Analyzing Stock Selection Models in Emerging Markets

AUGUST 2007

OVERVIEW

McKinley Capital is a Global Growth Specialist with a quantitative focus.

From December 1990 through January 2007, the Morgan Stanley Capital International Emerging Markets Index (MSCI EM) registered substantially higher returns and Sharpe Ratios than the Morgan Stanley Capital International Europe, Australasia, and Far East Index (MSCI EAFE) or the U.S. as measured by the Russell 3000 Index. This outperformance leads one to ask, "How far can they go?" The simple answer is that it is impossible to guess how far emerging markets can go when they have outperformed for an unprecedented six calendar years in a row as well as for the last five- and ten-year periods.[1] A more appropriate question is, "How does one protect against the inevitable downturn in emerging markets when it comes?" To answer this question, it seems fitting to begin with some background information and then arrange the research around five further questions:

- Do developed markets' factors work in emerging markets?
- How important is liquidity screening in emerging markets?
- Do developed markets' portfolio construction techniques work in emerging markets?
- Do your emerging markets' returns pass the Markowitz-Xu Data Mining Corrections test?
- How do emerging markets' returns and strategies compare to similar strategies in other stock universes?

Based on these five questions, a plan sponsor may be better able to answer his or her own question, "Is my dedicated emerging markets allocation strong enough to withstand a downturn or are there holes that need to be addressed?"

[1] See the overview of the EM space by McKinley Capital Management, Inc. entitled "Investment Analysis - Global Emerging Markets," March 2007.

BACKGROUND INFORMATION

As reflected in Exhibit 1, emerging markets registered higher geometric returns than MSCI All Country World, MSCI EAFE, and Russell 3000 securities from December 1990 through January 2007. While MSCI EM also posted higher standard deviations, they still produced the best Sharpe Ratios of all four benchmarks. Importantly, the correlation between the MSCI EM and Russell 3000 indices is 0.351 during the period. Thus, MSCI EM offered an effective diversification opportunity for U.S. investors as well.

Exhibit 1: Universe Geometric Means (GM) and Sharpe Ratios (SR)
December 1990 to January 2007

	GM	SR
MSCI All Country World	7.36	.261
MSCI EM	9.97	.448
MSCI EAFE	5.99	.221
Russell 3000	9.66	.436

Basic Statistical Properties of Economic Series

Is the past positive spread of the MSCI EM Index's returns to the Russell 3000 Index's returns likely to continue? We used time series analysis to attempt to answer this question.

The time series modeling of Box and Jenkins involves identifying, estimating, and forecasting stationary (or series transformed to stationarity) series through the analysis of the series autocorrelation and partial autocorrelation functions.[2] The autocorrelation function examines the correlations of the current value of the economic times series and its previous k-lags. That is, the correlation of a daily series, of shares, or other assets can be measured by calculating the following:

$$p_{jt} = a + b\, p_{jt-1} \quad (1)$$

where p_{jt} = today's price of stock j;
p_{jt-1} = yesterday's price of stock j;
and b is the correlation coefficient.

In a daily shares price series, b is quite large, often approaching a value of 1.00. As the number of lags, or previous number of periods increases, the correlation tends to fall. The decrease is usually very gradual.

[2] This section draws heavily from Box and Jenkins, *Time Series Analysis*, Chapters 2 and 3.

The partial autocorrelation function examines the correlation between p_{jt} and p_{jt-2}, holding constant the association between p_{jt} and p_{jt-1}. If a series follows a random walk, the correlation between p_{jt} and p_{jt-1} is one, and the correlation between p_j and p_{jt-2}, holding constant the correlation of p_{jt} and p_{jt-1}, is zero. Random walk series are characterized with decaying autocorrelation functions and a partial autocorrelation function with a "spike" at lag one, and zeros thereafter. Stationarity implies that the joint probability [p(Z)] distribution $P(Z_{t1},Z_{t2})$ is the same for all times t, t_1, and t_2 where the observations are separated by a constant time interval. The autocovariance of a time series at some lag or interval, k, is defined to be the covariance between Z_t and Z_{t+k}

$$_k = \mathrm{cov}[Z_t, Z_{t+k}] = E[(Z_t - \mu)(Z_{t+k} - \mu)]. \quad (2)$$

The autocovariance should be standardized in the same fashion that the covariance is standardized in traditional regression analysis before quantifying the statistically significant association between Z_t and Z_{t+k}. The autocorrelation of a time series is the standardization of the autocovariance of a time series relative to the variance of the time series, and the autocorrelation at lag k, ρ_k, is bounded between +1 and -1.

$$\rho_k = \frac{E[(Z_t - \mu)(Z_{t+k} - \mu)]}{\sqrt{E[(Z_t - \mu)^2]E[(Z_{t+k} - \mu)^2]}}$$

$$= \frac{E[(Z_t - \mu)(Z_{t+k} - \mu)]}{\sigma_Z^2} = \frac{r_k}{r_0} \quad (3)$$

The autocorrelation function of the process, {ρk}, represents the plotting of r_k versus time, the lag of k. The autocorrelation function is symmetric about series; thus, $\rho_k = \rho_{-k.}$ Accordingly, time series analysis normally examines only the positive segment of the autocorrelation function. The autocorrelation function may be referred to as the correlogram. The statistical estimates of the autocorrelation function are calculated from a finite series of N observations, Z_1, Z_2, Z_3, …, Z_n. The statistical estimate of the autocorrelation function at lag k, r_k, is found by

$$r_k = \frac{C_k}{C_0}$$

where

$$C_k = \frac{1}{N}\sum_{t=1}^{N-k}(Z_t - \bar{Z})(Z_{t+k} - \bar{Z}), k = 0,1,2,..., K.$$

C_k is the statistical estimate of the autocovariance function at lag k. In identifying and estimating parameters in a time series model, effort is made to identify orders (lags) of the time series that are statistically different from zero. The implication of testing whether an autocorrelation estimate is statistically different from zero leads back to the t-tests used in regression analysis to examine the statistically significant association between variables. A standard error of the autocorrelation estimate should be developed such that a formal t-test can be performed to measure the statistical significance of the autocorrelation estimate. Such a standard error, S_e, estimate was found by Bartlett, and in large samples, is approximated by

$$Var[r_k] \cong \frac{1}{N}, \text{ and}$$

$$S_e[r_k] \cong \frac{1}{\sqrt{N}}. \qquad (4)$$

A second statistical estimate useful in time series analysis is the partial autocorrelation estimate of coefficient j at lag k, ϕ_{kj}. The partial autocorrelations are found in the following manner:

$$\rho_j = \phi_{kl} p_{j-1} + \phi_{k2} p_{j-2} + \ldots + \phi_{k(k-1)}\, p_{jk-1} + \phi_{kk} p_{j-k} \qquad j = 1,2,\ldots,k$$

or

$$\begin{bmatrix} 1 & \rho_1 & \rho_2 & \cdots & \rho_{k-1} \\ \rho_1 & 1 & \rho_1 & \cdots & \rho_{k-2} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ \rho_{k-1} & \rho_{k-2} & \rho_{k-3} & \cdots & 1 \end{bmatrix} \begin{bmatrix} \phi_{k1} \\ \phi_{k2} \\ \vdots \\ \phi_{kk} \end{bmatrix} \begin{bmatrix} \rho_1 \\ \rho_2 \\ \vdots \\ \rho_k \end{bmatrix}$$

