# Mean Reversion Across National Stock Markets and Parametric Contrarian Investment Strategies

**Ronald Balvers, Yangru Wu, and Erik Gilliland** *

**Final Version: July 1999**

**Abstract**

For U.S. stock prices, evidence of mean reversion over long horizons is mixed, possibly due to lack of a reliable long time series. Using additional cross-sectional power gained from national stock-index data of eighteen countries during the period 1969 to 1996, we find strong evidence of mean reversion in relative stock-index prices. Our findings imply a significantly positive speed of reversion with a half-life of three to three and a half years. This result is robust to alternative specifications and data. Parametric contrarian investment strategies that fully exploit mean reversion across national indices outperform buy-and-hold and standard contrarian strategies.

*West Virginia University, Rutgers University, and West Virginia University, respectively. We would like to thank Jonathan Lewellen, Bill McDonald, Dilip Patro, John Wald and conference participants of the Eastern Finance Association, Western Finance Association and the Ninth Annual Conference on Financial Economics and Accounting at the Stern School of Business of New York University for helpful conversations and comments. We are especially grateful to René Stulz (the editor) and two anonymous referees whose comments and suggestions led to a substantial improvement in the quality of the paper. The usual disclaimer applies. We would also like to thank Morgan Stanley Capital International for providing part of the data used in this project. Balvers acknowledges the Faculty Research Associates program of the Bureau of Business and Economic Research at West Virginia University for research support.

Mean reversion refers to a tendency of asset prices to return to a trend path. The existence of mean reversion in stock prices is subject to much controversy. Fama and French (1988a) and Poterba and Summers (1988) are the first to provide direct empirical evidence that mean reversion occurs in U.S. stock prices over long horizons.[1] Others are critical of these results; Lo and MacKinlay (1988) find evidence against mean reversion in U.S. stock prices using weekly data; Kim, Nelson, and Startz (1991) argue that the mean reversion results are only detectable in pre-war data, while Richardson and Stock (1989) and Richardson (1993) report that correcting for small-sample bias problems may reverse the Fama and French (1988a) and Poterba and Summers (1988) results. Campbell, Lo, and MacKinlay (1997, p.80) summarize the debate concisely:

> "Overall, there is little evidence for mean reversion in long-horizon returns, though this may be more of a symptom of small sample sizes rather than conclusive evidence against mean reversion -- we simply cannot tell."

Thus, a serious obstacle in detecting mean reversion is the absence of reliable long time series, especially because mean reversion, if it exists, is thought to be slow and can only be picked up over long horizons. Standard econometric procedures in general lack power to reject the null hypothesis of a random walk in stock prices against the alternative of mean reversion. The detection of mean reversion is further complicated by the need to identify a trend path or fundamental value path for the asset under investigation. Fama and French (1988a), among others, avoid specifying a trend path by first-differencing the price series. The cost of such a transformation, however, is a loss of information that could otherwise aid in identifying a mean-reverting price component.

In this paper, we employ a panel of stock-price indices from Morgan Stanley Capital International (MSCI) for 18 countries with well-developed capital markets (16 OECD countries plus Hong Kong and Singapore) for the period 1969 to 1996 to test for mean reversion. Under the assumption that the difference between the trend path of one country's stock-price index and that of a reference index is stationary, and that the speeds of reversion in different countries are similar, mean reversion may be detected from stock-price indices relative to a reference index. By considering stock price indices relative to a reference index, the difficult task of specifying a fundamental or trend path can be avoided. In addition, the panel format allows us to utilize the information on cross-sectional variation in equity indices to increase the power of the test so that mean reversion can be more easily detected, if present.

While mean reversion has been examined most extensively for the U.S. stock market, some researchers have investigated mean reversion in the context of international stock markets as well.[2] Kasa (1992) finds that national stock indices of Canada, Germany, Japan, the United Kingdom, and the United States are cointegrated and share one common stochastic trend. The implication of this result is that the value of a properly weighted portfolio of shares in the markets of at least two countries is stationary and thus will display mean reversion. Richards (1995) criticizes the results of Kasa (1992) on the grounds that the use of asymptotic critical values by Kasa in the cointegration tests is not appropriate. When finite-sample critical values are employed, however, Richards finds no significant evidence of cointegration among a group of 16 OECD countries, containing the five countries in Kasa's sample. Interestingly, he detects a stationary component in relative prices (implying partial mean reversion) and reports that country-specific returns relative to a world index are predictable.

Based on a panel approach, we find significant evidence of full mean reversion in national equity indices. In particular, we conclude that a country's stock price index relative to the world index, or to a particular reference country's index, is a stationary process. The strong implication is that an accumulated returns deficit of, say, 10 percent of a particular country's stock market compared to the world should be fully reversed over time. Given an estimated half-life of three to three and a half years in our data, this country's stock market should experience an expected total returns surplus, relative to the world index, of five percent over the next three to three and a half years. Our results are robust to several alternative specifications and to another data set from the International Monetary Fund's *International Financial Statistics* (*IFS*) for 11 countries for the period 1949 to 1997.

Accordingly, we may trade on the finding of mean reversion and would expect to obtain results similar to Richards (1995, 1997) who implements the "contrarian" strategy developed by DeBondt and Thaler (1985) to exploit (partial) mean reversion across national stock markets.[3] We devise a parametric contrarian strategy that efficiently exploits the information on mean reversion across countries directly from the parameter estimates of our econometric model. Comparing the average return from our parametric contrarian strategy to that from the standard contrarian strategy, a buy-and-hold strategy, and a random-walk-based strategy, provides further support for the mean reversion findings and gives an estimate of the economic significance.

The remainder of the paper is organized as follows. Section I specifies the econometric model of equity index prices and introduces the empirical methodology. Section II describes the data and carries out some preliminary diagnostics of the data. In Section III, we report the main test results for mean reversion. Section IV investigates the robustness of the mean reversion results. Section V studies some implications of mean reversion by introducing a parametric contrarian strategy and comparing its performance against various other trading rules. Section VI puts our mean reversion results in the perspective of the literature and discusses possible explanations. Concluding remarks are contained in Section VII.

## I. The Econometric Model and Empirical Methodology

Equation (1) below provides a typical formulation of a stochastic process for the price of an asset displaying mean reversion:

$$P^i_{t+1} - P^i_t \ = \ a^i \ + \ l^i \,(P^{*\,i}_{t+1} \ - \ P^i_t) \ + \ e^i_{t+1}. \tag{1}$$

In the above equation, $P^i_t$ represents the log of the stock-index price for country *i* that includes dividends at the end of year *t* so that $(P^i_{t+1} - P^i_t)$ equals the continuously compounded return an investor realizes in period *t+1;* $P^{*\,i}_t$ indicates the log of the fundamental or trend value of the stock-price index in country *i*, which is unobserved; $a^i$ is a positive constant; $e^i_{t+1}$ is a stationary shock term with an unconditional mean of zero. The parameter $l^i$ measures the *speed of reversion*. If $0 < l^i < 1$, deviations of the log price from its fundamental or trend value are reversed over time. The conventional case is $l^i = 0$, in which the log price follows an integrated process so that there is no "correction" in subsequent periods. When $l^i = 1$, a full adjustment occurs in the subsequent period.

Empirically, to confirm mean reversion, a significant finding of $l^i > 0$ is needed. However, in obtaining such a result, two problems arise in practice. First, it is difficult to specify the fundamental process, $P_t^{*i}$.[4] Second, mean reversion, if it exists, is likely to occur slowly, and can therefore be detected only in long time series; yet reliable long-term data for stock returns are in general hard to come by. We manage to circumvent these problems in this paper by using the additional information in cross-country comparisons. To this end, we assume that the speeds of mean reversion, $l^i$, across countries are equal and let this common value be $l$. Thus, the process of mean reversion in stock-index prices need not be synchronized across countries but the speeds at which asset prices return to their fundamental values are deemed to be similar.

