Essays on the Arbitrage Pricing Theory and Portfolio Performance Measurement

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Abstract

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Essay one tests the mispricing of both an unconditional and a conditional APT with(out) a residual market factor. The time-series movements in the conditional covariances, V, are accounted for by the time-series movements of the conditional standard deviations of the mimicking portfolios. The first factor seems to be sufficient to span the efficient set, whether the model is estimated for a fixed or time-varying V that is (un)adjusted for nonsynchronous trading using the Shanken (1987) method.

Essay two applies the Jobson and Korkie (1981) Z score and the positive period weighting (PPW) score of Grinblatt and Titman (1989a) to various benchmarks of market and mimicking portfolios to study the benchmark invariancy problem. Portfolio performance inferences are affected significantly by choices dealing with the number of factors, nonsynchronous trading adjustment, and the sizes of the firms used for factor extraction. The returns of the portfolio benchmarks exhibit significant monthly seasonalities, which, in turn, significantly influence mutual fund performance inferences.

Essay three assesses the selection and timing abilities of equity mutual funds using an APT model with specified macrofactors and time-varying risk premia. Although a significant proportion of the funds exhibit abnormal selectivity performance based on the model's intercept [Jensen (1968) alpha], the direction of that performance is positively related to the postulated sign of the time-varying risk premia. The findings appear to be sensitive to the use of an inexact, unrestricted APT model. Some funds exhibit significantly superior abilities to forecast the movements of the priced macrofactors.

Essay four uses a multivariate (M-)CAPM with a time-varying ex ante market risk premium to assess the micro-selectivity and macro-timing abilities of a sample of equity mutual funds. Significant (and predominantly negative) Jensen estimates are found. This finding is probably due to the conditional E-V inefficiency of the chosen market proxies. In contrast to Cumby and Glenn (1990), the significant market timing coefficients are not attributable to small sample bias when a bootstrapping procedure is used.

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CHAPTER ONE: INTRODUCTION

The structure of asset prices is one of the most investigated topics in modern finance. A main paradigm of this field of research is the Arbitrage Pricing Theory (henceforth, APT) developed by Ross (1976). Based on arbitrage principals, Ross demonstrates that the expected returns of assets can be linearly, although approximately, explained by one or several systematic forces that have priced risks. The model rests on fairly simple assumptions; namely: investors prefer more wealth to less; there exists a factor structure composed of K factors that affect all assets when there are more assets than factors; and investors have homogeneous expectations. The model becomes exact in competitive equilibrium when the market portfolio is perfectly diversified. Connor (1984) shows that investors are then insured against idiosyncratic risk and that only systematic forces are priced. Empirically, the arbitrage and the equilibrium APT are indistinguishable.

Many empirical investigations of the APT use a two-pass procedure. In the first pass, the factor loadings are extracted using a factor analytic approach. In the second pass, the validity of the model is examined by estimating the excess returns on the arbitrage portfolios or on the mimicking portfolios. The second chapter of this thesis investigates the mispricing of the APT model using a factor analytic approach which is extended to account for several important recent contributions. To reflect the mounting evidence that the first two moments are time-varying, the investigation rests on both unconditional and conditional return distributions. Use of the former leads to the usual APT test, which was initially developed by Roll and Ross (1980), where the expected excess returns of the K arbitrage portfolios are estimated in a cross-sectional framework.

Use of a conditional return distribution leads to a time-series test of the APT. The methodology of Lehmann and Modest (1985b), that uses mimicking portfolios, is extended to a test of the APT based on time-varying moments by including a standard deviation equation in the estimation process to capture any time-series variation in the second moment. Specifically, the fluctuations across time in the conditional variance-covariance matrix of returns, V, is explained by the movements in the conditional variances of the mimicking portfolios. This approach is interesting since the numerous parameters of the variance-covariance matrix collapse into K second moments of the joint conditional distribution of the returns of the mimicking portfolios. Simultaneous estimation of the mean and standard deviation equations is performed using the iterative weighted least squares method. In order to obtain insignificant mispricing in the model, a residual market factor is included in both the unconditional and conditional mean equations. The conditional volatility of the residual market factor is included in the conditional standard deviation equation. The variance-covariance matrix of returns is adjusted to account for any nonsynchronous trading using the Shanken (1987) procedure.

APT concepts can be modified to consider asymetrical information across different groups of investors. This allows for the study of the quality of the information possessed by a portfolio manager, whose influence is negligible on equilibrium asset prices, but who may have access to privileged information. However, a number of complications arise when the APT is used for an empirical investigation of portfolio performance.

Based on Grinblatt and Titman (1987), mimicking portfolios are locally mean-variance efficient if the APT is an exact model. Since their respective Sharpe ratios are maximum, the minimum idiosyncratic risk mimicking portfolios of Lehmann and Modest (1985a,b) are appropriate benchmarks for assessing the performance of mutual funds. Several technical aspects are involved in the construction of the mimicking portfolios, such as the number of factors in the factor structure, the type of firms (small versus large) required for the estimation of the variance-covariance matrix, and the adjustment for nonsynchronous trading. Since mutual fund performance inferences may not be robust to the formation attributes of the mimicking portfolios (Lehmann and Modest (1987) and Grinblatt and Titman (1988)), the third chapter investigates whether or not a benchmark invariancy problem exists when mimicking portfolios are used to evaluate mutual fund performance in a Canadian context.

The Jobson and Korkie (1981) Z score to test for the equality of various Sharpe ratios and the Positive Period Weighting (PPW) measure of Grinblatt and Titman (1989a) are used to assess mutual fund performance. The Jensen measure is not used because its estimated value is directly dependent on the choice of an underlying asset pricing model, and Lehmann and Modest (1987) have identified an asset pricing invariancy problem. The two measures used herein are only indirectly dependent on the postulated asset pricing model, since they only require that the underlying portfolio benchmark be mean-variance efficient. Since mutual fund managers often manage their portfolios actively, the return distributions of these funds may be heteroskedastic. To deal with this problem, the Z score is also computed using the relevant variance and covariance terms using the estimator proposed by Newey and West (1987).

The extensive literature on the month-of-the-year effect suggests that the underlying portfolio benchmarks (both mimicking and market portfolios) may exhibit anomalous time-series variations. In the presence of such anomalous behavior, mutual fund performance inferences may be biased for the months in which the benchmark returns exhibit monthly effects. If different benchmarks have different monthly effects, a benchmark invariancy problem may result. To investigate these issues, the seasonality of both portfolio benchmarks and mutual fund performances using the Jobson and Korkie Z score is examined for each month of the year. This technique is well suited for this problem because it includes a monthly time-varying second moment that may explain any monthly movement in the first moment. To avoid biased estimations due to small samples caused by the categorization of returns by the month-of-the-year, a bootstrapping procedure is used to compute the Z scores.

In their seminal paper, Burmeister and McElroy (1988) implement an approach in which the return generating process and the APT equation are simultaneously estimated when macrofactors are explicitly included in the model. In addition to avoiding the errors-in-variables problem inherent in the traditional two-step procedure, their methodology allows for non-linear estimation with restriction on the risk premia estimates across equations. This macrofactor approach is further improved by Koutoulas and Kryzanowski (1991, henceforth KK). They account for the time-variation of the risk premia by the movements of the conditional standard deviations of the underlying macrofactors.

The KK model is also appropriate for investigating mutual fund performance using the Jensen measure. Admati, Battacharya, Pfleiderer and Ross (1976, henceforth ABPR) contend that most investigations of portfolio performance using the Jensen measure have evaluated timing abilities based on the movements of the portfolios. Such an approach seems inadequate since the portfolios may include securities for which selectivity information has been observed. In turn, this would result in an inconsistency with the theoretical dichotomy between micro-selectivity and macro-timing signals postulated in the literature. APT estimations based on macrofactors overcome this portfolio problem since macro-timing abilities are evaluated based on the movements of the macrofactors. Therefore, the fourth chapter investigates the attribution of Canadian mutual fund performance between micro-selectivity and macro-timing using the APT model of KK.

Tests of selectivity based on the Jensen measure, and tests of factor timing based on the quadratic regression approach of Lehmann and Modest (1987) can be performed when the APT model is restricted to have a unique proportionality parameter across the different risk premia. Depending on the assumptions invoked for the stacked variance-covariance matrix of residuals of the system of equations, different estimations may be obtained when the model is estimated using either non-linear and iterative non-linear ordinary least squares or non-linear and iterative non-linear seemingly unrelated regression techniques. KK find a significant intercept when the unrestricted version of the model is estimated. The impact of this potential bias on the Jensen measure can be investigated by comparing the estimated intercepts from the restricted and unrestricted estimation approaches.

The investigation of mutual fund performance based on the Jensen measure and on the timing test proposed by Lehmann and Modest (1987) obviously depends on the selected asset pricing model. Thus, chapter five replicates the analyses performed in chapter 4 when the underlying benchmark model is the CAPM, since this is the asset pricing model that has been the most extensively studied. To be consistent with the empirical literature on conditional asset pricing models, a conditional version of the CAPM that allows for the time-variation of the ex ante market risk premium is implemented.

In chapter six, some concluding remarks and directions for future research are offered.

CHAPTER TWO: SOME TESTS OF APT MISPRICING BASED ON MIMICKING PORTFOLIOS

2.1. INTRODUCTION

The approximate APT of Ross (1976) is an interesting alternative to the well-known CAPM for the pricing of asset risk. However, due to its approximate nature, the model may price some assets with error in an economy with a finite number of assets. APT mispricing can be made insignificant by the inclusion of a residual market factor (RMF). This factor spans the portion of the efficient set not priced by the j used factors, when j < K (where K is the number of factors in the true factor structure). Burmeister and Wall (1986) are the first to use a residual market factor. Wei (1988) and McElroy and Burmeister (1988) provide theoretical and econometrical justifications, respectively, for the relevance of the RMF. Burmeister and McElroy (1988), Berry, Burmeister and McElroy (1988), Brown and Otsuki (1989), amongst others, include the RMF in their empirical investigations of APT models with specified macroeconomic factors. Since these published empirical investigations of the APT use unconditional return moments, their inferences constitute a necessary (but not sufficient) condition for rejecting the APT.

The objectives of this chapter are two-fold. The first is to investigate the mispricing of the APT, and to assess the contribution of the RMF to eliminating any mispricing. The second objective is to test how mispricing changes from a one-period framework in which the unconditional distributions of stock returns are used to a multi-period framework in which the conditional distributions of stock returns are used. Due to the growing body of literature that finds that stock return distributions are nonstationary, it is necessary to conduct APT tests using conditional moments.

The remainder of this chapter is organized as follows. In section 2.2, the exact APT model is discussed. In section 2.3, two ex post APT models are reviewed. In section 2.4, the data and empirical procedures are described. In section 2.5, the empirical findings are presented and analyzed. In section 2.6, some concluding remarks are offered.

2.2. THE ARBITRAGE PRICING THEORY

Assume that a cross-sectional set of asset returns are explained by several economic forces. If their returns are normalized, this yields:

$$R_t = E(R) + B[F_t - E(F)] + \varepsilon_t \qquad (2.1)$$

where R_t is a N x 1 vector of realized asset returns at time t; $E(R)$ is a N x 1 vector of expected returns; $B=\{b_{ij}\}$ is a N x K matrix of factor loadings; b_{ij} is the risk sensitivity of security i to factor j; F_t is a K x 1 vector of K economic forces; and E(F) is the related vector of expected returns for the K economic forces. The underlying APT model is:

$$E(R) = \underline{1}\Gamma_o + B\Gamma \qquad (2.2)$$

where Γ_o is the risk-free rate; $\underline{1}$ is a N x 1 unit vector; and Γ is a K x 1 vector of expected risk premia. More precisely, $\Gamma_j = [E_j - R_f]$ is the excess return on the jth arbitrage portfolio that loads with one on the jth economic factor and is orthogonal to the K-1 other economic forces. Equation (2.2) can be motivated in either of two ways. First, if the idiosyncratic risk can be diversified away in a portfolio context, Ross (1976) uses an arbitrage argument to show that for large N, equation (2.2) holds approximately. Second, under the assumption of competitive equilibrium, Connor (1984) demonstrates that the APT model (2.2) holds if the market portfolio is perfectly diversified.[1] In this case, only the risk associated with the economic forces is priced since investors are insured against idiosyncratic risk by holding perfectly diversified portfolios. The Ross APT and the Connor APT are empirically indistinguishable.[2]

Within Connor's framework, complete diversification of idiosyncratic risk is unlikely in a finite economy where every asset must be held in precise positive proportions such that equation (2.2) may not hold exactly. Wei (1988) specifies conditions under which the equilibrium APT exists in a finite economy. It only requires the addition of a RMF such that:

$$E(R) = \underline{1}\Gamma_o + B\Gamma + B_m\Gamma_m \tag{2.3}$$

where Γ_m is the risk premium associated with the RMF; and B_m is a N x 1 vector of systematic risks of the RMF estimated from:

$$\varepsilon_t = B_m e_{mt} + u_t \tag{2.4}$$

where ε_t is the residual component of equation (2.1); e_{mt} is the idiosyncratic risk of the market; and u_t is a residual component with the usual properties. If the market portfolio is perfectly diversified and the factor structure contains the true number of factors, then $e_m=0$ such that $\Gamma_m=0$. If e_m is nonzero, then the APT equation should exhibit mispricing without the inclusion of Γ_m. In this case, e_m represents a linear combination of any missing factors in the true factor structure. Thus, the exactness of the APT rests on a test of equation (2.2) versus (2.3).

2.3. EX POST APT MODELS

The most widely estimated version of the APT is:

$$\overline{R} - \overline{R}_f = \delta + B\Gamma + u \tag{2.5}$$

where exactness of the model depends on the significance of δ. Equation (2.5) is estimated by Roll and Ross (1981), Dhrymes, Friend, Gultekin and Gultekin (1984, 1985), Gultekin and Gultekin (1987), Cho and Taylor (1987), amongst others.

Another version of the APT is based on a time-series where portfolios that mimick the movements of the K economic variables are constructed. A non-normalized version of equation (2.1) is given by:

$$R_t = BF_t + e_t \qquad (2.6)$$

If such mimicking portfolios can be formed, (2.6) becomes:

$$R_t = BR_{mt} + e_t \qquad (2.7)$$

where R_{mt} is the K x 1 vector of mimicking portfolio returns. Equation (2.7) suggests that:

$$R_{mt} = WR_t \qquad (2.8)$$

where W is a K x N matrix of mimicking portfolio weights (where $W' = \{w_1, \ldots, w_k\}$). Based on Litzenberger and Ramaswamy (1979), Lehmann and Modest (1985) contend that the K column vectors of W' are based on the solution to the quadratic program:

$$\text{Min } w_j' D\, w_j \quad j=1,2,\ldots,K \qquad (2.9)$$

st. $w_j' B_k = 0$ for all k different from j

$w_j' B_j = 1$

where D is a N x N diagonal matrix of idiosyncratic risks computed from the factor analysis procedure. Given suitable rescaling, $w_j' \underline{1} = \underline{1}$ (i.e., each mimicking portfolio has a unit cost). From Huberman, Kandel and Stambaugh (1987), the application of the expectation operator to (2.8) yields:

$$E(R_m) = WE(R) \qquad (2.10)$$

Replacing (2.2) into (2.10) gives:

$$E(R_m)=W[\underline{1}\Gamma_o + B\Gamma] \quad (2.11)$$

or

$$E(R_m)=W\underline{1}\Gamma_o + WB\Gamma \quad (2.12)$$

If W is appropriately estimated and WB=1, then:[3]

$$E(R_m)=W\underline{1}\Gamma_o + \Gamma, \text{ or} \quad (2.13)$$

$$E(R_m) - \underline{1}\Gamma_o=\Gamma \quad (2.14)$$

Equation (2.7) is a time-series version of the APT and a multi-factor version of the one-factor model of Black, Jensen and Scholes (1972), which is consistent with the APT theory.

Grinblatt and Titman (1987) contend that an exact APT model is obtained under the mean-variance (E-V) efficiency of a global portfolio of mimicking portfolios. This is equivalent to the local E-V efficiency of each of the mimicking portfolios included in the factor structure.[4,5] Thus, a test of the exact APT based on the conditional distribution of security returns displays an intertemporal nature since the E-V efficiency of the global portfolio is tested when the efficient set is time-varying since the first two moments of the return distribution are time-varying.[6]

APM tests based on conditional moments include the latent variable tests of Gibbons and Ferson (1985), amongst others, which allow for time-varying premia and stationary second moments. Ferson, Kandel and Stambaugh (1987) extend this approach to time-varying betas but a stationnary variance-covariance matrix, V. Bollerslev, Engle and Wooldridge (1988) allow the first two moments of stock returns to be time-varying in their tests of the CAPM. Because of the number of conditional covariances when the number of assets increases, their approach is not tractable for tests of the APT. Connor and Korajczyk (1987) test the APT for a size anomaly using an asymptotic principal component method which allows for time-varying risk premia.

An intertemporal, empirical formulation of the APT is proposed herein that captures time-variation in the first two conditional moments. The conditional mean is given by equation (2.7), which allows for time-variation in the risk premia. Modeling the time-varying conditional variance-covariance matrix $V_t(R_t|\Omega_t)=H_t$, where Ω_t represents the information set upon which economic agents update their rational expectations, depends on the conditional distribution of the K mimicking portfolios.[7] Applying the variance operator to equation (2.8) for the jth mimicking portfolio yields:

$$V_t(R_{jmt}|\Omega_t)=\Theta^2_{jt}=V_t[(w_j'R_t)|\Omega_t], \text{ or} \qquad (2.15)$$

$$\Theta^2_{jt}=w_j'H_tw_j \qquad (2.16)$$

since $V_t(R_t|\Omega_t)=H_t$. For the entire matrix of mimicking portfolio weights, the conditional V are linear combinations of the conditional variance of each of the K mimicking portfolios. This result is empirically consistent with Schwert and Seguin (1990) who find that the time-series movements of the elements of the V of size-sorted portfolios are significantly dependent on the movements in the conditional variance of the CRSP equally-weighted index. By applying the variance operator to the mean equation (2.7), the first two conditional moments can be modelled as:

$$R_t=\delta + BR_{mt} + \varepsilon_t \tag{2.17}$$

$$h^2_t=\alpha + \phi\Theta^2_t + e_t \tag{2.18}$$

where h^2_t is a N x 1 vector of conditional variances; Θ^2_t is a K x 1 vector of conditional variances at time t of the mimicking portfolios; ϕ is the N x K matrix of regression coefficients; and e_t is a N x 1 vector of residuals at time t.

Tests based on equation (2.5) are cross-sectional estimations based on the unconditional distributions of asset returns, while tests based on (2.17) and (2.18) are time-series estimations based on the conditional distributions of asset returns. The latter also test the intertemporal APT, since they test the E-V efficiency of a global portfolio of mimicking portfolios when the efficient set is time-varying.[8]

2.4. EMPIRICAL PROCEDURES

To ensure comparability with Roll and Ross (1980), data are extracted from the CRSP tape for the period starting in July 1962 and ending in December 1972 (i.e., 2617 daily returns for 1278 securities). Firms with more than 75 missing values are deleted. Although daily returns are subject to biases inherent to nonsynchronous trading or the existence of a bid-ask spread, they provide a time-series longer than the (usually more robust) monthly data. This is convenient when asymptotic convergency is required. The resulting sample of 1260 securities is ordered alphabetically, and then combined into 42 groups each containing 30 securities.

The empirical tests applied herein require the observation of the matrix B. In most studies,[9] B is estimated using maximum likelihood factor analysis (MLFA) to obtain the most efficient estimates.[10] A likelihood ratio test for the number of factors can be used, although it is very sensitive to any departures from normality and to sample size. Since the sample size studied herein is large, the number of factors identified by the test is probably overstated.

For daily returns, MLFA should be conducted on a V adjusted for nonsynchronous trading using the procedure suggested by Shanken (1987). The adjustment is given by

$Cov^{sh}(R_i, R_j) = \Sigma^3_{n=1}\Sigma^3_{m=1}Cov(R_{it-n}, R_{jt-m}) + Cov(R_{it}, R_{jt})$, where $Cov^{sh}(R_i, R_j)$ is the covariance between securities i and j when adjusted for nonsynchronicity using three lags [as in Shanken (1987)].

The estimation of the arbitrage portfolio excess returns is performed using either of the following cross-sectional regressions for the 42 groups of 30 securities:

$$\overline{R}-\overline{R}_f=\underline{1}\delta + B\Gamma + u, \text{ or} \tag{2.19}$$

$$\overline{R}-\overline{R}_f=\underline{1}\delta + B\Gamma + B_m\Gamma_m + e \tag{2.20}$$

where $\overline{R}$ is a N x 1 vector of average returns; δ is the deviation from the model; and all the other terms are defined as earlier. To obtain unbiased estimates of the risk premia, Roll and Ross (1980) suggest the following GLS estimator:[11]

$$\Gamma= (B^{*\prime}\Sigma^{-1}B^*)^{-1} B^{*\prime}\Sigma^{-1}\overline{R} \tag{2.21}$$

where Σ is the N x N variance-covariance matrix of security returns, and $B^*=(\underline{1}:B)$. The number of arbitrage portfolios that significantly affect security returns corresponds to the number of significant risk premia in (2.19) [or (2.20)].

Since no theoretical foundation exists for the true number of factors, a test of model exactness is relevant.[12] Since a small number of cross-sections are studied, the multivariate version of the cross-sectional regression (henceforth CSR) test of Shanken (1985) is used herein. The

CSR is not an asymptotic test in that the statistic follows approximately a T^2 distribution for which the equivalent F test is available. Also, the CSR incorporates an adjustment for the errors-in-variable problem inherent in B. The CSR test is given by:[13]

$$[(T\,\hat{e}'\,\hat{\Phi}^{-1}\hat{e})/(1+(\hat{\Gamma}'\hat{\Omega}^{-1}\hat{\Gamma}))] \times [(T-N-K)/N(T-K-1)] \sim F_{(N,T-K-N)} \tag{2.22}$$

where T is the sample size; N is the number of assets studied; $\hat{e}$ is the N x 1 vector of residuals of the return-generating process; $\hat{\Phi}$ is the N x N variance-covariance matrix of residuals;[14] and $\hat{\Omega}$ is the K x K variance-covariance matrix of the included factors.

The systematic risk of the RMF is easily obtained. For each security i, consider the factor-generating model (1) in algebric form for K factors:

$$R_{it} = E(R_i) + \Sigma^{K}_{j=1} b_{ij}[F_{jt} - E(F_j)] + e_{it,k} \tag{2.23}$$

where b_{ij} is an element of the matrix B. The residual component is obtained from (2.23) to estimate:

$$e_{it,k} = b_{im} e_{mt,k} + \varepsilon_{it} \tag{2.24}$$

where b_{im} is the systematic risk of the RMF associated with security i and is an element of B_m. The $e_{mt,k}$ can be obtained from:

$$r_{It} = \alpha_o + \Sigma^{k}_{j=1} b_{mj}[F_{jt} - E(F_j)] + e_{mt,k} \tag{2.25}$$

where r_{It} is the return on the market portfolio (as proxied by the CRSP value-weighted index).

The mimicking portfolios must be constructed so that they maximize their correlations with the true macroeconomic variables. This depends on the procedure chosen to estimate the weights of the matrix of mimicking portfolios in (2.8). The multivariate literature suggests to estimate the weight matrix, W, as:

$$W=(B'D^{-1}B)^{-1}B'D^{-1} \qquad (2.26)$$

Lehmann and Modest (1985) state that (2.26) generates poor estimates since the jth mimicking portfolio is constrained to load with one on the jth factor. When the factor loadings are measured with error, the magnitudes of the portfolio weights directly reflect this error. Lehmann and Modest use an estimator for which the mimicking portfolio loadings do not have to equal one. They generate minimum idiosyncratic risk (mir) weights that are theoretically biased but robust to measurement errors. For the jth mimicking portfolio, the vector of mir weights, w_j^{mir}, solves the following program:

$$\begin{aligned} &\text{Min } w_j' D\, w_j \qquad j=1,2,\ldots,K \qquad (2.27)\\ \text{st.}\ &w_j' B_k = 0 \qquad \text{for all k different from i}\\ &w_j' \underline{1} = 1 \end{aligned}$$

The solution to (2.27) is given by:

$$w_j^{mir\prime} = e_j' (B_j' D^{-1} B_j)^{-1} B'_j D^{-1} \qquad (2.28)$$

where B_j is the matrix of factor loadings when all securities load with one on the jth factor; and e_j is a vector of zeros except for a one at the jth position. Since $W^{mir\prime}=\{w_1^{mir}, \ldots, w_k^{mir}\}$, the mir portfolios are generated by:

$$R_{mt}^{mir}=W^{mir}R_t \tag{2.29}$$

The conditional variances of the securities and mimicking portfolios are also required to estimate (2.17) and (2.18). Based on Schwert and Seguin (1990), the conditional standard deviation of the jth mimicking portfolio can be computed as the projection of the following autoregressive process:[15]

$$\Theta_{jt}=\alpha_0 + \Sigma^{L}_{i=1}\alpha_i\Theta_{jt-i} + \varepsilon_{jt} \tag{2.30}$$

This estimate of the conditional standard deviation is almost identical to that obtained from GARCH (1,1) when L=12. Schwert and Seguin define the unbiased estimator of the unconditional standard deviation at time t as

$$\Theta_{jt}=(\pi/2)^{1/2}|(R_{jmt} - R_f)-(\overline{R_{jm} - R_f})|.$$

To account for the conditional heteroskedasticity in the residuals of (2.30), they estimate:

$$\Theta_{jt}=\alpha_0 + \Sigma^{12}_{i=1}\alpha_i\Theta_{jt-i} + \varepsilon_{jt} \tag{2.31}$$

$$(\pi/2)^{1/2}|\varepsilon_{jt}|=\beta_0 + \beta_1(FIT)_t + u_t \tag{2.32}$$

where FIT_t represents the fitted values at time t from equation (2.31). Equation (2.32) models conditional heteroskedasticity as in Glejser (1969). Equations (2.31) and (2.32) are estimated simultaneously using iterative weighted least squares (ITWLS) with three iterations [based on the suggestion of Davidian and Carrol (1987)]. Also, equations

(2.33) and (2.34) can be estimated using IWLS, where $h_{it}=(\pi/2)^{1/2}|e_{it}|$:

$$R_t=\delta + BR_{mt} + e_t \qquad (2.33)$$

$$h_t=\alpha + \phi\Theta_t + u_t \qquad (2.34)$$

If E-V efficiency of the global portfolio of mimicking portfolios is assumed, then the elements of δ should not be significantly different from 0. Following Lehmann and Modest (1985), the null hypothesis, $H_o:\delta=0$, is tested using:

$$[(T\ \hat{\delta}'\ \hat{\cap}^{-1}\ \hat{\delta})/(1+\overline{R}_m'\hat{\Sigma}^{-1}\overline{R}_m)] \times [(T-N-K)/N(T-K-1)] \sim F_{(N,T-K-1)} \qquad (2.35)$$

where $\hat{\delta}$ is a N x 1 vector of the estimated intercepts of equation (2.33); $\hat{\cap}$ is a N x N variance-covariance matrix of residual e_t; $\overline{R_m}$ is a K x 1 vector of the mean returns of the mimicking portfolios; and $\hat{\Sigma}$ is their K x K variance-covariance matrix.[16]

To test the significance of the RMF in equations (2.33) and (2.34), note that for each security:

$$R_{it}=\delta + B_J R_{mt,J} + e_{it,J} \qquad (2.36)$$

where B_J is a N x J matrix of factor loadings; and $R_{mt,J}$ is a J x 1 vector of mimicking portfolios. If K factors are observed, then (2.36) becomes

$$R_{it}=\delta + B_J R_{mt,J} + B_{K-J} R_{mt,K-J} + \varepsilon_{it,J} \qquad (2.37)$$

where B_{K-J} is a N x (K-J) matrix of loadings; and $R_{mt,K-J}$ is a (K-J) x 1 vector of mimicking portfolio returns. Substracting

(2.37) from (2.36) yields:

$$e_{it,J}=B_{K-J}R_{mt,K-J} + \varepsilon_{it,J} \qquad (2.38)$$

Define r_{It} as the excess return on the market portfolio. Application of (2.36) through (2.38) on the market portfolio yields:

$$e_{It,J}=B_{K-J}R_{mt,K-J} + a_{t,J} \qquad (2.39)$$

where $a_t = \Sigma^n_{i=1} w_i \varepsilon_{it}$. The RMF is $e_{It,J}$ (i.e., a linear combination of the excess returns on the K-J missing mimicking portfolios). The correlation between $e_{it,J}$ and $e_{It,J}$ will be such that the systematic risk of RMF is given by:

$$e_{it,J}=b_{im,J}e_{It} + n_{it} \qquad (2.40)$$

Independent of the number of J factors extracted, replacing (2.40) into (2.33) yields:

$$R_t=\delta + BR_{mt} + B_m e_{It} + n_t \qquad (2.41)$$

$$h_t=\alpha + \phi\Theta_t + \phi_m\Theta_{It} + u_t \qquad (2.42)$$

where e_{It} is the RMF; B_m is the N x 1 vector of RMF systematic risks; n_t is a N x 1 vector of residuals; Θ_{It} is the conditional standard deviations of the residual market portfolio; and ϕ_m is a N x 1 vector of its related sensitivities.