The partial autocorrelation function is estimated by expressing the current autocorrelation function estimates as a linear combination of previous orders of autocorrelation estimates

$$\hat{r}_1 = \hat{\phi}_{k1^r\, j-1} + \hat{\phi}_{k2^2\, j-2} + \ldots + \hat{\phi}_{k(k-1)^r\, j+k-1} + \hat{\phi}_{kk^2\, j-k} \qquad j = 1,2,\ldots,k.$$

The standard error of the partial autocorrelation function is approximately

$$Var[\hat{\phi}_{kk}] \cong \frac{1}{N},$$

and

$$S_e[\phi_{kk}] \cong \frac{1}{\sqrt{N}}.$$

The Autoregressive and Moving Average Processes

A stochastic process, or time series, can be repeated as the output resulting from a white noise input, α_t.[3]

$$\tilde{Z}_t = \alpha_t + \psi_1 \alpha_{t-1} + \psi_2 \alpha_{t-2} + \ldots$$

$$= \alpha_t + \sum_{j=1}^{\infty} \psi_j a_{t-j} \ . \qquad (5)$$

The filter weight, ψ_j, transforms input into the output series. The output, $\tilde{Z}_t$, is normally expressed as a deviation of the time series from its mean, μ, or origin

$$\tilde{Z}_t = Z_t - \mu.$$

The general linear process leads to the representation of the output of a time series, $\tilde{Z}_t$, as a function of the current and previous value of the white noise process, α_t which may be represented as a series of shocks. The white noise process, α_t, is a series of random variables characterized by

$$E[\alpha_t] \cong 0$$

$$Var[\alpha_t] = \sigma_\alpha^2$$

$$\gamma_k = E[\alpha_t \alpha_{t+k}] = \sigma_\alpha^2 \qquad k \neq 0$$

$$0 \qquad k = 0.$$

The autocorrelation function of a linear process may be given by

$$\gamma_k = \sigma_\alpha^2 \sum_{j=0}^{\infty} \psi_j \psi_{j+k} .$$

The backward shift operator, B, is defined as $BZ_t = Z_{t-1}$ and $B^j Z_t = Z_{t-j}$. The autocorrelation generating function may be written as

$$\gamma(B) = \sum_{k=-\infty}^{\infty} \gamma_k B^k$$

[3] Please see Box and Jenkins, *Time Series Analysis*, Chapter 3, for the most complete discussion of the ARMA (p,q) models.

For stationarity, the ψ weights of a linear process must satisfy that $\psi(B)$ converges on or lies within the unit circle.

In an autoregressive, AR, model, the current value of the time series may be expressed as a linear combination of the previous values of the series and a random shock, α_t.

$$\tilde{Z}_t = \phi_1 \tilde{Z}_{t-1} + \phi_2 \tilde{Z}_{t-2} + \ldots + \phi_p \tilde{Z}_{t-p} + \alpha_t$$

The autoregressive operator of order P is given by

$$\phi(B) = 1 - \phi_1 B^1 - \phi_2 B^2 - \ldots - \phi_p B^p$$

or

$$\phi(B) \tilde{Z}_t = \alpha_t \qquad (6)$$

In an autoregressive model, the current value of the time series, $\tilde{Z}_t$, is a function of previous values of the time series, $\tilde{Z}_{t-1}$, $\tilde{Z}_{t-2}$, … and is similar to a multiple regression model. An autoregressive model of order p implies that only the first p order weights are non-zero. In many economic time series, the relevant autoregressive order is one and the autoregressive process of order p, AR(p) is written as

$$\tilde{Z}_t = \phi_1 \tilde{Z}_{t-1} + \alpha_t$$

or

$$(1 - \phi_1 B) \tilde{Z}_t = {}_{t,} \text{ implying}$$

$$\tilde{Z}_t = \phi^{-1}(B) {}_t.$$

The relevant stationarity condition is $|B| < 1$, implying that $|\phi_1| < 1$. The autocorrelation function of a stationary autoregressive process,

$$\tilde{Z}_t = \phi_1 \tilde{Z}_{t-1} + \phi_2 \tilde{Z}_{t-2} + \ldots + \phi_p \tilde{Z}_{t-p} + \alpha_t$$

may be expressed by the difference equation

$$P_k = \phi_1 \rho_{k-1} + \phi_2 \rho_{k-2} + \ldots + \phi_k \rho_{k-p} \; k > 0.$$

In a q-order moving average (MA) model, the current value of the series can be expressed as a linear combination of the current and previous shock variables

$$\tilde{Z}_t = {}_1 - \theta_1 {}_{t-1} - \ldots - {}_q \theta_{t-q}$$
$$= (1 - \theta_1 B_1 - \ldots - \theta_q B_q) {}_{t.} \qquad (7)$$

The autocorrelation function of an MA(q) model cuts off, to zero, after lag q and its partial autocorrelation function tails off to zero after lag q. There are no restrictions on the moving average model parameters for stationarity; however, moving average parameters must be invertible. Invertibility implies that the π weights of the linear filter transforming the input into the output series lie outside the unit circle.

$$\pi(B) = \psi^{-1}(B)$$

$$= \sum_{j=0}^{a} \phi^j B^j$$

In a first-order moving average model, MA(1)

$$\tilde{Z}_t = (1 - \theta_1 B)\alpha_t$$

and the invertibility condition is $|\theta_1| < 1$. The autocorrelation function of the MA(1) model is

$$\rho_k = \frac{-\theta_1}{1+\theta_1^2} \quad \begin{matrix} k = 1 \\ k > 2. \end{matrix}$$

The partial autocorrelation function of an MA(1) process tails off after lag one and its autocorrelation function cuts off after lag one.

In many economic time series, it is necessary to employ a mixed autoregressive-moving average (ARMA) model of the form

$$\tilde{Z}_t = \phi_1 \tilde{Z}_{t-1} + \ldots + \phi_p \tilde{Z}_{t-p} + \alpha_t - \theta_1\alpha_{t-1} - \ldots - \theta_q \alpha_{t-q} \quad (8)$$

or

$$(1 - \phi_1 B - \phi_2 B^2 - \ldots - \theta_p B^p) \tilde{Z}_t = (1 - \theta_1 B - \theta_2 B^2 - \ldots - \theta_q B^q) \alpha_t$$

that may be more simply expressed as

$$\phi(B) \tilde{Z}_t = \theta(B)\alpha_{t.}$$

The autocorrelation function of the ARMA model is

$$\rho_k = \phi_1\rho_{k-1} + \phi_2\rho_{k-2} + \ldots + \phi_p\rho_{k-p}$$

or

The first-order autoregressive-first order moving average operator ARMA(1,1) process is written

$$\tilde{Z}_t - \phi_1 \tilde{Z}_{t-1} = \alpha_t - \theta_1\alpha_{t-1}$$

or

$$(1- \phi_1) \tilde{Z}_t = (1 - \theta 1B)\alpha_t.$$

The stationary condition is $-1 < \phi_1 < 1$ and the invertibility condition is $-1 < \phi_1 < 1$. The first two autocorrelations of the ARMA (1,1) model are

$$\rho_1 = \frac{(1-\phi_1\theta_1)(\phi_1-\theta_1)}{1+\theta_1^2 - 2\phi_1\theta_1}$$

and

$$\rho_2 = \phi_1\rho_1.$$

The partial autocorrelation function consists only of $\phi_{11} = \rho_1$ and has a damped exponential.