We further propose that cross-country differences in fundamental stock-index values are stationary. More specifically, the fundamental values for two countries are assumed to be related as follows:

$$P_t^{*i} = P_t^{*r} + z^i + h_t^i , \tag{2}$$

where $z^i$ is a constant, which may be positive or negative; $h_t^i$ is a zero-mean stationary process which can be serially correlated; and the superscript "$r$" indicates a reference index.

Support for the assumed stationarity in fundamental stock-price differences across countries, is grounded in the literature on economic growth. Barro and Sala-i-Martin (1995) find that real per capita GDP across the 20 original OECD countries displays absolute convergence; that is, real per capita GDP in these countries converges to the same steady state.[5] Convergence arises from catching up in either capital (lower per capita capital implies a higher marginal efficiency of investment, Barro (1991)) or technology (adapting an existing technology is less costly than inventing one, Barro and Sala-i-Martin (1995)). In either case, at least in the context of such standard general equilibrium models as Brock (1982) and Lucas (1978), the firms in the lagging country would initially be less productive, but would catch up as technology or capital per worker improves. Since values of the firms converge across countries, so should their fundamental stock prices. Thus, the differences in fundamental stock prices across countries that converge absolutely (like the OECD countries) should be stationary.

Combining equation (1) for country *i* and any other country, denoted as reference country *r*, and using equation (2) to eliminate their fundamental values produces:

$$R_{t+1}^{i} - R_{t+1}^{r} = a^{i} - l\,(P_{t}^{i} - P_{t}^{r}) + w_{t+1}^{i}, \tag{3}$$

where the instantaneously compounded returns are defined as $R_{t+1}^{i} = P_{t+1}^{i} - P_{t}^{i}$. Furthermore, we define $a^{i} = a^{i} - a^{r} + l\,z^{i}$ and $w_{t}^{i} = e_{t}^{i} - e_{t}^{r} + l\,h_{t}^{i}$, with $a^{i}$ a constant and $w_{t}^{i}$ a stationary process with an unconditional mean of zero. Notice that the new disturbance term $w_{t}^{i}$ inherits the statistical properties of $e_{t}^{i}$ and $h_{t}^{i}$ and, in particular, is allowed to be serially correlated.

Equation (3) describes the evolution of a price index relative to a reference index over time. For a positive $l$, it implies that the difference $P_{t}^{i} - P_{t}^{r}$, which, up to a normalization, equals the accumulated return differential $\sum_{s=0}^{t}(R_{s}^{i} - R_{s}^{r})$, provides a signal to investors to reallocate their portfolios from a market that has done well over time to a market that has done poorly over time. Investors are likely to gain a higher return by, say, shifting their portfolios towards international markets if the domestic market is priced “high” relative to a particular foreign index, and vice versa.

Notice that equation (3) has a standard Dickey and Fuller (1979) regression format for a unit root test in the cross-country difference of the price series $P_{t}^{i} - P_{t}^{r}$. If the disturbance term $w_{t}^{i}$ is serially uncorrelated, an ordinary least squares (OLS) regression of (3) can be run and the *t*-statistic for $l = 0$ can be used to test for the null hypothesis of no mean reversion against the alternative of mean reversion $(l > 0)$. If $w_t^i$ is serially correlated, lagged values of return differentials can be added as additional regressors to purge the serial correlation, and the following equation can be estimated:

$$R^i_{t+1} - R^r_{t+1} = a^i - l\,(P^i_t - P^r_t) + \sum_{j=1}^{k} f^i_j\,(R^i_{t+1-j} - R^r_{t+1-j}) + w^i_{t+1}. \qquad (4)$$

For this formulation, the augmented Dickey-Fuller (ADF) unit root test can be employed to test for the sign and significance of $l$ (Dickey and Fuller (1979, 1981)). The added lagged return differences capture the stationary dynamics of country-specific fundamental values and stochastic return shocks.

Econometric studies by Campbell and Perron (1991), Cochrane (1991), and DeJong *et al*. (1992), among others, indicate, however, that standard unit root tests have very low power against local stationary alternatives in small samples. Because of this inherent problem, researchers have recently advocated pooling data and testing the hypothesis within a panel framework to gain test power.[6] Given the fact that our sample has only 28 annual price observations for each country, the power problem can be especially serious, implying that failure to reject the null hypothesis of $l = 0$ might well be a result of power deficiency of test procedures rather than evidence against mean reversion in stock index series.[7] Therefore, our tests are conducted in a panel framework. We pool data of all 18 countries to estimate the common speed of mean reversion $l$. To further improve estimation efficiency and gain statistical power, we exploit the information in the cross-country correlation of relative returns and estimate equation (4) using the seemingly unrelated regression (SUR) technique.

The panel-based test for the null hypothesis of no mean reversion ($l = 0$) is based on the following two statistics: $z_l = T\,\hat{l}$ and $t_l = \hat{l}\,/\,s(l)$, where $\hat{l}$ is the SUR estimate of $l$, $s(\hat{l})$ is the standard error of $\hat{l}$, and $T$ is the sample size. It is well known that under the null hypothesis of $l = 0$, $\hat{l}$ is biased upwards and the above two statistics do not have limiting normal distributions. We will therefore estimate the bias and generate appropriate critical values for our exact sample size through Monte-Carlo simulations as described in the Appendix.

## II. Data and Summary Statistics

Annual data are obtained from Morgan Stanley Capital International (MSCI) for stock market price indices of 18 countries and a world index.[8] The sample covers the period from 1969 through 1996. The observations are end-of-period value-weighted indices of a large sample of companies in each country. Index prices in each market include reinvested gross (i.e., before withholding taxes) dividends, and are available in both U.S. dollar and home-currency terms. Following related studies in this area, our main focus is on the indices in dollar terms.

Since the primary interest of this paper is to examine mean reversion of equity indices over long horizons, we use annual data, rather than the more frequently sampled monthly data, for the following reasons: (1) seasonal effects, such as the January effect, can be avoided; (2) higher frequency data provide little additional information for detecting a slow mean-reverting component (see footnote 7), so that the use of annual data does not come at the expense of the power of the test; and (3) the problem that dividends are considered by MSCI ("Methodology and Index Policy," 1997, p.36) to be received on a continuous basis throughout the year while observed ex-dividend prices vary based on infrequent dividend distributions, is avoided.

Table I presents some summary statistics for our data set. We compute, for each country, the average returns, standard errors of returns, and a simple beta with the world index (the U.S. Treasury-bill rate, from *International Financial Statistics* line 60, is used as a proxy for the risk-free rate). These statistics vary from highs of a 19.3 percent mean return, 42.5 percent standard error, and beta of 1.89, all for Hong Kong, to lows of a 5.8 percent mean return (Italy), 15.3 percent standard error (U.S.) and beta of 0.37 (Norway). The Jarque and Bera (1980) test indicates that the hypothesis that returns relative to the world or the U.S., follow a normal distribution, cannot be rejected for most countries.

The correlations of the country indices' *excess* returns in dollar terms relative to the world index return (not shown) vary from 0.79 between Germany and Switzerland to -0.73 between the U.S. and Japan. Some of these point estimates are quite large in magnitude. In terms of statistical significance, among the total of 153 correlations, 43 are significantly different from zero at the 10 percent level, although only 27 returns observations are available for use to compute each correlation coefficient. We exploit this information in cross-country stock returns to further improve estimation efficiency.

## III. Empirical Results

Section I demonstrates that we can test for mean reversion by employing country indices relative to a reference index. However, no guidance is provided on how to choose a reference index. In principle, if the speeds of mean reversion are similar and the assumption in Equation (2) holds, any country index or average of country indices can serve as a legitimate candidate and we should obtain asymptotically equivalent estimates of the parameter $l$. In other words, it is not necessary to assume that the reference country is the benchmark in order for the estimation to work. But, in finite samples, we do in general obtain a different estimate of $l$ (even with the simple OLS regression) when a different reference index is used, because the relative returns series constructed with a different reference index is numerically different. We choose the world index as a natural candidate. Since the world index is a weighted average of all countries in the MSCI universe, it includes the country under investigation. It can be shown straightforwardly that in this case estimation is consistent, but may be less efficient compared to a case in which the reference index excludes the country under investigation (because subtracting part of the reference index reduces the useful variation in the regression). Accordingly, an individual country index may serve as a more attractive reference index because it does not contain the price index of the country under investigation. Therefore, we also reproduce results using the U.S. index as a reference index. Though we do not provide these results in a table, we check that the results reported for the U.S. index and the world index as reference indices hold when we use Australia, Germany, and Japan as reference indices. We find that our conclusions continue to hold for these reference indices.