Thus, the one-period version of the empirical APT, with the RMF to ensure exactness, will be tested using the cross-sectional equations (2.19) versus (2.20), based on the test for exactness given by (2.22). Similarly, the multi-period version of the empirical APT, with the RMF to ensure exactness, will be tested using the time-series equations (2.33) and (2.34) versus (2.41) and (2.42), based on the test for exactness given by (2.35).

2.5. EMPIRICAL FINDINGS

The results for the one-period APT estimated without the RMF are reported in Tables 2.1 through 2.3. The MLR test results for the required number of factors are given in Table 2.1. Only one out of the 42 groups rejects the null hypothesis of six factors in the factor structure at the one percent level.[17]

The average and the standard deviation of the covariances of security returns, adjusted and unadjusted for nonsynchronous trading, are reported in Panel A of Table 2.2. As in Shanken (1987), the adjustment substantially increases the covariance values.[18] Based on Panel B, most of the effect of the adjustment is captured by the first factor. This factor may be a "market" factor which is a linear combination of the K factors.[19]

For the adjusted V, the MLR test indicates that at least 18 factors are required. However, for the test to be applicable, the degrees of freedom must be positive (i.e , m must be less than 1/2 (2p + 1 - 8p + 1), where m is the number of factors and p is the number of variables on which factor analysis has been performed). Thus, for p=18 and m=30, the test is not reliable.[20] The computed average eigenvalues of the eighth and ninth factors are 1.02 and 0.92, respectively. Based on this criterion, eight factors should be an upper bound on the number of factors.[21] Thus, six and eight factors are extracted for the unadjusted and adjusted V, respectively.

The results for the approximate APT are presented in Table 2.3. The first and third columns of panels A and B report the values for the χ^2_k and the t-test, respectively. These are tests of the null hypothesis of a zero GLS estimated Γ for six and one factor structures, respectively.[22] For the six factor structure, H_o is rejected for only 7.1% of the groups. This is consistent with DFGG who reject H_o for only five groups for a five factor structure for the same time period.[23] Similar findings are reported for the adjusted V in panel B. The simultaneous significance of the risk premia for an eight factor structure cannot be rejected for only 13.5% of the groups. This suggests that less factors may adequately explain the covariance structure of security returns. As expected, the percentage of groups for which the risk premia are priced increases as the number of extracted factors decreases.[24] One factor is priced for the unadjusted (panel A) and adjusted V (panel B) for 24.2% and 31.7% of the groups, respectively. This suggests that one factor could explain the V structure for a significant number of the securities studied herein. However, this test provides no information about the empirical validity of the model.

Better results are obtained for the CSR test (2.22). Based on panels A and B of Table 2.3, the null hypothesis that the APT model is exact cannot be rejected for all groups. Thus, six (eight) factors seem sufficient to ensure an exact factor structure. In fact, a one factor APT is generally sufficient for all the 42 groups since its pricing error seems to be statistically insignificant.[25] In turn, this implies that the CSR test results given in Table 2.3 are robust to the number of factors extracted. Based on this evidence, the RMF should be an irrelevant addition to the APT model.

Equation (2.24) was estimated for one and six (eight) factors for the unadjusted (adjusted) V. The aggregate results when b_{im} is estimated for a six factor structure and an unadjusted V are reported in Table 2.4. For all cases, the estimated intercept is not significantly different from 0. This is consistent with the appropriateness of the specification of equation (2.24). In contrast, the estimated betas are significant for several securities in that the RMF does capture some time-series variation. Consistent with the prediction of Wei, the percentage of significant systematic risks for RMF generally increases for the one factor structure. Similar results are obtained for a one and eight factor structure for the adjusted V (see panel B). Although the RMF accounts for some missing factors, it may not be priced in the APT equation. In fact, based on the results reported in Table 2.3, the risk premium on the RMF is not expected to be significant.

The t-values of the GLS estimates of the risk premium for RMF are reported in Table 2.5. These results are generally consistent with those reported in Table 2.3. The RMF risk premium is basically not priced. The percentage of the groups for which the simultaneous significance of the estimated risk premia cannot be rejected is lower when the RMF systematic risk is included in the APT (compare Tables 2.5 and 2.3). Despite its significance in the time-series estimations (Table 2.4), the RMF systematic risk is not an important variable in determining expected returns cross-sectionally. The CSR test values are virtually unchanged. This is consistent with the empirical validity of the APT model.

The results for the conditional standard deviation estimations of equations (2.31) and (2.32) for the mimicking portfolios are reported in Table 2.6. Due to their similarity, only the results for the conditional standard deviations of the first mimicking portfolio for a six and one factor structure are reported in panel A. These results are fairly homogeneous. The number of significant coefficients in equation (2.31) is consistent with the time-varying nature of the standard deviations of the mimicking portfolios, and with a time-varying V. Based on the Box-Pierce statistics for the OLS and iterative WLS residuals of (2.31) [designated by Q(OLS) and Q(ITWLS), respectively], 12 lags in the mean equation generate an acceptable parsimonious fit of the standard deviation process.[26]

Application of the Box-Pierce statistic to the squared residuals, Q2(OLS), of the mean equation (2.31) provides evidence about the level of conditional heteroskedasticity.[27] The Q2(OLS) values are high for the squared residuals estimated by an OLS procedure. Estimation of (2.31) and (2.32) using iterative WLS eliminates almost all of the conditional heteroskedasticity as shown by the Q2(ITWLS) values. This is corroborated by the reduction in the studentized range values for the residuals of (2.31) when estimated by OLS versus ITWLS (denoted as ST(OLS) and ST(ITWLS), respectively).[28] This shows that the tails of the distribution of residuals more closely resemble a normal distribution when conditional heteroskedasticity is accounted for. Similar results are obtained for the adjusted V (see panel B). These results suggest that the ITWLS provides good estimates of the conditional standard deviations of the mimicking portfolios, which account for nearly all of the substantial conditional heteroskedasticity observed in the OLS residuals.[29]

The results of the time-series APT estimations using ITWLS without and with the RMF are reported in Tables 2.7 through 2.9, respectively. The number of securities in which the conditional standard deviation coefficient of a specific mimicking portfolio is significant is reported in Table 2.7. Since the conditional standard deviations move in systematic patterns proportional to some of the aggregate economic forces, the theoretical justification for equation (2.18) is empirically observed. The patterns are divided among the six or eight factor conditional standard deviations, although the number of significant regression coefficients is fairly low. The conditional standard deviation of the RMF is relevant only for a small proportion of the securities. For a one-factor structure, the factor's conditional standard deviation is significant for a large number of securities. Therefore, it seems that all the systematic economic forces that explain the patterns of security standard deviations can be aggregated into a unique factor. However, this factor's conditional standard deviation does not explain all the patterns, since the conditional standard deviation of the RMF for this one-factor structure is significant for 50% of the securities in the sample. Overall, these results suggest that a one-factor structure and the conditional standard deviation of the RMF explain well the time-series variability of the second moments of asset returns. This justifies the need to investigate the APT in a multi-period context.

Based on a comparison of average Q2(OLS) and Q2(ITWLS) statistics given in Table 2.8, the conditional standard deviations of the K mimicking portfolios are not the only determinants of the movements in the second moments of security returns. The differences in these average values generally imply that modeling the systematic effects of the time-variation of V by the time-series movements of K conditional standard deviations reduces the level of the conditional heteroskedasticity.[30] The iterative WLS residuals still exhibit fat tails as the reduction in the average studentized range from the OLS residuals to the iterative WLS residuals is very small.[31] The results are robust to the number of factors and the adjustment of V.

Similar results are obtained when the RMF and its conditional standard deviation are included in the mean and the standard deviation equations, respectively. Although the results reported in Table 2.7 suggest that the conditional standard deviation of the RMF picks up the systematic variations (especially in the one factor case), the ITWLS estimations exhibit conditional heteroskedasticity even when the RMF is included in the standard deviation equation. Thus, influences other than those of the APT factors' second moments may explain the time-series variations in the conditional V. Since the estimations are performed on individual securities, their volatilities may be affected by intertemporal changes in firm specific characteristics such as financial leverage.

Based on the results of the F-values presented in Table 2.8, the validity of the multi-period APT is robust to the number of factors and the adjustment of V for thin trading. Similar results were reported earlier for the one-period APT. Since a unique factor seems to be sufficient to ensure APT exactness in a single and multi-period framework, the RMF is irrelevant. Further, the F-values reported in Table 2.9 are about of the same magnitude as those reported before, and are consistent with the empirical validity of the APT model. Thus, one factor appears to be sufficient to ensure exactness of the APT model, and the RMF is not required to ensure such exactness.[32]

2.6. CONCLUDING REMARKS

The arbitrage pricing model was empirically investigated herein. Mispricing may be obtained if less than the true K exogenous and unobservable factors are extracted, unless a residual market factor (RMF) is included in the return-generating process. Wei (1988) theoretically demonstrates how the addition of the RMF ensures an exact APT model.

The factor analysis, cross-sectional approach of Roll and Ross (1980) was used to estimate risk sensitivities for various variance-covariance matrices (V) of security returns (un)adjusted for nonsynchronous trading. A multi-period (time-series) approach using mimicking portfolios, whose conditional first and second moments are time-varying, was also used to test the APT. The time-series movements in the conditional V are accounted for by the time-series movements of the conditional standard deviations of the K mimicking portfolios. This model was estimated using the ITWLS of Davidian and Carrol (1987) (with and without the RMF), as well as its related conditional standard deviation in both the mean and standard deviation equations.

More than 5000 asset pricing estimations were performed. Conclusions on APT mispricing were based on the Shanken (1985) cross-sectional regression test and on the Lehmann and Modest (1987) time-series test. The findings are generally consistent across the 42 groups of 30 securities. The results related to the first objective of this study indicate that the first factor seems to be sufficient to span the efficient set, whether the model is estimated for fixed or time-varying V that are (un)adjusted for nonsynchronous trading, and that the

RMF is irrelevant. With regard to the second objective, the findings are robust to the type of return distributions used. However, a one factor structure only explains 12.4 and 24.1 percent of the unadjusted and adjusted V, respectively.

Based on the OLS estimations, the conditional standard deviations of the K mimicking portfolios significantly explain the time-variability of security volatilities. For a multi-factor structure, the conditional standard deviations of the factors (but not the RMF) affect the conditional V of securities. This is consistent with the findings of Schwert and Seguin (1990). Furthermore, the conditional standard deviation of the RMF for a one-factor structure captures a significant proportion of the time-variation in V, because its coefficient is significant for about one-half of the studied securities. However, the residuals of the mean equation still exhibit heteroskedasticity in the presence of the conditional standard deviations of the K mimicking portfolios and the RMF. Thus, determinants in addition to the second moments of the APT factors (such as firm-specific characteristics) may explain the volatilities of individual securities.

CHAPTER THREE: BENCHMARK INVARIANCY, SEASONALITY AND APM-FREE PORTFOLIO PERFORMANCE MEASURES

3.1 INTRODUCTION

Investigations of mutual fund performance involve a joint test of the adequacy of both the benchmark and the performance measure. Lehmann and Modest (1987), Grinblatt and Titman (1988), amongst others, find that inferences about mutual fund performance are not robust across different benchmarks and performance measures.

While market indexes are generally used as portfolio benchmarks, empirical tests suggest that they are not mean-variance (E-V) efficient.[33] For such comparisons, abnormal performances may be identified for funds that use passive (buy-and-hold) strategies. When the APT is exact, Grinblatt and Titman (1987) demonstrate that a global portfolio of mimicking portfolios is globally E-V efficient, and that each mimicking portfolio is locally E-V efficient. Lehmann and Modest (1985b) observe that minimum idiosyncratic risk mimicking (MIRM) portfolios generate the best (empirical) estimators of the economic forces that move all assets.[34] However, construction choices (such as the number of factors, nonsynchronous trading adjustment, and so forth) may lead to a benchmark invariancy problem.

While some portfolio performance measures require specific information about the forecasts of managers,[35] others require the determination of the appropriate asset pricing model (APM).[36] Further, some assumptions dealing with, for instance, traded assets or preferences, that are required for the existence of particular APM's, may be incompatible with the framework generally used to evaluate portfolio performance. Thus, APM-free measures, such as the Sharpe ratio and the Grinblatt and Titman (1989a) positive period weighting (PPW) score, should be used to assess portfolio performance. Their only requirement is that the portfolio benchmark be E-V efficient. As portfolio performance inferences may be sensitive to the choice of the underlying APM, they may also be sensitive to the choice of the underlying benchmark when APM-free measures are used.

Thus, this chapter has three major objectives. The first is to use APM-free measures and MIRM portfolio benchmarks to assess mutual fund performance. The second objective is to assess the robustness of such inferences to the so-called benchmark invariancy problem. The 12 benchmark portfolios studied herein are designed to analyze the impact of various technical aspects involved in their construction. The third objective is to study the seasonal behavior of the portfolio benchmarks, and their impact on portfolio performance inferences. If portfolio returns are characterized by a martingale, the monthly time-variation in the first two moments of returns can be captured by the bootstrapped Jobson and Korkie (1981) Z scores.

This chapter complements the important work of Lehmann and Modest (1987) who conduct stock picking tests using the Jensen (1968) measure and the Treynor and Black (1972) appraisal ratio, and market timing tests using a quadratic regression based on the CAPM and the APT. In applying the APT-based tests, they use different types of factor analysis, different numbers of factors (5, 10 and 15), and different numbers of securities for the construction of the mimicking portfolios. In contrast, APM-free measures are used herein. Furthermore, the robustness of performance inferences is evaluated for seasonality in the portfolio benchmarks and three important aspects of mimicking portfolio construction; namely, the use of the Shanken (1987) nonsynchronous-trading adjustment for the covariance matrix, the number of factors (one and six or eight) and firm size (small versus large).

The remainder of this chapter is organized as follows. In section 3.2, the APM-free performance measures are reviewed. In section 3.3, the benchmark invariancy problem, and the construction and E-V efficiency of the mimicking portfolios are discussed. In section 3.4, the data and methodology are described. In section 3.5, the empirical findings are presented and analyzed. In section 3.6, some concluding remarks are offered.

3.2 APM-FREE PERFORMANCE MEASURES

In a multivariate framework, each benchmark portfolio is associated with a particular economic force for a K factor structure. For a managed portfolio to display an abnormal performance, its risk premium must be superior to that which an uninformed investor would receive from holding the K portfolio benchmarks. In this framework, the Jobson-Korkie Z score for the Sharpe performance measure becomes:

$$Z = \frac{SH}{(e'\Phi e)^{1/2}} \sim N(0,1) \tag{3.1}$$

where $SH = e'SH_r$; e is a K x 1 unit vector; and SH_r is a K x 1 vector whose ith element is $sh_i = (\sigma_i\mu_r - \sigma_r\mu_i)$. Φ is a K x K variance-covariance matrix whose i,j element is:

$$\Phi_{ij} = (1/T)\ [(\sigma^2{}_r\sigma_i\sigma_j - \sigma_{ij}\sigma_r\sigma_j + \sigma^2{}_r\sigma_{ij} + 0.5\ (\mu_i\mu_j\sigma^2{}_r) - \mu_r\mu_j/4\sigma_r\sigma_i\ (\sigma^2{}_{ir} + \sigma^2{}_i\sigma^2{}_r) - \mu_r\mu_i/4\sigma_r\sigma_j\ (\sigma^2{}_{jr} + \sigma^2{}_j\sigma^2{}_r) + \mu^2{}_r/4\sigma_i\sigma_r\ (\sigma^2{}_{ij} + \sigma_i\sigma_j)$$

where μ_r is the average excess return on managed portfolio F; μ_i and μ_j are the average excess returns on portfolio benchmarks i and j; σ_{ij} is the covariance between benchmark portfolios i and j; and σ_{ir} is the covariance between managed portfolio F and benchmark portfolio i. Equation (1) tests the null hypothesis:

$$H_o: (\mu_r/\sigma_r - \mu_1/\sigma_1) = \ldots = (\mu_r/\sigma_r - \mu_K/\sigma_K) = 0 \tag{3.2}$$

Given E-V efficiency of the multi-portfolio benchmark,[37] superior portfolio performance based on micro-selectivity is easily identified.[38] The Sharpe ratio for this portfolio will necessarily be superior to those of the benchmark portfolios. When the managed portfolios exhibit superior performance based on macro-timing or macro-timing and micro-selectivity, the Sharpe ratio comparisons may be misleading. As shown by Dybvig and Ross (1985), the performance of such a managed portfolio may appear to uninformed investors to be inside (or outside) of their efficient sets.

In contrast, the PPW measure does not result in misleading inferences for portfolios with market timing abilities.[39] An investor's optimization problem, when investing x_j dollars in portfolio j is:

$$\text{Max } E[u\ (1 + \Sigma^k_{j=1} x_j R_{jt} + (1 - \Sigma^k_{j=1} x_j) R_f)] \qquad (3.3)$$

where (r_j) R_j is the (excess) return on benchmark portfolio j; R_f is the risk-free rate; and u( ) is the investor's utility function. The first-order condition for (3.3) is given by:

$$E[wr_j] = 0 \text{ for all } j \qquad (3.4)$$

where $w=u'(W)$ is the marginal utility of wealth (W) obtained from holding all the benchmark j portfolios. If a managed portfolio can exploit micro-selectivity and/or macro-timing, Grinblatt and Titman (1989a) contend that the PPW value given by $\delta = E[wr_p]$ is positive.[40] This value measures the gain in marginal utility (w) from adding a small amount of the evaluated portfolio (F) to the portfolio of the uninformed investor. This measure is similar to the Jensen measure when the latter is constrained to be positive in the presence of market timing.

To apply the PPW measure, the marginal utility must be estimated. The expectations are replaced by summations to obtain:

$$\Sigma^{T}_{t=1}w_t r_{1t}=\ldots=\Sigma^{T}_{t=1}w_t r_{kt}=0 \tag{3.5}$$

and $\delta=\Sigma^{T}_{t=1}w_t r_{Ft}$ where $\Sigma^{T}_{i=1}w_t=1$ for $t=1,\ldots,T$ (3.6)

Cumby and Glenn (1990) show that the marginal utility at time t is equal to $w_t=u'(W_t)=W_t(x_i)^{-\Theta}$, where Θ is the relative risk aversion (RRA) parameter of a power utility function. If the beginning-of-period wealth is normalized to one, then $W_t(x_i)$ is equal to:[41]

$$1+\Sigma^{k}_{i=1}x_i R_{it}+(1-\Sigma^{k}_{i=1}x_i)R_f \tag{3.7}$$

The PPW score, δ, from equation (3.6) is zero when uninformed investors hold the K benchmark portfolios, and is positive when PM's exhibit significant micro-selectivity and/or macro-timing abilities.

3.3 ESTIMATION AND PROPERTIES OF MIMICKING PORTFOLIOS

The E-V efficiency requirement for the benchmark portfolios suggests that APT mimicking portfolios may be appropriate for performance evaluation. Grinblatt and Titman

(1987) demonstrate that a global portfolio of GLS-estimated, mimicking portfolios is E-V efficient for an exact APT.[42]

The APT return-generating process can be stated as:

$$R_t = BR_{mt} + e_t \tag{3.8}$$

where R_{mt} is a K x 1 vector of mimicking portfolio benchmarks, B is N x K matrix of factor loadings, and e_t is N x 1 vector of residuals. When B is estimated using maximum likelihood factor analysis (MLFA), the following GLS estimator can be used:

$$R_{mt} = (B'D^{-1}B)^{-1}B'D^{-1}R_t \tag{3.9}$$

where D is a N x N diagonal matrix of idiosyncratic risks. Letting A be the K x N matrix of mimicking portfolio weights such that $A = (B'D^{-1}B)^{-1}B'D^{-1}$, equation (3.9) is equivalent to:

$$R_{mt} = AR_t \tag{3.10}$$

where $A'=\{a_1,...,a_k\}$, and a_j is a N x 1 vector of portfolio weights associated with the jth mimicking portfolio. Each column vector of A′ is obtained as follows:

$$\begin{aligned} &\text{Min } a_j'Da_j && \text{for } j=1,..,K \\ &\text{s.t. } a_j'B_k = 0 && \text{for all } k \text{ different from } j \\ &\quad a_j'B_j = 1 && \end{aligned} \tag{3.11}$$

If suitably rescaled in a separate step, the portfolio weights sum to one.[43] If a risk-free asset exists, Grinblatt and Titman (1987) contend that rescaling can be effected by adding or substracting the risk-free rate from the mimicking portfolios in amounts that make the sum of the weights on all assets equal to one.

Lehmann and Modest (1985b) contend that the GLS estimate of A results in poor mimicking portfolios. Large (small) weights are placed on securities with large (small) factor loadings, although large factor loadings may be just an indication of large measurement errors. Lehmann and Modest propose the use of $A^{mir\prime}=\{a_1^{mir},\ldots,a_k^{mir}\}$, where a_j^{mir} is a N x 1 vector of MIRM portfolio weights for the jth mimicking portfolio. Lehmann and Modest contend that:

$$a_j^{mir} = D^{-1}B_j(B_j'D^{-1}B_j)^{-1}e_j \qquad (3.12)$$

where B_j is the N x K matrix of factor loadings when all securities load with one on the jth factor, and e_j is a K x 1 vector of zeros except for a one at the jth position. Each column vector of $A^{mir\prime}$ obtains from:

$$\begin{aligned} &\text{Min } a_j^{mir\prime} D a_j^{mir} \qquad (3.13)\\ &\text{s.t. } a_j^{mir\prime} B_k = 0 \qquad \text{for all k different from j}\\ &\qquad a_j^{mir\prime}\underline{1} = 1 \end{aligned}$$

Although a biased estimate of the jth mimicking portfolio results, the column vector weights of $A^{mir\prime}$ always sum to one so that no rescaling is required. As demonstrated by Lehmann and Modest (1985b), the MIRM weights are more precise since they are unaffected by measurement errors. As shown by Grinblatt and Titman (1987) for GLS estimated mimicking portfolios, an exact APT model is equivalent to the E-V efficiency of the global portfolio of mimicking portfolios.

A similar conclusion is obtained when the portfolios are estimated using the MIRM method. (A formal demonstration is available from the author.)

3.4 DATA AND METHODOLOGY

The sample is drawn from the Financial Post mutual fund data base. It contains 146 all equity funds which are not only available monthly between June 30, 1981 and March 31, 1989 but also have no more than 5% of their values missing. The 93 monthly returns for each fund are calculated using the net asset values per share and are adjusted for dividend payments. The 1955 daily returns on the 424 stocks, which are available on the TSE-Western tape and have no more than 5% of their values missing for this period, are used to construct the MIRM portfolios. To investigate the benchmark invariancy problem, 12 types of MIRM benchmark portfolios are used (see Table 3.1). The monthly returns on the TSE300 and the value-weighted TSE index are also used herein.

Since the factors are unknown, conventional practice is to use MLFA to estimate the matrices of factor loadings (B) and idiosyncratic risks.[44] Although factor analysis should be performed on the entire sample of securities, using 93 monthly returns for 424 stocks results in a non-positive number of degrees of freedom. While the use of daily returns increases the degrees of freedom, it introduces a nonsynchronous trading problem into the estimation. The variance-covariance matrix of security returns can be adjusted using Shanken's (1987) adjustment, $COV^{sh}(R_i,R_j)=\Sigma^3_{n=1}\Sigma^3_{m=1}$ $COV(R_{it-n},R_{jt-m})$ + $COV(R_i,R_j)$, where $COV^{sh}(R_i,R_j)$ is the covariance between securities i and j when adjusted for nonsynchronocity using three lags.[45]

While one factor appears to be sufficient to ensure the exactness of the APT model whether or not it is adjusted for nonsynchronous trading, the maximum likelihood ratio χ^2 test and the eigenvalue cut-off values indicate that six and eight factors are required for V's which are unadjusted and adjusted for nonsynchronous trading, respectively.[46] Thus, both one and multi-factor mimicking portfolio benchmarks are used herein.

The MIRM portfolios are constructed such that:

$$R_{mt}= A^{mir}R_t \tag{3.14}$$

where $\underline{1}A^{mir\prime}=\underline{1}$, $A^{mir\prime}=\{a_1^{mir},a_2^{mir},\ldots,a_k^{mir}\}$, $a_j^{mir} = D^{-1}B_j(B_j'D^{-1}B_j)^{-1}e_j$, and B and D are MLFA estimates for daily returns. The mimicking portfolio returns are obtained by multiplying A^{mir} by a matrix of monthly security returns.[47]

The economic factors that affect the returns of the samples of firms and mutual funds may differ, since mutual funds are more likely to invest in larger firms.[48] To investigate this possibility, MIRM benchmark portfolios are also formed for the 147 (277) firms whose average price was below (above) $5 at five specified dates within the sample period.

To empirically estimate w_t, a value of x_j, $j=1,\ldots,K$, must be chosen that satisfies the first-order condition (3.5). For each set of portfolio benchmarks, 100,000 solutions of the set of x_j for equation (3.7) are generated under the assumption that $\Theta=6$.[49] The set of x_j that best satisfies the first-order condition is selected to calculate the time-series vector of marginal utilities.

The return variance of an actively managed portfolio will be nonstationnary due to its continous rebalancing. Although the PPW score is unaffected by heteroskedasticity, its variance must be corrected to yield valid inferences.[50] To account for this heteroskedasticity (and possible serial correlation), the Jobson-Korkie Z score is calculated using the following estimator of Newey and West (1987):

$$COV^{nw}(R_i,R_j)=T[COV(R_i,R_j) + \Sigma^{m}_{j=1}\ w(j,m)COV(R_{it},R_{jt-k}) + \Sigma^{m}_{i=1}\ w(i,m)COV(R_{it-k},R_{jt})] \qquad (3.15)$$

where $w(k,m)=1-[k/(m+1)]$ for $k=i,j$.[51]

Gultekin and Gultekin (1983), Kryzanowski and Zhang (1992), amongst others, find that the TSE indexes exhibit a January seasonal, which suggests that the returns of the various portfolio benchmarks may have seasonal effects. This may result in a benchmark invariancy problem. This is examined by calculating Jobson-Korkie monthly Z scores for both mimicking portfolio and TSE market index benchmarks.

Jobson and Korkie demonstrate that both the first and second sample moments of SH_q in equation (3.1) are asymptotic estimators. To overcome the bias caused by the availability of only seven monthly returns, bootstrapped estimates (Efron, 1982) of the moments of the empirical distributions of SH_q are obtained by resampling each sample of portfolio returns L times.[52]

3.5 EMPIRICAL FINDINGS

3.5.1 Benchmark Invariancy

The Sharpe ratios of the portfolio benchmarks based on the small firms, which are reported in Table 3.2, are negative.[53] Mimicking portfolio returns have substantially higher ratios than those for the market indexes, regardless of whether or not the V matrix of security returns is adjusted for nonsynchronous trading, of the number of factors extracted and of the sizes of the firms for which factors are extracted. This result is consistent with the CAPM literature that generally rejects the E-V efficiency of the market indexes, and with the E-V efficiency of the MIRM portfolios discussed in section three. The high Sharpe ratios for the MIRM portfolio returns are consistent with the exactness of the APT model. Thus, the application of the Z and PPW scores is likely to result in an invariancy problem based on the relative E-V efficiency of the benchmarks (namely, market indexes versus mimicking portfolios).

Grinblatt and Titman (1988) contend that MIRM portfolios for a ten-factor structure exhibit a firm-size bias in that the Jensen measures for small (large) firm-sized portfolios tend to be positive (negative). This does not appear to be the case when the Sharpe ratio is used. The Sharpe ratios of the large- and all-firm mimicking portfolios are almost always larger than their small firm counterparts. If firm size biases the mimicking portfolio benchmarks, the Sharpe ratios of the small-firm mimicking portfolios would be expected to be superior to the Sharpe ratios of the large- and all-firm mimicking portfolios.