An integrated stochastic progress generates a time series if the series is made stationary by differencing (applying a time-invariant filter) the data. In an integrated process, the general form of the time series model is

$$\phi(B)(1 - B)^d X_t = \theta(B)\varepsilon_t \quad (9)$$

where $\phi(B)$ and $\theta(B)$ are the autoregressive and moving average polynomials in B of orders p and q, ε_t is a white noise error term, and d is an integer representing the order of the data differencing. In economic time series, a first-difference of the data is normally performed.[4] The application of the differencing operator, d, produces a stationary ARMA(p,q) process. The autoregressive integrated moving average, ARIMA, model is characterized by orders p, d, and q [ARIMA (p,d,q)]. Many economics series follow a random walk with drift; an ARMA (1,1) may be written as

$$\overline{V}^d X_t = X_t - X_{t-1} = \varepsilon_t + b\varepsilon_{t-1}. \quad (11)$$

An examination of the autocorrelation function estimates may lead to investigating using a first-difference model when the autocorrelation function estimates decay slowly. In an integrated process, the correlation $(X_t, X_{t-\tau})$ is approximately unity for small values of time, τ.

ARMA Model Identification in Practice

Time series specialists use many statistical tools to identify models; however, the sample autocorrelation and partial autocorrelation function estimates are particularly useful in modeling.

Univariate time series modeling normally requires larger data sets than regression and exponential smoothing models. It has been suggested that at least 30 to 60 observations be used to obtain reliable estimates.[5] The sample autocorrelation and partial autocorrelation estimates are normally calculated for the raw time series and its first (and possibly second) differences. The failure of the autocorrelation function estimates of the raw data series to die out as large lags implies that a first difference is necessary. The autocorrelation function estimates of an MA(q) process should cut off after q. To determine whether the autocorrelation estimates are statistically different from zero, a t-test is used where the standard error of $\upsilon\tau$ is

$$n^{1/2}[1 + 2(\rho_1^2 + \rho_2^2 + ... + \rho_q^2)]^{1/2} \text{ for } \tau > q.^6$$

The partial autocorrelation function estimates of an AR(p) process cut off after lag p. A t-test is used to statistically examine whether the partial autocorrelations are statistically different from zero. The standard error of the partial autocorrelation estimates is approximately

[4] Box and Jenkins, *Time Series Analysis*. Chapter 6; C.W.J. Granger and Paul Newbold, *Forecasting Economic Time Series*. Second Edition (New York: Academic Press, 1986), pp. 109-110, 115-117, 206.
[5] Granger and Newbo1d, *Forecasting Economic Time Series*. pp. 185-186.
[6] Box and Jenkins, *Time Series Analysis*. pp. 173-179.

$$\frac{1}{\sqrt{N}} \text{ for K } > p.$$

The normality assumption of large samples may be used in the t-tests of the autocorrelation and partial autocorrelation estimates. The identified parameters are generally considered statistically significant if the parameters exceed twice the standard errors.

The ARMA model parameters may be estimated using nonlinear least squares. Given the following ARMA framework, the initial parameter estimates are generally back-forecasted and the shock terms are assumed to be normally distributed.

$$\alpha_t = \widetilde{W}_t - \phi_1 \widetilde{W}_{t-1} - \phi_2 \widetilde{W}_{t-2} - \ldots - \phi_p \widetilde{W}_{t-p} + \theta_1 \alpha_{t-1} + \ldots + \theta_q \alpha_{t-q} \quad (12)$$

where

$$W_t = \overline{V}^d Z_t \text{ and } \widetilde{W}_t = W_t - \mu.$$

Several tests and procedures are available for checking the adequacy of fitted time series models. The most widely used test is the Box-Pierce test, where one examines the autocorrelation among residuals, α_t:

$$\hat{v}_k = \frac{t = \sum_{k+1}^{n} \alpha_t \alpha_{t-k}}{\sum_{t=1}^{n} \alpha_t^2}, k = 1, 2, \ldots$$

The test statistic, Q, should be X^2 distributed with (m-p-q) degrees of freedom.

$$Q = n \sum_{k=1}^{m} \hat{v}_k^2.$$

The Ljung-Box statistic is a variation on the Box-Pierce statistic. The Ljung-Box Q statistic tends to produce significance levels closer to the asymptotic levels than the Box-Pierce statistic for first-order moving average processes. The Ljung-Box statistic, the model adequacy check reported in the SAS system, can be written as

$$Q = n(n+2) \sum_{k=1}^{m} (n = k)^{-1} \hat{v}_k^2. \quad (13)$$

Residual plots are generally useful in examining model adequacy; such plots may identify outliers. The normalized cumulative periodogram of residuals should be examined.

It is generally recognized that the majority of economic series follow a random walk with drift, and are represented with an autoregressive integrated moving average (ARIMA) model with a first-order moving average operator applied to the first-difference of the data. The data is differenced to produce a stationary process, which has a (finite) mean and variance that do not change over time. The covariance between data points of two series depends upon the distance between the data points, not on the time itself. The random walk with drift (RWD) process, estimated with an ARIMA (0,1,1) model, is approximately equal to a first-order exponential smoothing model. The RWD model has been supported by the work of Nelson and Plosser (1982). We find, as is the case of most economic time series, that a random walk with drift adequately describes the process.

Examining the time series of the daily returns from December 30, 1990 through January 31, 2007 reveals that there are over 4100 daily observations in the dataset. We will estimate traditional time series models of the daily return differential between the MSCI EM Index and the Russell 3000 Index returns. Time series models in the tradition of Professors Box and Jenkins (1970) are built using 60 observations, DIFFEM. The drift term is statistically significant (see Exhibit 2).

Another important aspect of this issue lies in the forecasting efficiency of the traditional time series model. If the daily actual realized differential in index returns is regressed between the MSCI EM and Russell 3000 Index returns as a function of the predicted daily differential, it becomes evident that the persistence of the differential returns continues, such that the coefficient on the predicted daily differential return is positive and statistically significant. In other words, on days when the differential would be expected to be positive, the realized return differential is more likely to be positive.

Actual Realized DIFFEM= .000 +.160*Predicted DIFFEM.

(t = 6.13)

Evidence suggests that forecasting the daily return differential is possible; however, the realized magnitudes are small and the true test is to forecast monthly return differential and re-weight EM weights in the global portfolios upon the relative expected appreciation of EM.[7] However, this is well beyond the scope of this article.

Exhibit 2: Random Walk with Drift Estimation of the Differential Return of Emerging Market and Russell 3000 Indices
Dependent Variable: DIFFEM
Method: Least Squares

Variable	Coefficient	Std. Error	T-statistic	Probability
C	.000	.000	.121	.903
MA(1)	-.055	.015	-3.58	.000
R-Squared	.003	Mean dependent variable		.000
Adjusted R-Squared	.003	S.D. dependent variable		.025
S.E. of Regression	.025	Akaike info criterion		-4.53
Sum Squared Resid.	2.65	Schwarz criterion		-4.52
Log Likelihood	945	F-Statistic		12.7
Durbin-Watson Stat	2.00	Prob (F-Statistic)		.000

[7] Initial time series analyses of the monthly forecasts of models of the differential returns of emerging markets less the Russell 3000 stocks indicate that the forecasts are positively associated with actual, realized returns.

