.046*	0.126*	0.319
VDP1	-0.047*	-0.005	-0.008*	0.239*	**2.763***	0.070*	0.252
VDP10	-0.075*	-0.006	-0.012*	0.269*	**4.066***	0.080*	0.237
JAN1	-0.049*	-0.002	-0.007*	0.215*	2.666*	**0.039***	0.227
JAN10	-0.071*	-0.007	-0.013*	0.330*	4.145*	**0.136***	0.322
			Post-Ranking 5 SCALED CONSTRAINED Port. Returns: Reg. Coefficients				
TRMmn	-0.055*	**-0.010***	-0.012*	0.335*	3.647*	0.162*	0.366
TRMmx	-0.086*	**-0.004**	-0.012*	0.206*	4.396*	0.037	0.173
YBLmn	-0.054*	-0.010	**-0.014***	0.391*	4.032*	0.151*	0.323
YBLmx	-0.072*	-0.002	**-0.010***	0.246*	3.573*	0.027	0.162
RCEmn	-0.040*	-0.005	-0.009*	**0.220***	2.670*	0.056*	0.184
RCEmx	-0.082*	-0.005	-0.011*	**0.315***	4.066*	0.121*	0.276
VDPmn	-0.056*	-0.012*	-0.015*	0.386*	**4.224***	0.157*	0.329
VDPmx	-0.073*	-0.002	-0.011*	0.231*	**3.784***	0.026	0.161
JANmn	-0.044*	-0.004	-0.008*	0.246*	2.740*	**0.055***	0.189
JANmx	-0.075*	-0.005	-0.010*	0.280*	3.637*	**0.097***	0.219

Table 5

Results of performing hypothesis tests on the coefficients of the following OLS regression using monthly post ranking returns over the period 1/68 - 12/89 (264 observations):

$$rp(t) = \alpha_{1,p} + \alpha_{2,p}\,TRM(t\text{-}1) + \alpha_{3,p}\,YBL(t\text{-}1) + \alpha_{4,p}\,RCE(t\text{-}1) + \alpha_{5,p}\,VDP(t\text{-}1) + \alpha_{6,p}\,JAN(t\text{-}1) + \epsilon_p(t)$$

for p =
i. a long term government bond portfolio (GB) and a low grade bond portfolio (HY);
ii. the value weighted size deciles (S1-S10);
iii. the five pairs of 10% SCALED EXTREME portfolios (s:TRM1,s:TRM10,...,s:JAN10); and,
iv. the five pairs of 5% SCALED CONSTRAINED portfolios (s:TRMmn,s:TRMmx,...,s:JANmx).

Descriptions of the symbols are contained in Table 1. All portfolios are described in detail in Section 2.2 with the five information variables as defined in Section 2.1.

Briefly, the SIZE deciles are obtained from the CRSP index series. The 10% SCALED EXTREME portfolios consist of five pairs of weighted extreme portfolios formed in the following manner. Each firm's coefficients for a given 5 year regression are scaled by their standard deviations as estimated by that regression. Each year, the scaled coefficients for each information variable are ranked and the top and bottom 10% are used to obtain a pair of weighted extreme portfolios for the next 12 months. Portfolio 1 has the 10% of stocks with the smallest coefficients. To obtained a pair of 5% SCALED CONSTRAINED portfolios for a given information variable, portfolio weights are chosen each year to maximize (minimise) the portfolio's scaled coefficient for the relevant information variable subject to the following constraints:
1) all weights are non-negative but less than 0.05; and
2) the portfolio's scaled coefficient for each of the other information variables equals the cross-sectional average.
Each firm's coefficients for a given 5 year regression are scaled by their standard deviations as estimated by that regression. Each year, the scaled coefficients for each information variable are ranked and the top and bottom 10% are used to obtain a pair of weighted extreme portfolios for the next 12 months. Portfolio 1 has the 10% of stocks with the smallest coefficients.

For each test, two statistics are reported. The "Wald" statistic is a standard Wald test while the value labelled "Het" is a Wald statistic obtained using White's [1980] heteroscedasticity consistent covariance estimator.