The Jobson-Korkie Z scores for the 14 portfolio benchmarks are reported in Table 3.3. With the exception of the market indexes, the Z scores are negative. Mutual funds do not appear to be able to economically exploit information based on a comparison of their Sharpe ratios with those of the mimicking benchmark portfolios. The use of the Newey-West adjustment for heteroskedasticity for the mutual fund returns, and for the variances and covariances of returns for the benchmarks does not change the results materially. Consistent with the results presented in Table 3.2, the Z scores are the lowest when mutual fund Sharpe ratios are compared to those of the mimicking portfolios. The average Z scores and their associated standard deviations increase when the Sharpe ratios of the mutual funds are compared with those of the market indexes. When the Newey-West estimator is used, similar results are obtained.

Since significantly different Z scores appear to result for different portfolio benchmarks, the equality of the mean vectors of two samples is tested. Formally, the null hypothesis, H_o: $\theta = (\mu_1 - \mu_2) = 0$, is tested using the χ^2 test:

$$N\ (\bar{D} - \theta)'\ S_d^{-1}\ (\bar{D} - \theta)\ \sim \chi^2_P \qquad (3.16)$$

where $D_j = [D_{1j}, \ldots, D_{Pj}]$, $j = 1, \ldots, N$; P is the number of pairs of Z score vectors that are simultaneously being tested; $D_{ij} = Z_{vij} - Z_{wij}$; $\bar{D}$ is a Px1 vector of means of Z score differences; S_d is the corresponding covariance matrix; and N is the number of mutual funds (146 in this study). The χ^2 non-centrality values for various mean vector comparisons of Z scores are presented in Table 3.4. Each bivariate χ^2 value is obtained for P=1 in (3.16) when the null hypothesis is that the Z score means obtained for specific benchmarks are not significantly different when the benchmarks only differ by a specific attribute. To illustrate, based on the χ^2 value of 761.23, the equality of the average Z scores obtained for portfolio benchmarks MN1P147 (one factor mimicking portfolio benchmark, a V unadjusted for nonsynchronous trading, and small firms) and MN6P147 (six factor mimicking portfolio benchmark, a V unadjusted for nonsynchronous trading and small firms) is rejected. Each multivariate χ^2 value is obtained for P>1 in (3.16).

Similar χ^2 values based on the Jobson-Korkie Z scores, when V is adjusted for heteroskedasticity using the Newey and West (1987) estimator, are reported in Table 3.5. As reported earlier, the importance of the E-V efficiency of the benchmark is illustrated in Panel F. The average Z scores obtained for a mimicking portfolio benchmark are significantly different than those based on the market indexes.

Based on Panels A and B of Tables 3.4 and 3.5, the number of factors in the factor structure and the V adjustment for nonsynchronous trading lead to significantly different average Z scores. The average Z scores are significantly different depending on firm size, which suggests that different factors affect "small" and "large" firms. Based on Panel F of Tables 3.4 and 3.5, the use of market indexes lead to significantly different average Z scores although the χ^2 values have a smaller magnitude.

General performance statistics based on the PPW are reported in Table 3.6. The average PPW values indicate that the lowest mutual fund performances generally occur for mimicking portfolio benchmarks, and that the number of funds exhibiting positive abnormal performance is generally higher when the TSE300 is used as a benchmark. This seems to be consistent with the Sharpe ratio values reported in Table 3.2, and with the E-V efficiency condition required by Grinblatt and Titman (1989a) for the application of the PPW. The numbers of significantly positive and negative abnormal performances change only slightly when t-tests adjusted for heteroskedasticity are used. A comparison of the numbers of funds that display abnormal positive performances in Tables 3.3 and 3.6 suggests that little market timing is displayed by these funds. This is supported by the similar magnitude of the correlations between the Z scores (when V is computed using the ordinary and the Newey-West estimators), and the PPW scores, which are presented in Table 3.7.

PPW mean vector comparisons, which are based on the same characteristics as those used in Tables 3.4 and 3.5, are reported in Table 3.8. Based on the magnitude of the χ^2 non-centrality parameters, the various benchmark attributes generally have a significant impact on the PPW scores. Specifically, the average PPW scores based on mimicking portfolios are significantly different than those based on market indexes. Thus, the E-V efficiency condition for the portfolio benchmarks has a significant impact on the PPW values. The multivariate χ^2 test results indicate that H_o is rejected only for all of the portfolio benchmarks. As for the Z scores, the PPW scores are significantly different when the number of factors, nonsynchronous trading, and firm size are considered in the construction of the mimicking portfolios.

3.5.2 Seasonality

The bootstrapped and Newey-West Z scores for tests of the null hypothesis (H_o) that the Sharpe ratios of mimicking portfolios (market indexes) for a specific month are not significantly different than those of the remaining eleven months are reported in Table 3.9.[54] Rejection of H_o suggests that the underlying returns of the portfolio benchmarks have an anomalous monthly nature, since the expected returns vary significantly across months even when a monthly time-varying risk component is accounted for. Based on Table 3.9, the returns, for example, for benchmark MN1P147 have an anomalous behavior for the months of February, August, September, October and December (their Z scores exceed 1.96).[55] Furthermore, most benchmarks exhibit an anomalous behavior for the months of September, October and December. These results contradict a major implication of market efficiency, which states that the Sharpe ratios for the benchmarks should not differ significantly for the months of the year. This should not depend on whether or not the random walk or the martingale is deemed to be the appropriate time-series model for asset returns. No January effect is observed for any of the portfolio benchmarks [56] These results have important implications for portfolio performance inferences. Specifically, measures of portfolio performance may contain a bias which is proportional to the monthly effects for the Sharpe ratio of the underlying portfolio benchmark.

The statistics on the Z scores based on the returns for the 146 mutual funds are presented in Table 3.10. The mean and standard deviation of the Z scores for a specific month are designated by E(Z) and STD(Z). The hypothesis, $H_o: E(Z)_i=0$ for i=January, ...,December, is tested using a t-test. The hypothesis, $H_o: E(Z)_{Ja}=\ldots=E(Z)_{De}=0$, is tested using a F-test. For all months, the t-tests reject the hypothesis that the average Z scores are equal to zero. Together with the large F-values, this implies that the average monthly Z scores are fairly homogenous across the sample for the mutual funds. The magnitudes of the average Z scores across the months indicate that mutual funds display a monthly risk-return relationship which is similar to that of the market indexes.

The monthly behavior of the bootstrapped Z scores for portfolio performance are reported in Table 3.11. This allows for a determination of whether or not mutual fund performance is significantly driven by the monthly effects in the benchmark Sharpe ratios (reported earlier in Table 3.9). Several average Z scores are lower than -1.96 or greater than 1.96 across the various portfolio benchmarks. This is consistent with the presence of seasonality in mutual fund performance.

An important conclusion can be drawn after relating the months for which the Sharpe ratios of the portfolio benchmarks display anomalous monthly effects (Table 3.9) with the months for which the null hypothesis of equality of the Sharpe ratios between mutual funds and portfolio benchmarks is rejected (Table 3.11). The inferences about mutual fund performances reached earlier are biased due to the material influence of the monthly effects of the Sharpe ratios of the chosen mimicking portfolio benchmarks, particularly for the months of September and December. In contrast, based on the average Z scores reported in Table 3.11, no significant differences exist in the Sharpe ratios for mutual funds and the market indexes for all the months of the year. Based on a comparison of Tables 3.9 and 3.10, the Sharpe ratios for the mutual funds and the market indices exhibit a very similar seasonal behavior both in terms of magnitude and trend.

A benchmark invariancy problem can exist because the underlying portfolio benchmarks have returns that display significant monthly effects or because the returns have different monthly effects. To test these possibilities, the χ^2 test is applied for each month of the year. The null hypothesis is the equality of two mean Z scores, where each mean is calculated from a vector of bootstrapped Z scores when the underlying portfolio benchmark has unique attributes. These results are presented in Tables 3.12 and 3.13. The covariance terms required in the computation of the bootstrapped Z scores are based on the ordinary and Newey-West V estimators, respectively. The results presented in Panel A of Table 3.12 are inconsistent with expectations. If the anomalous patterns of monthly returns on the portfolio benchmark are the only explanation for the benchmark invariancy problem, clusters would be expected to appear for the months of the year where monthly effects are observed in Table 3.11. For all the attributes of the mimicking portfolios, the average χ^2 values and the number of rejections of H_0 are not only similar across the months of the year but are similar to the numbers of rejections reported in Table 3.4. This is confirmed by the χ^2 values presented in Panel B. In Table 3.11, the mutual fund performances based on the mimicking portfolio returns exhibit seasonal effects only for the months of September and December, while the performances based on the market indexes exhibit no seasonal effects. However, based on Panel B of Table 3.12, the hypothesis of mean equality is rejected for months other than those for which seasonality in mutual fund performance has been observed earlier. Therefore, anomalous monthly variations in mutual fund performance based on portfolio benchmarks with distinctive attributes appear not to be the unique determinants of the benchmark invariancy problem.

3.6 CONCLUDING REMARKS

To study the benchmark invariancy problem, the Jobson-Korkie (1981) Z score and the positive period weighting (PPW) score of Grinblatt and Titman (1989a) were applied to 14 different portfolio benchmarks (including 12 minimum idiosyncratic risk mimicking (MIRM) portfolios constructed to reflect various attributes). Although the benchmarks that differ by the number of factors, nonsynchronous trading adjustment, and firm size in their construction led to different performance results for the same measure, the results were fairly homogenous across the measures. The effect of this benchmark invariancy problem caused by the construction of the mimicking portfolios is similar for the PPW score.

One important attribute was the mean-variance (E-V) efficiency of the portfolio benchmarks. Mimicking portfolios had Sharpe ratios that were subtantially higher than those based on market indexes. This led to significantly different portfolio performance inferences based on mimicking portfolios versus market indexes. The implication is that investigators should be careful in analyzing mutual fund performance when market indexes constitute the benchmark.

Several seasonal issues related to portfolio performance inference were studied to avoid biased estimations when returns are categorized by the month of occurrence. Bootstrapped Jobson-Korkie Z scores were estimated for this purpose. The returns of the different portfolio benchmarks exhibited significantly different monthly effects when a monthly time-varying risk component was incorporated into the Jobson and Korkie Z score. This implies that anomalies due to monthly effects cannot be explained by the time-variation of the underlying second moment of returns. Nevertheless, the monthly effects of the benchmarks significantly influence mutual fund performance inferences. The underlying portfolio benchmarks display anomalous seasonal variations for the months (particularly, December) for which the hypothesis of equality between the Sharpe ratios of the mutual funds and the portfolio benchmarks are (on average) rejected. Thus, mutual fund performance measurements are biased.

Based on an analysis performed for each month of the year, it appears that the benchmarks that exhibited monthly effects were not the only determinants of the benchmark invariancy problem. This problem persisted even when the returns of the portfolio benchmark exhibited no seasonality.

CHAPTER 4: PERFORMANCE ATTRIBUTION USING AN APT WITH PRESPECIFIED MACROFACTORS AND TIME-VARYING RISK PREMIA

4.1 INTRODUCTION

The central problem in the evaluation of mutual fund performance is determining the quality and type of information possessed by portfolio managers (PM's). The Jensen (1968) measure is the most widely used of the performance techniques available in the literature. It is used to assess whether PM's use economically valuable information to select (avoid) stocks that promise returns higher (lower) than are commensurate with their respective risk levels. As discussed more fully in the next section of this chapter, the results of the studies using the Jensen measure are contradictory. Further, several authors have criticised the theoretical bias inherent in the Jensen measure, especially when the PM's of mutual funds attempt to time movements of macrofactors that have priced risks.

An evaluation of mutual fund performance using the Jensen measure must account for the inexactness of the underlying asset pricing model (APM), the methodological problem raised by Admati, Battacharya, Pfleiderer and Ross (ABPR)(1986), and the measurement error associated with the estimation of timing portfolios. Thus, the primary purpose of this chapter is to make micro-selectivity and macro-timing inferences using the

Jensen (1968) alpha and the Lehmann and Modest (1987) quadratic regression approaches. An APT with observable macroeconomic variables and factor risk premia which vary proportionally with their factor volatilities is used as the underlying APM. The macro-timing inferences are based on the ability of PM's to time movements in priced macrofactors. Unlike Lehmann and Modest (1987) who test timing abilities by examining the covariance between the mutual fund risk premia and the square of the underlying factor risk premia, the test used herein rests upon the covariance between the mutual fund risk premia and the conditional volatilities of the underlying factors. Our measure avoids the problems identified by ABPR while still capturing any correlation between the time-varying-deviations from the average sensitivities of the funds and the excess returns of the mimicking portfolios.

The remainder of this chapter is organized as follows. In section 4.2, a brief review of the literature is presented. In section 4.3, the APT model and the proposed tests of micro-selectivity and macro-timing are detailed. In section 4.4, the sample of mutual funds and the data are described. In section 4.5, the empirical findings are presented and analyzed. In section 4.6, some concluding remarks are offered.

4.2 BRIEF REVIEW OF THE LITERATURE

The empirical evidence on the selection and timing abilities of mutual funds is somewhat contradictory. Jensen (1968) and Kon (1983) find that more than half of the mutual funds studied have negative and positive Jensen measures, respectively. Kon concludes that his evidence seems to reject the strong form of the efficient market hypothesis (EMH) for stock selection but not for market timing. Although Chang and Lewellen (1984) report that the Jensen measure is positive for almost two thirds of the funds in their sample, they conclude that mutual funds generally do not exhibit either micro-selectivity or macro-timing abilities. Henriksson (1984) reports that half of the mutual funds in his sample display a positive Jensen measure, and no evidence exists for significant positive market timing abilities. Although Lee and Rahman (1990) find similar selectivity results, they observe positive timing abilities for some funds. All of these studies implicitly require that the benchmark market index be mean-variance efficient.

Jensen measures based on the APT are estimated by Lehmann and Modest (1987) and by Grinblatt and Titman (1988, 1989b). Lehmann and Modest find that the Jensen estimate is very sensitive to the construction of the APT benchmarks and to the postulated APM. For all the benchmarks, persistently large and negative Jensen measures are observed. Grinblatt and Titman (1989b) explain similar results as being due to the substraction of transaction costs, fees, and other expenses from the returns of mutual funds. While Lehmann and Modest (1987) report inconclusive evidence on timing, Grinblatt and Titman find no evidence of timing abilities.

Several authors question the theoretical validity of the Jensen measure under certain circumstances. When mutual fund managers have market timing skills, Dybvig and Ross (1985) show that the sign of the Jensen measure becomes an unreliable indicator of micro-selectivity abilities. In the presence of market timing, Grinblatt and Titman (1989a) demonstrate that the systematic risk estimator is biased (and, thus, affects the measure of selectivity abilities). If the CAPM is used as the benchmark APM, the Jensen measure is estimated under the assumption that the market portfolio is mean-variance efficient in order that passively managed portfolios display insignificant Jensen measures. Unfortunately, Banz (1981), Reinganum (1981), Shanken (1985), amongst others, find that the CAPM cannot adequately explain the returns on size-sorted portfolios. Improved results are obtained when the APT is the postulated APM, and its factors are approximated using the minimum idiosyncratic mimicking portfolios of Lehmann and Modest (1985a,b).[57] Grinblatt and Titman (1988, 1989b) explain the persistently negative Jensen values observed by Lehmann and Modest (1987) as being caused by the mean-variance inefficiency of the mimicking portfolios.

Most tests of portfolio performance implicitly assume that a theoretical dichotomy exists between the signals for micro-selectivity and macro-timing. ABPR criticize empirical formulations where portfolios represent the separating funds, because timing portfolios are likely to include securities for which selectivity signals are observed. This would violate the statistically imposed condition of independence between the two types of signals when the appropriate APM is estimated.

Econometrically, portfolios whose returns mimic the realizations of the K factors are subject to measurement error. This is true even for the minimum idiosyncratic mimicking portfolios of Lehmann and Modest. Burmeister and McElroy (1988) report that APT estimates are sensitive to this problem, and may lead to invalid inferences based on biased and inconsistent Jensen estimates.

4.3 PROPOSED TESTS OF MICRO-SELECTIVITY AND MACRO-TIMING

Asset pricing theory suggests that the excess returns on securities are exactly explained by K separating funds, where $K \geq 1$. Consider a portfolio manager (PM) who has significant abilities in forecasting the performance of N firms by observing N independent selectivity signals which are unobserved by uninformed investors. The PM will realize an excess return that exceeds that implied by a linear combination of the excess returns on the K separating funds, which is captured by the Jensen α. If the APT is the postulated APM, the Jensen measure is the intercept, α_p, of the time-series regression:

$$R_{pt}=\alpha_p + \beta_{p1}\Gamma_{1t} +...+ \beta_{pK}\Gamma_{Kt} + \varepsilon_{pt} \tag{4.1}$$

where R_{pt} is the excess return on portfolio p at time t; β_{pj} is the risk sensitivity measure of portfolio p to mimicking portfolio j; Γ_{jt} is the excess return on mimicking portfolio j at time t, that has a unit cost, that loads with one on factor j and that is orthogonal to the other factors; and ε_{pt} is a residual component with the usual properties.[58] This formulation has been used by Lehmann and Modest (1987) and Grinblatt and Titman (1988).

Unlike the usual one-step mutual fund performance inferences based on the CAPM, inferences based upon the APT usually involve a two-step procedure. The first step involves the construction of K mimicking portfolios whose returns mimic the realizations of the common factors based on an initial sample of N assets. Since Huberman, Kandel and Stambaugh (1987) demonstrate that both mimicking and arbitrage portfolios have the same expected excess returns, expression

(4.1) is consistent with an ex post version of the APT when the risk premia are time-varying. This ex post APT is a multivariate extension of Black, Jensen and Scholes (1972). As shown by Lehmann and Modest (1985a) and Grinblatt and Titman (1988), the several methods for mimicking portfolio construction lead to different sets of proxies for the APT risk premia proxies.

When a PM has macro-timing abilities, s/he is able to forecast the future movements of the timing portfolios, and will shift wealth among the K portfolios.[59] ABPR contend that the definitions of micro-selectivity and macro-timing are inconsistent with the statistical implications of equation (4.1). If N selectivity signals are observed and N assets are used in the construction of the K mimicking portfolios, basic algebra implies that only N-K independent selectivity signals will exist. It follows from equation (4.1) that selectivity can not be informative for all N individual assets. Thus, selectivity would be any information that is uninformative about the timing of the mimicking portfolios but informative about asset returns.

This inconsistency can be avoided by utilizing conditional asset pricing based on macrofactors. In an intertemporal framework [as in Cox, Ingersoll and Ross (1985)], Roll and Ross (1980) demonstrate that each conditional risk premium of the APT model is equal to a parameter R times the conditional volatility of each underlying factor, where R is a constant of proportionality that corresponds to the product of the aggregate relative risk aversion parameter times the elasticity of consumption with respect to changes in the underlying state variable. This approach is supported empirically by French, Schwert and Stambaugh (1987) and Lauterbach (1989). Formally:

$$\Gamma_{jt}=\phi + R\sigma_{jt} + u_{jt} \tag{4.2}$$

where σ_{jt} is the volatility of factor j at time t; R is as was defined earlier ; ϕ is an intercept;[60] and u_{jt} is a residual component with the usual properties. If (4.2) holds for each of the K risk premia, then replacing (4.2) into (4.1) gives:

$$R_{pt} = \alpha_p + R\{\beta_{p1}\sigma_{1t} + \ldots + \beta_{pK}\sigma_{Kt}\} + v_{pt} \tag{4.3}$$

where $v_{pt}=\Sigma^{K}_{j=1}\beta_{pi}u_{it} + \varepsilon_{pt}$.

Intertemporal multi-beta asset pricing models are theoretically developed by Constantinides (1989), Cox, Ingersoll and Ross (1985), amongst others. These models are well-suited for performing micro-selectivity and macro-timing tests, because the underlying utility function generally only has to be twice differentiable, monotonic increasing, and strictly concave. For the intertemporal APT to become a testable model compatible with equation (4.3), Constantinides (1989) requires three maintainable hypotheses. First, the observable subset of assets must have a factor structure.

Second, the noise term of the observable assets must be uncorrelated with the returns of the unobservable assets. Third, the factors span the state variables that influence the rates of return of the unobservable assets.

For the model to be applicable to the detection of economically valuable (macro) timing signals, an extra assumption is required. Specifically, the conditional covariances of the monthly returns of the mutual funds with the priced factor realizations must be time-varying only as a result of managerial macro-timing attempts. Fortunately, the conditional covariances of the underlying stocks in which most Canadian funds invest have been constant over the sample period studied herein.[61] This is consistent with the findings of Ferson and Harvey (1987) who observe that the time-variation in the factor risk premia (and not the risk sensitivities) account for most of the time-variation in portfolio expected returns using a multi-beta APM based on macrofactors.

In the spirit of ABPR, equation (4.3) is more consistent with the theoretical structure imposed on the private information held by PM's, since the time-varying risk premia are not proxied by the excess returns of the mimicking portfolios that are a repackaging of the N securities for which N selectivity signals may be observed. Instead, the realizations of the time-varying risk premia are accounted for by the time-series movements of the volatility components of the priced macrofactors.

The derivation of the APT model used herein builds on the work of Burmeister and McElroy (1988), Kryzanowski and Koutoulas (KK) (1991), amongst others, and begins with the following APT return generating process:

$$R_{pt} = E(R_{pt}) + \beta_{p1}\delta_{1t} + \ldots + \beta_{pK}\delta_{Kt} + e_{pt} \tag{4.4}$$

where $E(R_p)$ is the expected return of portfolio p at time t; δ_{jt} is an innovation in the observable macrofactor j at time t; β_{pj} is the measure of risk sensitivity between portfolio p and macrofactor j at time t; and e_{pt} is a residual component with the usual properties.[62] Applying the expectation operator to equation (4.3) and substituting the result into equation (4.4) yields:

$$\begin{aligned} R_{pt} = {} & \alpha_p + \beta_{p1}\delta_{1t} + \ldots + \beta_{pK}\delta_{Kt} \\ & + R\{\beta_{p1}\sigma_{1t} + \ldots + \beta_{pK}\sigma_{Kt}\} + e_{pt} \end{aligned} \tag{4.5}$$

The methodology of Burmeister and McElroy (1988) suggests that equation (4.5) is a multivariate system of N equations where N is the number of portfolios being investigated. Estimation can be based on a stacked N x N diagonal or on the full variance-covariance matrix of residuals.[63] In the latter case, a nonlinear seemingly unrelated regression (SUR) method allows for multiple nonpriced macrofactors to affect security returns. The system also allows for the imposition of restrictions such as the equality of R in equation (4.5).[64] Since the macrofactors are directly included in the return-generating process, pervasive forces that have priced risk can be directly related to the macroeconomic variables. Although measurement error exists in the macrofactor innovations, the use of macrofactors avoids the measurement error in the factor loadings resulting from the well-known two-pass procedure required for the construction of mimicking portfolios. As Burmeister and McElroy (1988) show, avoiding this source of measurement error positively affects the robustness of the resulting estimations.

KK (1991) estimate the following restricted multivariate system, based on equation (4.5), for Canadian equities:

$$R_{it} = \alpha + \beta_{i1}USINDEX_t + \beta_{i2}EX_t + \beta_{i3}CINDEX_t$$
$$+\beta_{i4}EXPORTS_t + \beta_{i5}LINDUS_t + \beta_{i6}MONEY_t + \beta_{i7}RMF_t + R\{\beta_{i2}CEX_t + \beta_{i3}CCINDEX_t\} + \varepsilon_{it} \quad (4.6)$$

where R_{it} is the excess return for size-sorted portfolio i at time t; α_i is the intercept of the model (the estimated Jensen measure); $USINDEX_t$ is the innovation of the U.S. Composite Index of 12 leading indicators at time t; EX_t is the innovation of the Canada/U.S. exchange rate at time t; $CINDEX_t$ is the orthogonal component of the Canadian composite index of ten leading indicators on the return on the TSE index, money, USINDEX and industrial production at time t; $EXPORTS_t$ is the innovation of total exports at time t; $LINDUS_t$ is the innovation of the lag of the industrial production index at time t; $MONEY_t$ is the innovation of the money supply (M1) at time t;[65] and RMF_t is the value of the residual market factor at time t, which has been theoretically justified by Wei (1989)[66] and empirically estimated as the residual component of the six macroeconomic variables previously regressed on the TSE300 index; R is the constant proportionality parameter as in equation (4.3); CEX_t is the value of the conditional standard deviation of EX at time t; and $CCINDEX_t$ is the conditional standard deviation of $CINDEX_t$ at time t.[67]

KK estimate the restricted and unrestricted versions of the multivariate system based on equation (4.6) using both nonlinear ordinary least squares (NOLS) and nonlinear seemingly unrelated regressions (NSUR). In the unrestricted version, R is not constrained to be the same for the various macrofactor volatilities. KK reject the hypothesis that the return-generating model and the APT pricing relationship are not significantly different, and the hypothesis that the risk premia are jointly invariant. Most importantly, KK find that the restricted version of the APT is exact since the estimated intercept is insignificant when size-sorted portfolios are investigated. This suggests that "passive" portfolio management strategies, including those based on firm size, should not lead to abnormal performance. Unlike the beta estimates, KK find that their estimates of the risk premium proportionality pricing parameter, R, are affected by the choice of the estimation technique and the number of portfolios used to estimate their model (for greater details, see Table 4.1).

For a sample of N mutual funds, the N Jensen estimates can be obtained by estimating the multivariate system of N equations based on equation (4.6) by sequentially using the R values estimated by KK, and those obtained using a fully stacked residual matrix. For the latter R estimates, a similar framework for evaluating mutual fund performance is used in order to be consistent with KK.[68] The advantage of this two-step procedure of estimating the APT with only security returns, macrofactors and the measure of fund performance using the first-stage risk premia estimates taken from KK is that the compensations required by uninformed investors are not intermingled with the effects of the managerial abilities of the mutual fund managers. This approach is identical to that of Lehmann and Modest (1987), amongst others. KK find that the intercept of the unrestricted version of equation (4.2) is significant for size-sorted portfolios. To evaluate the implications of this potential bias, comparisons are subsequently made between the Jensen estimates for the restricted and the unrestricted versions of equation (4.6).

As noted earlier, spurious conclusions can be reached about stock picking when PM's use timing strategies. In the presence of timing, Dybvig and Ross (1985) demonstrate that the Jensen measure could be positive when PM's are unsuccessful stock pickers and vice versa.[69] When the timing component is ignored in the benchmark model, Grant (1977) demonstrates that the Jensen measure tends to be underestimated [also see Chang and Lewellen (1984), Henriksson (1984) and Lee and Rahman (1990), amongst others]. The inclusion of a timing measure in the benchmark APM leads to another problem. Based on Kon (1983) and Henriksson (1984) who find a negative correlation between measures of selectivity and timing, Jagannathan and Korajczyk (1986) show how to create a portfolio having artificial positive or negative timing performance and an artificial countereffect on its selectivity performance.

While these problems are associated with timing evaluations using portfolios that represent separating funds, they may not exist in a theoretical framework where PM's attempt to time the movements of macroeconomic variables that have priced risks by directly including these macrofactors in the APM model. The timing test proposed by Lehmann and Modest (1987) involves a quadratic regression where the own-squared terms of the mimicking portfolios that have priced risks are included in the model as extra variables in equation (4.1).[70]

Given two priced factors, the model is:[71]

$$R_{pt}= \alpha_p + \beta_{p1}\Gamma_{1t} + \beta_{p2}\Gamma_{2pt} + \beta_{p3}(\Gamma_{1t})^2 + \beta_{p4}(\Gamma_{2t})^2 + \beta_{p5}(\Gamma_{1t}\Gamma_{2t}) + \varepsilon_{pt} \tag{4.7}$$

If the excess returns on the mimicking portfolios are replaced by the time-varying volatilities of the macrofactors given by equation (4.3), then equation (4.7) becomes:

$$R_{pt}= \alpha_p + R\{\beta_{p1}\sigma_{1t} + \beta_{p2}\sigma_{2pt}\} + R^2\{\beta_{p3}(\sigma_{1t})^2 + \beta_{p4}(\sigma_{2t})^2 + \beta_{p3}(\sigma_{1t}\sigma_{2t})\} + \varepsilon_{pt} \tag{4.8}$$

Applying the expectation operator to equation (4.8), and substituting into equation (4.4) using the Canadian macro-factors of KK, gives:

$$\begin{aligned} R_{pt}= {} & \alpha_p + \beta_{p1}USINDEX_t + \beta_{p2}EX_t + \beta_{p3}CINDEX_t + \beta_{p4}EXPORTS_t \\ & + \beta_{p5}LINDUS_t + \beta_{p6}MONEY_t + \beta_{p7}RMK_t + R\ \{\beta_{p2}CEX_t \\ & + \beta_{p3}CCINDEX_t\} + R^2\ \{\beta_{p8}(CEX_t)^2 + \beta_{p9}(CCINDEX_t)^2 \\ & + \beta_{p10}(CEX_t \times CCINDEX_t)\} + e_{pt} \end{aligned} \tag{4.9}$$

If PM's display factor timing abilities, the null hypothesis, $H_0: \beta_{p8}=\beta_{p9}=\beta_{p10}=0$, will be rejected. If the β_{p8} and/or β_{p9} are positive, then the PM of mutual fund p has exhibited significant abilities for forecasting the movements of EX_t (the innovation of the Canada/U.S. exchange rate at time t) and/or $CINDEX_t$ (the orthogonal component of the Canadian composite index of ten leading indicators at time t). The significance (and not the sign) of β_{p10} is an unambiguous indicator of timing quality. In the framework of Lehmann and Modest (1987), cov(R_{pt}, CEX_t x $CCINDEX_t$) is affected by parameters other than the covariance between the fluctuations of the fund's betas and CEX_t or $CCINDEX_t$. Thus, unlike most studies that investigate the abilities of PM's to forecast the realizations of the equity markets when the CAPM is the postulated APM, equation (4.9) is designed to test whether PM's have significant abilities to forecast the realizations of the macroeconomic variables that have priced risks.