The first-order is consistently negative in the DIFFEM throughout the estimation period, and the persistence leads to encouraging evidence for further forecasting efforts. The forecastability of the EM return differential is of great importance to the investment manager if the manager can gauge the correct direction of the spread.

The variance of the traditional time series models does not appear to be constant. We estimate an ARCH model to incorporate information regarding the mean error, its news of the volatility from the previous period (the ARCH term), and the previous period's forecast variance (the GARCH term).

Exhibit 3: Random Walk with Drift Estimation of the Differential Return of Emerging Market and Russell 3000 Indices
Dependent Variable: DIFFEM
Method: ML – ARCH (Marquardt)

Variable	Coefficient	Std. Error	Z-statistic	Probability
C	.000	.000	1.03	.301
MA(1)	-.054	.016	-3.44	.001
Variance Equation				
C	.000	.000	4.77	.000
ARCH (1)	.067	.006	11.6	.000
GARCH (1)	.928	.006	153	.000
R-Squared	.003	Mean dependent variable		.000
Adjusted R-Squared	.002	S.D. dependent variable		.025
S.E. of Regression	.025	Akaike info criterion		-4.74
Sum Squared Resid.	2.65	Schwarz criterion		-4.73
Log Likelihood	9893	F-Statistic		3.04
Durbin-Watson Stat	2.00	Prob (F-Statistic)		.016

ARCH Test				
F-Statistic	.665	Probability		.772
Obs* R-Squared	8.91	Probability		.710

Variable	Coefficient	Std. Error	T-statistic	Probability
C	2.93	.948	3.09	.004
STD_RESID^2 (-1)	-.122	.166	-0.73	.468
STD_RESID^2 (-2)	-.086	.165	-0.52	.608
STD_RESID^2 (-3)	-.247	.167	-1.48	.148
STD_RESID^2 (-4)	-.313	.168	-1.87	.071
STD_RESID^2 (-5)	-.137	.168	-0.82	.421
STD_RESID^2 (-6)	.009	.167	.053	.958
STD_RESID^2 (-7)	-.069	.164	-.422	.676
STD_RESID^2 (-8)	-.249	.164	-1.52	.136
STD_RESID^2 (-9)	-.160	.186	-.862	.394
STD_RESID^2 (-10)	-.014	.185	-.077	.939
STD_RESID^2 (-11)	-.200	.185	-1.08	.286
STD_RESID^2 (-12)	-.125	.186	-.675	.504
R-Squared	.186	Mean dependent variable		1.11
Adjusted R-Squared	-.093	S.D. dependent variable		1.49
S.E. of Regression	1.56	Akaike info criterion		3.95
Sum Squared Resid.	85.0	Schwarz criterion		4.46
Log Likelihood	-81.8	F-Statistic		.665
Durbin-Watson Stat	2.06	Prob (F-Statistic)		.772

The test equation of the residuals shows no overwhelming evidence that the ARCH model is necessary; moreover, regression of the realized daily differential returns as a function of ARCH-predicted return differential leads to the following results:

Actual Realized DIFFEM= .000 +.152*ARCH- Predicted DIFFEM.

(t = 6.05)

The ARCH model estimations offer no statistically significant enhancement in daily out-of-sample forecasting relative to the traditional time series model.[8]

Based on time series analysis, the positive spread between the MSCI EM Index and the Russell 3000 Index can be expected to continue.

DO DEVELOPED MARKETS' FACTORS WORK IN EMERGING MARKETS?

There is a significant book-to-price (BP) effect in emerging markets [Rouwenhorst (1999); Van Der Hart, Slagter, and van Dijk (2003); Bekaert and Harvey, (2003)]. In addition to BP, we examined several other developed markets' factors as well as the corresponding information coefficients and t-statistics in the emerging markets (EM) universe. We also tested price growth, earnings-per-share revisions, and earnings-to-price variables for the December 1995 through March 2007 period.[9] Lastly, we reviewed an equally-weighted proprietary composite variable (denoted as MQ).

Exhibit 4: MSCI EM
December 1995 to March 2007

	ALL		Liquidity-Screened	
	ICs	T-statistics	ICs	T-statistics
Price Growth	.031	11.4	.028	5.40
EPS Revisions	.009	3.29	.016	3.26
EP	.021	7.64	.025	11.3
BP	-.011	-4.08	-.017	-2.91
MQ	.036	9.98	.040	5.81

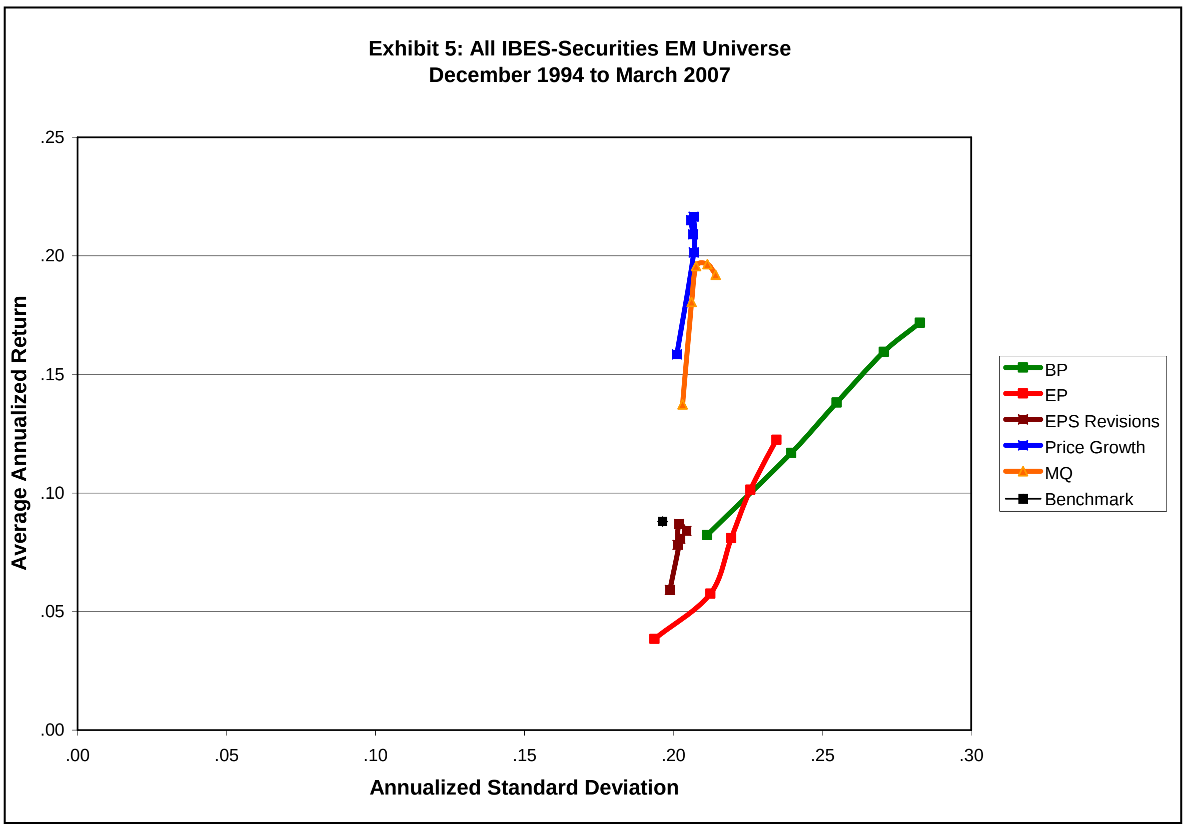
Exhibit 4 shows the information coefficients (ICs) and the corresponding t-statistics of the factors for both the full and liquidity-screened universes, where 70% of the most illiquid MSCI EM securities are removed. The justification for eliminating 70% of the universe was given in a previous paper (2006) and gives confidence that the factors are tenable even if the more illiquid (and difficult to trade) names are eliminated. Post liquidity screening, the MQ variable is statistically