For the purpose of comparison, we first estimate equation (4) country by country, and conduct the standard ADF test. Following Said and Dickey (1984), we choose the lag length, *k*, to be equal to $T^{1/3}$, or three for our sample with 28 price observations. Table II reports the test results where all indices are expressed in U.S. dollar terms, with the world index and the U.S. index serving as reference indices. Critical values are obtained from Fuller (1976). It is observed that the null hypothesis of no mean reversion ($l$ = 0) cannot be rejected for most countries at conventional significance levels. In particular, at the five percent level of significance and using the world index as a reference index, we find mean reversion for only two countries: Denmark and Germany. Using the U.S. index as a reference, an additional country (Norway) is found to exhibit mean reversion. These results are perhaps not surprising, given that there are only 28 price-index observations for each country, implying that the power of the test can be very low. A Monte-Carlo experiment discussed at the end of this section will make this point more transparent.

Equation (4) is estimated for a system of either 18 (when the world is used as the reference index) or 17 (when the U.S. is used as the reference index) countries using SUR, where the optimal lag length, *k*, is chosen using the Schwarz Bayesian criterion (SBC). We find $k = 1$ in both cases.[9] As the test statistics, $z_l$ and $t_l$, do not follow standard distributions asymptotically under the null hypothesis of no mean reversion, we generate the empirical distribution using Monte-Carlo simulation and compute the associated *p*-values, as described in the Appendix.

Table III reports the panel-test results. The point estimates of $l$ are quite sizable and the null hypothesis of no mean reversion can be rejected at the one percent significance level based on the $z_l$ test using either reference index. While the $t_l$ test appears to be somewhat less powerful (as demonstrated numerically below, and similar to the single-equation findings reported in Schwert (1989)), the null hypothesis can nevertheless be rejected at the five percent level. These results are in sharp contrast with those from the single-equation test reported in Table II where the null hypothesis of no mean reversion can be rejected only for two to three countries, and demonstrate the gains in power from pooling the data.

Having reported the strong evidence of mean reversion, we proceed to use the estimate of $l$ to characterize the speed at which equity indices revert to their fundamental or trend values following a one-time shock. As is well known, the point estimate of $l$ is biased upwards. We therefore correct for the small-sample bias under the alternative hypothesis, using Monte-Carlo simulation described in the Appendix. The calculated median-unbiased estimates of $l$ equal 0.182 for the world reference index, with a 90 percent confidence interval of (0.110, 0.250), and 0.202 for the U.S. reference index, with a 90 percent confidence interval of (0.135, 0.270). These median-unbiased estimates of $l$ imply a half-life of 3.5 years for the world reference index case and 3.1 years for the U.S. reference index case.[10]

It is interesting to compare our results with those of Cutler, Poterba, and Summers (1991), who estimate equation (1) for 13 countries (all included in our sample), using the logarithm of the dividend-price ratio as the fundamental $P_t^{*i}$. They find a speed of reversion of 0.14 on average, below our estimates of 0.27 and 0.29. When the speeds of reversion are constrained to be equal across all 13 countries, they obtain a value of 0.16. Their estimates of the speed of reversion imply a half-life between 4.0 and 4.6 years. We find stronger evidence of mean reversion in this study with a half-life roughly one year shorter, which we believe is partly due to the fact that we estimate our equation (4) rather than equation (1), thereby avoiding the need for the, necessarily imperfect, specification of the fundamental value, $P_t^{*i}$.

Our finding that stock indices are mean reverting, relative to a reference index, is largely in line with Kasa (1992) who reports that real national stock price indices are cointegrated. Our results are based on national stock price indices in nominal dollar terms rather than in real terms, and are somewhat stronger in that we impose, *a priori*, a cointegrating vector of [1, -1]. While Richards (1995) detects predictability across national stock returns, no significant evidence of cointegration is found in his study. It is likely that Richards's result of no cointegration can be partly attributable to the low power of the cointegration tests, given the relatively short period in the data (25 full years in his sample). The panel-based test allows us to pool data of all 18 countries, which greatly enhances the power of the test, as demonstrated numerically below.

We carry out a simple Monte-Carlo experiment to compare the power of the panel procedure to that of the equation-by-equation test under four alternatives, $l$ = 0.150, 0.100, 0.050, and 0.182. The first three values are typically adopted in the literature when researchers examine power properties of unit-root test procedures, while the fourth choice is set equal to our bias-adjusted parameter estimated with the actual data (for the world reference index). The simulation methodology is described in the Appendix and the results are summarized in Table IV, from which several observations can be drawn. First, based on either test statistic, the panel-based test always outperforms the corresponding single-equation test under all four alternative values of $l$ and at all nominal sizes. Second, it is striking that when the observations are generated from the parameter estimated with the actual data ($l$ = 0.182), the power of both panel-based statistics is nearly perfect even at the one percent nominal size. In contrast, the corresponding power of the single-equation test is only 19.4 percent ($z_l$) and 11 percent ($t_l$) at the five percent level. These dramatic differences in power could explain the opposite conclusions drawn from the single-equation test (Table II) and the panel test (Table III).[11] Finally, for both test procedures, the $z_l$ statistic is in general more powerful than the $t_l$ statistic under all alternative specifications.

## IV. Robustness of the Mean Reversion Results

Based on our panel estimation by SUR for the world reference index we find a median-unbiased estimate of the speed of mean reversion of 0.182, implying a half-life of 3.5 years. We examine here how robust this result is to some changes in the choice of empirical specification and the choice of data. For all cases examined below, the world index is used as the reference index, except for the indices in real local currencies and the *IFS* data where the world index is not available and the U.S. index is used as the reference index.

First, we consider panel estimation by OLS. While the SUR estimation in principle improves the efficiency of the estimates, it requires the estimation of the 18x18 covariance matrix of cross-country residuals from only 28 annual observations. Column (1) in Table V displays the results of the OLS estimation. The estimate of $l$ is significantly positive at the one percent level for both the $z_l$ and $t_l$ tests, with *p*-values *lower* than the corresponding values in the SUR case. The median-unbiased estimate of $l$ is somewhat lower, however, than in the SUR case at 0.140, with a half-life of 4.6 years.

Second, we examine the robustness of the results with respect to the group of countries included in the sample. Excluding the largest-capitalization country, the U.S., has little impact on the results as seen in Column (2) of Table V. Excluding other potential outliers also has little effect. Column (3) shows that excluding Japan has a negligible effect on the results. Column (4) shows that excluding the non-OECD countries (Hong Kong and Singapore) has only a small impact: mean reversion is still significant (with *p*-values of 0.008 for the $z_l$ test and 0.051 for the $t_l$ test). The median-unbiased estimate of $l$ equals 0.143 with a half-life of 4.5 years. Last, as shown in Column (5), excluding another group of potential outliers, the two countries with significant mean reversion in univariate testing (Denmark and Germany), again does not damage the mean reversion results: the $z_l$ test yields a *p*-value of 0.004 and the $t_l$ test produces a *p*-value of 0.033; the half-life is 4.1 years.

Third, we consider the importance of exchange rate fluctuations in affecting the mean-reversion results. Abuaf and Jorion (1990), Engel and Hamilton (1990), Wu (1996), and others show that at low frequencies real and nominal exchange rates may be mean reverting. It is possible that the results obtained here are merely picking up the mean reversion in exchange rates. To check this we compare local-currency real returns across countries, instead of dollar-denominated returns. The difference in comparing local-currency returns and dollar returns is of course due to real exchange rate fluctuations. Column (6) in Table V indicates that results for local-currency real returns are quite similar to those for dollar returns. The median-unbiased estimate of the speed of mean reversion for local-currency real returns equals 0.204 with a half-life of 3.0 years.