4.4 DATA

The sample of mutual funds is drawn from the Financial Post mutual fund database. It contains the 146 all equity funds which have no more than 5 percent of their values missing over the period from June 30, 1981 through March 31, 1989. The 93 monthly returns for each fund are calculated using the monthly change in the net asset value per share and are adjusted for dividend payments.[72] The macroeconomic variables are extracted from the CANSIM database, and their innovations are estimated using the state-space procedure available in SAS/ETS. Statistical tests performed on the innovations reveal that they are generally white noise and normally distributed.

Since the sample has more funds than return observations, the stacked residual variance-covariance matrix of the full multivariate system is singular. Therefore, all estimations are performed on two groups of 73 funds. While the statistics reported subsequently combine the results for each of the two groups of mutual funds, the inferences are robust for each of the two groups.

4.5 EMPIRICAL FINDINGS

The mean macrofactor beta estimates (sensitivities) and their associated mean t-values, and the mean R^2 values for the restricted and unrestricted forms of equation (4.6) are reported in Panels A and B of Table 4.2, respectively. The beta estimates presented are based on a specific set of APT separate fund time-varying risk premia, where each time-varying risk premium is represented by the conditional standard deviation of the underlying priced macrofactor weighted by the constant proportionality parameter previously estimated by KK. Iterative NOLS (ITNOLS) and NSUR estimations were also performed where the residual covariance matrix was successively updated and new parameter estimates were obtained for each iteration.[73]

As was found by KK, the ß estimates are robust to various estimated values of R for the restricted and unrestricted cases and the nature of the residual variance-covariance matrix. Based on the R^2 values, the postulated APT model explains mutual fund excess returns well. As in KK, the U.S. composite index of 12 leading indicators (USINDEX), the exchange rate (EX) and the residual market factor (RMF) have significant factor sensitivities. The only exception is for EX for NSUR with $\hat{R}_1$=-5.8533 and $\hat{R}_2$=3.1889.

The Jensen estimates for the restricted APT are reported in Panel A of Table 4.3. The first two statistics presented relate to the mean and standard deviation across the 146 mutual funds of the sample for a specified value of $\hat{R}$. The mean corresponds to the average monthly excess return realized after transaction costs. The standard deviation provides a measure of dispersion relative to the mean excess return across the sample of mutual funds. The statistically significant χ^2 values clearly show that the Jensen values are not only different among the mutual funds but that they are significantly different from 0.[74] Because some mutual funds actively manage their portfolios, the underlying return distributions may be heteroscedastic. Although NOLS and NSUR are robust to nonnormality, Burmeister and McElroy (1988) advocate the use of iterative procedures when the residuals are normally distributed. NOLS and ITNOLS lead to identical results which is consistent with Lehmann and Modest (1987) who report similar inferences based on results adjusted and unadjusted for heteroskedasticity.

Although the estimates of the factor sensitivities and their related t-values are insensitive to the R estimate (Table 4.2), the Jensen estimates on the stock picking abilities of mutual funds depend upon the sign of $\hat{R}$. For similar R estimates, the mean Jensen and absolute t-values, and the number of funds with significantly positive or negative micro-selectivity abilities are robust to the inclusion of nonpriced factors in the APT system. These results are consistent with Lehmann and Modest in that the Jensen estimates are significantly influenced by the set of mimicking portfolios chosen as the benchmarks. The finding that NOLS and NSUR generate similar estimates is not surprising since mutual funds supposedly provide diversification services. A significant proportion of the funds have Jensen estimates which are significantly different from 0. Furthermore, for all positive $\hat{R}$, a significant proportion of the funds exhibit positive stock selection abilities. In short, whenever $\hat{R}$ is positive (as would be expected), mutual funds display, on average, a positive monthly excess return after transaction costs. These findings do not appear to support the conjecture of Grinblatt and Titman (1989b) that negative Jensen estimates are due to the presence of significant transaction costs. Of course, differences between their results and those reported herein may also be caused by the choice of different asset pricing models (portfolios versus macrofactors) and/or different data sets (American versus Canadian).

These conclusions are supported by the correlation coefficients of the Jensen estimates for the various restricted APT equations given in Panel A of Table 4.4. The correlations between the various pairs of Jensen estimates for the three estimation techniques are close to or equal to one for specific $\hat{R}$ or for $\hat{R}$ with similar signs, and are much less correlated (0.33 to 0.56) for $\hat{R}$ with different signs.

The Jensen estimates for the unrestricted KK APT are reported in Panel B of Table 4.3. This model is used in order to assess the effect on mutual fund performance inference of using an inexact APT model. For their sets of size-sorted portfolios, KK observe significant negative intercepts for their unrestricted APT. This is consistent with the results reported in Panel B of Table 4.3. The magnitude of this downward bias is so large for all $\hat{R}$ and estimation techniques that the statistics for the Jensen estimates and their absolute t-values are nearly identical for all cases. Not only are all mean Jensen estimates largely negative but few (many) funds have an abnormal performance significantly greater (lower) than 0. This finding is confirmed by the strong correlations reported in Panel B of Table 4.4. The bias leads to estimated Jensen values that are highly correlated (0.96 or greater). Comparisons of the Jensen estimates between Panels A and B of Table 4.3 clearly demonstrate the importance of using an exact APM benchmark, as was conjectured by Grinblatt and Titman (1988, 1989b).

The influence of the bias due to the inexactness of the unrestricted model is highlighted in Panel C of Table 4.4, which reports the correlations between the Jensen estimates of the restricted and unrestricted models for the same estimation technique and $\hat{R}$. The correlations range from -0.36 to 0.91, which suggests that the sensitivity of the estimated intercepts across mutual funds to model exactness varies by estimation technique.

If the Jensen estimates in Table 4.3 are strongly influenced by a structural event, no relationship should exist between past and future performance. To test for this possibility, the multivariate systems of equations are sequentially estimated for the first and second half of the total time period. The statistics on the Jensen estimates are reported in Table 4.5. The N x N stacked residual variance-covariance matrix for each subperiod is singular since the multivariate system contains substantially more equations than observations. As in Brown and Otsuki (1989), the flexibility of the nonlinear multivariate SUR developed by Burmeister and McElroy (1988) is used to overcome this problem. Specifically, the N x N residual variance-covariance matrix required for the subperiod estimations is taken to be the full residual matrix estimated for the entire period.

From Panels A and B of Table 4.5, the mean Jensen estimates have similar magnitudes and signs for both subperiods for all estimation procedures and $\hat{R}$ for the restricted APT. The stability of these statistics is consistent with the positive and significant correlation coefficients between the Jensen estimates for each subperiod presented in Panel C of Table 4.5. The bias induced by the inexact unrestricted APT is persistent across the subperiods although the Jensen estimates now have different mean values. While the number of funds whose Jensen measure is greater or lower than 0 and the average absolute t-values for both subperiods are similar, they are typically smaller than those for the whole period. This implies that the standard deviations of the Jensen estimates are higher for the subperiods than for the total period.[75] Since these subperiod Jensen estimates are stable, it is unlikely that unique structural events had a significant effect on these results.[76]

The findings for the macrofactor timing tests for the restricted APT [equation (4.10)] are presented in Table 4.6. As observed previously, both NOLS and ITNOLS generate exactly the same estimates of β_{p8}, β_{p9} and β_{p10} [i.e., the regression coefficients of (CEX_t) , ($CCINDEX_t$) , and (CEX_t x $CCINDEX_t$), respectively]. As was shown earlier in Table 4.3, the results are sensitive to the value of $\hat{R}$ and not to the inclusion of nonpriced macrofactors in the estimated multivariate system. Furthermore, for similar values of $\hat{R}$, NOLS and NSUR yield similar results, which is consistent with the large amount of diversification provided by mutual funds.

The low average absolute t-values of the factor timing coefficients tend to indicate that the average mutual fund does not seem to exhibit the ability to exploit private timing signals for all postulated values of R and estimation techniques. However, some funds display significant timing abilities since the χ^2 statistic rejects $H_o: \beta_{p8}=\beta_{p9}=\beta_{p10}=0$. Depending on the estimated value of R, a nonnegligible proportion of the funds seem capable of correctly forecasting the movements of EX_t (the innovation at time t of the Canada/U.S. exchange rate, whose factor timing measure is β_{p8}) and $CINDEX_t$ (the orthogonal component at time t of the Canadian composite index of ten leading indicators on the return on the TSE index, money, USINDEX and industrial production, whose factor timing measure is β_{p9}). This is also consistent with the number of funds for which β_{p10} is significant.[77] Interestingly, the timing literature based on the important contributions of Henriksson (1984), Cumby and Glenn (1990), and Lehmann and Modest (1987), amongst others, which use CAPM and/or mimicking APT portfolios, report timing coefficient estimates that are predominantly and persistently negative. For all $\hat{R}$, a large proportion of the funds generally exhibit positive values of β_{p8} and β_{p9}. For most values of $\hat{R}$, portfolio managers appear to have better abilities in forecasting the realizations of CEX_t than those of $CINDEX_t$. This is consistent with the finding that the former risk is priced for the sample of mutual funds.

The inclusion of a test for timing abilities in the restricted APT model does not seem to materially affect the sign of the α estimates. A comparison of the Jensen estimates in Tables 4.3 and 4.6 suggests that the sign of α (and the numbers of funds whose Jensen estimates are greater and lower than 0) are driven by the sign of $\hat{R}$, and not by the inclusion or exclusion of the factor timing tests. This implies that the observed factor timing abilities are not "artificial". This does not support the conjecture of Connor and Korajcyzk (1986) that positive (negative) "artificial" timing performance leads to negative (positive) "artificial" stock selection performance. In contrast, the average absolute t-values systematically decrease for the various $\hat{R}$ when timing variables are included in the estimated model because a portion of the performance is now captured by the timing variables.

Use of the inexact, unrestricted APT model generates similar findings for macrofactor timing. Although many portfolio managers attempt such timings, only a low proportion of the funds exhibit significant positive abilities to anticipate the movements of the priced macrofactor volatilities. As for the restricted APT model, the significance of the macrofactor timing estimates is sensitive to the postulated sign of $\hat{R}$. This suggests that APT exactness is much less of a concern in the investigation of timing than the postulated sign of $\hat{R}$.

A comparison of the Jensen estimates in Tables 4.3 and 4.7 indicates that the inclusion of timing variables does not materially affect the bias in the Jensen measure caused by model inexactness. The average Jensen estimates are lowered slightly for the model with the timing measures. This does not support the conjecture of Grant (1977) that the Jensen measure is biased downward when timing is ignored. It may reflect merely the fact that the estimated coefficients of the omitted variables, β_{p8} and β_{p9}, are generally positive.

4.6 CONCLUDING REMARKS

In this chapter, the ability of Canadian portfolio managers to use observed micro-selectivity and macro-timing signals was assessed using the APT model with macrofactors of Koutoulas and Kryzanowski (1991). The time-varying risk premia of this model were accounted for by the parameter R (the constant proportionality parameter) weighted by the vectors of the conditional volatilities of the underlying macrofactors that have priced risk. This allowed the Jensen parameter to reflect the potential presence of N independent selectivity signals, since timing portfolios that are constructed merely as a repackaging of N assets were excluded from the model. Koutoulas and Kryzanowski find that this model is exact for "passive" strategies such as size-sorted portfolios. This APT model is used in a multivariate system where the N equations are estimated simultaneously using the nonlinear ordinary least squares (NOLS) and nonlinear seemingly unrelated regression (NSUR) methods [as in the spirit of Burmeister and McElroy (1988)]. Not only does the model explain mutual fund excess returns very well but both estimation methods generate similar estimates of micro-selectivity and macro-timing. This is consistent with mutual funds providing diversification services. Based on the intertemporal stability of these results, little evidence is found to support the hypothesis that the findings were due to a major structural event (or shock).

The findings indicate that the intercept of the model (Jensen's alpha) is somewhat sensitive to the postulated set of time-varying risk premia for the APT separating funds (i.e., postulated value of the constant proportionality parameter). Although a significant proportion of the funds experienced abnormal selectivity performance, the direction of that performance is sensitive to the sign of the constant proportionality parameter.

For the unrestricted version of the model, Koutoulas and Kryzanowski observe significant negative intercepts for size-sorted portfolios. Similarly, for the mutual funds studied herein, the Jensen estimates are systematically smaller, and a large number of funds have negative (but generally insignificant) estimated intercepts. This demonstrates the importance of using an exact asset pricing model as a benchmark in portfolio performance evaluation.

Unlike most studies reported in the literature, this study finds that the estimated factor timing coefficients are positive. Although these estimates are sensitive to the postulated value of parameter R, some funds appear to have significantly superior abilities to forecast the movements of the two priced macrofactors. These macrofactors are the innovation at time t of the Canada/U.S. exchange rate and the orthogonal component at time t of the Canadian composite index of ten leading indicators on the return on the TSE index, money, USINDEX and industrial production. In summary, some funds earn superior returns from both stock selection and macrofactor timing when the postulated model is the restricted

APT of Koutoulas and Kryzanowski.

CHAPTER FIVE: PERFORMANCE ATTRIBUTION USING THE CAPM WITH A TIME-VARYING RISK PREMIUM

5.1 INTRODUCTION

The assessment of portfolio performance is based on a theoretical structure that divides the information structure available to portfolio managers (PM's) into two components: micro-selectivity and macro-timing. The former relates to the abilities of PM's to identify firms whose returns are expected to be higher (or lower) than suggested by their level of priced risk. The latter refers to the abilities of PM's to forecast the movements of the stock market and/or the pervasive macroforces that have priced risks. The Jensen (1968) measure is often used to assess micro-selectivity, and the approach of Treynor and Mazuy (1966), which has been improved by Lehmann and Modest (1987), amongst others, is often used to assess macro-timing. The empirical evidence on the presence of micro-selectivity and macro-timing abilities are mixed and almost nonexistent, respectively.

The purpose of this chapter is to study the micro-selectivity and macro-timing abilities of Canadian mutual funds using the Jensen measure and the market timing test proposed by Lehmann and Modest (1987), and a conditional capital asset pricing model (CAPM) with a time-varying market risk premium similar to that of Koutoulas and Kryzanowski

(1991).[78] The empirical design is based on the multi-factor formulation of Burmeister and McElroy (1988). Burmeister and McElroy demonstrate how the APT return generating process and asset pricing model (APM) can be simultaneously estimated when macro-economic variables are directly included in the model. They advocate the estimation of a multivariate system of N equations that rests on a stacked N x N diagonal or full covariance matrix of residuals. Koutoulas and Kryzanowski reformulate this model into an APT with time-varying ex ante risk premia, which vary proportionally with the volatilities of the priced factors. Their approach is adapted readily herein to the case when the CAPM is assumed to hold.

This multivariate version of the CAPM (M-CAPM) has at least four attractive features for assessing portfolio performance. First, the conditional M-CAPM includes a time-varying ex ante market risk premium, which varies proportionally with the conditional second moment of the market return. Second, Admati, Battacharya, Pleiderer and Ross (1986) contend that portfolio performance attribution requires that the micro-selectivity measure be statistically independent of the return on the timing portfolio. This may not be possible if the timing portfolio is the market portfolio because the latter will probably include securities for which micro-selectivity signals are observed. The M-CAPM satisfies the independence assumption better, since the movements of the time-varying risk premium of the market (i.e., the excess return of the timing portfolio) are related to the time-varying conditional second moment of the market portfolio (which depends on the innovations of the returns on the market portfolio). Third, heteroskedasticity of portfolio returns caused by timing is unlikely to affect the estimates of the M-CAPM since Burmeister and McElroy (1988) state that the estimators of their multivariate system are robust to non-normality of the residuals. Fourth, the M-CAPM can be estimated with cross-equation restrictions. This allows for the implementation of micro-selectivity and macro-timing tests that are more stringent than those usually reported in the literature.

The remainder of the chapter is organized as follows. In section 5.2, the M-CAPM and the tests of micro-selectivity and macro-timing are presented. In section 5.3, the data are described. In section 5.4, the empirical findings are presented and analyzed. In section 5.5, some concluding remarks are offered.

5.2 M-CAPM AND MEASURES OF PORTFOLIO PERFORMANCE

The traditional market model is given by:

$$R_{pt} = \Phi + \beta_p R_{mt} + e_{pt} \qquad (5.1)$$

where R_{pt} and R_{mt} are the returns on portfolio p and the market m at time t respectively; β_p is the systematic risk measure for portfolio p;[79] and e_{pt} is the residual component observed at time t (its distribution possesses the usual properties). Equation (5.1) can be expressed in a mean-deviation form with a time-varying expected return as:

$$R_{pt} = E(R_p)_t + \beta_p \delta_{mt} + e_{pt} \tag{5.2}$$

where δ_{mt} is the innovation in the return of the selected market index at time t. This innovation is obtained using the Akaike (1976) state-space procedure [as in Brown and Otsuki (1989), Kryzanowski and Zhang (1992), amongst others].

Given the existence of a risk-free rate, the conditional CAPM is given by:

$$E(R_p)_t = R_{ft} + \beta_p \lambda_{mt} \tag{5.3}$$

where λ_{mt} is the ex ante, time-varying risk premium of the market portfolio at time t. Equation (5.3) implies that the predictable component of asset returns is explained at each point in time t by the ex ante conditional market risk premium weighted by a constant factor loading measure. Hansen and Richard (1987) justify the importance of information conditioning for CAPM tests. Equation (5.3) is consistent with the empirically-supported formulations of Lauterbach (1989), Koutoulas and Kryzanowski (1991), amongst others. Equation (5.3) is suitable for examining managerial market-timing abilities within the context of a conditional asset pricing model. For this purpose, the time-variation in the conditional covariances of the returns of the studied portfolios with the returns of the selected market index must be attributed entirely to market timing attempts. Otherwise, the uninformed investor can not observe the difference between superior managerial performance and time-variation in the risk component of the market model.[80]

The contributions of, for example, French, Schwert and Stambaugh (1987) provide empirical support for a positive relation between the expected premium on the stock market and the conditional standard deviation of the return on the stock market.[81] Lauterbach (1989) and Koutoulas and Kryzanowski (1991) use this formulation within the context of a multi-beta APM. The specific functional form used herein is:

$$\lambda_{mt} = R \cdot \sigma_{mt} \tag{5.4}$$

where R is a constant of proportionality; and σ_{mt} is the conditional standard deviation of the market at time t. Substituting (5.4) into (5.3), and the resulting equation into (5.2) yields:

$$R_{pt} - R_{ft} = \beta_p \delta_{mt} + \beta_p \{R \cdot \sigma_{mt}\} + e_{pt} \tag{5.5}$$

Adding the Jensen measure, α_p, to (5.5) yields:

$$R_{pt} - R_{ft} = \alpha_p + \beta_p \delta_{mt} + \beta_p \{R \cdot \sigma_{mt}\} + e_{pt} \tag{5.6}$$

Jagannathan and Korajcyzk (1986) show that PM's may display artificial market timing abilities and negatively correlated micro-selectivity abilities, when the payoffs from their strategies are nonlinear. To account for this possibility, Lee and Rahman (1990), Grinblatt and Titman (1988), amongst others, argue that the measures of selectivity and timing should be estimated simultaneously. The timing test proposed by Lehman and Modest (1987) is easily introduced into equation (5.6) to yield:[82]

$$R_{pt} - R_{ft} = \alpha_p + \beta_p \, \delta_{mt} + \beta_p \, \{R \cdot \sigma_{mt}\} + \Theta_p \, \{R \cdot \sigma_{mt}\}^2 + e_{pt} \qquad (5.7)$$

In (5.6) and (5.7), α_p measures the deviations of the managed portfolio from the conditional SML, and whether the portfolio plots inside or outside the conditional efficient set under the assumption that PM's and uninformed investors are mean-variance maximizers.[83]

Equations (5.6) and (5.7) provide the basis of the multivariate system of N CAPM equations (the "M-CAPM") being investigated herein. The estimation uses a stacked N x N diagonal or full covariance matrix of residuals. The former corresponds to a nonlinear ordinary least squares (NOLS) method; the latter corresponds to a nonlinear seemingly unrelated regression (NSUR) method that allows for missing (non-)priced factors to affect security returns. Iterative NOLS (ITNOLS) and iterative NSUR (ITNSUR) estimation methods are also used, where the residual covariance matrix is successively updated at each iteration. Since the system can include restrictions across equations, multivariate tests of micro-selectivity and macro-timing can be performed. The former tests whether the Jensen measures across equations are simultaneously equal to zero; the latter tests whether the Θ_i's in (5.7) are simultaneously equal to zero.

5.3 D'

The sample of mutual funds is drawn from the Financial Post mutual fund data base. It contains the 146 Canadian equity funds which have no more than five percent of their values missing over the period from 30 June 1981 through 31 March 1989. The 93 monthly returns for each fund are calculated using the monthly changes in the net asset values per share and are adjusted for dividend payments.[84] The monthly returns of both the value-weighted (VW) and equally-weighted (EW) indexes are extracted from the TSE-Western Tape. Their return innovations are estimated using the state-space procedure available in SAS/ETS.[85] The time-varying conditional standard deviations for each market index are estimated in a similar fashion as in Koutoulas and Kryzanowski (1991).[86]

The various sets of time-varying ex ante market risk premia, $\{R \cdot \sigma_{mt}\}$, that correspond to the different $\hat{R}$ obtained by Koutoulas and Kryzanowski (1991) are used to estimate the M-CAPM's represented by equations (5.6) and (' 7). The sign of R must be the same as the expected risk premium of the market (i.e., positive if the CAPM is assumed to hold). This is consistent with the finding of French, Schwert and Stambaugh (1987).

5.4 EMPIRICAL FINDINGS

The mean beta estimates, their respective t-values, and the mean R^2 values for M-CAPM (5.6) are reported in Table 5.1. Unlike Koutoulas and Kryzanowski (1991) and chapter four for a multi-factor version of (5.6), both the mean beta estimates and their respective mean t-values are not robust to the postulated time-varying risk premium. As expected given the holdings of the funds,[87] the risk premia for the value-weighted index better explain the excess returns of the mutual funds than those for the equally-weighted index.

The mean and standard deviation ("std.") of the Jensen estimates for M-CAPM (5.6) for various estimation methods (E.M.'s) and $\hat{R}$'s are reported in Table 5.2. The mean values refer to the average monthly excess returns after transaction costs for the 146 equity funds. All of the Jensen estimates are negative. The average absolute t-values suggest that the Jensen estimates are also significant at the 0.05 level (with the exception of the estimations for $\hat{R}$ of 4.3617). Most (no) funds have an abnormal performance which is significantly lower (greater) than zero. Based on the χ^2 test statistics, the Jensen values are not only different from zero but are also different across mutual funds.

These findings are consistent with those in the literature that find a downward bias in the Jensen measure when portfolio performance is measured using benchmark portfolios which are not mean-variance efficient.[88] Thus, the reported Jensen estimates are unlikely to be representative of the "true" performance of the mutual funds studied herein. Thus, the initial estimations of the M-CAPM (i.e., the multivariate CAPM system with a time-varying ex ante market risk premium) do not seem robust to the conditional mean-variance inefficiency of the chosen proxies for the market portfolio. This is supported by the high correlation coefficients of 0.91 or greater for the Jensen estimates, which are reported in Panels A and B of Table 5.3, for the value-weighted and equally-weighted market indexes, respectively.

The results for the entire period may be caused by an intertemporal instability in the capital markets. To test for this possibility, the M-CAPM (5.6) was sequentially estimated for the first and second half of the total time period. The Jensen estimates, which are reported in Table 5.4, have similar magnitudes and signs for both subperiods.[89] The stability of these results is collaborated by the sign and magnitude of the correlation coefficients for the corresponding subperiod Jensen estimates, which are presented in Panel C of Table 5.4. Since the bias induced by the inexactness of the market proxy portfolio seems to persist across time, the negativity of the Jensen estimates does not seem to be attributable to one or more unique structural events.

Based on the χ^2 values, the across-equation restriction, $H_0: \Theta_p = 0$, is rejected. Not only do a significant proportion of the funds attempt to time market movements but most exhibit a significantly negative timing measure. This is consistent with the findings of Henriksson (1987), Lehmann and Modest (1987), Cumby and Glenn (1990), amongst others. The findings for the market timing test based on (5.7) are presented in Panel A of Table 5.5. All of the mean absolute t-values of the estimated timing coefficient (Θ_p) are significant. These results are robust for the various $\hat{R}$, estimation methods and market indexes used to calculate the conditional standard deviations.

Based on the findings of Cumby and Glenn (1990), these significantly negative timing measures may be explained partially by the small sample properties of the regression coefficient estimates. Since they obtained better results by using a bootstrapping procedure, the M-CAPM (5.7) was bootstrapped using the algorithm detailed in the Appendix.[90]

Since the bootstrapped t-values yield similar results, the initial estimates from M-CAPM (5.7) appear to be robust for small samples.

The Jensen estimates for the market timing M-CAPM model, given by the multivariate system of equations (5.7), are reported in Panel B of Table 5.5. The inclusion of a term to capture the effects of market timing does not seem to materially affect the α estimates. A comparison of the Jensen estimates reported in Tables 5.2 and 5.5 indicates that the sign of α, and the number of funds whose α are significantly greater and smaller than zero are not affected materially by the inclusion of the market timing measure. No support is found for the conjectures of Grant (1977) that the Jensen measure is biased downward when market timing is ignored and of Connor and Korajcyzk (1986) that positive (negative) "artificial" timing performance leads to negative (positive) "artificial" stock selection performance.

5.5 CONCLUDING REMARKS

The ability of Canadian managers of all equity mutual funds to make superior micro-selectivity and macro-timing decisions was assessed using a multivariate CAPM with a time-varying ex ante market risk premium. The premia were calculated using the proportionality parameter estimates of

Koutoulas and Kryzanowski (1991) weighted by the conditional volatility of the underlying market index. This model was estimated using a multivariate system where the N equations are estimated simultaneously using the (iterative) nonlinear ordinary least squares and (iterative) nonlinear seemingly unrelated regressions in the spirit of Burmeister and McElroy (1988).

Significant (and predominantly negative) Jensen estimates are obtained for the various $\hat{R}$, estimation methods, market indexes and time periods. These findings are probably due to the conditional mean-variance inefficiency of the market proxy portfolios used herein. They are consistent with those of Grinblatt and Titman (1988). The incorporation of a market timing component does not materially affect the estimated Jensen values. Consistent with the literature, the market timing coefficients are significantly negative. This cannot be attributed to a small sample problem since similar t-values resulted from a bootstrapping procedure.

CHAPTER SIX: MAJOR FINDINGS, IMPLICATIONS AND DIRECTIONS FOR FUTURE RESEARCH

This dissertation studied two main issues. The first is the mispricing of the APT model using tests that rest on both unconditional and conditional distributions. The second is the benchmark invariancy and seasonality problems involved in the evaluation of mutual fund performance using APM-free measures, and the performance of mutual funds using both a conditional APT based on macrofactors and a conditional CAPM.

There are three major findings of this dissertation. First, only one factor seems sufficient to ensure exactness of the APT model, whether the corresponding functional form is based on conditional or unconditional return distributions when the covariance matrix of security returns is (un)adjusted for nonsynchronous trading. Based on the estimated second moment equations, the conditional standard deviations of the K mimicking portfolios explain the time-variability of security volatilities. This is consistent with the findings of Schwert and Seguin (1990) when their framework is extended to a multi-beta APM.

Second, the performance of the mutual funds is sensitive to the choice of a portfolio benchmark when APM-free measures, such as the Jobson and Korkie (1981) Z score and the positive period weighting score of Grinblatt and Titman (1989a), are used. Different portfolio benchmarks lead to different performance results for the same measure, although the results are homogeneous across the measures. The portfolio benchmarks are characterized by different underlying attributes; namely, the number of extracted factors, the adjustment for nonsynchronous trading of the covariance matrix of security returns, and the sizes of the firms (small and/or large) used in the factor analyses. The returns for the different portfolio benchmarks exhibit different seasonal patterns. In turn, this significantly influences mutual fund performance evaluation.