[8] The monthly ARCH model forecasts are slightly more correlated with realized return differentials than the traditional time series models. Current research involves integrating these forecasts into a monthly portfolio construction analysis.
[9] This is a different time line than for Exhibit 1 because liquidity screening begins in December 1995 with daily emerging markets' trading volume on most securities. Additionally, APT Associates' simulated data capabilities do not precede this date with complete coverage.

significant at the 5% level (t-statistic of 1.96 or greater) as are the analysts' revisions and price-growth factors.

While the factors were generally statistically significant during the test period, portfolios reflecting these variables may not necessarily have outperformed the market. The next step was to examine portfolio implementation issues. Our intention was to simulate a separate portfolio for each variable listed above, as well as one with balanced exposures to many systematic influences such as country and sector, while approximating realistic turnover in relation to an actual long-only portfolio during the same time frame. We wanted to determine if basic portfolio construction rules would allow an investor to capture favorable returns in this liquidity-screened universe, as suggested by the factor testing.

To do this, we constrained each simulated portfolio, using the APT Associates risk model, by 400 basis points of roundtrip transaction costs (100 basis points of hard commission and 300 basis points of market impact); equally actively weighted positions by using a +/- 3% active weight by security; and assumed 8% monthly turnover to approximate actual turnover for other managed portfolios during the period. Exhibit 5 displays the trade-off curves for all EM securities[10] by five factor-specific portfolios; we used each variable to create several portfolios along a risk-return spectrum that allows the profiles of the respective variables to be compared with one another.



[10] The IBES database of all EM securities was used. This is a larger universe than the constituents of the MSCI EM Index, but arguably a more appropriate one for investors.

Exhibit 5 further shows that the factors used as "tilt" variables in these APT optimizations often offered statistical outperformance of the benchmark at the higher ranges of the risk-return trade-off curve. The APT methodology seeks to create portfolios that look exactly like the market on a risk profile, but allow the investment manager to tilt a portfolio toward financial attributes that the manager believes should generate higher returns than the market on a risk-adjusted basis.

We show the data associated with the several trade-off curves in Exhibit 6. Generally, at least 50 to 60 stocks for diversified EM portfolios are necessary. Investors seeking tracking errors of 6% to 8% may more likely be satisfied with portfolios of 80 to 90 stocks.

Exhibit 6: Trade-off Curve Analysis EM ALL IBES Securities
December 1994 to March 2007

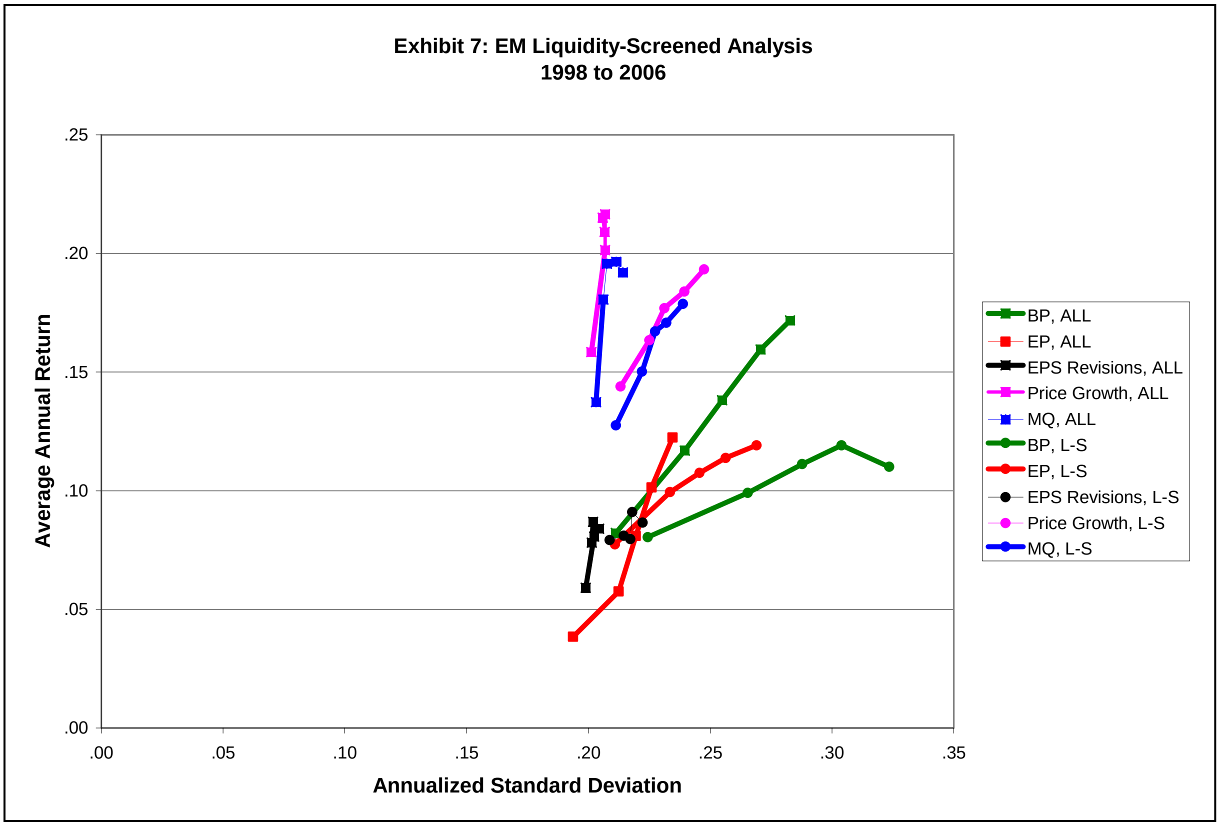
			BP		
Lambda	**AR**	**STD**	**SR**	**T Error**	**Nstks**
500	.172	.283	.477	11.2	51.9
200	.160	.271	.453	9.82	64.5
100	.138	.255	.397	8.75	75.6
50	.117	.240	.334	7.72	92.3
10	.082	.211	.214	5.18	158
			EP		
500	.122	.235	.364	10.1	55.0
200	.101	.226	.286	9.00	67.9
100	.081	.219	.201	7.96	79.0
50	.058	.212	.097	6.96	96.2
10	.038	.194	.008	4.62	155
			EPS Revisions		
500	.084	.204	.230	7.00	86.0
200	.087	.202	.248	6.20	110
100	.078	.201	.205	5.45	138
50	.081	.202	.216	4.85	158
10	.059	.199	.112	3.26	204
			Price Growth		
500	.209	.207	.833	8.58	58.9
200	.215	.206	.866	7.67	73.2
100	.217	.207	.869	6.95	87.1
50	.201	.207	.795	6.12	105
10	.158	.201	.604	4.12	164
			MQ		
500	.192	.214	.724	9.86	49.3
200	.196	.211	.755	8.68	58.0
100	.196	.208	.765	7.70	71.0
50	.181	.206	.697	6.59	90.0
10	.137	.203	.494	4.11	152

The portfolio returns indicate that the first three factors were less powerful than the last two. Interestingly, the BP effect was not as powerful as might have been expected. The reason for this is given in the following section.