Fourth, we explore the importance of exchange rate regimes. With the break-up of the Bretton

Woods exchange rate stabilization agreement, the switch from fixed exchange rates to a managed float in 1973 may have substantially affected the riskiness of some national markets relative to others, depending for instance on the degree of openness of their economies. Thus, we consider the post-Bretton Woods sample period only. Column (7) of Table V demonstrates that the mean reversion result is somewhat stronger, with a median-unbiased estimate of 0.198 and a half-life of 3.1 years.

Finally, we consider an extension of the sample period by employing another data set. We examine industrial share price data for 11 countries in the period 1949 to 1997 from the IMF's *International Financial Statistics (IFS)*.[12] While there are fewer countries in the panel, the longer time series allows us to estimate a smaller cross-country error covariance matrix more efficiently than the MSCI data. Column (8) of Table V displays significant mean reversion for this data set, with a $z_l$ test *p*-value of 0.006 and a $t_l$ test *p*-value of 0.001. The median-unbiased estimate of $l$, however, appears much lower than for the shorter time series of MSCI data, at 0.090 with a half-life of 7.3 years. Since the data here mix the pre- and post-Bretton Woods samples, we include for each country a dummy variable in the intercept to capture a permanent jump for the post-Bretton Woods period due to fundamental changes in national markets caused by the change in exchange-rate regime. Column (9) of Table V presents the results which now yield further strong support for mean reversion with *p*-values of 0.000 for both the $z_l$ and $t_l$ tests, and a median-unbiased $l$ estimate of 0.195 with a half-life of 3.2 years, which is very close to the base case.

In summary, the results presented in this section further suggest that national stock indices exhibit significant mean reversion and demonstrate that the results obtained in the preceding section are robust. In the succeeding section, we explore some important implications of the strong mean reversion findings.

## V. Portfolio Switching Strategies and Economic Significance

To determine if the mean reversion findings would allow investors to increase expected returns, we examine the implications of some simple portfolio switching strategies. The benefits of exploring such trading rules are that they allow measurement of the economic significance of the mean reversion results, provide a further robustness check (on the specification of the returns process), and give us a metric to compare our results to other approaches suggesting return predictability, such as the traditional contrarian strategies.

Consider the following strategy, which we employ with necessary changes as we consider different approaches. First, estimate the system of equations (4), using data from the beginning of the sample up to a point $t_0$.[13] We then use the parameter estimates and observations up to time $t_0$ to calculate the expected return for each country at time $t_0+1$, and invest 100 percent of the portfolio in the country with the highest expected return. As an additional data point at time $t_0+1$ becomes available, the regression is run with one more observation and the portfolio is switched to the country with the highest expected return at time $t_0+2$. This process is repeated until the end of the sample. We call this strategy the "Max1" strategy. Specifically, we set $t_0$ at 1/3 of the sample (year 1978) to ensure that a reasonable number of observations is available to estimate the first set of parameters. Forecasting starts at $t_0+1$ (year 1979), so the initial forecast period is 18 years.

Analogously, we define the "Min1" strategy as the strategy of investing 100 percent of the portfolio in the country with the lowest expected return. Accordingly, "Max1-Min1" involves buying the "Max1" portfolio and selling short the "Min1" portfolio and the corresponding "return" is an excess payoff from the zero net investment per dollar invested in the "Max1" portfolio (or, equivalently, per dollar received in shorting the "Min1" portfolio). The method employed here can be regarded as a parametric version of the contrarian strategy devised by DeBondt and Thaler (1985) to be examined below, and we term it the "parametric contrarian" strategy.

As a benchmark, we use the geometric average *buy-and-hold* strategy return for the period 1979 to 1996. Row (1) in Table VI shows returns of 13.7 percent for holding the World portfolio, 15.0 percent for the U.S. portfolio, and 14.2 percent for the equal-weighted portfolio of the 18 country indices.

We first consider the "Max1" *rolling regression* strategy based on estimating the panel equations (4) with $l$ constrained to be equal across countries. Row (2) in Table VI indicates an average return of 20.7

percent, clearly higher than the buy-and-hold returns. More impressively, this figure is higher than the, *ex post*, highest return for a buy-and-hold strategy, holding any national index portfolio (19.9 percent from holding the Hong Kong index over this time period). In terms of statistical significance, our average return is 7.0 percent above that on holding the world index, with a *t*-statistic of 1.37. Based on the finite-sample *t*-distribution, we compute the *p*-value equal to 0.094. Therefore, if we conduct a test for the two strategies against our one-sided mean-reversion alternative, i.e., $R_{max1} > R_{wld}$, the test is significant at the 10 percent level, despite the fact that there are only 18 forecasting points. The zero-net-investment strategy ("Max1-Min1") produces a considerable excess return of 9.0 percent, with a *t*-value of 1.80 and a *p*-value of 0.044.[14]

The *random-walk-with-drift-based* strategy relies on rolling regressions of equation (4) with the restriction that $l = 0$. If country indices are not mean reverting, this strategy should outperform the previous strategies. The reason is that it would simply pick those country indices with the highest past returns, which presumably would have higher risk and thus higher expected returns. The converse is true if mean reversion exists. Row (3) of Table VI shows a "Max1" return of 9.3 percent, *below* that of all previous strategies. Additionally, the "Max1-Min1" mean return is negative.

The *contrarian* strategy is a non-parametric trading strategy based on DeBondt and Thaler (1985) and further explored, for U.S. data by DeBondt and Thaler (1987), Chopra, Lakonishok, and Ritter (1992), and others, and for international stock price data by Richards (1995, 1997).[15] This strategy in our case involves investing in the country with the lowest average return over the previous three years and shorting the country with the highest average return over the previous three years. As displayed in Row (4) of Table VI, this strategy produces a "Max1-Min1" excess return of 6.1 percent, confirming the DeBondt and Thaler (1985) results for international data as in Richards (1997). This figure is, however, lower than that from our rolling regression (9.0 percent), although not significantly so. Moreover, the "Max1" return for the contrarian strategy of 13.5 percent is 7.2 percent lower than that of our rolling regression, with a *t*-statistic of 1.29 and a *p*-value of 0.107.

Conceptually, the DeBondt and Thaler (1985) contrarian strategy is also based on the idea that stock indices may revert to means over long horizons, and that returns are forecastable from past price information. Our rolling regression strategy, however, goes one step further. We fully exploit the information on mean reversion by estimating a parametric model so as to forecast future returns. This more efficient use of information may largely explain the better performance of our strategy as compared to DeBondt and Thaler (1985).

As a check for the robustness of the above findings, we calculate the average returns from investing equally in the *three* countries with the highest (lowest) expected returns, i.e., the "Max3" ("Min3") portfolio. From Table VI, results regarding the "Max3" and "Max3-Min3" strategies are quite similar, and the implications discussed above remain largely unchanged.

We further check for the robustness of these results to the choice of forecasting period. The results of Table VI discussed so far are obtained by using 1/3 of the sample to estimate the first rolling regression and by starting forecasting onwards. We reproduce all results by starting the rolling regression at different points in sample. Namely, $t_0$ is allowed to vary between 1974 and 1992.[16] Figure 1 depicts the mean returns for the "Max1" portfolio for the rolling regression, DeBondt and Thaler contrarian, random walk, and buy-and-hold world index strategies, with alternative years to start forecasting $(t_0+1)$. Strikingly, we find that for each starting forecast point, our rolling regression strategy outperforms all three other strategies. In particular, it yields a higher average return than the DeBondt and Thaler strategy for all starting forecast points: the return premium ranges from 3.8 percent (starting forecast year 1976) to 11.5 percent (starting forecast year 1991) with a typical figure between six to 10 percent. In Figure 2, we compare the mean excess returns of the zero-net-investment portfolio ("Max1-Min1") from the rolling regression, the DeBondt and Thaler contrarian, and the random walk strategies, with different starting forecast points. Our rolling regression strategy outperforms the DeBondt and Thaler strategy, often by a substantial margin (four to five percent) for all but three starting points.