Third, mutual funds exhibit micro-selectivity and macro-timing abitilites when a conditional APT based on macrofactors is used as the benchmark model. These findings are generally robust to the assumption that is imposed on the covariance matrix of the residual component. However, significant and predominantly negative micro-selectivity and macro-timing abitilities are observed when the performance evaluation rests upon a conditional CAPM. While these micro-selectivity findings are probably driven by the conditional mean-variance inefficiency of the market proxies used, the market timing findings cannot be explained by a small sample problem.

Several other issues can be investigated based on the research undertaken herein. First, the various tests of mutual fund performance presented herein can be replicated using American data. Second, tests of both the unconditional and conditional APT and mutual fund performance assessment based on the Jensen measure can be applied when the common forces that have a priced risk are approximated by Mei's (1991) semi-autoregressive mimicking portfolios. A semi-autoregressive factor structure avoids the arbitrariness associated with the selection of the macrofactors as well as the pitfalls of maximum likelihood factor analysis noted by Kryzanowski and To (1983), Brown (1989), amongst others. Finally, the iterative non-linear seemingly unrelated regression formulation of the APT used herein should be extended to account for time-varying betas.

FOOTNOTES

1. Also, see Kandel and Huberman (1987), amongst others.

2. See Roll and Ross (1981), Chen (1983), Brown and Weinstein (1983), Dhrymes, Friend, Gultekin and Gultekin (1984, 1985), Lehmann and Modest (1985, 1987), amongst others, for empirical work on the APT.

3. $W=(B'D^{-1}B)^{-1}B'D^{-1}$ is a solution to the quadratic program given by (2.9).

4. The ith subset of feasible portfolio returns will have the same covariance with the returns of the kth mimicking portfolio as the return on the ith mimicking portfolio has for all k different from i.

5. This is unchanged when the RMF is included in the factor structure.

6. Merton (1972) discusses the relationship between an intertemporal asset pricing model and the time-variability of the efficient set within the CAPM framework.

7. See Engle, Ng and Rothschild (1990) for a formal justification of this approach.

8. Other methodologies are available. One of the most promising is proposed by McElroy, Burmeister and Wall (1985), and extended by Burmeister and McElroy (1988). Their approach is based on the estimation of the factor model (2.1) when the APT is nested in the intercept and the factors are associated with fundamental economic variables. Theoretically, $E(\varepsilon\varepsilon')=\Phi$ in equation (2.1), where Φ is a diagonal matrix if stock returns are exactly explained by the K factors. Extending this result to Wei's proposition allows the V of the residuals of (2.2) to be nondiagonal. The inclusion of the RMF in (2.2) restores the diagonality of V.

9. For example, see Roll and Ross (1980).

10. See Lehmann and Modest (1985) for a complete discussion of the use of this procedure within the APT context.

11. $\Gamma^* = (B^{*\prime}\Sigma^{-1}B^*)^{-1}\ B^{*\prime}\Sigma^{-1}\overline{R,}$ where $\Gamma^* = (\Gamma, \Gamma_m)$, if (2.20) is estimated.

12. To test the significance of the estimated risk premia and the number of factors, t-tests are not used. Orthogonal rotations of the factor loadings cause the t-values to be under-estimated when $k > 1$. Dhrymes, Friend, Gultekin and Gultekin (1984) use the following χ^2 test: $1/T(\Gamma' V^{-1}\Gamma) \sim \chi^2_k$ where Γ is the vector of estimated risk premia, and V is the corresponding covariance matrix. This test not only reduces the marginal impact of a particular factor as the number of factors increases but does not provide any indication about the exactness of the model. Nevertheless, it is used herein to provide general insights about the number of significant risk premia.

13. Assume that the APT model is investigated when K-1 factors are estimated knowing that the true factor structure contains K factors. The null and alternative hypothesis to be tested are:

H_o: $(E(R) - R_f) = B_{k-1}\Gamma_{k-1}$

H_1: $(E(R) - R_f) \approx B_{k-1}\Gamma_{k-1}$

where H_1 could imply: $E(R) - R_f = B_{k-1}\Gamma_{k-1} + B_m\Gamma_m$.

14. The factor model is $R_t = E(R) + B[F_t - E(F)] + u_t$ (with or without a RMF). This implies: $\Sigma = BB' + \Phi$.

15. Davidian and Carrol (1987) contend that a specification using the standard deviation is more robust.

16. The t-tests of the coefficients of the mean equation (2.32) do not reveal information about the number of factors in the APT model. The number of factors corresponds to the number of arbitrage portfolios that have significant expected excess returns. The χ^2 test, given by $\bar{R}_m' \Sigma^{-1} \bar{R}_m$ with k degrees of freedom, provides information on the number of significant risk premia. Like the multivariate χ^2 test for cross-sectional tests (see footnote 12), the χ^2 test is a weak test for

determining the true number of factors since it does not test the exactness of the model.

17. As noted earlier, Roll and Ross (1981) find evidence for a maximum of five factors, Kryzanowski and To (1983) find at most two factors, and Dhrymes, Friend, Gultekin and Gultekin (1985) find five and seven factors when 30 securities are included in a group. Trzincka (1986) finds that at least one factor exists in the factor structure.

18. In Tables 2.2 through 2.9, only aggregated results across the 42 groups are presented due to space limitations. The unaggregated results are available upon request.

19. Chen, Roll and Ross (1986) find that the value-weighted New York Stock Exchange Index explains a large portion of stock return variability. However, in comparison with the economic variables, it has no influence on expected returns.

20. The possibility that the MLR test could provide misleading inferences has been recognized by Shanken (1987).

21. Hair, Anderson and Tathman (1987) state that the rationale for this criterion is that any extracted factor that has an eigenvalue equal or greater than one accounts for the variability of at least one variable. This criterion is most reliable when the number of variables is between 20 and 50.

22. A simple t-test can be used for a one factor structure since a univariate inference is not affected by factor rotation.

23. Similar findings are obtained by Cho and Taylor (1987) and Gultekin and Gultekin (1987) using a more recent sample.

24. As mentionned in footnote 8, when the number of factors included in the factor structure increases, the marginal impact of each risk premium of the entire factor structure decreases. Therefore, even if a factor structure of six factors is rejected, one or two risk premia could be priced. This is likely since the MLR test tends to overstate the number of factors.

25. Chen (1983) reports that, although the APT results are invariant to rotation, the number of priced factors is not. If the factor structure contains K factors, then the number of priced factors may be lower than K. Brown (1989) suggests that an APT model that depends on only one priced factor may indicate that the factor solution of the MLE has been rotated by the Helmert matrix at the stage of the principal factor solution. Brown points out that such a rotation understates the significance of the risk premia on factors beyond the first one. This depends directly on the structure of the Helmert matrix since the first column sums to one while the others sum to 0. Thus, the first factor loading is proportional to an equally-weighted average of the original factor loadings, while the remaining ones are proportional to 0. Brown contends that the inverse of the rotation would allow for the retrievel of the K factor loadings, and generate more powerful tests. The inverse rotation on the factor loadings matrices was applied herein. However, it neither changed the results reported nor the individual significance of each of the K risk premia.

26. The common practice in the time-series and forecasting literature is to apply a portmanteau test to assess the level of serial autocorrelation in the residuals of a model. The most widely used portmanteau tests are based on the Box-Pierce and the Ljung-Box statistics. The first is defined as $T \times \Sigma^{K}_{k=1} r^{2}_{k}$, and is distributed as χ^{2}_{K-L}, where r_k is the autocorrelation coefficient of order k, and L is the number of lags in equation (2.31). The second is defined as $T(T+2) \times \Sigma^{K}_{k=1} r^{2}_{k}/T-K$ and is also distributed as χ^{2}_{K-L}. Davies and Newbold (1977) demonstrate that the Box-Pierce statistic may not exactly follow a χ^{2} distribution when the sample size is small. Such is not the case herein.

27. The existence of conditional heteroskedasticity in a time-series implies that the variance of the residuals is endogenously not stationnary. Therefore, the squared residuals are autocorrelated proportionnally to this non-stationnarity. This intuition is rigorously captured by applying a portmanteau test. See Bollerslev (1986, 1987), Engle, Ng and Rotschild (1990), amongst others, for the use of this test on the squared residuals.

28. Based on Schwert and Seguin (1990), the studentized range is a non-parametric measure of heteroskedasticity. Thus, it is not affected by non-normality of the distribution of residuals.

29. Similar results are obtained for the RMF conditional standard deviation estimations.

30. These effects are also fully integrated into the mean equation under the iterative WLS. All the mimicking portfolio conditional standard deviation coefficients of (2.34) and (2.42) that are significant in Table 2.9 become insignificant after three WLS iterations as anticipated by Davidian and Carrol (1987).

31. These results are consistent with Schwert and Seguin (1990). Based on the monthly returns for five size-sorted portfolios, they find that the portfolio variances exhibit time-series patterns that are significantly explained by the movements of the conditional standard deviations of the CRSP equally-weighted index. They obtain values around 15 on average for the ST(ITWLS) of their five portfolios. This is of the same order as the average ST(ITWLS) obtained herein. Nevertheless, Schwert and Seguin contend that their functional form accounts for most of the conditional heteroskedasticity.

32. The t-values for excess return coefficients of each of the mimicking portfolios are significant for the majority of securities of the sample for all of the extracted factor numbers. This is consistent with the hypothesis that the first factor is probably a linear combination of K factors. Due to space limitations, these results are not presented herein.

33. For example, see Banz (1981), Shanken (1985), Grinblatt and Titman (1988), amongst others.

34. Due to their E-V efficiency, MIRM portfolios based on a one-factor structure are sufficient to ensure model exactness.

35. These include measures proposed by Merton and Henriksson (1981), Cumby and Modest (1987) and Korkie (1990).

36. While the measures of Jensen (1968, 1972), Cumby and Glenn (1990), Bhattacharya and Pfleiderer (1983), Lee and Rahman (1990), amongst others, use the CAPM, the measure of Lehmann and Modest (1987) uses the APT.

37. The concept of local portfolio E-V efficiency of Grinblatt and Titman (1987) applies to this situation.

38. The portfolios of the sample of Canadian equity funds subsequently studied are composed of traded equities. Thus, their portfolio managers can be assumed to be mean-variance maximizers given normally distributed equity returns.

39. Nevertheless, Grinblatt and Titman (1988) and Cumby and Glenn (1990) find that the Jensen and the PPW measures give nearly identical results.

40. The PPW is derived under the assumption that investors have power utility functions. Since this utility function does not exhibit satiation, its marginal utilities are positive. In contrast, the satiation associated with quadratic utility functions leads to negative marginal utilities and to negative Jensen values.

41. Glosten and Jagannathan (1988) propose an alternate method to estimate equation (3.6). They show that $E[wr_r]$ is equivalent to $E[we(r_r)]$, when the value of this contingent claim is equal to the conditional mean of r_r. This contingent claim is approximated by a polynomial projection such that:

$$e(r_r)=E(R_r|R_I)=\Sigma^n{}_{i=1}\beta_i r_{Ii} \qquad (F.1)$$

where R_I is the return on the portfolio benchmark. A necessary condition for the fund to have an abnormal performance is that all the coefficients (except for β_1)

not be equal to zero. The PPW measure given by equation (3.4) embodies both the necessary and sufficient conditions to measure abnormal p---formance, and is easily applied using equations (3.5) a.. (3.6).

42. For both one- and multi-period frameworks, one factor is sufficient to ensure exactness of the APT model. This factor is probably a linear combination of several factors.

43. If the constraint $\underline{1}A'=\underline{1}$ is directly incl-ded in the minimization (3.11), $A = (B'D^{-1}B)B'D^{-1}$ will not be a solution. Huberman, Kandel and Stambaugh (1987) demonstrate that the mimicking portfolios must have a unit cost if they are to exist.

44. Lehmann and Modest (1985b) show that this technique yields the most efficient estimates.

45. As predicted by Korkie (1989), the Shanken (1987) adjustment for nonsynchronous trading generates a non-positive definite V which cannot be factor analyzed. Following Korkie (1989), each adjustment matrix is weighted by a scalar correction factor, f, which is lower than 1. $V^*=V+fK$ where V^* is the adjusted variance-covariance matrix, K is the matrix that contains the lagged covariances, and f is the adjustment factor. The f values for adjustment matrices based on 147, 277 and all stocks are 0.78, 0.59 and 0.54, respectively.

46. As noted by Johnson and Wichern (1982), amongst others, the χ^2 test for the number of factors is affected by the sample size.

47. The mimicking portfolios can be constructed in either of two ways. First, the portfolio weights constructed from daily data can be multiplied by the daily security returns for the N assets, and then the resulting daily portfolio returns can be aggregated to obtain the monthly portfolio returns. Second, the portfolio weights constructed from the daily data can be multiplied by the monthly returns (or equivalently the aggregated daily returns) on the individual securities. Unfortunately, the first method is unrealistic since Blume and Stambaugh (1983) find that the returns on a portfolio which is rebalanced daily are significantly biased by the average

of the bid-ask bias in individual security returns. Roll (1983) argues that portfolio returns calculated using daily rebalancing do not represent a realistic investor strategy given transaction costs. As a result, both the mutual fund portfolios and the mimicking portfolios used herein represent "buy-and-hold" strategies with monthly rebalancing.

48. For empirical support for the effect of the small firm anomaly, see Shanken (1985), Lehmann and Modest (1987), amongst others.

49. This assumption was invoked by Cumby and Glenn (1990). They also find that the results are insensitive to the choice of Θ.

50. For homoscedastic residuals, the variance of δ is given by $\sigma^2_{\varepsilon r}\Sigma w^2_t$. For heteroscedastic residuals, the variance of δ is given by $\Sigma\ w^2_t \varepsilon^2_r$, where ε_{rt} are the residual components of the time-series regression of the K mimicking portfolio excess returns on the mutual fund excess returns.

51. The required degrees of convergence and independence are as specified by Newey and West (1987).

52. A description of the actual procedure used herein is available upon request.

53. A mimicking portfolio risk premium is the compensation an investor requires for bearing the risk on the economic variable on which the portfolio loads. Positive (negative) risk premium occur when investors want to be rewarded for (hedged against) the systematic risk of that portfolio. The premium provides insurance (hedging). As the absolute value of the Sharpe ratio increases, the mimicking portfolio provides more compensation for the variance risk. For an interpretation of the risk premia values, see Chen, Roll and Ross (1986).

54. More formally, H_o: $(u_1/\sigma_1-u_k/\sigma_k)=\ldots=(u_1/\sigma_1-u_n/\sigma_n)$, where u_q is the average excess return on a portfolio for month q and σ_q is the associated standard deviation.

55. This test is conservative since statistical theory suggests that the second moment of SH_j is larger for small samples. In turn, this causes a decrease in the Z score.

56. A possible reason for not observing the January seasonal observed by Kryzanowski and Zhang (1992), amongst others, may be the shorter time period used herein.

57. This expectation is based on unreported results. Specifically, in a Canadian context, the Sharpe ratios of the minimum idiosyncratic risk mimicking portfolios are much larger than those of the market indexes.

58. For a formal justification of the Jensen measure within the APT framework, see Connor and Korajzyck (1986).

59. These correspond to the mimicking (or market) portfolios if the APT (or the CAPM) holds.

60. Without loss of generality, ϕ is assumed to be statistically insignificant in equation (4.2).

61. For a sample of 277 Canadian firms (those whose average price exceeded $5), the Ljung-Box statistics based on the autocorrelation coefficients applied to the conditional covariances could not reject stationarity for 96% of the cases. The conditional covariances were calculated as in Schwert and Seguin (1990).

62. The properties of the innovations are those discussed more fully in the APT literature.

63. The asset pricing literature usually assumes that this matrix is diagonal.

64. For empirical applications of a similar multivariate system without time-varying risk premia, see Brown and Otsuki (1989) and Kryzanowski and Zhang (1991), amongst others.

65. All innovations are estimated using the state-space

procedure of Akaike (1974).

66. RMF ensures the exactness of the model since it is a linear combination of the factors of the true factor structure which have been omitted from the model.

67. From Schwert (1989), the conditional standard deviation is estimated using:

$$(\Pi/2)\ |F_{jt}| = \Sigma^{12}_{j=1}\Theta_j D_{jt} + \Sigma^{12}_{i=1}\alpha_i (\Pi/2)\ |F_{jt-i}| + e_{it}$$

where F_{jt} is the innovation of the macroeconomic variable j; and D_{jt} is a dummy variable with a value of 1 at time t.

68. Although the majority of the investigations of portfolio performance based on the Jensen measure assume that the idiosyncratic components are contemporaneously independent across mutual funds, the NSUR technique accounts for the influence of the nonpriced factors that would affect the time-varying expected returns of mutual funds.

69. Although the proof of Dybvig and Ross (1985) depends upon the efficient set concept (and, thus, is not related to the implications of the APT model used herein), Lehmann and Modest (1987) obtain similar conclusions without any reference to the efficient set concept.

70. Cross-product terms are not included in their empirical tests in order to maintain an adequate number of degrees of freedom.

71. For a theoretical justification of why β_{pi} (i=3,4) tests the abilities of PM's to forecast the realizations of factor i, whose time-varying risk premium is Γ_{it}, see Lehmann and Modest (1987).

72. Average mutual fund returns based on different frequencies are available upon request.

73. Since the iterative NSUR estimations did not converge (even after 80 iterations), they are not reported herein.

74. Both χ^2 tests are based on the procedure SYSNLIN which is available in SAS/ETS. They are based on the constrained model estimation using the full residual matrix of the unconstrained model.

75. The significance of the macrofactor betas and the magnitude of the R^2 values are also lower for the subperiods than for the entire period. Due to space constraints, these findings are not reported herein.

76. In contrast, Cumby and Glenn (1990) observe that their large, negative Jensen estimates were influenced substantially by mediocre mutual fund performance during the month of the world market crash (namely, October 1987).

77. As noted earlier, the magnitude (and not the sign) of β_{p10} is informative of timing ability because the sign is affected by parameters other than the covariance between fluctuations of the fund's betas and the movements of the conditional standard deviations of the priced macrofactors.

78. For a multi-factor formulation of this type of model and test of mutual fund performance, see Chapter four.

79. Since the conditional systematic risk measure is assumed to be stationary over time, no distinction is made between the conditional and the unconditional beta herein.

80. The conditional covariances of the underlying stocks in which most Canadian funds invest have been constant over the sample time period studied herein. For a sample of 277 Canadian firms (those whose average price exceeded $5), the Ljung-Box statistics based on the autocorrelation coefficients applied to a specific time-series vector of covariances could not reject the stationarity assumption for 96% of the cases. The covariances observed at each time t were calculated as in Schwert and Seguin (1990).

81. Their framework implies a constant price of risk.

82. For a formal justification of this timing test, see Lehmann and Modest (1987).

83. The portfolios of the sample of Canadian equity funds subsequently studied consist of traded equities. Thus, their portfolio managers can be assumed to be mean-variance maximizers given assets with normally distributed returns.

84. Since the sample has more funds than return observations, the stacked residual covariance matrix of the multivariate system is singular. All the estimations are performed on two groups of 73 funds. The statistics reported herein combine the results for these two groups of mutual funds.

85. Statistical tests performed on the innovations reveal that they are generally white noise and normally distributed. A description of these tests is provided in Koutoulas and Kryzanowski (1991).

86. The conditional standard deviations for each market index are estimated as the fitted values for:

$$(\Pi/2)\ |\delta_{mt}| = \Sigma^{12}{}_{j=1}\Theta_j D_{jt} + \Sigma^{12}{}_{i=1}\alpha_i(\Pi/2)\ |\delta_{mt-i}| + e_{it}$$

where δ_{mt} is the innovation of the market index m; and D_{jt} is a dummy variable with a value of one at time t.

87. This occurs even though the equally weighted index better accounts for the size anomaly which exists in the CAPM. For example, see Banz (1981).

88. As reported in, for example, Banz (1981), Shanken (1985) and Grinblatt and Titman (1988).

89. The N X N stacked residual covariance matrix for each subperiod is singular since the multivariate system contains more equations than observations. However, as in Brown and Otsuki (1989), the flexibility of the nonlinear multivariate SUR applied by Burmeister and McElroy (1988) is used to overcome this problem. Basically, the subsample residual covariance matrices are taken to be the full residual covariance matrix estimated for the entire period.

90. Since non-bootstrapped iterative and non-iterative techniques provided similar results, the bootstrapping procedure was only applied to the non-iterative procedures. The application of a thousand replications of a multivariate system of 73 equations when each replication is based on an iterative procedure did not seem to justify the costs of doing so.

TABLE 2.1

The results for the Maximum Likelihood Ratio (MLR) test for the number of factors required to replicate the unadjusted variance-covariance matrix are reported below. Each cell contains the number of groups out of 42 for which the p-value of the MLR test is greater than one (or five) percent. The null hypothesis is that the K factors represent an exact factor structure of the variance-covariance matrix of security returns.

p value	k=1	k=2	k=3	k=4	k=5	k=6
p > .01	1	11	28	36	40	41
p > .05	0	6	17	31	38	41

TABLE 2.2

The average (un)adjusted covariances of security returns for the 42 groups and their standard deviations (std.) are reported below. The average percentage explanation for each factor for a six-factor structure for the (un)adjusted covariance matrices are reported below. The covariances have been adjusted for nonsynchronous trading using the Shanken adjustment. Each reported covariance has been multiplied by 1000.

Panel A: Average covariances and their standard deviations

	Covariances		Percentage Improvement
	Unadjusted	Adjusted	
Average	0.043	0.101	140.75
Std.	0.009	0.022	46.52

Panel B: Average percentage explanation for each factor

	Covariance matrix		
Factor	Unadjusted (%)	Adjusted (%)	Change (%)
1	12.50	24.10	92.80
2	4.076	4.945	21.31
3	3.823	4.261	11.45
4	3.698	3.945	6.69
5	3.597	4.204	16.87
6	3.523	3.578	1.56

TABLE 2.3

Summary statistics are presented below for tests of the significance of the risk premia and the exactness of the following cross-sectional APT equation (2.19): $E(R)-R_f=B\Gamma$. The null hypothesis, $H_o:\Gamma=0$, is tested using a χ^2 and t-test for a six-(eight) and one-factor structure, respectively. The null hypothesis, $H_o:E(R)-R_f=B\Gamma$, is tested using the CRST test (2.22). The summary statistics include the average, standard deviation (std.) and the percentage of rejections of the null hypothesis for the 42 groups of 30 securities. The covariance matrices have been adjusted for nonsynchronous trading using the Shanken adjustment.

Panel A: Six and one factor structures based on the unadjusted covariance matrices

	Six factors		One factor	
	χ^2 test	CSRT	t-test	CSRT
Average	6.216	0.004	1.432	0.092
Std.	3.420	0.006	1.061	0.254
% of Rejections	7.1	0	24.3	0

Panel B: Eight and one factor structures based on the adjusted covariance matrices

	Eight factors		One factor	
	χ^2 test	CSRT	t-test	CSRT
Average	11.593	0.009	1.676	0.073
Std.	10.307	0.028	1.141	0.182
% of Rejections	13.5	0	31.7	0

TABLE 2.4

Summary statistics are presented below for the t-values for tests of the intercept and of the betas for the residual market factor (RMF) for equation (2.24) for each of the 1260 securities. The summary statistics include the average, standard deviation (std.) and the percentage of rejections of the null hypothesis for each type of test. The covariance matrices have been adjusted for nonsynchronous trading using the Shanken adjustment.

Panel A: Six and one factor structures based on the unadjusted covariance matrices

	Six factors		One factor	
	Intercept	Beta	Intercept	Beta
Average	-0.000	0.458	-0.000	0.838
Std.	0.000	1.556	0.000	1.232
% of Rejections	0	18.2	0	34.7

Panel B: Eight and one factor structures based on the adjusted covariance matrices

	Eight factors		One factor	
	Intercept	Beta	Intercept	Beta
Average	-0.000	1.464	-0.000	1.110
Std.	0.001	2.132	0.000	2.279
% of Rejections	0	31.6	0	37.3

TABLE 2.5

Summary statistics are presented below for tests of the significance of the risk premia and the exactness of the following cross-sectional APT equation which includes the residual market factor (RMF): $E(R)-R_f=B\Gamma+B_m\Gamma_m$. The null hypothesis, $H_0:\Gamma=0$, is tested using a χ^2 and t-test for a six (eight) and one factor structure, respectively. The null hypothesis, $H_0:\Gamma_m$, is tested using a t-test. The null hypothesis, $H_0:E(R)-R_f=B\Gamma+B_m\Gamma_m$, is tested using the CRST test (2.22). The summary statistics include the average, standard deviation (std.) and the percentage of rejections of the null hypothesis for the 42 groups of 30 securities. The covariance matrices have been adjusted for nonsynchronous trading using the Shanken adjustment.

Panel A: Six and one factor structures based on the unadjusted covariance matrices

	Six Factors			One Factor		
	t-test (RMF)	χ^2 test	CSRT	t-test (RMF)	χ^2 test	CSRT
Average	0.475	8.788	0.004	0.213	4.039	0.137
Std.	1.002	9.403	0.133	0.961	5.181	0.249
% of Rejections	7.1	4.7	0	4.9	19.5	0

Panel B: Eight and one factor structures based on the adjusted covariance matrices

	Eight Factors			One Factor		
	t-test (RMF)	χ^2 test	CSRT	t-test (RMF)	χ^2 test	CSRT
Average	0.157	11.321	0.004	0.105	5.057	0.031
Std.	0.903	10.520	0.008	0.957	8.584	0.046
% of Rejections	5.3	7.9	0	2.4	21.9	0

TABLE 2.6

General statistics from the iterative weighted-least-squares (ITWLS) estimations of the conditional standard deviations of the first mimicking portfolio for various factor structures are reported below. The conditional standard deviation is modelled as follows:

$$\Theta_{jt}=\alpha_o + \Sigma^{12}_{i=1}\alpha_i\Theta_{jt-i} + \varepsilon_{jt} \qquad (2.31)$$

$$(\pi/2)^{1/2}|\varepsilon_{jt}|=\beta_o + \beta_1(FIT)_t + u_t \qquad (2.32)$$

"Coef." refers to the estimated coefficients in (2.31) that are significant at the 0.05 level. "Q( )" is the Box-Pierce statistic which is defined as $Tx\Sigma^{K}_{k=1}r^2_k$. It is distributed as χ^2_{K-L} where L is the number of lags in (2.31). "Q2( )" is the Box-Pierce statistic for the squared residuals of (2.31). ST( ) is the studendized range statistic for the residuals of (2.31). Both Box-Pierce statistics are based on a 24 lag structure.

Panel A: Six and one factor structures based on the unadjusted covariance matrices

Six Factor Structure

	Coef.	Autocorrelation		Heteroscedasticity			
		Q(OLS)	Q(ITWLS)	Q2(OLS)	Q2(ITWLS)	ST(OLS)	ST(ITWLS)
Average	6.047	26.909	12.055	274.735	19.683	13.143	8.866
Std.	2.104	17.375	5.471	211.939	18.012	14.779	1.444

One Factor Structure

	Coef.	Autocorrelation		Heteroscedasticity			
		Q(OLS)	Q(ITWLS)	Q2(OLS)	Q2(ITWLS)	ST(OLS)	ST(ITWLS)
Average	7.405	30.297	20.959	497.643	26.907	11.395	8.206
Std.	1.236	8.083	5.773	182.414	8.180	1.416	1.041

Panel B: Eight and one factor structures based on the adjusted covariance matrices

Eight Factor Structure

	Coef.	Autocorrelation		Heteroscedasticity			
		Q(OLS)	Q(ITFLS)	Q2(OLS)	Q2(ITWLS)	ST(OLS)	ST(ITWLS)
Average	5.861	24.699	23.539	181.961	18.452	10.610	9.027
Std.	2.070	11.468	53.798	143.723	9.332	3.210	2.789

One Factor Structure

	Coef.	Autocorrelation		Heteroscedasticity			
		Q(OLS)	Q(ITWLS)	Q2(OLS)	Q2(ITWLS)	ST(OLS)	ST(ITWLS)
Average	6.780	31.263	21.954	505.536	28.009	11.463	8.159
Std.	1.179	9.541	7.076	206.529	8.632	1.453	1.068

TABLE 2.7

The number of securities with significant conditional standard deviation coefficients at the 0.05 level for each mimicking portfolio for the multi-period APT for factor structures of "six", "eight" and "one" are reported below. The covariance matrices ("V") are "adjusted" and "unadjusted" for nonsynchronous trading using the Shanken adjustment. The conditional standard deviation equations are:

$$h_t = \alpha + \phi\Theta_t + u_t \qquad (2.34)$$

$$h_t = \alpha + \phi\Theta_t + \phi_m\Theta_{It} + u_t \qquad (2.42)$$

"No Θ_{It}" and "Θ_{It}" refer to the estimations of equations (2.34) and (2.42), respectively. While the former does not include the conditional standard deviation, Θ_{It}, on the residual market factor (SFM), the latter does.