HOW IMPORTANT IS LIQUIDITY SCREENING IN EMERGING MARKETS?

Exhibit 7 displays each factor's trade-off curves within the universe[11] versus those of all securities to point out the specific effect of the liquidity impact. For example, note that the BP variable's effectiveness is substantially reduced by liquidity screening. On the other hand, while not a powerful variable overall, liquidity had less of an impact on the EPS revisions factor.

This is an important analysis because it deals directly with the ability to invest in each factor-driven portfolio. Demonstrating the significance of a factor is helpful only if one can capture returns associated with that factor in a real investment environment.[12] Eliminating 70% of the MSCI EM universe each month essentially assures that each security has sufficient funds available regularly which can be invested within the confines of an institutional portfolio.



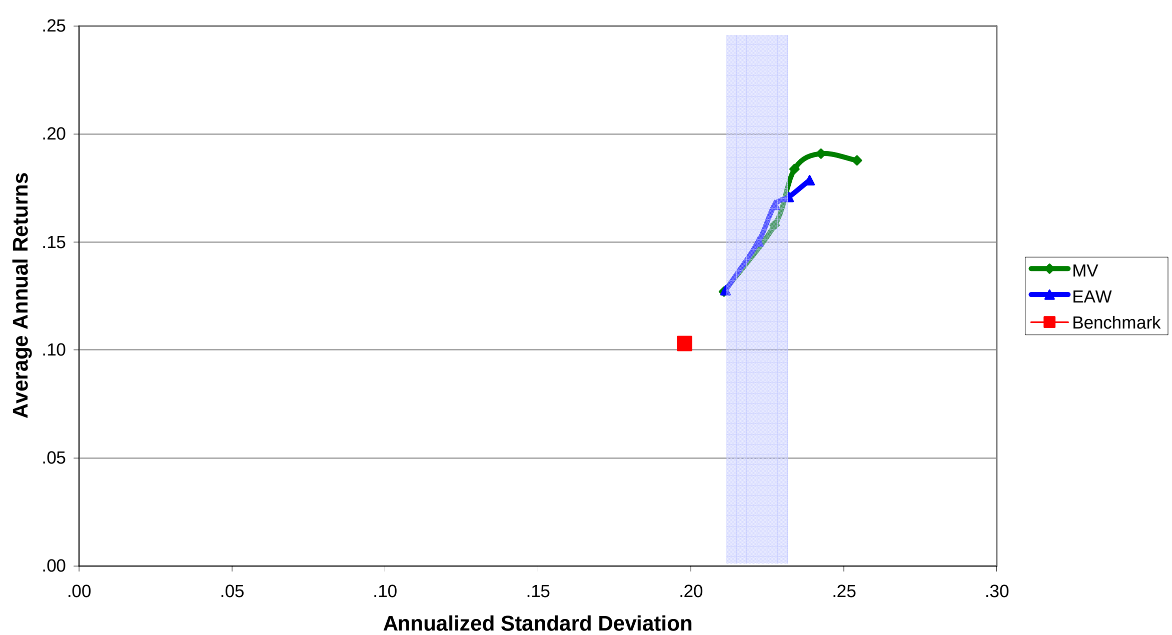
[11] The IBES database of all EM securities was used. This is a larger universe than the constituents of the MSCI EM Index, but arguably a more appropriate one for investors.
[12] Earnings revisions are not as effective in emerging markets as they are in identifying mis-priced U.S. and developed markets stocks. EM stocks are covered by fewer analysts than are the U.S. and developed markets stocks, and there was little analyst coverage in the EM universe prior to 1998.

DO DEVELOPED MARKETS' PORTFOLIO CONSTRUCTION TECHNIQUES WORK IN EMERGING MARKETS?

Traditional Markowitz (1959) mean-variance analysis generally implies that securities enter portfolios relative to fixed minimum and maximum weights. Markowitz (1987) recognized several enhancements to the traditional mean-variance analysis and discussed a special case of "tracking an index" that is extremely relevant to portfolio construction in the emerging markets universe where five securities often comprise 10% to 20% of the index weights. The Markowitz enhanced index tracking (EIT) analysis, in which portfolios are constructed using the absolute deviations of security weights less the index weights, is reported in Guerard, Takano, and Yamane (1993). EIT analysis is very similar to mean-variance analysis in its trade-off curves but tends to produce smaller estimated tracking errors. Equal active weighting (EAW) stipulates, in this case, that the optimal weight may deviate from its target weight in the index by less than 3%. That is, a security with an index weight of 8.5% cannot have a position in the portfolios exceeding 11.5% or less than 5.5%. The EAW philosophy is consistent with benefits associated with the Markowitz EIT methodology.

Portfolio simulations using lambda, a measure of the risk-return trade-off, showed that to maximize the Sharpe Ratio (SR), a fairly high lambda should be used. Nonetheless, at the middle part of the trade-off curves where tracking error is most appropriate for institutional investment portfolios (3% to 7%), an interesting observation can be made. In Exhibit 8, note that the 3% equal active weighting (EAW 3%) curve matches the mean-variance (MV) curve, for which we used a 10% maximum weighting. This suggests that the same benefit can be achieved by simple active weight management as by using the more complex mean-variance optimization techniques.

**Exhibit 8: Portfolio Construction Strategies,
Equal Active Weight (EAW) and Mean-Variance (MV) Analysis
December 1995 to March 2007**



DO YOUR EMERGING MARKETS' RETURNS PASS THE MARKOWITZ-XU DATA MINING CORRECTIONS TEST?

We used Model 2 of Markowitz and Xu's (1994) Data Mining Correction Tests (DMC), which examines returns from the optimized portfolios and determines whether the return for the model one intends to use is statistically different from the average excess return of other strategies considered, shown in Exhibit 9. An average excess return was created by using the portfolios' additional variables, such as the forecasted EPS to price (using one- and two-year-ahead EPS forecasts), one- and two-year-ahead EPS revisions, and a second price-growth variable.