Table 5 cont

Panel A: Monthly Returns, NYSE & AMEX, 1/68 - 12/89 (T=264,Y=22)

Hypothesis	j	TRM	YBL	RCE	VDP	JAN
Size						
$H_0: \alpha_{j,S1}=\alpha_{j,S2} = \dots = \alpha_{j,S10}$	Waldχ^2	15.45	17.49	57.23	34.21	208.7
	p-val	.0794	.0416	.0000	.0001	.0000
df=9	Hetχ^2	12.45	13.58	44.30	24.61	261.6
	p-val	.1892	.1380	.0000	.0034	.0000
$H_0: \alpha_{j,S1}=\alpha_{j,S2}=\dots =\alpha_{j,S10}=\alpha_{j,GB}=\alpha_{j,HY}$	Waldχ^2	16.62	26.56	64.44	41.68	219.1
	p-val	.1197	.0054	.0000	.0000	.0000
df=11	Hetχ^2	14.38	21.35	57.66	31.16	270.2
	p-val	.2124	.0299	.0000	.0010	.0000
10% SCALED EXTREME						
$H_0: \alpha_{j,s:j1} \leq \alpha_{j,s:j10}$	Waldχ^2	8.07	6.53	40.57	16.12	107.1
	p-val	.0023	.0053	.0000	.0001	.0000
df=1[a]	Hetχ^2	7.87	7.22	29.73	10.72	44.28
	p-val	.0025	.0036	.0000	.0005	.0000
$H_0: \alpha_{j,s:k1}=\alpha_{j,s:k10} = \dots = \alpha_{j,s:n10}$	Waldχ^2	21.80	26.05	31.40	33.75	95.55
	p-val	.0028	.0005	.0001	.0000	.0000
$k,\dots,n \neq j$ df=7	Hetχ^2	18.85	24.39	24.30	29.27	52.90
	p-val	.0087	.0010	.0010	.0001	.0000
5% SCALED CONSTRAINED						
$H_0: \alpha_{j,s:jmn} \leq \alpha_{j,s:jmx}$	Waldχ^2	1.78	1.33	14.09	0.60	33.52
	p-val	.0913	.1244	.0001	.2189	.0000
df=1[a]	Hetχ^2	1.60	0.87	14.15	0.33	15.09
	p-val	.1028	.1759	.0001	.2836	.0001
$H_0: \alpha_{j,s:kmn}=\alpha_{j,s:kmx} = \dots = \alpha_{j,s:nmx}$	Waldχ^2	14.09	31.29	13.18	18.90	93.70
	p-val	.0496	.0001	.0679	.0085	.0000
$k,\dots,n \neq j$ df=7	Hetχ^2	13.60	28.98	11.70	18.01	26.20
	p-val	.0589	.0001	.1110	.0119	.0005

a Since the test is one sided, the appropriate p-value is half the chi-square p-value.

Table 5 cont

Panel B: Monthly Returns, NYSE Only, 1/68 - 12/89 (T=264,Y=22)

Hypothesis	j	TRM	YBL	RCE	VDP	JAN
Size						
$H_0{:}\alpha_{j,S1}=\alpha_{j,S2}$ $=\ldots=\alpha_{j,S10}$	Waldχ^2 p-val	13.88 .1267	18.14 .0336	34.84 .0000	34.68 .0000	98.13 .0000
df=9	Hetχ^2 p-val	13.10 .1582	14.57 .1034	31.24 .0003	28.16 .0009	44.61 .0000
$H_0{:}\alpha_{j,S1}=\alpha_{j,S2}=\ldots$ $=\alpha_{j,S10}=\alpha_{j,GB}=\alpha_{j,HY}$	Waldχ^2 p-val	15.29 .1694	28.57 .0026	38.47 .0000	44.31 .0000	102.9 .0000
df=11	Hetχ^2 p-val	14.24 .2199	24.61 .0104	37.91 .0000	38.40 .0000	54.92 .0000
10% SCALED EXTREME						
$H_0{:}\alpha_{j,s:j1}\leq\alpha_{j,s:j10}$	Waldχ^2 p-val	7.79 .0027	8.08 .0023	24.64 .0000	13.94 .0001	54.23 .0000
df=1[a]	Hetχ^2 p-val	6.70 .0048	7.94 .0024	26.92 .0000	10.09 .0007	19.53 .0000
$H_0{:}\alpha_{j,s:k1}=\alpha_{j,s:k10}$ $=\ldots=\alpha_{j,s:n10}$	Waldχ^2 p-val	15.58 .0292	26.98 .0003	17.10 .0168	38.25 .0000	33.67 .0000
$k,\ldots,n\neq j$ df=7	Hetχ^2 p-val	11.30 .1259	27.48 .0003	23.49 .0003	34.68 .0000	19.81 .0060
5% SCALED CONSTRAINED						
$H_0{:}\alpha_{j,s:jmn}\leq\alpha_{j,s:jmx}$	Waldχ^2 p-val	2.89 .0446	1.96 .0806	13.80 .0001	0.15 .3489	6.70 .0097
df=1[a]	Hetχ^2 p-val	2.41 .0601	1.35 .1228	13.20 .0001	0.09 .3801	4.50 .0169
$H_0{:}\alpha_{j,s:kmn}=\alpha_{j,s:kmx}$ $=\ldots=\alpha_{j,s:nmx}$	Waldχ^2 p-val	14.80 .0386	24.45 .0009	17.80 .0129	11.29 .1263	78.26 .0000
$k,\ldots,n\neq j$ df=7	Hetχ^2 p-val	11.54 .1167	20.97 .0038	18.72 .0091	9.82 .1990	20.62 .0044