The results presented in this section thus far suggest that the strategies predicated on mean reversion in country indices yield excess returns that are economically important. How can these results be explained? First, we have not considered transactions costs. In reality, costs of international transactions may be substantial, especially when short selling is involved and stock index futures contracts do not exist, making actual excess returns lower. It is worth pointing out, however, that our strategies require at most one switch a year, that the "Max1" strategies do not require short selling, and that the country indices constructed by MSCI consist of mostly larger stocks that are highly liquid.[17] Second, a few countries were subject to some degree of capital controls in the early part of the sample (in particular, Japan prior to 1974), which would have limited international speculation. Note, however, that as shown in Figures 1 and 2, our strategies produce substantial excess returns even when we start the forecast period in the late 1980s when capital controls for the countries in our sample would be negligible. Further, Table V shows that excluding Japan or only considering the OECD countries does not substantially affect the results. Nevertheless, the mean-reversion based strategies discussed should not necessarily be viewed as profitable investment strategies in practice (even for risk neutral investors). We would, however, like to interpret these results as providing complementary support for our earlier mean reversion results obtained from the panel-based tests.

Can the excess returns reported above from parametric contrarian strategies be explained by risk factors? To answer this question, we look first at the simple covariance risk. The fourth column of Table VI presents the betas of the returns obtained under the various strategies, with the world index used as the market portfolio and the U.S. T-bill rate as the risk free rate. These beta values suggest that the higher returns of the strategies exploiting mean reversion cannot be easily explained by simple beta risk.[18] Interestingly, non-systematic (stand-alone) risk appears to explain the excess returns reasonably well. The last column in Table VI shows that the Sharpe ratio of 0.485 for the rolling regression "Max1" strategy is lower than that of 0.644 for the buy-and-hold U.S. index strategy. The apparent importance of country-specific risk in affecting returns may be understood in the context of the well-documented home bias observation (see French and Poterba (1991)): If enough investors are unwilling to diversify fully across countries, global investors could benefit by marginally shifting their portfolios towards those countries (like the U.S.) with the higher Sharpe ratios, but they would not necessarily force all country-specific Sharpe-ratios to lie below that of the world index, as required by the simple CAPM.

We do not intend to fully explore the possibilities of explaining the excess returns on the switching strategies as a payment for systematic risk. Our point here is only that beta risk does not provide a simple explanation. This is not to say that risk could not explain our results. Adler and Dumas (1983) and Stulz (1995) demonstrate that very strong assumptions would be required for the simple CAPM to hold in an international context. Thus, risk related to exchange rate fluctuations, or related to changes in investment opportunities across nations, may affect relative returns. But, even if the parametric contrarian strategy results are explainable by risk or transactions costs, they still provide additional support for our mean reversion findings.

## VI. Discussion

Transaction costs or risk may explain the excess returns from exploiting mean reversion but do not explain the existence of mean reversion itself. Previous literature has provided various explanations for mean reversion in individual stock prices that can be extended to the national markets level. A first explanation is based on Chan (1988) and Ball and Kothari (1989). Their arguments imply that after substantial losses, the firms in a country index are more highly leveraged (if no adjustments to capital structure are made). Thus, the betas of their equities rise and returns are expected to be higher. Zarowin (1990) and Richards (1997) provide a second explanation, based on size. According to their reasoning, the country indices that have lost more tend to end up with smaller firms and, to the extent that size captures a risk factor, these lower-priced country indices are thus expected to produce higher returns. A third explanation is provided by Conrad and Kaul (1993), and Ball, Kothari, and Shanken (1995), who indicate that low-priced stocks are subject to serious micro-structure biases which could produce abnormal returns.

These theories provide plausible explanations for the mean reversion results that we obtain. They do not, however, explain the persistence in returns (price *continuation*) and the related profitability of momentum strategies (typically for higher-frequency data) obtained by Jegadeesh and Titman (1993), and Chan, Jegadeesh, and Lakonishok (1996) for the U.S. stock market, and by Rouwenhorst (1998) for international firm-level data. As variance-ratio tests by Poterba and Summers (1988) and Cecchetti, Lam, and Mark (1990) show, U.S. equity returns are positively correlated over short horizons and negatively correlated over longer horizons. We present next an explanation which in principle may account for both mean reversion at low frequencies and price continuation at high frequencies in the context of national equity markets.

Recent studies by Brennan and Cao (1997), Choe, Kho, and Stulz (1999), and Clark and Berko (1996) suggest that one may think of investors as having an informational advantage in their home markets, explaining why investors might have a home bias. In this view, suppose that favorable news is released involving the home market. Foreign investors now raise their valuation by more than domestic investors (the news has less impact on domestic investors who generally have more precise information and might have received this news earlier). Thus, these foreign investors purchase domestic equity at higher prices. As a result, domestic investors, left holding less domestic equity, become better diversified and, for a given perceived distribution of future dividends, may accept lower expected returns. Domestic equity prices thus initially rise further, but then revert over the longer horizon as the broadening of the investors base lowers expected returns.

Alternatively, an "overreaction" explanation of the pattern of price continuation followed by mean reversion can be provided along the lines of DeLong *et al*. (1990), where positive-feedback traders push asset prices away from fundamentals. Some empirical support exists, however, for the investor-base-broadening argument. Clark and Berko (1996) find in the case of Mexico that stock price increases are associated with an inflow of foreign investment and with a subsequent reduction in expected returns. Choe, Kho, and Stulz (1999), using order and trade data, show for the Korean stock market that positive feedback trading occurs among foreign investors. They also find that positive returns which coincide with purchases by foreign investors are not accompanied by abnormal subsequent returns. Thus, positive feedback trading by international investors need not involve overreaction in the stock market.

While our study differs substantially from the above studies – in its basic methodology, a focus on mature national markets, and the use of a longer time horizon – exploring the investor-base-broadening hypothesis and other efficient market perspectives as explanations for our results would seem to provide a useful avenue for future research.

## VII. Conclusion

We believe our paper contributes to the finance literature in general by developing and applying two methodological innovations and specifically through our findings in the context of national stock markets.

The first methodological contribution consists of our implementation of a novel panel approach to test for mean reversion. By exploiting cross-sectional variation, the power of the panel test under plausible alternatives is enhanced tremendously as compared to the standard single-equation tests with an equivalent sample period. Since our panel estimation is more efficient, it provides a relatively accurate estimate of the speed of mean reversion.

The second methodological contribution concerns our development of a new strategy for exploiting the existence of mean reversion to better forecast stock returns and as a guide in portfolio choice. This strategy is termed a “parametric contrarian” strategy, akin to the DeBondt and Thaler (1985) strategy for capitalizing on mean reversion, but utilizing information more efficiently directly from the parameters of a rolling regression version of our panel estimation approach.

Applying these innovations to a panel of national equity prices of 18 countries over the period 1969 to 1996, we reach several important conclusions that add to the findings of Kasa (1992) and Richards (1995, 1997) in a similar international context. First, the gain in test power of our approach allows us to reject the absence of mean reversion at the five or one percent significance level, thereby firmly establishing the occurrence of mean reversion among stock indices. Furthermore, this finding is re-confirmed with the *IFS* data set. This is a key result as it adds to the controversial evidence of mean reversion first provided for U.S. stock prices by DeBondt and Thaler (1985), Fama and French (1988a), and Poterba and Summers (1988). The uncovering of a strong relation in substantially different data sets decreases the likelihood of earlier mean reversion findings as attributable to “data mining.”

Second, our panel approach, together with Monte-Carlo simulations to correct for small-sample bias, produces relatively reliable, unbiased estimates of the speed of reversion of between 18 percent to 20 percent per year. This implies that following a one-time shock to stock prices, it takes approximately between three to three and a half years for these prices to revert half-way to their fundamental values.

Third, the simple parametric contrarian investment strategies that we derived directly from our panel parameter estimates from prior data, produce statistically and economically significant excess returns. These strategies also appear to outperform buy-and-hold strategies and the contrarian strategy of DeBondt and Thaler (1985). The results provide additional support for mean reversion and complement those of our direct test. We further find that the excess returns from our parametric contrarian strategy cannot be easily explained by simple beta risk but appear to be related to non-systematic (stand-alone) country risk. The latter is consistent with the observation of home bias.