Factors	6		8		1		1	
V	Unadjusted		Adjusted		Unadjusted		Adjusted	
Coef.	θ_{It}	no θ_{It}	θ^{It}	no θ_{It}	θ_{It}	no θ_{It}	θ_{It}	no θ_{It}
α	1187	1162	963	916	961	1257	953	906
θ_1	115	109	119	106	942	1097	1105	1024
θ_2	148	142	173	149				
θ_3	284	224	125	109				
θ_4	114	108	129	104				
θ_5	137	136	114	101				
θ_6	249	244	167	152				
θ_7			125	109				
θ_8			121	100				
θ_I	47	--	45	--	641	--	638	--

TABLE 2.8

General statistics from the iterative weighted-least-squares (ITWLS) estimations are reported below for the following multi-period APT without a residual market factor (RMF):

$$R_t=\delta + BR_{mt} + u_t \qquad (2.33)$$

$$h_t=\alpha + \phi\Theta_t + e_t \qquad (2.34)$$

The null hypothesis, $H_0:\delta=0$, is tested using the F-test (F-exact) (2.35). The "χ^2 test" of $\bar{R}_m'\Sigma^{-1}\bar{R}_m$ has K degrees of freedom, and is used to assess the number of factors in (2.33). "Q2 ( )" is the Box-Pierce statistic based on the 24 lag structure for the squared residuals of (2.33). "ST ( )" is the studentized range statistic for the residuals (2.33). The averages, standard deviations (std.) and the % of rejections of H_0 are based on the 42 groups of 30 securities.

Panel A: Six and one factor structures based on the unadjusted covariance matrices

	F-exact	χ^2-Test	Heteroscedasticity			
Six Factor Structure			Q2(OLS)	Q2(ITWLS)	ST(OLS)	ST(ITWLS)
Average	0.045	6338.78	170.685	139.325	12.809	12.173
Std.	0.081	1092.57	69.912	37.622	2.509	0.609
% of Rejections	0	100				

	F-exact	χ^2-Test	Heteroscedasticity			
One Factor Structure			Q2(OLS)	Q2(ITWLS)	ST(OLS)	ST(ITWLS)
Average	0.263	4992.57	187.509	150.433	13.095	12.833
Std.	0.171	862.55	39.858	26.603	0.577	0.595
% of Rejections	0	100				

Panel B: Eight and one factor structures based on the adjusted covariance matrices

	F-exact	χ^2-Test	Heteroscedasticity			
Eight Factor Structure			Q2(OLS)	Q2(ITWLS)	ST(OLS)	ST(ITWLS)
Average	0.111	5772.54	204.319	157.125	13.684	12.022
Std.	0.153	1138.29	506.428	38.181	5.647	0.608
% of Rejections	0	100				

	F-exact	χ^2-Test	Heteroscedasticity			
One Factor Structure			Q2(OLS)	Q2(ITWLS)	ST(OLS)	ST(ITWLS)
Average	0.243	4814.68	183.892	152.190	13.648	13.468
Std.	0.556	994.45	43.276	28.907	1.082	1.186
% of Rejections	97.5	100				

TABLE 2.9

General statistics from the iterative weighted-least-squares (ITWLS) estimations are reported below for the following multi-period APT with a residual market factor (RMF):

$$R_t = \delta + BR_{mt} + B_m e_{It} + u_t \qquad (2.41)$$
$$h_t = \alpha + \phi\Theta_t + \phi_m\Theta_{It} + e_t \qquad (2.42)$$

The null hypothesis, H_0: δ=0, is tested using the F-test (F-exact) (2.35). The "χ^2 test" of $\bar{R}_a'\hat{\Sigma}^{-1}\bar{R}_a$ has K+1 degrees of freedom, and is used to assess the number of factors in (2.33) (including the RMF). "Q2 ( )" is the Box-Pierce statistic based on the 24 lag structure for the squared residuals of (2.33). "ST ( )" is the studentized range statistic for the residuals (2.33). The averages, standard deviations (std.) and the % of rejections of H_0 are based on the 42 groups of 30 securities.

Panel A: Six and one factor structures based on the unadjusted covariance matrices

	Six Factor Structure					
	F-exact	χ^2-Test	Heteroscedasticity			
			Q2(OLS)	Q2(ITWLS)	ST(OLS)	ST(ITWLS)
Average	0.043	6371.12	160.612	131.376	12.765	12.165
Std.	0.084	1026.04	38.183	28.492	2.918	0.570
% of Rejections	0	100				

	One Factor Structure					
	F-exact	χ^2-Test	Heteroscedasticity			
			Q2(OLS)	Q2(ITWLS)	ST(OLS)	ST(ITWLS)
Average	0.141	4864.25	185.400	146.959	13.093	12.766
Std.	0.101	829.76	36.999	26.124	0.576	0.608
% of Rejections	0	100				

Panel B: Eight and one factor structures based on the adjusted covariance matrices

	Eight Factor Structure					
	F-exact	χ^2-Test	Heteroscedasticity			
			Q2(OLS)	Q2(ITWLS)	ST(OLS)	ST(ITWLS)
Average	0.091	6916.46	154.862	121.229	13.172	11.978
Std.	0.129	5906.44	37.927	39.242	4.149	0.604
% of Rejections	0	100				

	One Factor Structure					
	F-exact	χ^2-Test	Heteroscedasticity			
			Q2(OLS)	Q2(ITWLS)	ST(OLS)	ST(ITWLS)
Average	0.124	4906.73	187.151	144.392	13.087	12.810
Std.	0.088	775.82	40.571	34.549	0.551	0.583
% of Rejections	0	100				

TABLE 3.1

The portfolio benchmark abbreviations are described in this table. Portfolio benchmarks are minimum idiosyncratic risk mimicking portfolios (MIRMP) or market indexes (INDEX). The number of factors in the factor structure is one, six or eight. The variance-covariance matrix of returns (V) can be unadjusted or adjusted for nonsynchronous trading. The MIRMP are formed using the 147 firms whose average price was below $5 (Small), the 277 firms whose average price was above $5 (Large), or using all firms (All).

Identifier	Type	Returns	Factor Structure	V	Sample
MN1P147	MIRMP	Monthly	1 Factor	Unadjusted	Small
MN1P277	MIRMP	Monthly	1 Factor	Unadjusted	Large
MN1P424	MIRMP	Monthly	1 Factor	Unadjusted	All
MS1P147	MIRMP	Monthly	1 Factor	Adjusted	Small
MS1P277	MIRMP	Monthly	1 Factor	Adjusted	Large
MS1P424	MIRMP	Monthly	1 Factor	Adjusted	All
MN6P147	MIRMP	Monthly	6 Factors	Unadjusted	Small
MN6P277	MIRMP	Monthly	6 Factors	Unadjusted	Large
MN6P424	MIRMP	Monthly	6 Factors	Unadjusted	All
MS8P147	MIRMP	Monthly	8 Factors	Adjusted	Small
MS8P277	MIRMP	Monthly	8 Factors	Adjusted	Large
MS8P424	MIRMP	Monthly	8 Factors	Adjusted	All
TSE300	INDEX	Monthly			
VWI	INDEX	Monthly			

TABLE 3.2

The Sharpe ratios (S_i) given by μ_i/σ_i, where μ_i is the average excess return of portfolio i and σ_i is the associated standard deviation, for the minimum idiosyncratic risk mimicking (MIRM) portfolios for various factor structures and the market indexes are reported below. The subscript of the Sharpe ratio refers to the MIRM for factor i. For a description of each benchmark portfolio, see Table 3.1.

Benchmark	S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8
MN1P147	-0.015							
MN1P277	0.077							
MN1P424	0.064							
MS1P147	-0.014							
MS1P277	0.075							
MS1P424	0.064							
MN6P147	-0.021	-0.019	-0.017	-0.016	-0.002	-0.013		
MN6P277	0.079	0.079	0.076	0.081	0.075	0.079		
MN6P424	0.069	0.068	0.071	0.069	0.063	0.069		
MS8P147	-0.021	-0.026	-0.017	-0.005	-0.006	-0.024	-0.027	-0.018
MS8P277	0.099	0.091	0.093	0.087	0.091	0.088	0.092	0.085
MS8P424	0.073	0.076	0.077	0.075	0.075	0.077	0.075	0.069
TSE300	0.005							
VWI	0.005							

TABLE 3.3

The Mean and Standard deviation (Std.) for the Jobson-Korkie Z-scores for the mutual funds for each benchmark, and the numbers of funds with significantly positive performances (G) and significantly negative performances (L), are reported in this table. The Z-scores are based on estimated variance-covariances using ordinary and Newey-West estimators, and on the 14 different portfolio benchmarks described in Table 3.1. The Z scores are given by equation (3.1). The Newey and West estimator is given by equation (3.15). It adjusts the variance-covariance matrix (V) of security returns for autocorrelation and heteroskedasticity.

	Z-Score							
	Ordinary V estimates				Newey-West V estimates			
Benchmark	Mean	Std.	G	L	Mean	Std.	G	L
MN1P147	-0.109	0.845	0	6	-1.112	1.172	7	10
MN1P277	-1.228	1.236	0	38	-1.462	1.853	8	56
MN1P424	-0.997	1.211	0	25	-1.181	1.824	8	45
MS1P147	-0.106	0.846	0	7	0.004	1.174	6	10
MS1P277	-1.229	1.236	0	38	-1.463	1.853	8	56
MS1P424	-0.999	1.211	0	25	-1.184	1.824	8	45
MN6P147	-0.127	0.852	0	6	-0.022	1.183	6	10
MN6P277	-1.299	1.236	0	41	-1.576	1.914	6	56
MN6P424	-1.069	1.211	0	25	-1.267	1.868	7	48
MS8P147	-0.141	0.845	0	6	-0.044	1.192	6	10
MS8P277	-1.343	1.098	0	35	-1.716	1.933	2	58
MS8P424	-1.180	1.211	0	30	-1.440	1.902	7	55
TSE300	0.105	1.242	9	8	0.243	1.769	8	16
VWI	0.086	1.210	6	9	0.282	1.762	18	15

TABLE 3.4

The χ^2 values for various tests of the equality of multiple mean vectors of Z-scores for various types of portfolio benchmarks are reported below. The χ^2 test is given by equation (3.16). In Panel F, the Z-scores are averaged across the 12 portfolio benchmarks for each mutual fund to have a vector of Z-scores which is comparable to those obtained for the market indexe: An "*" indicates significance at the 0.05 level. "Port. n" refers to portfolio n.

Panel A: MIRM portfolios which are based on different factor structures (one- versus multi-factor structures)

Port. 1	MN1P147	MN1P277	MN1P424	MS1P147	MS1P277	MS1P424
Port. 2	MN6P147	MN6P277	MN6P424	MS8P147	MS8P277	MS8P424
χ^2	761.23*	644.90*	859.66*	5952.12*	50.05*	1552.51*

MULTIVARIATE χ^2: 7111.51*

Panel B: MIRM portfolios based on different variance-covariance matrices (unadjusted versus adjusted for nonsynchronous trading)

Port. 1	MN1P147	MN1P277	MN1P424	MN6P147	MN6P277	MN6P424
Port. 2	MS1P147	MS1P277	MS1P424	MS8P147	MS8P277	MS8P424
χ^2	1849.62*	13.89*	604.26*	420.66*	7.14*	1922.92*

MULTIVARIATE χ^2: 3450.47*

Panel C: MIRM portfolios which are based on the samples of small versus large firms

Port. 1	MN1P147	MN6P147	MS1P147	MS8P147
Port. 2	MN1P277	MN6P277	MS1P277	MS8P277
χ^2	510.64*	545.57*	514.71*	1037.61*

MULTIVARIATE χ^2: 2864.06*

Panel D: MIRM portfolios which are based on the samples of small versus all firms

Port. 1	MN1P147	MN6P147	MS1P147	MS8P147
Port. 2	MN1P424	MN6P424	MS1P424	MS8P424
χ^2	419.56*	464.74*	425.37*	535.22*

MULTIVARIATE χ^2: 2640.46*

Panel E: MIRM portfolios which are based on the samples of large versus all firms

Port. 1	MN1P277	MN6P277	MS1P277	MS8P277
Port. 2	MN1P424	MN6P424	MS1P424	MS8P424
χ^2	476.19*	445.36*	473.46*	535.22*

MULTIVARIATE χ^2: 2640.46*

Panel F: Market indexes and MIRM portfolio benchmarks versus market indexes

Port. 1	MIRM	MIRM	TSE300
Port. 2	TSE300	VWI	VWI
χ^2	772.39*	976.35*	4.58*

TABLE 3.5

The χ^2 values for various tests of the equality of multiple mean vectors of Z-scores when the variances and covariances are estimated using the Newey-West estimator for various types of portfolio benchmarks are reported below. The χ^2 test is given by equation (3.16). In Panel F, the Z scores are averaged across the 12 portfolio benchmarks for each mutual fund to have a vector of Z-scores which is comparable to those obtained for the market indexes. An "*" indicates significance at the 0.05 level. "Port. n" refers to portfolio n.

Panel A: MIRM portfolios which are based on different factor structures (one- versus multi-factor structures)

Port. 1	MN1P147	MN1P277	MN1P424	MS1P147	MS1P277	MS1P424
Port. 2	MN6P147	MN6P277	MN6P424	MS8P147	MS8P277	MS8P424
χ^2	148.41*	52.10*	46.77*	213.24*	12.74*	259.45*

MULTIVARIATE χ^2: 744.14*

Panel B: MIRM portfolios based on different variance-covariance matrices (unadjusted versus adjusted for nonsynchronous trading)

Port. 1	MN1P147	MN1P277	MN1P424	MN6P147	MN6P277	MN6P424
Port. 2	MS1P147	MS1P277	MS1P424	MS8P147	MS8P277	MS8P424
χ^2	247.06*	0.06	10.53*	174.80*	4.84*	398.83*

MULTIVARIATE χ^2: 781.48*

Panel C: MIRM portfolios which are based on the samples of small versus large firms

Port. 1	MN1P147	MN6P147	MS1P147	MS8P147
Port. 2	MN1P277	MN6P277	MS1P277	MS8P277
χ^2	227.74*	229.31*	229.94*	263.94*

MULTIVARIATE χ^2: 364.93*

Panel D: MIRM portfolios which are based on the samples of small versus all firms

Port. 1	MN1P147	MN6P147	MS1P147	MS8P147
Port. 2	MN1P424	MN6P424	MS1P424	MS8P424
χ^2	176.43*	177.48*	178.97*	205.03*

MULTIVARIATE χ^2: 433.02*

Panel E: MIRM portfolios which are based on the samples of large versus all firms

Port. 1	MN1P277	MN6P277	MS1P277	MS8P277
Port. 2	MN1P424	MN6P424	MS1P424	MS8P424
χ^2	88.66*	98.43*	87.33*	39.42*

MULTIVARIATE χ^2: 258.99*

<u>Panel F:</u> Market indexes and MIRM portfolio benchmarks versus market indexes

Port. 1	MIRM	MIRM	TSE300
Port. 2	TSE300	VWI	VWI
χ^2	364.28*	367.29*	23.57*

TABLE 3.6

The Mean and Standard deviation (Std.) of the PPW scores for the mutual funds for each benchmark, and the numbers of funds with significantly positive and negative performances are reported below. The PPW scores are based on the assumption of homoscedasticity (and heteroskedasticity), and on the 14 different portfolio benchmarks described in Table 3.1. The numbers of funds that have significantly positive performances based on a t-test of the null hypothesis that the average PPW is not significantly different from 0 when the standard deviation of the PPW score is calculated under the assumptions of homoscedasticity and heteroskedasticity are denoted by "GHO" and "GHE", respectively. Similarly, the corresponding numbers of funds that have significantly negative performances are denoted by "LHO" and "LHE", respectively.

Benchmark	Mean	Std.	GHO	GHE	LHO	LHE
MN1P147	0.00044	0.00440	1	1	6	6
MN1P277	-0.00288	0.00465	0	0	29	33
MN1P424	-0.00245	0.00463	0	0	24	25
MN6P147	0.00046	0.00440	1	1	7	7
MN6P277	-0.00309	0.00446	0	0	39	41
MN6P424	-0.00268	0.00465	0	0	26	28
MS1P147	0.00044	0.00440	1	1	6	6
MS1P277	-0.00289	0.00465	0	0	30	33
MS1P424	-0.00246	0.00463	0	0	24	25
MS8P147	0.00082	0.00436	2	3	6	6
MS8P277	-0.00345	0.00468	0	0	43	45
MS8P424	-0.00291	0.00467	0	0	29	31
TSE300	-0.00016	0.00446	11	12	9	10
VWI	-0.00161	0.00456	0	1	17	17

TABLE 3.7

The correlation coefficients for various pairs of Z- and PPW scores are reported below. The Z scores estimated using the variance-covariance matrix of returns adjusted for heteroskedasticity using the Newey and West (1987) method are denoted by Z^*. The various portfolio benchmarks are described in Table 3.1.

Benchmark	Z AND Z^*	PPW AND Z	PPW AND Z^*
MN1P147	0.918	0.942	0.853
MN1P277	0.889	0.819	0.682
MN1P424	0.742	0.904	0.661
MN6P147	0.918	0.934	0.846
MN6P277	0.889	0.827	0.684
MN6P424	0.876	0.794	0.657
MS1P147	0.918	0.942	0.853
MS1P277	0.889	0.818	0.683
MS1P424	0.742	0.905	0.661
MS8P147	0.919	0.905	0.830
MS8P277	0.856	0.867	0.682
MS8P424	0.869	0.819	0.672
TSE300	0.922	0.878	0.733
VWI	0.913	0.901	0.733

TABLE 3.8

The χ^2 values for various tests of the equality of multiple mean vectors of PPW-scores for various types of portfolio benchmarks are reported below. The χ^2 test is given by equation (3.16). In Panel F, the PPW scores are averaged across the 12 portfolio benchmarks for each mutual fund to obtain a vector of PPW-scores which is comparable to those obtained for the market indexes. An "*" indicates significance at the 0.05 level. "Port. n" refers to portfolio n.

Panel A: **MIRM portfolios which are based on different factor structures (one- versus multi-factor structures)**

Port. 1	MN1P147	MN1P277	MN1P424	MS1P147	MS1P277	MS1P424
Port. 2	MN6P147	MN6P277	MN6P424	MS8P147	MS8P277	MS8P424
χ^2	1921.21*	5531.50*	5099.56*	1797.72*	4281.96*	4606.08*

MULTIVARIATE χ^2: 6031.71*

Panel B: **MIRM portfolios based on different variance-covariance matrices (unadjusted versus adjusted for nonsynchronous trading)**

Port. 1	MN1P147	MN1P277	MN1P424	MN6P147	MN6P277	MN6P424
Port. 2	MS1P147	MS1P277	MS1P424	MS8P147	MS8P277	MS8P424
χ^2	102.65*	3440.29*	3405.78*	1745.42*	3171.58*	3956.72*

MULTIVARIATE χ^2: 4950.56*

Panel C: **MIRM portfolios which are based on the samples of small versus large firms**

Port. 1	MN1P147	MN6P147	MS1P147	MS8P147
Port. 2	MN1P277	MN6P277	MS1P277	MS8P277
χ^2	3714.75*	3767.01*	3715.12*	3781.33*

MULTIVARIATE χ^2: 4950.24*

Panel D: MIRM portfolios which are based on the samples of small versus all firms

Port. 1	MN1P147	MN6P147	MS1P147	MS8P147
Port. 2	MN[illegible]424	MN6P424	MS1P424	MS8P424
χ^2	34[illegible]2.36*	3540.30*	3492.51*	3404.10*

MULTIVARIATE χ^2: 6024.44*

Panel E: **MIRM portfolios which are based on the samples of large versus all firms**

Port. 1	MN1P277	MN6P277	MS1P277	MS8P277
Port. 2	MN1P424	MN6P424	MS1P424	MS8P424
χ^2	4610.93*	4572.09*	4616.94*	3990.99*

MULTIVARIATE χ^2: 4769.62*

Panel F: Market indexes and MIRM portfolio benchmarks versus market indexes

Port. 1	MIRM	MIRM	TSE300
Port. 2	TSE300	VWI	VWI
χ^2	20.98*	4194.62*	368.71*

TABLE 3.9

Two bootstrapped Z-scores for each month of the year for each portfolio benchmark are reported below. The Z-scores on the first and second lines for each portfolio benchmark are based on a variance-covariance matrix unadjusted and adjusted for heteroskedasticity, respectively. The adjustment of Newey and West (1987) is used for this purpose. The portfolio benchmarks are described in Table 3.1. Z-values higher and lower than 1.96 and -1.96 are denoted by "+" and "*", respectively.

	JA	FE	MA	AP	MY	JU	JL	AU	SE	OC	NO	DE
MWLP147	1.1	-3.6*	1.7	1.8	0.9	0.0	0.2	3.4+	-5.9*	-2.4*	0.4	2.7+
	1.4	-4.0*	1.6	1.9	1.1	0.0	0.3	2.8+	-6.8*	-3.2*	0.4	3.7+
MWLP277	0.9	0.1	2.6+	0.2	-0.9	-1.5	-0.2	1.6	-4.4*	-2.5*	1.8	5.5+
	1.3	0.1	2.0+	0.3	-1.3	-1.4	-0.2	1.7	-5.5*	-3.1*	1.6	6.1+
MWLP424	0.9	-0.4	2.5+	0.5	-0.6	-1.3	-0.2	1.8	-5.0*	-2.5*	1.7	5.7+
	1.5	-0.4	2.0+	0.7	-0.9	-1.2	-0.2	1.8	-6.1*	-3.2*	1.5	6.9+
MSLP147	1.1	-3.6*	1.7	1.9	0.9	0.0	0.3	3.4+	-5.9*	-2.4*	0.4	2.7+
	1.4	-4.0*	1.6	2.0+	1.1	0.0	0.3	2.8+	-6.8*	-3.3*	0.4	3.6+
MSLP277	0.9	0.1	2.6+	0.2	-0.8	-1.5	-0.2	1.6	-4.5*	-2.5+	1.8	5.5+
	1.3	0.1	2.0+	0.3	-1.2	-1.4	-0.2	1.7	-5.5*	-3.1+	1.6	6.1+
MSLP424	0.9	-0.4	2.5+	0.5	-0.6	-1.3	-0.2	1.8	-5.0*	-2.5*	1.7	5.7+
	1.5	-0.4	2.0+	0.6	-0.9	-1.2	-0.2	1.8	-6.1*	-3.2*	1.5	6.9+
MW6P147	1.1	-3.5*	1.7	1.7	1.1	-0.1	0.2	3.5+	-6.0*	-2.4*	0.5	2.7+
	1.4	-3.8*	1.6	1.8	1.3	-0.1	0.2	2.9+	-6.7*	-3.2*	0.5	3.6+
MW6P277	0.9	0.2	2.4+	0.2	-0.9	-1.5	-0.2	1.7	-4.7*	-2.4*	1.8	5.6+
	1.4	0.2	2.0+	0.3	-1.3	-1.4	-0.2	1.7	-5.7*	-3.0*	1.6	6.2+
MW6P424	1.0	-0.3	2.4+	0.5	-0.7	-1.3	-0.2	1.8	-5.3*	-2.5*	1.7	5.3+
	1.5	-0.3	2.0+	0.7	-0.9	-1.2	-0.2	1.9	-6.4*	-3.1*	1.5	7.2+
MS8P147	1.1	-3.5*	1.6	1.8	1.4	0.0	0.2	3.4+	-6.0*	-2.4*	0.3	2.7+
	1.4	-3.6*	1.5	1.9	1.6	0.0	0.2	2.9+	-6.9*	-3.2*	0.3	3.6+
MS8P277	1.3	0.9	1.8	0.4	-1.0	-1.4	-0.7	1.4	-6.2*	-2.8*	2.4+	4.4+
	2.1+	0.8	1.7	0.5	-1.7	-1.4	-0.8	1.5	-7.9*	-4.0*	2.5+	4.8+
MS8P424	0.9	-0.2	2.5+	0.6	-0.5	-1.3	-0.2	1.8	-5.5*	-2.5*	1.6	5.7+
	1.4	-0.2	2.1+	0.8	-0.7	-1.2	-0.2	1.8	-6.3*	-3.1*	1.4	7.1+
TSE300	-0.4	-0.2	1.9	-0.1	-1.4	-1.4	-0.4	2.3+	-4.3*	-1.8	2.0+	3.9+
	-0.6	-0.2	1.7	-0.2	-1.9	-1.3	-0.4	2.6+	-4.4*	-2.0*	2.1+	4.4+
VWI	-0.5	-0.3	2.6+	0.9	-0.9	-1.6	-0.7	2.4+	-4.0*	-2.0*	1.4	3.3+
	-0.6	-0.3	2.2+	1.4	-1.3	-1.5	-0.6	2.6+	-4.3*	-2.3*	1.6	4.0+

TABLE 3.10

The average (ave.) bootstrapped Z-score and the associated standard deviation (std.) for each month of the year across the sample of mutual fund returns are reported below. Z and Z* refer to the Z-scores based on a variance-covariance matrix unadjusted and adjusted for heteroskedasticity, respectively. The adjustment of Newey and West (1987) is used for this purpose. The t-values are for the test of $H_0: E(Z)_i = 0$ for i=January,...,December, and the F-values are for the test of $H_0: E(Z)_{JA} = \ldots = E(Z)_{DE} = 0$. t-values higher and lower than 1.96 and -1.96 are denoted by "+" and "*", respectively. "*" denotes significance at the 0.05 level.

	JA	FE	MA	AP	MY	JU	JL	AU	SE	OC	NO	DE
ave.(Z)	0.5	0.6	1.5	0.4	-1.2	0.3	-1.6	1.8	-3.3*	-1.9	1.1	3.2+
std.(Z)	1.2	1.5	1.6	1.2	1.4	2.5	1.8	0.9	1.4	0.5	1.2	1.8
t-value	5.1*	4.8*	11.3*	4.0*	-10.9*	1.6	-10.3*	24.6*	-27.4*	-42.8*	10.5*	21.8*
F-value	2615.6*											
ave.(Z*)	0.6	0.5	1.3	0.5	-1.6	0.3	-1.5	2.1+	-3.6*	-2.3*	1.2	3.4+
std.(Z*)	1.5	1.6	1.6	1.7	1.9	2.6	1.8	1.1	1.4	0.8	1.4	2.0
t-value	4.9*	3.8*	9.5*	3.5*	-10.3*	1.4	-10.3*	23.2*	-30.6*	-33.5*	10.2*	20.2*
F-value	2447.3*											

TABLE 3.11

Averages across the sample of mutual funds of bootstrapped Z-score pairs for each month of the year for mutual fund performance based on each portfolio benchmark are reported below. The Z-scores on the first and second lines for each portfolio benchmark are based on a variance-covariance matrix unadjusted and adjusted for heteroskedasticity, respectively. The adjustment of Newey and West (1987) is used for this purpose. The portfolio benchmarks are described in Table 3.1. An "*" indicates statistical significance at the 0.05 level.