Exhibit 9: Model Returns for Data-Mining Corrections Test
December 1995 to March 2007

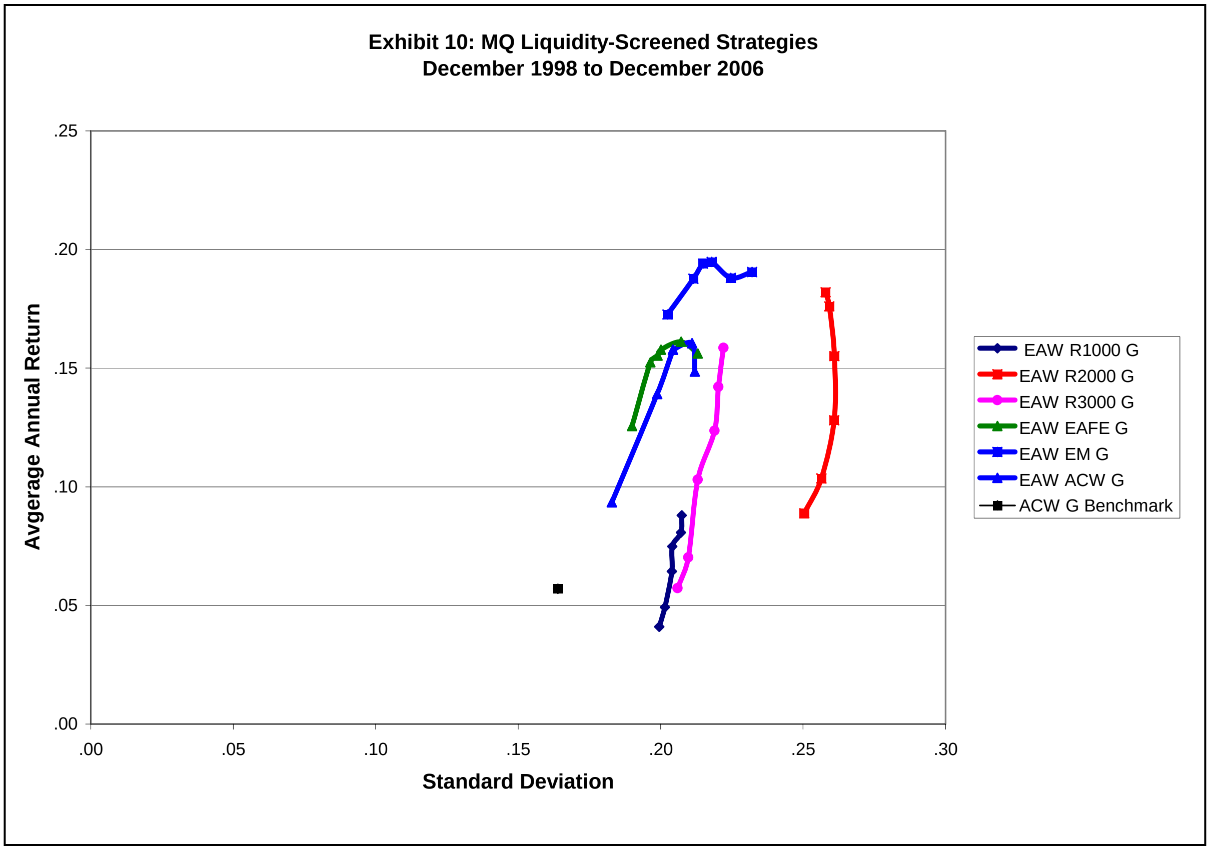
Model/Variable	Historic Returns
BP	.120
EP	.114
FEP1	.104
FEP2	.104
Price Growth 1	.156
Price Growth 2	.182
EPS Revisions 1	.083
EPS Revisions 2	.094
MQ	.172
Average Model	.120

With regard to MQ, the null hypothesis that there is no association with the MSCI EM universe is rejected. The MQ variable returns were regressed as a function of the average model returns and the resulting slope of the DMC line was 0.926 with a corresponding t-value of 59.6, which is highly statistically significant. We conclude that the MQ model returns were not random and that data-mining was not used in determining that MQ effectively dominated the average return of the models considered in the test. A similar argument can be made for the Price Growth 1 and Price Growth 2 variables, but not for the others.

HOW DO EMERGING MARKETS' RETURNS AND STRATEGIES COMPARE TO SIMILAR STRATEGIES IN OTHER STOCK UNIVERSES?

Emerging markets offer not only higher index Sharpe Ratios (see Exhibit 1), but higher Sharpe Ratios for portfolios constructed within the EM universe. The MQ trade-off curve (see Exhibit 10), estimated on EM-only stocks, dominates MQ curves built using domestic, as measured by the Russell 1000 growth stocks (R1000G, the growth stocks within the 1000 largest U.S. stocks), the Russell 2000 growth stocks (R2000G, the smallest U.S. growth stocks), and the Russell 3000 growth stocks (R3000G, the sum of R1000G and R2000G); larger, developed non-U.S. growth stocks

(EAFE G); and growth stocks from countries in the All Country World Growth Index (ACWG). The ACWG trade-off MQ curve dominates the U.S., Russell 3000 Index curve, a result consistent with Harvey (1995). The developed markets, defined as MSCI EAFE plus Canada, produce a higher return-to-risk trade-off curve than the U.S. securities; moreover, the EM countries dominate the developed markets curve. In a global world, an investor must pay attention to the EM investment opportunity.



CONCLUSION

Forecasting emerging market returns seems impossible. Few observers foretold their rise accurately, and most are likely to miss precisely forecasting their fall. While no one can predict the downturn in EM, the dedicated EM investor can guard against such an event by having exposure to a broad array of powerful risk factors. The research discussed in this paper leads to the following conclusions:

- Long-term risk-return characteristics remain attractive, and during the last 17 years, a time frame that includes significant bear- and bull-market environments, emerging markets had the best Sharpe Ratios of the universes tested and generated higher returns than U.S. and developed markets. (See Exhibit 1.)

- Many traditional investment factors are powerful in the EM space even when liquidity is considered, and price growth and related strategies should be considered important components of a dedicated allocation to EM. (See Exhibit 7.)
- Both active factor exposure and portfolio-construction techniques are critical to success. (See Exhibits 4, 5, and 8.)
- Less complicated portfolio-construction techniques such as equal active weighting can be used in lieu of mean-variance techniques for lower levels of tracking error. (See Exhibit 8.)
- Several strategies pass the data-mining test and provide support that strategies exist for which model returns are not random. (See Exhibit 9.)
- Emerging markets' returns and strategies compare favorably with other stock universes. (See Exhibit 10.)

RELEVANT REFERENCES

APT Associates. Analytics Guide. 2005.

Ashley, R.A. 2003. "Statistically Significant Forecasting Improvements: How Much Out-of-sample Data is Likely Necessary?" *International Journal of Forecasting* 19, 229-240.

Ashley, R. 1998. "A New Technique for Postsample Model Selection and Validation." *Journal of Economic Dynamics and Control* 22, 647-665.

Ashley, R., C.W.J. Granger and R. Schmalensee. 1980. "Advertising and Aggregate Consumption: An Analysis of Causality." *Econometrica* 48, 149-1167.

Bollerslev, T. 1986. "Generalized Autoregrssive Conditional Heteroskedasticity." *Journal of Econometrics* 31, 307-327.

Box, G.E.P. and G.M. Jenkins. 1970. Time Series Analysis: Forecasting and Control. San Francisco: Holden-Day.

Bekaert, G. and C.R. Harvey. 2003. "Emerging Markets Finance." *Journal of Empirical Finance* 10, 3-55.

Bloch, M., J.B. Guerard, Jr., H. M. Markowitz, P. Todd, and G.L. Xu. 1993. "A Comparison of Some Aspects of the U.S. and Japanese Equity Markets." *Japan & the World Economy* 5, 3-26.