## Appendix

This appendix describes the three Monte-Carlo experiments carried out in this paper to generate empirical distributions of the test statistics under various hypotheses. For all experiments, let *N* be the number of relative country indices and *T* the number of price observations in each series. For the MSCI data, *N* is 18 with the world reference index and 17 with the U.S. reference index, and *T* is 28, while for the *IFS* data, *N* is 10 and *T* is 49.

*(1) Testing for no mean reversion $l = 0$*. This involves 3 steps. Step 1: Simulate *N* random walk processes with *T* price observations each, where the innovations are generated from a multivariate normal distribution with mean zero and cross-country covariance matrix equal to the historical covariance matrix. Step 2: Estimate the system with the simulated observations with the restriction that all $l^i$ are equal, and calculate the two statistics, $z_l$ and $t_l$. Step 3: Repeat steps 1 and 2 a total of 5,000 times to produce the empirical distribution of the test statistics under the null of $l = 0$. The *p*-values reported in Tables III and V are defined as the percentage of the Monte-Carlo distribution having values greater than the corresponding historical test statistics computed with the data.

*(2) Estimating the small-sample bias of $\hat{l}$*. Similar to the above experiment, we first use equation (3) to simulate *N* price series with *T* observations each, with a specific value of $l$, and then obtain an estimate $\hat{l}$. Replicating this process 1,000 times yields the empirical distribution of $\hat{l}$ under this particular value of $l$. We conduct the experiment for various values of $l$, ranging from 0.00 to 0.50, in increments of 0.01. Using interpolation, we estimate the values of $l$ that equate the median and the five and 95 percent fractiles of the simulated $\hat{l}'s$ to our historical $\hat{l}$. This yields the median-unbiased estimate of $l$ and its 90 percent confidence interval, as reported in Tables III and V.

*(3) Power comparison*. We compare the small-sample power of the panel procedure to that of the equation-by-equation test, under four alternative values of $l$. As the cross-country error covariance matrix

under an alternative value of $l$ is unknown, we employ a diagonal covariance matrix for the panel procedure. Step 1: Simulate observations under model (3), where the intercept terms are set to zero and the innovations are drawn from mutually independent iid $N(0,1)$ distributions. Four alternative values, $l$ = 0.150, 0.100, 0.050, and 0.182, are considered. For the equation-by-equation test, a price series of 28 observations is generated; while for the panel-based test, a panel of 18 series with 28 observations each is simulated. Step 2: Compute the test statistics $z_l$ and $t_l$. Determine whether the hypothesis of no mean reversion can be rejected at the pre-specified significance levels, one, five and 10 percent, respectively, with corresponding critical values obtained under the null hypothesis of $l=0$. Step 3: Under each alternative value of $l$, replicate the above steps 5,000 times. The empirical power of each test statistic at each significance level, as reported in Table IV is the number of rejections of the null hypothesis of $l=0$ as a percentage of the total number of replications (5,000).

## REFERENCES


Abuaf, Niso, and Phillippe Jorion, 1990, Purchasing power parity in the long run, *Journal of Finance* 45, 157-174.

Adler, Michael, and Bernard Dumas, 1983, International portfolio choices and corporation finance: A synthesis, *Journal of Finance* 38, 925-984.

Ball, Ray, and S. P. Kothari, 1989, Nonstationary expected returns: Implications for tests of market efficiency and serial correlations in returns, *Journal of Financial Economics* 25, 51-74.

Ball, Ray, S. P. Kothari, and Jay Shanken, 1995, Problems in measuring portfolio performance: An application to contrarian investment strategies, *Journal of Financial Economics* 38, 79-107.

Balvers, Ronald J., Thomas F. Cosimano, and Bill McDonald, 1990, Predicting stock returns in an efficient market, *Journal of Finance* 45, 1109-1128.

Barro, Robert, 1991, Economic growth in a cross section of countries, *Quarterly Journal of Economics* 106, 407-444.

Barro, Robert, and Xavier Sala-i-Martin, 1995, *Economic Growth* (McGraw-Hill, New York).

Brennan, Michael J., and H. Henry Cao, 1997, International portfolio investment flows, *Journal of Finance* 52, 1851-1880.

Brock, William A., 1982, Asset prices in an exchange economy, in J.J. McCall, ed.: *The Economics of Information and Uncertainty* (University of Chicago Press, Chicago, IL).

Campbell, John Y., and Pierre Perron, 1991, Pitfalls and opportunities: What macroeconomists should know about unit roots: *NBER Macroeconomics Annual* (MIT Press, Boston).

Campbell, John Y., Andrew W. Lo, and A. Craig MacKinlay, 1997, *The Econometrics of Financial Markets* (Princeton University Press: Princeton, New Jersey).

Cecchetti, Stephen, Pok-Sang Lam, and Nelson Mark, 1990, Mean reversion in equilibrium asset prices, *American Economic Review* 80, 398-418.

Chan, K. C., 1988, On the contrarian investment strategy, *Journal of Business* 61, 147-163.

Chan, Louis K. C., Narasimhan Jegadeesh, and Josef Lakonishok, 1996, Momentum strategies, *Journal of Finance* 51, 1681-1713.

Choe, Hyuk, Bong-Chan Kho, and René Stulz, 1999, Do foreign investors destabilize stock markets? The Korean experience in 1997, *Journal of Financial Economics,* forthcoming.

Chopra, Navin, Josef Lakonishok, and Jay R. Ritter, 1992, Measuring abnormal performance: Do stocks overreact?, *Journal of Financial Economics* 31, 235-268.

Clark, John, and Elizabeth Berko, 1996, Foreign investment fluctuations and emerging market stock returns: The case of Mexico, *Federal Reserve Bank of New York Research Paper 9635.*

Cochrane John H., 1991, A critique of the application of unit root tests, *Journal of Economic Dynamics and Control* 15, 275-284.

Conrad, Jennifer, and Gautam Kaul, 1993, Long-term market overreaction or biases in computed returns?, *Journal of Finance* 48, 39-64.

Cutler, David M., James M. Poterba, and Lawrence H. Summers, 1991, Speculative dynamics, *Review of Economic Studies* 58, 529-546.

DeBondt, Werner, and Richard Thaler, 1985, Does the stock market overreact?, *Journal of Finance* 40, 793-805.

DeBondt, Werner, and Richard Thaler, 1987, Further evidence of overreaction and stock market seasonality, *Journal of Finance* 42, 557-581.

DeJong, David N., John C. Nankervis, N.E. Savin, and Charles H. Whiteman, 1992, The power problems of unit root tests in time series with autoregressive errors, *Journal of Econometrics* 53, 323-343.

DeLong, J. Bradford, Andrei Shleifer, Lawrence H. Summers, and Robert J. Waldmann, 1990, Positive feedback investment strategies and destabilizing rational speculation, *Journal of Finance* 45, 379-395.

Dickey, David A., and Wayne A. Fuller, 1979, Distribution of the estimators for autoregressive time series with a unit root, *Journal of the American Statistical Association* 74, 427-481.

Dickey, David A., and Wayne A. Fuller, 1981, Likelihood ratio statistics for autoregressive time series with a unit root, *Econometrica* 49, 1057-1072.

Engel, Charles, and James D. Hamilton, 1990, Long swings in the dollar: Are they in the data and do markets know it? *American Economic Review* 80, 689-713.

Fama, Eugene, and Kenneth French, 1988a, Permanent and temporary components of stock prices, *Journal of Political Economy* 96, 246-273.

Fama, Eugene, and Kenneth French, 1988b, Dividend yields and expected stock returns, *Journal of Financial Economics* 22, 3-25.

Ferson, Wayne E., and Campbell Harvey, 1993, The risk and predictability of international equity returns, *Review of Financial Studies* 6, 527-566.

Ferson, Wayne E., and Campbell Harvey, 1998, Fundamental determinants of national equity market returns: A perspective on conditional asset pricing, *Journal of Banking and Finance* 21, 1625-1665.