a Since the test is one sided, the appropriate p-value is half the chi-square p-value.

Table 5 cont

Panel C: Monthly Returns, AMEX Only, 1/68 - 12/89 (T=264,Y=22)

Hypothesis	j	TRM	YBL	RCE	VDP	JAN
Size						
$H_0: \alpha_{j,S1}=\alpha_{j,S2} = \ldots = \alpha_{j,S10}$	Waldχ^2	10.21	9.95	31.63	11.29	234.1
	p-val	.3642	.3543	.0002	.2567	.0000
df=9	Hetχ^2	10.39	10.24	27.82	14.63	177.2
	p-val	.3198	.3315	.0010	.1017	.0000
$H_0: \alpha_{j,S1}=\alpha_{j,S2}=\ldots = \alpha_{j,S10}=\alpha_{j,GB}=\alpha_{j,HY}$	Waldχ^2	17.47	27.41	48.23	33.59	247.2
	p-val	.0948	.0040	.0000	.0004	.0000
df=11	Hetχ^2	16.54	27.10	51.64	31.02	245.6
	p-val	.1222	.0044	.0000	.0011	.0000
10% SCALED EXTREME						
$H_0: \alpha_{j,s:j1} \leq \alpha_{j,s:j10}$	Waldχ^2	7.33	2.01	17.49	10.02	103.5
	p-val	.0034	.0782	.0000	.0008	.0000
df=1[a]	Hetχ^2	7.10	2.40	16.30	6.37	55.88
	p-val	.0038	.0605	.0000	.0058	.0000
$H_0: \alpha_{j,s:k1}=\alpha_{j,s:k10} = \ldots = \alpha_{j,s:n10}$	Waldχ^2	18.40	16.47	14.95	16.01	104.8
	p-val	.0103	.0211	.0367	.0250	.0000
$k,\ldots,n \neq j$ df=7	Hetχ^2	18.48	17.41	14.75	16.60	68.48
	p-val	.0100	.0149	.0393	.0202	.0000
5% SCALED CONSTRAINED						
$H_0: \alpha_{j,s:jmn} \leq \alpha_{j,s:jmx}$	Waldχ^2	3.52	2.12	3.20	0.37	16.16
	p-val	.0303	.0727	.0367	.2728	.0000
df=1[a]	Hetχ^2	3.90	1.51	3.70	0.23	8.96
	p-val	.0248	.1095	.0271	.3158	.0014
$H_0: \alpha_{j,s:kmn}=\alpha_{j,s:kmx} = \ldots = \alpha_{j,s:nmx}$	Waldχ^2	8.36	14.92	10.89	19.91	165.7
	p-val	.3023	.0371	.1437	.0058	.0000
$k,\ldots,n \neq j$ df=7	Hetχ^2	5.79	10.45	12.43	14.53	78.71
	p-val	.5643	.1647	.0871	.0425	.0000

a Since the test is one sided, the appropriate p-value is half the chi-square p-value.

Table 6

The first section in each panel contains GMM tests of J factor models (5) over the sample period 1/68 to 12/89 using monthly real returns for various sets of assets (T=264). $\mathbf{Z}_{t-1}$ consists of the five information variables described in Section 2.1 plus a constant (L=6). The following sets of assets are used:
SIZE-S SET = {S1,..., S10, GB, TB};
SIZE-U SET = {U1,..., U10, GB, TB};
SIZE-A SET = {A1,..., A10, GB, TB};
S:EXTM-10 SET = {s:TRM1, s:TRM10,..., s:JAN10, GB, TB, S1, S10, B1, B10};
U:EXTM-10 SET = {u:TRM1, u:TRM10,..., u:JAN10, GB, TB, S1, S10, B1, B10};
The portfolios used to form the sets of assets are described in Section 2.2. while the symbols used to denote the portfolios are described in Table 1.

Assumptions required to imply (5) from a J factor model are discussed in Section 3.2 together with the statistical assumptions of the GMM methodology and the iterated estimation method employed.