Blin, J.M., S. Bender, and J. B. Guerard, Jr. 1997. "Earnings Forecasts, Revisions and Momentum in the Estimation of Efficient Market-Neutral Japanese and U.S. Portfolios." In *Research in Finance* 15, edited by A. Chen.

Capaul, C, I. Rowley, and W.F. Sharpe. 1993. "International Value and Growth Stock Returns." *Financial Analysts Journal*, January/February, 27-36.

Clemen, R.T. and J.B. Guerard. 1989. "Econometric GNP Forecasts: Incremental Information Relative to Naive Extrapolation." *International Journal of Forecasting* 5, 417-426.

Diebold, F.X. and G.D. Rudebusch. 1999. Business Cycles: Durations, Dynamics and Forecasting. Princeton: Princeton University Press.

Diebold, F.X. and R.S. Mariano. 1995. "Comparing Predictive Accuracy." *Journal of Business and Economic Statistics* 13, 253-263.

Engle, R. F. 1995. "ARCH: Selected Readings." Oxford University Press.

Engle, R. F. 1982. "Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation," *Econometrica* 50, 987-1006.

Granger, C.W.J. 1980. "Testing for Causality: A Personal Viewpoint." *Journal of Economic Dynamics and Control* 2, 329-352.

Granger, C.W.J. and P. Newbold. 1977. Forecasting Economic Time Series. New York Academic Press.

Guerard, J.B. Jr., M. Takano, and Y. Yamane. 1993. "The Development of Efficient Portfolios in Japan with Particular Emphasis on Sales and Earnings Forecasting." *Annals of Operations Research* 45, 91-108.

Hamilton, J.D. 1994. Time Series Analysis, Princeton, Princeton University Press.

Harvey, C.R. 1995. "Predictable Risk and Returns in Emerging Markets." *The Review of Financial Studies* Vol. 8, 773-816.

Markowitz, H.M. 1959. Portfolio Selection: Efficient Diversification of Investment. Cowles Foundation Monograph No. 16. New York, John Wiley & Sons.

Markowitz, H.M. 1987. Mean-Variance Analysis in Portfolio Choice and Capital Markets. Oxford: Basil Blackwell.

Markowitz, H.M. and G. Xu. 1994. "Data Mining Corrections." *Journal of Portfolio Management* 21, 60-69.

Mincer, J. and V. Zarnowitz. (1969). "The Evaluation of Economic Forecasts," J. Mincer editor, Economic Forecasts and Expectations, New York, Columbia University Press.

McCracken, M. 2000. "Robust out-of-sample inference." *Journal of Econometrics* 39, 195-223.

McKinley Capital Management, Inc. 2006. "An Assessment of the McKinley Capital Non-U.S. Developed Growth and Non-U.S. Growth Portfolios," November.

McKinley Capital Management, Inc. 2007. "Investment Analysis - Global Emerging Markets," March.

Montgomery, A.L., V. Zarnowitz, R.S. Tsay, and G.C. Tiao. 1998. "Forecasting the U.S. Unemployment Rate," *Journal of the American Statistical Association* 93, 478-493.

Nelson, C.R. and C.I. Plosser. 1982. "Trends and Random Walks in Macroeconomic Time Series." *Journal of Monetary Economics* 10, 139-162.

Rouwenhorst, K.G. 1999. "Local Return Factors and Turnover in Emerging Markets," *Journal of Finance* 54, 1439-1464.

Sharpe, W. F. 1964. "Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk." *The Journal of Finance* 19, 425-442.

Sharpe, W.F. 1966. "Mutual Fund Performance." *Journal of Business* 39, 119-138.

Sharpe, W.F. 1970. Portfolio Theory and Capital Markets. New York: McGraw-Hill.

Sharpe, W.F. 1994. "The Sharpe Ratio." *The Journal of Portfolio Management*, Fall.

Theil, H. 1966. Applied Economic Forecasting. Amsterdam, North-Holland.

Thomakos, D. and J. Guerard. 2004. "Naïve, ARIMA, Transfer Function, and VAR Models: A Comparison of Forecasting Performance." *The International Journal of Forecasting* 20, 53-67.

Van Der Hart, J.V., E. Slagter, and D. van Dijk. 2003. "Stock Selection Strategies in Emerging Markets," *Journal of Empirical Finance* 10, 107-134.

West, K. and M. McCracken. 1998. "Regression-based Tests of Predictive Ability." *International Economic Review* 39, 817-840.

Zarnowitz, V. 2004. "The Autonomy of Recent U.S. Growth and Business Cycles." In P. Dua, Ed., Business Cycles and Economic Growth: An Analysis Using Leading Indicators. New York: Oxford University Press, 44-82.

Zarnowitz, V. 2001. "The Old and the New in the U.S. Economic Expansion." The Conference Board. EPWP #01-01.

Zarnowitz, V. and A. Ozyildirim. 2001. "On the Measurement of Business Cycles and Growth Cycles." *Indian Economic Review* 36, 34-54.

Zarnowitz, V. 1992. Business Cycles: Theory, History, Indicators, and Forecasting. Chicago, University of Chicago Press.

Portfolio Performance Gross and Net of Management Fees

McKinley Capital Management, Inc. (MCM) is a registered investment adviser. Annualized performance shown is model performance generated by MCM using tools provided by APT Associates and by Statistical Analysis System (SAS) and adjusted for transaction costs. MCM does not make any representation or endorsement as to the accuracy or proprietary nature of information and/or tools provided or generated by these vendors or any other third party. Model performance shown is trade date and does not reflect the reinvestment of realized gains, dividends, interest, and other earnings. It is gross of management fees. Detailed security inclusion/exclusion methodologies are available upon request. Attribution information was prepared using tools provided by BARRA and Zephyr. Past performance is no guarantee of future results. No guarantee can be made that the model performance reflects a statistically accurate presentation of the performance of any specific account. Fees are collected quarterly, which produces a compounding effect on the total rate of return net of management fees. As an example, the effect of investment management fees on the total value of a client's portfolio assuming (a) $1,000,000 investment, (b) portfolio return of 8% a year, and (c) 1.00% annual investment advisory fee would be $10,416 in the first year, and cumulative effects of $59,816 over five years and $143,430 over ten years. Actual investment advisory fees incurred by clients may vary. A fee schedule, available upon request, is described in Part II of the firm's ADV. This unaudited report is not an offer or solicitation to sell any security. Nor does it include most of the information which an ordinary investor would consider material in deciding to invest in any product sponsored by McKinley Capital Management, Inc. Investing in emerging markets carries potential risks such as liquidity risks, increased price volatility and less government regulation and supervision of emerging markets stock exchanges, brokers and listed companies. To receive a complete list and description of MCM's composites and/or a presentation that adheres to the GIPS® standards, please contact us at (907) 563-4488 or visit our website, www.mckinleycapital.com.

This unaudited report is not an offer or solicitation to sell any security. Nor does it include most of the information which an ordinary investor would consider material in deciding to invest in any product sponsored by McKinley Capital Management, Inc. To receive a complete list and description of McKinley Capital Management, Inc.'s composites and/or a presentation that adheres to the GIPS® standards, please contact us at (907) 563-4488 or visit our website, www.mckinleycapital.com.