	JA	FE	MA	AP	MY	JU	JL	AU	SE	OC	NO	DE
MW1P147	-0.2	-0.3	0.1	-0.6	-1.0	0.2	-0.8	-0.7	-2.7*	-1.0	0.3	0.6
	-0.1	-0.7	0.0	-0.3	-1.2	0.1	-1.5	-1.0	-2.8*	-1.1	0.2	0.6
MW1P277	-0.4	-0.1	-0.6	-0.2	-0.5	0.0	-0.9	-0.2	-1.9	-0.8	-0.6	-2.0*
	-0.5	0.0	-0.9	-0.2	-0.5	0.0	-1.8	-0.3	-1.4	-0.8	-1.1	-2.4*
MW1P424	-0.4	0.2	-0.6	-0.3	-0.5	0.1	-0.9	-0.3	-2.0*	-0.8	-0.6	-2.1*
	-0.5	0.3	-0.8	-0.3	-0.6	0.1	-1.8	-0.5	-1.5	-0.9	-1.0	-2.5*
MS1P147	-0.2	-0.9	0.1	-0.7	-1.0	0.2	-0.9	-0.7	-2.7*	-1.0	0.2	0.6
	-0.1	-0.7	0.0	-0.3	-1.2	0.1	-1.5	-1.0	-2.8*	-1.1	0.2	0.6
MS1P277	-0.4	-0.1	-0.6	-0.2	-0.5	0.0	-0.9	-0.2	-1.9	-0.8	-0.6	-2.0*
	-0.5	0.0	-0.9	-0.2	-0.5	0.0	-1.8	-0.3	-1.4	-0.8	-1.1	-2.4*
MS1P424	-0.4	0.2	-0.6	-0.3	-0.6	0.1	-0.9	-0.3	-2.0*	-0.8	-0.6	-2.1*
	-0.5	0.3	-0.8	-0.3	-0.6	0.1	-1.8	-0.5	-1.6	-0.9	-1.0	-2.5*
MW6P147	-0.2	-0.8	0.1	-0.6	-1.1	0.2	-0.8	-0.7	-2.7*	-1.0	0.2	0.6
	-0.1	-0.6	0.1	-0.8	-1.3	0.1	-1.5	-1.0	-2.8*	-1.1	0.2	0.6
MW6P277	-0.5	-0.1	-0.6	-0.2	-0.5	0.0	-0.9	-0.2	-1.9	-0.8	-0.6	-2.1*
	-0.6	-0.1	-0.8	-0.2	-0.5	0.0	-1.8	-0.4	-1.4	-0.8	-1.1	-2.6*
MW6P424	-0.5	0.2	-0.6	-0.3	-0.6	0.1	-0.9	-0.3	-2.1*	-0.8	-0.6	-2.4*
	-0.5	0.2	-0.7	-0.3	-0.6	0.1	-1.8	-0.5	-1.6	-0.8	-1.0	-2.7*
MS8P147	-0.2	-0.8	0.1	-0.6	-1.3	0.2	-0.8	-0.7	-2.8*	-1.0	0.3	0.6
	-0.1	-0.6	0.1	-0.8	-1.5	0.1	-1.4	-1.0	-2.8*	-1.1	0.3	0.6
MS8P277	-0.7	-0.4	-0.4	-0.4	-0.5	0.1	-0.8	-0.1	-2.1*	-0.8	-0.9	-1.4
	-1.0	-0.6	-0.5	-0.4	-0.6	0.1	-1.6	-0.2	-1.6	-0.9	-1.2	-1.8
MS8P424	-0.4	0.1	-0.6	-0.4	-0.6	0.1	-0.9	-0.3	-2.1*	-0.8	-0.6	-2.2*
	-0.5	0.1	-0.8	-0.3	-0.7	0.1	-1.8	-0.5	-1.6	-0.8	-1.0	-2.6*
TSE300	0.4	0.3	-0.1	0.2	-0.8	-0.1	-0.6	-0.3	-1.8	-0.8	-0.5	-0.5
	0.6	0.4	-0.1	0.2	-1.0	0.0	-1.2	-0.5	-1.4	-0.8	-0.7	-0.7
VWI	0.3	0.4	-0.4	-0.3	-0.7	-0.1	-0.7	-0.4	-1.8	-0.8	-0.2	-0.4
	0.6	0.4	-0.5	-0.3	0.7	-0.1	-1.3	-0.6	-1.4	-0.9	-0.3	-0.6

TABLE 3.12

The average χ^2-values of the mean Z-score vectors for comparisons between various pairs of portfolio benchmark groupings based on a specific portfolio construction attribute for each month of the year are reported below. For greater details on the portfolio benchmarks and their groupings, see Tables 3.1 and 3.4, respectively. "*" denotes statistical significance at the 0.05 level.

Panel A: Comparisons between minimum idiosyncratic risk mimicking (MIRM) portfolios that differ according to one attribute used for portfolio benchmark construction. The integer in each cell corresponds to the number of pairs (out of a total of 6 pairs) for which the null hypothesis of the equality of the mean Z-scores is rejected.

	ONE-FAC. MULTI-FAC.	UNADJUS. ADJUSTED	SMALL FIR. LARGE FIR.	SMALL FIR. ALL FIRMS	LARGE FIR. ALL FIRMS
JA	9367.65* 6	8035.58* 6	1523.97* 4	1209.59* 4	2664.45* 4
FE	6081.08* 6	2238.59* 6	1944.51* 4	5659.73* 4	4942.07* 4
MA	3259.23* 6	2681.57* 6	6249.60* 4	6341.33* 4	2036.35* 4
AP	2779.05* 6	3062.97* 6	4888.05* 4	3379.48* 4	5572.78* 4
MY	3214.86* 6	5893.33* 6	11510.63* 4	10921.78* 4	6983.54* 4
JU	757.64* 6	1065.71* 6	144.33* 4	66.08* 4	160.91* 4
JL	702.40* 6	1426.05* 5	211.39* 4	501.57* 4	226.89* 4
AU	7026.50* 5	8525.78* 6	19884.88* 4	15738.65* 4	18772.05* 4
SE	471.39* 5	721.64* 6	2494.46* 4	2332.99* 4	1849.96* 3
OC	1693.85* 5	2395.07* 6	20931.85* 4	24411.94* 4	23871.25* 4
NO	2314.56* 6	5551.89* 6	16431.34* 4	15913.63* 4	7405.39* 4
DE	614.89* 6	418.69* 6	3650.35* 4	3468.04* 4	868.49* 4

Panel B: Comparisons between pairs of market index benchmarks and between the MIRM and value-weighted market indexes.

	MONTHLY		TSE300
	TSE300	VWI	VWI
JA	18547.93*	22952.71*	203.31*
FE	16550.79*	14215.78*	477.10*
MA	2037.46*	273.37*	4895.54*
AP	10279.87*	8184.21*	6447.85*
MY	585.24*	266.92*	2591.14*
JU	714.39*	832.46*	351.36*
JL	8210.84*	1924.50*	9523.14*
AU	1210.99*	165.62	5932.17*
SE	870.18*	2065.24*	8.46*
OC	11341.64*	17125.69*	7033.28*
NO	4781.46*	2516.31*	14005.00*
DE	1060.61*	1117.97*	591.78*

TABLE 3.13

The average χ^2-values of the mean Z-score vectors (when the Z-score estimations are based on variances and covariances adjusted using the Newey-West estimator given by equation (3.15)) for comparisons between various pairs of portfolio benchmark groupings based on a specific portfolio construction attribute for each month of the year are reported below. For greater details on the portfolio benchmarks and their groupings, see Tables 3.1 and 3.4, respectively. "*" denotes statistical significance at the 0.05 level.

Panel A: Comparisons between minimum idiosyncratic risk mimicking (MIRM) portfolios that differ according to one attribute used for portfolio benchmark construction. The integer in each cell corresponds to the number of pairs (out of a total of 6 pairs) for which the null hypothesis of the equality of the mean Z-scores is rejected.

	ONE-FAC. MULTI-FAC.	UNADJUS. ADJUSTED	SMALL FIR. LARGE FIR.	SMALL FIR. ALL FIRMS	LARGE FIR. ALL FIRMS
JA	1849.40* 6	1422.16* 6	398.92* 4	311.91* 4	456.76* 4
FE	1342.67* 6	789.60* 6	187.83* 3	655.97* 4	1290.68* 4
MA	302.74* 6	722.11* 6	1008.13* 4	1047.76* 4	322.20* 4
AP	580.08* 6	693.32* 6	467.10* 4	365.13* 4	1365.56* 4
MY	625.16* 6	976.97* 6	1788.49* 4	1478.36* 4	1654.43* 4
JU	185.57* 6	280.39* 6	5.41* 3	0.46 0	595.87* 3
JL	300.71* 6	257.13* 5	36.30* 3	60.78* 4	27.49* 4
AU	1212.72* 6	923.23* 6	2019.27* 4	1269.22* 4	1672.92* 4
SE	303.04* 5	430.74* 6	506.19* 4	474.55* 4	1054.64* 4
OC	1930.38* 6	774.54* 5	6868.89* 4	6928.41* 4	3964.75* 4
NO	310.09* 6	506.97* 5	1758.66* 4	1262.24* 4	550.45* 4
DE	224.58* 5	191.43* 5	1237.29* 4	1386.58* 4	75.16* 4

Panel B: Comparisons between pairs of market index benchmarks and between the MIRM and value-weighted market indexes using aggregate daily and monthly returns.

	MONTHLY		TSE300
	TSE300	VWI	VWI
JA	1082.83*	1158.97*	3.57
FE	4324.37*	3744.81*	235.28*
MA	1098.59*	1.26	1434.37*
AP	1833.06*	337.01*	2118.39*
MY	344.94*	37.84*	5006.25*
JU	124.23*	195.16*	100.31*
JL	149.82*	78.85*	272.32*
AU	25.12*	23.57*	939.08*
SE	318.24*	560.64*	75.08*
OC	14779.09*	9321.50*	15615.84*
NO	152.78*	642.86*	1279.66*
DE	135.17*	189.68*	43.57*

TABLE 4.1

The estimates of the risk premium proportionality pricing parameter, R, found by Kryzanowski and Koutoulas (1991) for various estimation techniques and numbers of size-sorted portfolios are presented in this table. The associated t-values are given in the parentheses. The R estimates for the restricted model are given by $\hat{R}$, and those for the unrestricted model by $\hat{R}_{EX}$ and $\hat{R}_{CINDEX}$. NOLS and NSUR refer to nonlinear ordinary least squares and nonlinear seemingly unrelated regressions, respectively.

Estimation Technique	Size-Sorted Portfolios	$\hat{R}$	$\hat{R}_{EX}$	$\hat{R}_{CINDEX}$
NOLS	10	1.5079 (3.82)	-1.4571 (-3.11)	3.3224 (4.94)
NSUR	10	-0.9417 (-1.71)	-3.1433 (-2.88)	2.2220 (2.24)
NOLS	20	0.8590 (3.09)	-1.2756 (-3.52)	3.3725 (6.41)
NSUR	20	1.8280 (3.48)	-3.7841 (-3.15)	3.2779 (3.15)
NOLS	50	1.2584 (5.09)	-1.6185 (-5.41)	3.6263 (7.20)
NSUR	50	4.3617 (5.96)	-5.8533 (-4.14)	3.1889 (4.52)

TABLE 4.2

The mean factor beta estimates for the restricted and unrestricted versions of the APT equation (4.6) for the 146 equity mutual funds for various $\hat{R}$ values and estimation techniques are reported in panels A and B, respectively. The associated mean t-values are reported in the parentheses. The constant proportionality pricing parameters, $\hat{R}$, are those estimated by Kryzanowski and Koutoulas (for greater details, see Table 4.1). The mean R^2-values are also reported below. NOLS, ITNOLS and NSUR refer to nonlinear ordinary least squares, iterative nonlinear ordinary least squares and nonlinear seemingly unrelated regression, respectively.

	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_3$	$\hat{\beta}_4$	$\hat{\beta}_5$	$\hat{\beta}_6$	$\hat{\beta}_7$	R^2
<u>PANEL A:</u>	**Restricted APT equation (4.6)**							
$\hat{R}$=1.5079 NOLS	1.765 (5.36)	-0.676 (-3.21)	0.285 (0.37)	-0.041 (-1.06)	0.009 (0.10)	-0.157 (-0.85)	0.819 (16.12)	0.741
$\hat{R}$=1.5079 ITNOLS	1.765 (5.36)	-0.676 (-3.21)	0.285 (0.37)	-0.041 (-1.06)	0.009 (0.10)	-0.157 (-0.85)	0.819 (16.12)	0.741
$\hat{R}$=-0.3417 NSUR	1.779 (5.63)	-0.774 (-3.92)	0.089 (0.23)	-0.037 (-0.39)	0.094 (0.55)	-0.087 (-0.39)	0.784 (16.20)	0.747
$\hat{R}$=0.8590 NOLS	1.740 (5.46)	-0.825 (-3.69)	0.261 (0.79)	-0.036 (-0.32)	0.019 (0.15)	-0.119 (-0.68)	0.815 (16.70)	0.747
$\hat{R}$=0.8590 ITNOLS	1.740 (5.45)	-0.825 (-3.69)	0.261 (0.79)	-0.036 (-0.32)	0.019 (0.15)	-0.119 (-0.68)	0.815 (16.70)	0.747
$\hat{R}$=1.8280 NSUR	1.780 (5.35)	-0.602 (-3.28)	0.281 (1.07)	-0.044 (-1.12)	0.009 (0.09)	-0.172 (-0.92)	0.820 (15.87)	0.738
$\hat{R}$=1.2584 NOLS	1.755 (5.39)	-0.736 (-3.40)	0.282 (0.92)	-0.039 (-1.01)	0.012 (0.11)	-0.145 (-0.79)	0.818 (16.35)	0.743
$\hat{R}$=1.2584 ITNOLS	1.755 (5.39)	-0.736 (-3.40)	0.282 (0.92)	-0.039 (-1.01)	0.012 (0.11)	-0.145 (-0.79)	0.818 (16.35)	0.743
$\hat{R}$=4.3817 NSUR	1.858 (5.39)	-0.234 (-3.40)	0.168 (0.92)	-0.054 (-1.01)	0.028 (0.11)	-0.225 (-0.79)	0.812 (16.35)	0.723
<u>PANEL B:</u>	**Unrestricted APT equation (4.6)**							
$\hat{R}_1$=-1.4571 $\hat{R}_2$=3.3224 NOLS	1.805 (5.61)	-0.657 (-3.28)	0.008 (0.04)	-0.041 (-1.06)	0.111 (0.56)	-0.073 (-0.40)	0.776 (15.57)	0.743
$\hat{R}_1$=-1.4571 $\hat{R}_2$=3.3224 ITNOLS	1.805 (5.61)	-0.657 (-3.28)	0.008 (0.04)	-0.041 (-1.06)	0.111 (0.56)	-0.073 (-0.40)	0.776 (15.57)	0.743
$\hat{R}_1$=-3.1433 $\hat{R}_2$=2.2220 NSUR	1.886 (5.57)	-0.321 (-2.28)	0.049 (0.12)	-0.053 (-1.36)	0.124 (0.57)	-0.129 (-0.55)	0.772 (14.51)	0.730
$\hat{R}_1$=-1.2756 $\hat{R}_2$=3.3725 NOLS	1.793 (5.51)	-0.702 (-3.42)	0.009 (0.03)	-0.039 (-1.01)	0.110 (0.54)	-0.088 (-0.38)	0.778 (15.86)	0.745
$\hat{R}_1$=-1.2756 $\hat{R}_2$=3.3725 ITNOLS	1.793 (5.51)	-0.702 (-3.42)	0.009 (0.03)	-0.039 (-1.01)	0.110 (0.54)	-0.088 (-0.38)	0.778 (15.86)	0.745
$\hat{R}_1$=-3.7841 $\hat{R}_2$=3.2779 NSUR	1.901 (5.55)	-0.251 (-2.00)	0.042 (0.13)	-0.055 (-1.41)	0.123 (0.56)	-0.142 (-0.71)	0.773 (14.31)	0.727
$\hat{R}_1$=-1.6185 $\hat{R}_2$=3.6263 NOLS	1.815 (5.60)	-0.619 (-3.16)	0.005 (0.06)	-0.042 (-1.09)	0.114 (0.57)	-0.078 (-0.42)	0.775 (15.50)	0.742
$\hat{R}_1$=-1.6185 $\hat{R}_2$=3.6263 ITNOLS	1.815 (5.60)	-0.619 (-3.16)	0.005 (0.06)	-0.042 (-1.09)	0.114 (0.57)	-0.078 (-0.42)	0.775 (15.50)	0.742
$\hat{R}_1$=-5.8533 $\hat{R}_2$=3.1889 NSUR	1.925 (5.51)	-0.124 (-1.38)	0.074 (0.28)	-0.060 (-1.51)	0.118 (0.51)	-0.174 (-0.84)	0.776 (14.00)	0.721

TABLE 4.3

The mean Jensen estimates ($\hat{\alpha}$) and their standard deviations (std.) for the 146 equity mutual funds for various $\hat{R}$ values and estimation techniques for the restricted and unrestricted versions of equation (4.6) are reported in panels A and B, respectively. χ^2-tests of whether the Jensen estimates are simultaneously equal to zero across portfolios (test 1) and whether the Jensen estimates are equivalent across portfolios (test 2) are reported below. The numbers of mutual funds with positive $\hat{\alpha}$, and the numbers of mutual funds with statistically significant positive and negative $\hat{\alpha}$ are also reported below. NOLS, ITNLOS and NSUR refer to nonlinear ordinary least squares, iterative nonlinear ordinary least squares and nonlinear seemingly unrelated regressions, respectively. "a" indicates statistical significance at the 0.05 level.

PANEL A: Restricted APT equation (4.6)

Estimation Method $\hat{R}$	NOLS 1.5079	ITOLS 1.5079	NSUR -0.9417	NOLS 0.8590	ITNOLS 0.8590	NSUR 1.8280	NOLS 1.2584	ITNOLS 1.2584	NSUR 4.3617
				Jensen Estimates ($\hat{\alpha}$)					
Mean	0.0071	0.0071	-0.0061	0.0053	0.0053	0.0074	0.0066	0.0066	0.0056
Std.	0.0080	0.0080	0.0079	0.0066	0.0066	0.0086	0.0076	0.0076	0.0162
				Absolute t-Values					
Mean	2.049	2.049	1.967	2.147	2.147	2.043	2.121	2.121	1.377
Std.	1.263	1.263	1.382	1.406	1.406	1.203	1.337	1.337	0.771
				χ^2-Tests					
χ^2 (test 1)			300140^{a}			10308122^{a}			35223^{a}
χ^2 (test 2)			18818^{a}			54292^{a}			20710^{a}
				Number of Funds					
$\hat{\alpha} > 0$									
	128	128	20	124	124	126	128	128	120
$\hat{\alpha} > 0$ and statistically significant at the 0.05 level (two-tailed test)									
	71	71	4	77	77	72	76	76	36
$\hat{\alpha} < 0$ and statistically significant at the 0.05 level (two-tailed test)									
	3	3	62	3	3	3	3	3	2

PANEL B: Unrestricted APT equation (4.6)

Estimation Method	NOLS	ITOLS	NSUR	NOLS	ITNOLS	NSUR	NOLS	ITNOLS	NSUR
$\hat{R}_1$	-1.4571	-1.4571	-3.1433	-1.2756	-1.2756	-3.7841	-1.6185	-1.6185	-5.8533
$\hat{R}_2$	3.3224	3.3224	2.2220	3.3725	3.3725	3.2779	3.6263	3.6263	3.1889
				Jensen Estimates ($\hat{\alpha}$)					
Mean	-0.0086	-0.0086	-0.0093	-0.0081	-0.0081	-0.0088	-0.0089	-0.0089	-0.0071
Std.	0.0104	0.0104	0.0116	0.0101	0.0101	0.0122	0.0110	0.0110	0.0123
				Absolute t-Values					
Mean	1.932	1.932	1.855	1.866	1.866	1.671	1.938	1.938	1.371
Std.	1.216	1.216	1.173	1.186	1.186	1.077	1.213	1.213	0.339
				χ^2-Tests					
χ^2 (test 1)			11709^{a}			12363^{a}			12326^{a}
χ^2 (test 2)			4426^{a}			4368^{a}			4933^{a}
				Number of Funds					
$\hat{\alpha} > 0$									
	68	68	68	63	63	53	72	72	34
$\hat{\alpha} > 0$ and statistically significant at the 0.05 level (two-tailed test)									
	2	2	3	2	2	3	2	2	3
$\hat{\alpha} < 0$ and statistically significant at the 0.05 level (two-tailed test)									
	24	24	23	24	24	24	24	24	31

TABLE 4.4

The correlation matrices of the Jensen estimates for various estimation techniques (E.T.) and constant proportionality pricing parameters (R̂) for the restricted, unrestricted and restricted-versus-unrestricted APT equations are reported in panels A, B and C, respectively. NOLS, ITNLOS and NSUR refer to nonlinear ordinary least squares, iterative nonlinear ordinary least squares and nonlinear seemingly unrelated regressions, respectively.

Panel A: Restricted APT equation (4.6)

E.T./	R̂ /	NOLS	ITNOLS	NSUR	NOLS	ITNOLS	NSUR	NOLS	ITNOLS	NSUR
		1.5079	1.5079	-0.9417	0.8590	0.8590	1.8280	1.2584	1.2584	4.3617
NOLS	1.5079	1.00								
ITNOLS	1.5079	1.00	1.00							
NSUR	-0.9417	0.33	0.33	1.00						
NOLS	0.8590	0.98	0.35	0.97	1.00					
ITNOLS	0.8590	0.98	0.35	0.97	1.00	1.00				
NSUR	1.8280	0.99	0.39	0.36	0.97	0.97	1.00			
NOLS	1.2584	0.99	0.99	0.33	0.99	0.99	0.99	1.00		
ITNOLS	1.2584	0.99	0.99	0.33	0.99	0.99	0.99	1.00	1.00	
NSUR	4.3617	0.92	0.92	0.56	0.86	0.86	0.94	0.90	0.90	1.00

PANEL B: Unrestricted APT equation (4.6)

E.T./	$\hat{R}_1$ /	$\hat{R}_2$ /	NOLS	ITNOLS	NSUR	NOLS	ITNOLS	NSUR	NOLS	ITNOLS	NSUR
			-1.4571 3.3224	-1.4571 3.3224	-3.1433 2.2220	-1.2756 3.3725	-1.2756 3.3725	-3.7841 3.2779	-1.6185 3.6263	-1.6185 3.6263	-5.8533 3.1889
NOLS	-1.4571	3.3224	1.00								
ITNOLS	-1.4571	3.3224	1.00	1.00							
NSUR	-3.1433	2.2220	0.98	0.98	1.00						
NOLS	-1.2756	3.3725	0.99	0.99	0.97	1.00					
ITNOLS	-1.2756	3.3725	0.99	0.99	0.97	1.00	1.00				
NSUR	-3.7841	3.2779	0.98	0.98	0.99	0.97	0.97	1.00			
NOLS	-1.6185	3.6263	0.99	0.99	0.98	0.99	0.99	0.98	1.00		
ITNOLS	-1.6185	3.6263	0.99	0.99	0.98	0.99	0.99	0.98	1.00	1.00	
NSUR	-5.8533	3.1889	0.96	0.96	0.99	0.96	0.96	0.99	0.97	0.97	1.00

Panel C: Restricted-versus-unrestricted APT equation (4.6)

NOLS	ITNOLS	NSUR	NOLS	ITNOLS	NSUR	NOLS	ITNOLS	NSUR
0.55	0.55	0.91	-0.36	-0.36	0.57	0.53	0.53	0.81

TABLE 4.5

The mean Jensen estimates (α), their standard deviations (std.), the number of mutual funds with positive $\hat{\alpha}$, and the numbers of mutual funds with statistically significant positive and negative $\hat{\alpha}$ for the 146 equity mutual funds for various R values and the nonlinear seemingly unrelated regression (NSUR) technique for the restricted and unrestricted versions of equation (4.6) for the first and second subperiods are reported in panels A and B, respectively. The correlations (corr.) for the $\hat{\alpha}$'s for given R for the two subperiods are given in panel C. The residual covariance matrix for each subperiod was taken to be the full residual covariance matrix estimated for the entire period using NSUR.

	Restricted APT equation (4.6)									Unrestricted APT equation (4.6)						
	Jensen $\hat{\alpha}$		Abs. t-Values		Number of Funds					Jensen $\hat{\alpha}$		Abs. t-Values		Number of Funds		
						Sign.									Sign.	
R	Mean	Std.	Mean	Std.	$\hat{\alpha} > 0$	$\hat{\alpha} > 0$	$\hat{\alpha} < 0$	$\hat{R}_1$	$\hat{R}_2$	Mean	Std.	Mean	Std.	$\hat{\alpha} > 0$	$\hat{\alpha} > 0$	$\hat{\alpha} < 0$
Panel A:	**First Subperiod**															
-0.9147	-0.0054	0.0079	1.395	14.270	28	2	37	-3.1433	2.2220	-0.0543	0.0126	1.129	12 836	42	1	19
1.8280	0.0062	0.0851	1.283	13.686	123	34	0	-3.7841	3.2779	-0.0048	0.0132	1.035	12.295	14	1	15
4.3617	0.0053	0.0115	1.028	12.256	111	12	0	-5.8533	3.1889	-0.0031	0.0133	0.906	11.504	59	1	12
Panel B:	**Second subperiod**															
-0.9147	-0.0063	0.0104	1.383	14.209	30	2	41	-3.1433	2.2220	-0.0125	0.0126	1.495	14.775	14	2	40
1.8280	0.0081	0 0106	1.468	14.644	119	45	1	-3.7841	3.2779	-0.0115	0.0135	1.340	13.991	20	3	32
4.3617	0.0071	0.0295	1.051	12.385	115	13	0	-5.8533	3.1889	-0.0098	0.0138	1.119	12.785	2	2	18

Panel C: Correlation between the Jensen estimates for the two subperiods

$\hat{R}$	-0.9417	1.8280	4.3617			
$\hat{R}_1$				-3.1433	-3.7841	-5.8533
$\hat{R}_2$				2.2220	3.2779	3.1889
Corr.	0.568	0.390	0.390	0.592	0.572	0.578

TABLE 4.6

The means and standard deviations (std.) of the estimates of the macrofactor timing coefficients and of their absolute (abs.) t-values, the χ^2 values for a test of whether the factor timing coefficients are simultaneously equal to zero across portfolios, and the number of significant macrofactor timing coefficients for the 146 mutual funds for various $\hat{R}$ values and estimation techniques for the restricted version of equation (4.9) are reported in panel A. β_{P8}, β_{P9} and β_{P10} refer to the ability to time movements in innovations of the Canada/U.S. exchange rate, the orthogonal component of the Canadian composite index of ten leading indicators and the cross-product of these two variables, respectively. The mean Jensen estimates (α), their standard deviations (std.), the number of mutual funds with positive α, and the numbers of mutual funds with statistically significant positive and negative α for the 146 equity funds for various $\hat{R}$ values and estimation techniques for the restricted version of equation (4.9) are reported in panel B. Significance is measured at the 0.05 level, and is indicated by an "a" for the χ^2 test.

Estimation Method	NOLS	ITNOLS	NSUR	NOLS	ITNOLS	NSUR	NOLS	ITNOLS	NSUR
$\hat{R}$	1.5079	1.5079	-0.9417	0.8590	0.8590	1.8280	1.2584	1.2584	4.3617
Panel A: Macrofactor timing coefficient estimates and tests of their significance									
Absolute t-Values of $\hat{\beta}_{P8}$									
Mean	1.691	1.691	0.781	1.237	1.237	1.825	1.586	1.586	2.470
Std.	0.895	0.895	0.565	0.843	0.843	0.922	0.856	0.856	1.232
$\hat{\beta}_{P9}$									
Mean	0.920	0.920	1.302	1.222	1.222	0.890	0.948	0.948	0.753
Std.	0.575	0.575	0.686	0.724	0.724	0.553	0.585	0.585	0.511
$\hat{\beta}_{P10}$									
Mean	0.996	0.996	1.273	1.029	1.029	0.974	1.015	1.015	0.868
Std.	0.606	0.606	0.679	0.621	0.621	0.585	0.613	0.613	0.609
χ^2-test $H_o: \beta_{p8}=\beta_{p9}=\beta_{p10}=0$									
χ^2			31750[a]			84311[a]			38009[a]
Number of Funds									
$\hat{\beta}_{P8}$ and $\hat{\beta}_{P9}$ > 0									
$\hat{\beta}_{P8}$	142	142	108	79	79	142	122	139	144
$\hat{\beta}_{P9}$	119	119	134	131	131	117	122	122	103
$\hat{\beta}_{P8}$ and $\hat{\beta}_{P9}$ > 0 and statistically significant									
$\hat{\beta}_{P8}$	55	55	5	15	15	61	46	46	97
$\hat{\beta}_{P9}$	7	7	28	22	22	6	8	8	2
$\hat{\beta}_{P8}$ and $\hat{\beta}_{P9}$ < 0 and statistically significant									
$\hat{\beta}_{P8}$	0	0	0	5	5	0	0	0	1
$\hat{\beta}_{P9}$	0	0	0	0	0	0	0	0	0
$\hat{\beta}_{P10} \neq 0$ and statistically significant									
$\hat{\beta}_{P10}$	11	11	24	11	11	9	12	13	13
Panel B: Jensen estimates ($\hat{\alpha}$) and tests of their significance									
Jensen Estimates									
Mean	0.0032	0.0032	-0.0060	0.0013	0.0013	0.0042	0.0024	0.0024	0.0102
Std.	0.0099	0.0099	0.0106	0.0092	0.0092	0.0101	0.0098	0.0098	0.0123
Absolute t-Values									
Mean	1.375	1.374	1.384	1.066	1.066	1.468	1.264	1.264	1.871
Std.	0.931	0.931	0.946	0.760	0.760	1.008	0.862	0.862	1.364
Number of Funds									
$\hat{\alpha}$ > 0	115	115	23	101	101	119	111	111	124
$\hat{\alpha}$ > 0 and statistically significant (two-tailed test)	33	33	2	11	11	44	26	26	55
$\hat{\alpha}$ < 0 and statistically significant (two-tailed test)	5	5	35	7	7	3	5	5	2

TABLE 4.7

The means and standard deviations (std.) of the estimates of the macrofactor timing coefficients and of their absolute (abs.) t-values, the χ^2 values for a test of whether the factor timing coefficients are simultaneously equal to zero across portfolios, and the number of significant macrofactor timing coefficients for the 146 mutual funds for various $\hat{R}$ values and estimation techniques for the unrestricted version of equation (4.9) are reported in panel A. β_{P8}, β_{P9} and β_{P10} refer to the ability to time movements in innovations of the Canada/U.S. exchange rate, the orthogonal component of the Canadian composite index of ten leading indicators and the cross-product of these two variables, respectively. The mean Jensen estimates (α), their standard deviations (std.), the number of mutual funds with positive α, and the numbers of mutual funds with statistically significant positive and negative α for the 146 equity funds for various $\hat{R}$ values and estimation techniques for the unrestricted version of equation (4.9) are reported in panel B. Significance is measured at the 0.05 level, and is indicated by an "a" for the χ^2 test.