Frankel, Jeffrey A., and Andrew K. Rose, 1996, A panel project on purchasing power parity: Mean reversion within and between countries, *Journal of International Economics* 40, 209-224.

French, Kenneth R., and James M. Poterba, 1991, Investor diversification and international equity markets, *American Economic Review* 81, 222-226.

Fuller, Wayne A., 1976, *Introduction to Statistical Time Series* (John Wiley and Sons, New York).

Jarque, Carlos M., and Anil K. Bera, 1980, Efficient tests for normality, heteroskedasticity and serial independence of regression residuals, *Economics Letters* 6, 255-259.

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *Journal of Finance* 48, 65-91.

Kasa, Kenneth, 1992, Common stochastic trends in international stock markets, *Journal of Monetary Economics* 29, 95-124.

Kim, Myung Jig, Charles R. Nelson, and Richard Startz, 1991, Mean reversion in stock prices? A reappraisal of the empirical evidence, *Review of Economic Studies* 58, 515-528.

Levin, Andrew, and Chien-Fu Lin, 1993, Unit root tests in panel data: Asymptotic and finite-sample properties, *Mimeo*, University of California, San Diego.

Lo, Andrew W., and A. Craig MacKinlay, 1988, Stock market prices do not follow random walks: Evidence from a simple specification test, *Review of Financial Studies* 1, 41-66.

Lucas, Robert E., 1978, Asset prices in an exchange economy, *Econometrica* 46, 1426-1445.

Morgan Stanley Capital International, 1997, *Methodology and Index Policy*.

Perron, Pierre, 1989, Testing for a random walk: A simulation experiment of power when the sampling interval is varied, in B. Raj, ed.: *Advances in Econometrics and Modeling* (Kluwer, Boston).

Perron, Pierre, 1991, Test consistency with varying sampling frequency, *Econometric Theory* 7, 341-368.

Poterba, James, and Lawrence Summers, 1988, Mean reversion in stock prices: Evidence and implications, *Journal of Financial Economics* 22, 27-59.

Richards, Anthony J., 1995, Comovements in national stock market returns: Evidence of predictability, but not cointegration, *Journal of Monetary Economics* 36, 631-654.

Richards, Anthony J., 1997, Winner-loser reversals in national stock market indices: Can they be explained?, *Journal of Finance* 52, 2129-2144.

Richardson, Matthew, 1993, Temporary components of stock prices: A skeptic's view, *Journal of Business and Economic Statistics* 11, 199-207.

Richardson, Matthew, and James Stock, 1989, Drawing inferences from statistics based on multi-year asset returns, *Journal of Financial Economics* 25, 323-348.

Rouwenhorst, K. Geert, 1998, International momentum strategies, *Journal of Finance* 53, 267-284.

Said, S.E., and David A. Dickey, 1984, Testing for unit roots in autoregressive moving average models of unknown order, *Biometrica* 71, 599-608.

Schwert, G. William, 1989, Tests for unit roots: A Monte-Carlo investigation, *Journal of Business and*

*Economic Statistics* 7, 147-160.

Stulz, René, 1995, International portfolio choice and asset pricing: An integrative survey, in R. Jarrow, M. Maximovich and W. Ziemba, eds.: *Handbook of Modern Finance* (North Holland-Elsevier, Amsterdam).

Wu, Yangru, 1996, Are real exchange rates non-stationary? Evidence from a panel-data test, *Journal of Money, Credit and Banking* 28, 54-63.

Zarowin, Paul, 1990, Size, seasonality, and stock market overreaction, *Journal of Financial and Quantitative Analysis* 25, 113-125.

Table I

## Summary Statistics of National Stock-Index Returns

The table reports summary statistics for the annual returns data from Morgan Stanley Capital International over the period 1970 to 1996. In computing the betas, the U.S. treasury-bill rate is used as the risk-free rate of return. The test for normality of the excess returns of a country index relative to a reference index is by Jarque and Bera (1980). The test statistic follows the $c^2(2)$ distribution under the null hypothesis that the excess returns are normally distributed.

| Country | Mean | Standard Error | β with World Index | Test for Normality in Excess Returns | |
|---|---|---|---|---|---|
| | | | | World Reference index | US Reference index |
| AUS | 0.089 | 0.243 | 1.286 | 0.760 | 1.446 |
| AUT | 0.108 | 0.263 | 0.463 | 4.175 | 2.010 |
| BEL | 0.144 | 0.192 | 0.793 | 12.607** | 0.156 |
| CAN | 0.096 | 0.159 | 0.759 | 2.535 | 1.404 |
| DEN | 0.132 | 0.247 | 0.828 | 0.117 | 0.048 |
| FRA | 0.116 | 0.248 | 1.115 | 0.569 | 0.308 |
| GER | 0.113 | 0.228 | 0.755 | 2.055 | 2.053 |
| HKG | 0.193 | 0.425 | 1.887 | 0.583 | 0.188 |
| ITA | 0.058 | 0.307 | 1.229 | 1.160 | 1.662 |
| JPN | 0.140 | 0.285 | 1.321 | 1.378 | 0.784 |
| NLD | 0.153 | 0.162 | 0.880 | 2.972 | 1.581 |
| NOR | 0.126 | 0.355 | 0.371 | 6.938* | 5.284 |
| SIG | 0.141 | 0.359 | 1.523 | 4.856 | 3.938 |
| SPN | 0.093 | 0.277 | 0.742 | 0.743 | 0.111 |
| SWE | 0.153 | 0.218 | 0.856 | 0.254 | 1.377 |
| SWT | 0.127 | 0.202 | 0.874 | 0.032 | 0.608 |
| UKM | 0.126 | 0.272 | 1.312 | 0.831 | 1.619 |
| USA | 0.111 | 0.153 | 0.806 | 0.949 | |
| WLD | 0.112 | 0.155 | 1.000 | | |

"*", "**", --- denote statistical significance at the five and one percent levels, respectively.

Table II

## ADF Tests for Mean Reversion of Stock Indices

The table reports single-equation augmented Dickey-Fuller test results for mean reversion in stock price indices relative to a reference index. The model for the equity index of country *i* relative to a reference index is specified as:

$$R^i_{t+1} - R^r_{t+1} = a^i - l^i(P^i_t - P^r_t) + \sum_{j=1}^{k} f^i_j (R^i_{t+1-j} - R^r_{t+1-j}) + w^i_{t+1}$$

where $i = 1,..., N$. The superscript "*r*" denotes a reference index series. The null hypothesis is $H_0$: $l^i = 0$, and the alternative hypothesis is $H_1$: $l^i > 0$. The table reports the *t*-statistic defined as $\hat{l}^i / s(\hat{l}^i)$ , where $\hat{l}^i$ is the OLS estimate of $l^i$ and $s(\hat{l}^i)$ is the standard error of $\hat{l}^i$. The critical values are obtained from Fuller (1976).

| Country | World Reference Index | U.S. Reference Index |
|---|---|---|
| AUS | 1.667 | 2.562 |
| AUT | 1.784 | 2.327 |
| BEL | 1.354 | 1.750 |
| CAN | 0.705 | -0.116 |
| DEN | 3.763** | 3.854** |
| FRA | 1.740 | 2.194 |
| GER | 3.151* | 3.569* |
| HKG | 0.162 | 0.582 |
| ITA | 2.005 | 1.837 |
| JPN | 1.322 | 1.403 |
| NLD | -0.307 | 1.222 |
| NOR | 2.949 | 4.710** |
| SIG | 2.177 | 1.796 |
| SPN | 1.863 | 2.083 |
| SWE | 0.754 | 1.490 |
| SWT | 2.103 | 2.928 |
| UKM | 1.244 | 1.408 |
| USA | 1.888 | |
| Critical Values | | |
| 10% | 2.63 | 2.63 |
| 5% | 3.00 | 3.00 |
| 1% | 3.75 | 3.75 |

"*", "**", --- denote statistical significance at the five and one percent levels, respectively.