Principal components analysis for the same sets of assets is contained in the second section of each panel. The cumulative proportion of the total variation explained by the first five principal components is reported for the predictable portion of returns. The predictable portion is obtained by regressing asset return on the five information variables plus a constant.

Table 6 cont

Panel A: NYSE and AMEX

GMM				
Set of Assets	J	$T\ \mathbf{g}_T'\ \mathbf{W}_T\ \mathbf{g}_T$[a]	df	p-value
SIZE-S	1	77.679	55	.0237
	2	56.864	40	.0406
	3*	32.271	27	.2186
SIZE-U	1*	76.972	55	.0268
	2	52.603	40	.0875
S:EXTM-10	1*	118.470	75	.0010
	2	87.538	64	.0045
	3*	55.126	39	.0450
	4	27.645	24	.2750
U:EXTM-10	1	115.424	75	.0019
	2	81.325	64	.0152
	3	51.070	39	.0933

Principal Components					
Set of Assets	1st	2nd	3rd	4th	5th
E[SIZE-S|Z]	.8387	.9597	.9945	.9997	1
E[SIZE-U|Z]	.8405	.9639	.9946	.9998	1
E[S:EXTM-10|Z]	.8623	.9684	.9937	.9988	1
E[U:EXTM-10|Z]	.8678	.9712	.9955	.9995	1

a Asymptotically, the GMM statistic is chi square distributed with (N-J)(L-J) degrees of freedom.

* The objective function ($T\ \mathbf{g}_T'\ \mathbf{W}_T\ \mathbf{g}_T$[a]) had not converged or stopped declining monotonically after 40 iterations. The 40th iteration result is reported if the difference between the objective function at the 40th and 39th iteration is greater than 0.01. Otherwise an iteration is reported for which the difference from the previous iteration is less than 0.01.

Table 6 cont

Panel B: NYSE Only

GMM				
Set of Assets	J	$T\ \mathbf{g}_T'\ \mathbf{W}_T\ \mathbf{g}_T$[a]	df	p-value
SIZE-S	1	68.038	55	.1114
SIZE-A	1	64.691	55	.1743
S:EXTM-10	1 2**	102.706 70.385	75 64	.0186 .0935
U:EXTM-10	1	95.786	75	.0532

Principal Components					
Set of Assets	1st	2nd	3rd	4th	5th
E[SIZE-S|Z]	.8611	.9619	.9932	.9991	1
E[SIZE-A|Z]	.8237	.9557	.9949	.9993	1
E[S:EXTM-10|Z]	.8709	.9673	.9927	.9985	1
E[U:EXTM-10|Z]	.8770	.9699	.9938	.9992	1

a Asymptotically, the GMM statistic is chi square distributed with (N-J)(L-J) degrees of freedom.

* The objective function ($T\ \mathbf{g}_T'\ \mathbf{W}_T\ \mathbf{g}_T^a$) had not converged or stopped declining monotonically after 40 iterations. The 40th iteration result is reported if the difference between the objective function at the 40th and 39th iteration is greater than 0.01. Otherwise an iteration is reported for which the difference from the previous iteration is less than 0.01.

** A singularity in the matrix used to calculate the direction vector was encountered at the 9th iteration using the L-M Gauss Newton procedure. The results for the 8th iteration are reported.

Table 6 cont

Panel C: AMEX Only

GMM				
Set of Assets	J	$T\, g_T'\, \mathbf{W}_T\, g_T$[a]	df	p-value
SIZE-S	1 2	76.416 48.024	55 40	.0296 .1796
SIZE-A	1 2	78.925 51.398	55 40	.0189 .1069
S:EXTM-10	1* 2 3	122.599 82.513 43.817	75 64 39	.0004 .0121 .2745
U:EXTM-10	1 2 3	121.905 82.920 46.907	75 64 39	.0005 .0112 .1800

Principal Components					
Set of Assets	1st	2nd	3rd	4th	5th
E[SIZE-S|Z]	.8426	.9574	.9962	.9987	1
E[SIZE-A|Z]	.8195	.9465	.9954	.9984	1
E[S:EXTM-10|Z]	.8844	.9622	.9842	.9884	1
E[U:EXTM-10|Z]	.8868	.9744	.9959	.9990	1

a Asymptotically, the GMM statistic is chi square distributed with (N-J)(L-J) degrees of freedom.

* The objective function ($T\, g_T'\, \mathbf{W}_T\, g_T^a$) had not converged or stopped declining monotonically after 40 iterations. The 40th iteration result is reported if the difference between the objective function at the 40th and 39th iteration is greater than 0.01. Otherwise an iteration is reported for which the difference from the previous iteration is less than 0.01.