Estimation Method	NOLS	ITNOLS	NSUR	NOLS	ITNOLS	NSUR	NOLS	ITNOLS	NSUR
$\hat{R}_1$	-1.4571	-1.4571	-3.1433	-1.2756	-1.2756	-3.7841	-1.6185	-1.6185	-5.8533
$\hat{R}_2$	3.3224	3.3224	2.2220	3.3725	3.3725	3.2779	3.6263	3.6263	3.1889
Panel A: Macrofactor timing coefficient estimates and tests of their significance									
Absolute t-value of $\hat{\delta}_{P8}$									
Mean	0.778	0.778	1.058	0.786	0.786	1.068	0.781	0.781	1.263
Std.	0.599	0.599	0.826	0.593	0.593	0.858	0.609	0.609	0.966
$\hat{\delta}_{P9}$									
Mean	1.119	1.118	1.356	1.096	1.096	1.369	1.119	1.119	1.488
Std.	0.627	0.627	0.704	0.622	0.622	0.663	0.625	0.625	0.693
$\hat{\delta}_{P10}$									
Mean	1.404	1.404	1.607	1.375	1.375	1.770	1.433	1.433	1.945
Std.	0.748	0.748	0.842	0.737	0.737	0.829	0.760	0.760	0.861
χ^2-test of H_0: $\delta_{P8} = \delta_{P9} = \delta_{P10} = 0$									
χ^2			50273[a]			21753[a]			17132[a]
Number of Funds									
$\hat{\delta}_{P8}$ and $\hat{\delta}_{P9}$ > 0									
$\hat{\delta}_{P8}$	91	91	57	97	97	44	85	85	32
$\hat{\delta}_{P9}$	133	133	139	131	131	139	132	132	139
$\hat{\delta}_{P8}$ and $\hat{\delta}_{P9}$ > 0 and statistically significant									
$\hat{\delta}_{P8}$	5	5	10	5	5	2	3	3	2
$\hat{\delta}_{P9}$	13	13	30	12	12	28	12	12	34
$\hat{\delta}_{P8}$ and $\hat{\delta}_{P9}$ < 0 and statistically significant									
$\hat{\delta}_{P8}$	3	3	15	3	3	20	3	3	29
$\hat{\delta}_{P9}$	1	1	0	1	1	1	1	1	1
$\hat{\delta}_{P10} \neq 0$ and statistically significant									
$\hat{\delta}_{P10}$	33	33	54	32	32	60	36	36	66
Panel B: Jensen estimates ($\hat{\alpha}$) and tests of their significance									
Jensen Estimates									
Mean	-0.0098	-0.0098	-0.0160	-0.0090	-0.0090	-0.0189	-0.0106	-0.0106	-0.0242
Std.	0.0110	0.0110	0.0125	0.0110	0.0110	0.0132	0.0112	0.0112	0.0147
Absolute t-values									
Mean	1.933	1.933	2.843	1.796	1.797	3.019	2.029	2.029	3.105
Std.	1.223	1.223	1.315	1.115	1.115	1.702	1.265	1.265	1.675
Number of Funds									
$\hat{\alpha}$ > 0	18	18	18	20	20	8	15	15	6
$\hat{\alpha}$ > 0 and statistically significant (two-tailed test)	2	2	2	2	2	2	2	2	0
$\hat{\alpha}$ < 0 and statistically significant (two-tailed test)	66	66	93	63	63	104	72	72	106

TABLE 5.1

The mean beta estimates for M-CAPM (5.6) for the value-weighted (VW) and the equally-weighted (EW) TSE-Western indexes for the 146 equity mutual funds for various estimates of the proportionality parameter, R, and estimation method (E.M.) are reported below. The associated mean t-values are reported in the parentheses. The values of $\hat{R}$ are from Koutoulas and Kryzanowski (1991). NOLS, ITNOLS, NSUR and INTSUR refer to nonlinear ordinary least squares, iterative nonlinear ordinary least squares, nonlinear seemingly unrelated regression, and iterative nonlinear seemingly unrelated regression, respectively.

$\hat{R}$	E.M.	Beta Estimates VW	Beta Estimates EW	R^2-values VW	R^2-values EW
0.8590	NSUR	0.647 (9.986)	0.606 (7.183)	0.534	0.387
	ITNSUR	0.647 (9.986)	0.606 (7.183)	0.534	0.387
1.0579	NOLS	0.452 (6.887)	0.429 (5.267)	0.369	0.261
	ITNOLS	0.452 (6.887)	0.429 (5.267)	0.369	0.261
1.2584	NOLS	0.522 (7.857)	0.495 (5.933)	0.428	0.306
	ITNOLS	0.522 (7.857)	0.495 (5.933)	0.428	0.306
1.8280	NSUR	0.374 (5.975)	0.365 (5.241)	0.304	0.210
	ITNSUR	0.374 (5.975)	0.365 (5.241)	0 304	0.210
4.3617	NSUR	0.104 (2.588)	0.083 (1.720)	0.083	0.041
	ITNSUR	0.104 (2.588)	0.083 (1.720)	0.083	0.041

TABLE 5.2

The mean Jensen estimates ($\hat{\alpha}$'s), the mean of their respective absolute t-values, and their standard deviations (std.) for the 146 equity mutual funds for various estimates of the proportionality parameters ($\hat{R}$'s) and estimation methods (E.M.'s) for the M-CAPM (5.6) for the value-weighted (VW) and equally-weighted (EW) TSE-Western indexes are reported below. Tests of whether the Jensen estimates are simultaneously equal to zero across portfolios (test 1) and whether the Jensen estimates are equivalent across portfolios (test 2) are also reported below. The number of mutual funds with positive $\hat{\alpha}$'s, and the number of mutual funds with statistically significant positive and negative $\hat{\alpha}$'s are also reported below. NOLS, ITNOLS, NSUR and ITNSUR refer to nonlinear ordinary least squares, iterative nonlinear ordinary least squares, nonlinear seemingly unrelated regression, and iterative nonlinear seemingly unrelated regression, respectively. Significance (as reported by an "a") is measured at the 5% level.

E.M. $\hat{R}$	NOLS 0.8590	ITNOLS 0.8590	NOLS 1.2584	ITNOLS 1.2584	NOLS 1.5079	ITNOLS 1.5079	NSUR 1.8280	ITNSUR 1.8280	NSUR 4.3617	ITNSUR 4.3617
				Jensen Estimates for the VW Index						
Mean	-0.0211	-0.0211	-0.0242	-0.0242	-0.0247	-0.0247	-0.0243	-0.0227	-0.0134	-0.0134
Std.	0.0074	0.0074	0.0081	0.0081	0.0082	0.0082	0.0083	0.0088	0.0074	0.0074
				Jensen Estimates for the EW Index						
Mean	-0.0177	-0.0177	-0.0209	-0.0209	-0.0214	-0.0214	-0.0228	-0.0210	-0.0089	-0.0089
Std.	0.0078	0.0078	0.0086	0.0086	0.0088	0.0088	0.0089	0.0091	0.0080	0.0080
				Absolute t-values for the Jensen Estimates for the VW Index						
Mean	4.862	4.862	4.497	4.497	4.137	4.137	3.276	3.276	1.556	1.556
Std.	1.529	1.529	1.194	1.194	1.058	1.058	0.993	0.993	0.552	0.552
				Absolute t-values for the Jensen Estimates for the EW Index						
Mean	3.427	3.427	3.395	3.395	3.181	3.181	2.846	2.846	0.965	1.965
Std.	1.222	1.222	1.055	1.055	0.978	0.978	0.888	0.888	0.582	0.582
				χ^2-tests using the VW Index						
χ^2 (test 1)							627[a]		447[a]	
χ^2 (test 2)							708[a]		545[a]	
				χ^2-tests using the EW Index						
χ^2 (test 1)							534[a]		370[a]	
χ^2 (test 2)							610[a]		428[a]	
				Number of Funds						
$\hat{\alpha} > 0$										
VW	2	2	2	2	2	2	2	2	5	5
EW	2	2	2	2	2	2	2	2	10	10
$\hat{\alpha} > 0$ and statistically significant[a]										
VW	0	0	0	0	0	0	0	0	0	0
EW	0	0	0	0	0	0	0	0	0	0
$\hat{\alpha} < 0$ and statistically significant[a]										
VW	142	142	143	141	141	141	140	140	37	37
EW	132	132	174	135	133	133	135	122	9	9

TABLE 5.3

The correlation matrices for the Jensen estimates ($\hat{\alpha}$'s) for various estimation methods (E.M.'s) and proportionality parameter estimates ($\hat{R}$) for the M-CAPM (5.7) based on the value-weighted and equally-weighted TSE-Western market indexes are reported in Panels A and B, respectively. NOLS, ITNOLS, NSUR and ITNSUR refer to nonlinear ordinary least squares, iterative nonlinear ordinary least squares, nonlinear seemingly unrelated regression, and iterative nonlinear seemingly unrelated regression, respectively.

Panel A: M-CAPM (5.7) based on the value-weighted TSE-Western index

NOLS 0.8590	1.00									
ITNOLS 0.8590	1.00	1.00								
NOLS 1.2584	0.99	0.99	1.00							
ITNOLS 1.2584	0.99	0.99	1.00	1.00						
NOLS 1.5079	0.99	0.99	0.99	0.99	1.00					
ITNOLS 1.5079	0.99	0.99	0.99	0.99	1.00	1.00				
NSUR 1.8280	0.98	0.98	0.99	0.99	0.99	0.99	1.00			
ITNSUR 1.8280	0.98	0.98	0.99	0.99	0.99	0.99	1.00	1.00		
NSUR 4.3617	0.93	0.93	0.95	0.95	0.96	0.96	0.97	0.97	1.00	
ITNSUR 4.3617	0.93	0.93	0.95	0.95	0.96	0.96	0.97	0.97	1.00	1.00

Panel B: M-CAPM (5.7) based on the equally-weighted TSE-Western index

NOLS 0.8590	1.00									
ITNOLS 0.8590	1.00	1.00								
NOLS 1.2584	0.99	0.99	1.00							
ITNOLS 1.2584	0.99	0.99	1.00	1.00						
NOLS 1.5079	0.99	0.99	0.99	0.99	1.00					
ITNOLS 1.5079	0.99	0.99	0.99	0.99	1.00	1.00				
NSUR 1.8280	0.98	0.98	0.99	0.99	0.99	0.99	1.00			
ITNSUR 1.8280	0.98	0.98	0.99	0.99	0.99	0.99	1.00	1.00		
NSUR 4.3617	0.91	0.91	0.94	0.94	0.94	0.94	0.96	0.96	1.00	
ITNSUR 4.3617	0.91	0.91	0.94	0.94	0.95	0.95	0.96	0.96	1.00	1.00

TABLE 5.4

The mean Jensen estimates (α's), the mean absolute t-values, their respective standard deviations (std.), the number of mutual funds with positive α, and the numbers of mutual funds with statistically significant positive and negative α for the 146 equity mutual funds for various estimates of the proportionality parameter (R) for M-CAPM (5.6) for the value-weighted (VW) and equally-weighted (EW) TSE-Western indexes for the first and second subperiods are reported in panels A and B, respectively. The correlations for the α's for a given $\hat{R}$ across the two subperiods are given in panel C. The residual covariance matrix for each subperiod was taken to be the full residual covariance matrix estimated for the entire period using NSUR. Significance (as represented by an "a") is measured at the 5% level.

$\hat{R}$	Index	Jensen Estimates		Absolute t-values		Number of Funds		
							Significant[a]	
		Mean	Std	Mean	Std	$\hat{\alpha} > 0$	$\hat{\alpha} > 0$	$\hat{\alpha} < 0$
Panel A: First subperiod								
1.8280	VW	-0.0179	0.0074	1.377	0.697	4	0	72
1.8280	EW	-0.0135	0.0078	1.429	0.687	0	4	30
4.3617	VW	-0.0159	0.0072	1.382	0.496	4	0	18
4.3617	EW	-0.0121	0.0076	0.973	0.519	5	0	7
Panel B: Second subperiod								
1.8280	VW	-0.0327	0.0114	3.286	0.779	2	0	134
1.8280	EW	-0.0349	0.0123	3.224	0.839	1	0	134
4.3617	VW	-0.0059	0.0098	0.569	0.439	24	2	3
4.3617	EW	-0.0027	0.0108	0.449	0.441	35	3	0

Panel C: Correlations between the Jensen estimates for the two subperiods

Index	$\hat{R}$ 1.8280	4.3617
VW	0.639	0.441
EW	0.627	0.507

TABLE 5.5

The means and standard deviations (std.'s) of the absolute and absolute bootstrapped t-values of the coefficient θ_p (which measures the ability to time the movements of the innovations in the returns of the market index), χ^2 test values of whether the timing coefficients are simultaneously equal to zero across portfolios, and the number of significant market timing coefficients for the 146 mutual funds for various $\hat{R}$ values and estimation methods (E.M.'s) for the M-CAPM (5.7) for the value-weighted (VW) and equally-weighted (EW) TSE-Western indexes are reported in panel A. The mean Jensen estimates ($\hat{\alpha}$), the mean absolute t-values, their standard deviations (std.'s), the number of mutual funds with positive $\hat{\alpha}$, and the numbers of mutual funds with statistically significant positive and negative $\hat{\alpha}$ for the 146 equity funds for various $\hat{R}$ values and estimation methods for the M-CAPM (5.7) for the value-weighted (VW) and equally-weighted (EW) TSE-Western indexes are reported in panel B. Significance (as represented by an "a") is measured at the 5% level.

E.M. $\hat{R}$	NOLS 0.8590	ITNOLS 0.8590	NOLS 1.2584	ITNOLS 1.2584	NOLS 1.5079	ITNOLS 1.5079	NSUR 1.8250	ITNSUR 1.8250	NSUR 4.3617	ITNSUR 4.3617
Panel A: The absolute t-values for the market timing coefficients and tests of their significance										
Absolute t-values of the estimated coefficient, $\hat{\theta}_p$, for the VW Index										
Mean	7.565	7.565	8.345	8.345	8.204	8.204	9.144	9.144	7.759	7.759
Std.	3.033	3.033	3.358	3.358	3.169	3.169	3.296	3.296	1.988	1.388
Absolute t-values of the bootstrapped estimated coefficient, $\hat{\theta}_p$, for the VW Index										
Mean	7.676		8.981		8.345		9.249		7.980	
Std.	3.342		3.594		3.223		3.258		2.054	
Absolute t-values of the estimated coefficient, $\hat{\theta}_p$, for the EW Index										
Mean	5.216	5.216	6.382	6.382	6.913	6.913	7.405	7.405	7.825	7.825
Std.	1.521	1.521	1.810	1.810	1.942	1.942	2.058	2.058	1.999	1.399
Absolute t-values of the bootstrapped estimated coefficient, $\hat{\theta}_p$, for the EW Index										
Mean	5.466		6.435		7.011		7.788		7.789	
Std.	1.678		2.028		2.078		2.198		2.201	
χ^2-test										
VW							10020[a]		3949[a]	
EW							16260[a]		12624[a]	
Number of Funds										
$\hat{\theta}_p > 0$										
VW	0	0	0	0	0	0	0	0	0	0
EW	0	0	0	0	0	0	0	0	0	0
$\hat{\theta}_p > 0$ and statistically significant[a]										
VW	0	0	0	0	0	0	0	0	0	0
EW	0	0	0	0	0	0	0	0	0	0
$\hat{\theta}_p < 0$ and statistically significant[a]										
VW	145	145	146	146	146	146	146	146	146	146
EW	145	145	145	145	146	146	146	146	146	146
Panel B: Jensen estimates ($\hat{\alpha}$) and tests of their significance										
Jensen Estimates for the VW Index										
Mean	-0.0107	-0.0107	-0.0159	-0.0159	-0.0157	-0.0157	-0.0227	-0.0227	-0.0367	-0.0367
Std.	0.0064	0.0064	0.0072	0.0072	0.0087	0.0087	0.0082	0.0082	0.0108	0.0108
Jensen Estimates for the EW Index										
Mean	-0.0049	-0.0049	-0.0091	-0.0091	-0.0119	-0.0119	-0.0146	-0.0146	-0.0288	-0.0288
Std.	0.0068	0.0068	0.0074	0.0074	0.0079	0.0079	0.0082	0.0082	0.0105	0.0105
Absolute t-values for the Jensen Estimates for the VW Index										
Mean	3.172	3.172	4.305	4.305	3.569	3.569	5.232	5.232	5.132	5.132
Std.	1.608	1.608	1.888	1.888	2.088	2.088	1.991	1.991	1.483	1.483
Absolute t-values for the Jensen Estimates for the EW Index										
Mean	1.140	1.140	1.822	1.822	2.235	2.235	2.623	2.523	3.820	3.820
Std.	0.897	0.897	1.051	1.051	1.092	1.092	1.167	1.167	1.257	1.257
Number of Funds										
$\hat{\alpha} > 0$										
VW	4	4	2	2	2	2	2	2	2	2
EW	25	25	6	6	4	4	3	3	2	2
$\hat{\alpha} > 0$ and statistically significant[a]										
VW	1	1	0	0	0	0	0	0	0	0
EW	2	2	1	1	0	0	0	0	0	0
$\hat{\alpha} < 0$ and statistically significant[a]										
VW	113	113	134	134	107	107	140	140	142	142
EW	71	71	63	63	82	82	96	96	138	138

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APPENDIX I

Proof that the global portfolio of mimicking portfolios is mean-variance efficient when the mimicking portfolios are estimated using the minimum idiosyncratic method.

A regrouping of the miminum idiosyncratic risk mimicking (MIRM) portfolios into a global, mean-variance (E-V) efficient portfolio is necessary if the MIRM portfolios are to be E-V efficient benchmarks for portfolio performance inference using the Z and PPW scores. To demonstrate this, let the return at time t, R^g_t, on the global portfolio, which is a linear combination of portfolios of risky and risk-free assets, be:

$$R^g_t = R'_t Q + R_f(1 - \underline{1}Q) \tag{I.1}$$

where Q is a N x 1 vector of global portfolio weights for the N risky assets. To derive the E-V efficient portfolio, find the Q that solves:

$$\text{Min } Q'VQ \tag{I.2}$$

$$\text{s.t. } \overline{R^g} = \overline{R'}Q + \overline{R_f}(1 - \underline{1}Q)$$

where V is the N x N variance-covariance matrix of security returns. From Grinblatt and Titman (1987), matrix Q can be defined as:

$$Q = A'X \tag{I.3}$$

where X is a K x 1 vector of weights of the mimicking portfolios in the global portfolio, and A is a K x N matrix of mimicking portfolio weights. Substituting (I.3) into (I.2), and constraining the security excess returns to be priced by the exact APT, yields:

$$L(AX,\Theta) = X'A'VAX - 2\Theta[(\bar{R}^g - \bar{R}_f) - (B\Gamma + e)] \tag{I.4}$$

where Θ is the lagrangian multiplier; Γ is 1 x K vector of APT arbitrage portfolios; and e is a N x 1 vector of APT residuals. According to Grinblatt and Titman, when the APT pricing equation holds, the first-order condition for the E-V efficiency of the global portfolio is:

$$A'X = D^{-1}B(B'D^{-1}B)^{-1}\ B'A'X \tag{I.5}$$

It is easy to show that $A = (B'D^{-1}B)^{-1}B'D^{-1}$ is a solution to (I.5). If the MIRM portfolios are to be consistent with E-V efficiency of the global portfolio, A^{mir} must be a solution to the first-order condition (I.5). This can be shown as follows. Let B_1 be the matrix where all the stock returns load with one on the first factor, and the remaining columns contain factor loadings obtained from ML factor analysis. Let $A_1=(B_1'D^{-1}B_1)^{-1}B_1'D^{-1}$ be the corresponding K x N matrix of portfolio weights, where the first column vector of A_1 contains weights that are minimum idiosyncratic. Stated differently, $A_1'=\{a_1^{mir}, a_2, \ldots, a_k\}$, where a_1^{mir} is the N x 1 vector of MIRM portfolio weights, and $a_2, \ldots, a_k$ are the N x 1 vectors of GLS estimated weights of the mimicking portfolios. Since A_1 is consistent with (I.5), the return on the corresponding global portfolio of mimicking portfolios is given by:

$$R^g_{1t}=R_t'Q_1=R_t'A_1'X^1 \tag{I.6}$$

This procedure can be used to estimate each of the K MIRM portfolios. This sequential procedure generates K global portfolios. Since $A_j=(B_j'D^{-1}B_j)^{-1}B_j'D^{-1}$ is a solution to (I.5), all the K global portfolios are E-V efficient. Thus, any linear combination of the K global portfolios will also be a E-V efficient portfolio, R^g_{It}, given by:

$$R^g_{It}=k_1R^g_{1t} + k_2R^g_{2t} +\ldots+ k_kR^g_{kt} \tag{I.7}$$

where we assume that $k_i=k_j$ for all i and j. Using the value of R^g_{jt} from (I.6) in (I.7) yields:

$$R^g_{It}=k_1R_t'A_1'X + k_2R_t'A_2'X +\ldots + k_kR_t'A_k'X \tag{I.8}$$

Because the resulting global portfolio is a scalar and $k_i=k_j$, the different vectors of portfolio weights contained in each matrix A_j in (I.8) can be permutated across the j without altering the value of R^g_{It}. This is possible provided that each column vector initially in the matrix A_j' occupies the same column position in the matrix, A^*_j, that contains the permuted column vectors. Thus, all the vectors of MIRM weights can be regrouped into the same matrix of portfolio weights, $A^{mir\prime}$, where the weight vector of the jth column is associated with the returns of the jth MIRM portfolio. The permutations in the portfolio weight vectors imply that (I.8) becomes:

$$R^g_{It}=k_1R_t'A^{mir\prime}X + k_2R_t'A^{*\prime}_2X +\ldots + k_kR_t'A^{*\prime}_kX \tag{I.9}$$

It then follows that R^g_{It} is E-V efficient since it remains unaltered by the permutation in the mimicking portfolio weight vectors, and that the K global portfolios (including the one based on A^{mir}) are E-V efficient. Furthermore, a global portfolio formed from the K MIRM portfolios is also E-V efficient.

APPENDIX II

The bootstrap algorithm used to obtain unbiased estimates of the first and second moments of SH_v for the multivariate Jobson-Korkie Z score given by equation (3.1).

Define the J-K Z score obtained from a bootstrapping procedure, Z^{bs}, as:

$$Z^{bs} = \frac{SH}{(e'\Phi^{bs}e)^{1/2}} \sim N(0,1) \qquad \text{(II.1)}$$

where Φ^{bs} is the V (variance-covariance matrix of returns) based on the k samples of bootstrapped $sh_q^*(b)$ (where $sh_q^*(b)$ is the qth element of the k x 1 vector SH_r given that $SH=e'SH_r$, see equation (3.1)), and q=1,...,K and b=1,...,L. Let r_{qt} be the monthly excess return of portfolio q at time t. For each month, assume that two portfolios, i and q, have bivariate, normally distributed monthly returns of $P_i=[r_{i1},...,r_{iT}]$ and $P_q=[r_{q1},...,r_{qT}]$, where T is the number of available returns (herein T=7).

The specific bootstrap algorithm used herein is as follows:

1) Estimate the empirical return distributions of portfolios i and q by putting a mass probability of 1/T on each return r_{it} and r_{qt}.

2) Using a random number generator, draw L bootstrap samples $P_i^*(1), P_q^*(1)$, $P_i^*(2), P_q^*(2)$, ..., $P_i^*(L), P_q^*(L)$ where $P_i^*(b)=[r_{i1}^*,...,r_{iT}^*]$ and $P_q^*(b)=[r_{q1}^*,...,r_{qT}^*]$, and each r_{it}^* and r_{qt}^* ,for t=1,...T, are drawn randomly with replacement from

the observed values of $[r_{i1},\dots,r_{iT}]$ and $[r_{q1},\dots,r_{qT}]$, respectively.

3) For each pairing of bootstrap samples i and q, calculate the statistic $sh_q^*(b)=(\sigma_q u_i-\sigma_i u_q)$.

4) Repeat steps 2 and 3 a large number of (L) times.

5) Steps 1 through 4 are performed k times in order to calculate the statistics $sh_1^*(b)=(\sigma_1 u_i-\sigma_i u_1)$, $sh_2^*(b)=(\sigma_2 u_i-\sigma_i u_2),\dots,sh_k^*(b)=(\sigma_k u_i-\sigma_i u_k)$.

Since portfolio i is compared to K portfolio benchmarks, the bootstrapping procedure generates K samples of size L (where L is the number of bootstrapping replications) of the statistic $sh_q^*(b)$, where $q=1,\dots,K$ and $b=1,\dots,L$. From these K samples, the K x K matrix, Φ^{b*}, has an i,j element defined as:

$$\Phi^{b*}_{i,j}=(1/L-1)\ \Sigma^L_{i=1}\Sigma^L_{j=1}\ (sh_{ix}-E(sh_x))(sh_{jy}-E(sh_y))$$

For most situations, Efron and Tibshirani (1986) contend that L should be in the range of 50 to 200. A value of 200 is used herein.

APPENDIX III

The bootstrap algorithm used to obtain an estimate of the standard deviation of the market timing coefficient, Θ_p, for M-CAPM (5.7) is detailed below.

Step 1: Estimate M-CAPM (5.7) for a postulated value of R and estimation method in order to obtain $\hat{\alpha}_p$, $\hat{\beta}_p$ and $\hat{\Theta}_p$. The residuals of (5.7) follow an empirical distribution such that a mass probability of 1/T (where T corresponds to the number of observations) is attributed to e_{pt}.

Step 2: A bootstrapped sample of $R_{pt}^*(B)$ (where p=1,2,...,146; t=1,2,...,81; and B corresponds to the number of bootstrapped replications) is obtained by computing:

$$R_{pt}^* - R_{Ft} = \hat{\alpha}_p + \hat{\beta}_p \delta_{mt} + \hat{\beta}_p \{R \cdot \sigma_{mt}\} + \hat{\Theta}_p \{R \cdot \sigma_{mt}\} + e_{pt}^*$$

where e_{pt}^* are randomly drawn with replacement from the sample $\{e_{p1},...,e_{p81}\}$ and $\hat{\alpha}_p$, $\hat{\beta}_p$ and $\hat{\Theta}_p$ are obtained from step 1.

Step 3: For each bootstrapped sample of $R_{pt}^*(B)$, M-CAPM (5.7) is estimated as:

$$R_{pt}^* - R_{Ft} = \alpha_p^* + \beta_p^* \delta_{mt} + \beta_p^* \{R \cdot \sigma_{mt}\} + \Theta_p^* \{R \cdot \sigma_{mt}\} + u_{pt}$$

Step 4: The bootstrapped standard deviation of the parameter Θ_p (which is denoted as $s^*_{\Theta p}$), is computed using the sample of estimated Θ_p^* that contains B observations. The bootstrapped t-value is given by $\hat{\Theta}_p/s^*_{\Theta p}$.

Based on Efron and Tibishrani (1986), steps 2 and 3 are repeated 1000 times (B=1000). Steps 1 through 4 are repeated for each combination of $\hat{R}$ value and estimation method.

FOOTNOTES TO APPENDIX I

1. Without loss of generality, assume that $X'\underline{1}=1$. Since $A^{air}\underline{1}=\underline{1}$, then $Q'\underline{1}=\underline{1}$ and the global portfolio is composed exclusively of risky assets.