Appendix 1: Some Useful Facts about Latent Variables Tests

It is worth noting the following result. Suppose returns conform to a J factor model such that $\phi^{J-K} = \phi^{K}\ \Omega$ where ϕ^{K} is a LxK matrix such that $\phi = [\ \phi^{K} : \phi^{J-K}\ ]$ and Ω is a Kx(J-K) matrix of constants. In other words, each of the last J-K risk premia can be expressed as a linear combination of the first K risk premia. Under these assumptions, $\phi\ \mathbf{b}^{p}$ can be expressed as $\phi^{K}\ (\mathbf{b}^{p,K} + \Omega\ \mathbf{b}^{p,(J-k)})$ irrespective of the choice of $\mathbf{X}$, where $\mathbf{b}^{p,K}$ KxN matrix such that $\mathbf{b}^{p} = [\mathbf{b}^{p,K'} : \mathbf{b}^{p,(J-k)'}]'$. It follows that there exists α_I and $\mathbf{I}_K$ such that $E[\mathbf{u}^{\#}_{t} \otimes \mathbf{Z}_{t-1}] = 0$. So the GMM test has no power to detect an additional factor whose risk premium is a linear combination of the risk premia of the first K factors.

Yet the stated assumption guarantees that there exists K new factors each a linear combination of the J old factors such that a K factor pricing model holds for these K new factors. Thus, the GMM approach can detect only the minimum number of factors needed for the risk loadings to vary proportionally through time. At the same time, the number of detectable factors declines monotonically as the number of information variables declines.

Lets assume that there is a J factor model such that the rank of ϕ is J. The rank condition is assumed to illustrate that the result is not being driven by the issue raised in the previous subsection. Further assume that $\mathbf{b}^{p} = [\mathbf{b}^{p,K-1'} : \mathbf{b}^{p,(J-K+1)'}]'$ where $\mathbf{b}^{p,K-1}$ is a (K-1)Xn matrix,

$\mathbf{b}^{p,(J-K+1)} = [\mathbf{b}_1^{p,(J-K+1)} : \mathbf{b}_1^{p,(J-K+1)} : \ldots : \mathbf{b}_1^{p,(J-K+1)}]$

and $\mathbf{b}_1^{p,(J-K+1)}$ is a (K-1)x1 vector. In other words, all assets have the same factor loadings on the last J-K+1 factors. Then there exists $\phi^{\#}$ a LxK matrix and $\mathbf{b}^{\#\,p}$ a KxN matrix such that

$$\mathbf{Z}_{t-1}\ \phi\ \mathbf{b}^{p} = \mathbf{Z}_{t-1}\ \phi^{\#}\ \mathbf{b}^{\#\,p}.$$

Thus, under these assumptions, the GMM test has no power to detect more than a K factor model.

The above result can be used to assess the power of forming portfolios on the basis of a proxy for one of the risk loadings Suppose the true model is a J>2 factor model where the rank of ϕ is J. A GMM test is conducted whereby portfolios are formed on the basis of a proxy for the risk loading on the first factor and this proxy is independent of the loading on any other factor, i.e. $\hat{b}_{i,1}$ is independent of $b_{i,k}$ for all $k \neq 1$ where $\hat{b}_{i,1}$ is the proxy for the first factor loading and $b_{i,k}$ is the risk loading on factor k for the ith asset. Then for these N portfolios, the $E[b_{p,1}]$'s will vary systematically from p=1 to N while for k>1, $E[b_{p,k}] = E[b_k]$ for all p. So, invoking the argument of the previous paragraph for K=1, GMM would be able to reject a one factor model but the addition of an additional factor in the null kills any power the test has. This could explain why GMM tests using size deciles are usually only able to reject a one factor model. The assumption that size proxies for a risk loading is reasonable (see Fama and French [1991]) but the assumption of independence across factor loadings is less so. Notice that orthogonalizing the factor is not sufficient to guarantee that the loadings are independent.[18]

Suppose a J factor model holds and there exist proxies for the factor loadings such that each factor loading proxy is independent of the other factor loadings. Then forming extreme portfolios on the basis of each of the J proxies insures that the GMM test has at least some power to detect all J factors. So a way to potentially improve the power of the GMM test is to use extreme portfolios obtained from ranking on a number of risk loading proxies. Using industry portfolios is a step in this direction since it would be expected that the risk loadings of more than one factor would vary with industry.

[18] The reason is that independence of the factors per se places no restrictions on the factor loadings.