Table III

## Panel Tests for Mean Reversion of Stock Prices

The table presents panel-based estimation results for stock price indices relative to a reference index. The model is specified as:

$$R^{i}_{t+1} - R^{r}_{t+1} = a^{i} - l\,(P^{i}_{t} - P^{r}_{t}) + \sum_{j=1}^{k} f^{i}_{j}(R^{i}_{t+1-j} - R^{r}_{t+1-j}) + w^{i}_{t+1}$$

where $i = 1,..., N$. "$N$" is the panel size. The superscript "$r$" denotes a reference index series. The null hypothesis is $H_0$: $l = 0$, and the alternative hypothesis is $H_1$: $l > 0$. The test statistics are defined as: $z_l = T\hat{l}$ and $t_l = \hat{l}/s(\hat{l})$, where $T$ is the time periods in the sample, and $s(\hat{l})$ is the standard error of $\hat{l}$. The $p$-values are computed from 5,000 Monte-Carlo replications. The median-unbiased estimate of $l$ is the estimate of $l$ corrected for small-sample bias. The small-sample bias under the alternative hypothesis that $l > 0$, as well as its 90 percent confidence interval, are estimated from Monte-Carlo simulation with 5,000 replications. The half-life is calculated as ln(1/2)/ln(1-$l$), where $l$ takes the median-unbiased estimate.

| | World Reference Index | U.S. Reference Index |
|---|---|---|
| Point Estimate of $l$ | 0.274 | 0.292 |
| $z_l$ | 7.407 | 7.894 |
| $p$-value | 0.002 | 0.000 |
| $t_l$ | 11.431 | 11.277 |
| $p$-value | 0.044 | 0.022 |
| Median-Unbiased Estimate of $l$ | 0.182 | 0.202 |
| 90% Confidence Interval of $l$ | [0.110, 0.250] | [0.135, 0.270] |
| Implied Half-Life (Years) | 3.5 | 3.1 |

Table IV

**Power Comparison of Test Procedures**

The table reports empirical power of both the single-equation and panel-based test procedures under alternative values of $l$. The power is calculated in all cases using Monte-Carlo simulation with 5,000 replications. For the single-equation test, in each replication, a price series with 28 observations is simulated for a specific value of $l$. Analogously, for the panel test, 18 mutually independent price series with 28 observations each are generated for each replication. A nominal size is a pre-specified significance level at which the null hypothesis of no mean reversion can be rejected when the observations are generated from the model with a specific value of $l$. The test statistics are defined as: $z_l = T\hat{l}$ and $t_l = \hat{l}/s(\hat{l})$, where $\hat{l}$ is the OLS estimate of $l$, $T$ is the time periods in the sample, and $s(\hat{l})$ is the standard error of $\hat{l}$.

| | Nominal Size = 1% | | | | Nominal Size = 5% | | | | Nominal Size = 10% | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Alternative Values of $l$ | 0.150 | 0.100 | 0.050 | 0.182 | 0.150 | 0.100 | 0.050 | 0.182 | 0.150 | 0.100 | 0.050 | 0.182 |
| | | | | | Panel Test | | | | | | | |
| Power of $z_l$ Test | 0.978 | 0.768 | 0.288 | 0.999 | 0.998 | 0.932 | 0.554 | 1.000 | 0.999 | 0.973 | 0.714 | 1.000 |
| Power of $t_l$ Test | 0.593 | 0.226 | 0.064 | 0.827 | 0.901 | 0.593 | 0.265 | 0.980 | 0.965 | 0.765 | 0.425 | 0.996 |
| | | | | | Univariate Test | | | | | | | |
| Power of $z_l$ Test | 0.034 | 0.023 | 0.015 | 0.043 | 0.162 | 0.118 | 0.080 | 0.194 | 0.283 | 0.214 | 0.160 | 0.336 |
| Power of $t_l$ Test | 0.018 | 0.015 | 0.013 | 0.023 | 0.092 | 0.074 | 0.062 | 0.110 | 0.181 | 0.142 | 0.120 | 0.212 |

Table V

**Further Tests for Mean Reversion of Stock Prices**

The table reports panel-based estimation results for stock indices relative to a reference index for alternative specifications: (1) estimation with a diagonal error covariance matrix (OLS); (2) estimation by excluding the U.S.; (3) estimation by excluding Japan; (4) estimation for OECD countries only; (5) estimation by excluding the countries that exhibit mean reversion by the single-equation test; (6) estimation using indices in local currencies; (7) estimation with the post-Bretton Woods sample period; (8) estimation with *IFS* data from 1949 to 1997 for 11 countries; and (9) estimation using the *IFS* data with country-specific intercept dummy variables in 1973. The world index is used as the reference index, except in cases (6), (8) and (9) where the world index is not available and the U.S. index is used as the reference index.

In each case, the model is specified as:

$$R^i_{t+1} - R^r_{t+1} = a^i - l\,(P^i_t - P^r_t) + \sum_{j=1}^{k} f^i_j (R^i_{t+1-j} - R^r_{t+1-j}) + w^i_{t+1}$$

where $i = 1,..., N$. "$N$" is the panel size. The superscript "$r$" denotes a reference index series. The null hypothesis is $H_0$: $l = 0$, and the alternative hypothesis is $H_1$: $l > 0$. The test statistics are defined as: $z_l = T\hat{l}$ and $t_l = \hat{l}/s(\hat{l})$, where $T$ is the number of time periods in the sample, and $s(\hat{l})$ is the standard error of $\hat{l}$. The $p$-values are computed from 5,000 Monte-Carlo replications. The median-unbiased estimate of $l$ is the estimate of $l$ corrected for small-sample bias. The small-sample bias under the alternative hypothesis that $l > 0$, as well as its 90 percent confidence interval, are estimated from Monte-Carlo simulation with 5,000 replications. The half-life is calculated as $\ln(1/2)/\ln(1-l)$, where $l$ takes the median-unbiased estimate.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| Point Estimate of $l$ | 0.235 | 0.267 | 0.280 | 0.241 | 0.251 | 0.294 | 0.311 | 0.140 | 0.291 |
| $z_l$ | 6.351 | 7.211 | 7.548 | 6.519 | 6.786 | 7.935 | 7.153 | 6.744 | 13.968 |
| $p$-value | 0.000 | 0.001 | 0.000 | 0.008 | 0.004 | 0.000 | 0.001 | 0.006 | 0.000 |
| $t_l$ | 8.894 | 10.893 | 10.950 | 9.819 | 10.333 | 10.259 | 17.175 | 7.750 | 11.012 |
| $p$-value | 0.000 | 0.030 | 0.030 | 0.051 | 0.033 | 0.056 | 0.030 | 0.001 | 0.000 |
| Median-Unbiased Estimate of $l$ | 0.140 | 0.174 | 0.187 | 0.143 | 0.145 | 0.204 | 0.198 | 0.090 | 0.195 |
| 90% Confidence Interval of $l$ | [0.062, 0.203] | [0.094, 0.227] | [0.109, 0.256] | [0.063, 0.215] | [0.072, 0.224] | [0.125, 0.268] | [0.127, 0.275] | [0.029, 0.133] | [0.120, 0.261] |
| Implied Half-Life (Years) | 4.6 | 3.6 | 3.3 | 4.5 | 4.1 | 3.0 | 3.1 | 7.3 | 3.2 |

Table VI

**Results of Portfolio Switching Strategies**

The table reports means, *b's* and Sharpe ratios for the returns based on various portfolio switching strategies. The Sharpe ratio is defined as $(\overline{R} - R_f)/s(R)$ where $\overline{R}$ is the sample mean of returns over the forecasting years, *s(R)* is the standard deviation of the excess returns and $R_f$ is the risk free rate which is approximated by the U.S. Treasury-bill rate averaged over the forecasting period. For the "Max - Min" cases, the risk free rate is not subtracted. Results are obtained by starting the forecast period at the 1/3 sample point for all strategies.

Strategy 1 is the buy-and-hold strategy, where we report the average returns from holding the world index, the U.S. index, and the equal-weighted portfolio of all 18 country indices in the sample; Strategy 2 uses rolling regressions to estimate model parameters for each period where the parameter $l$ is constrained to be identical across countries; Strategy 3 is similar to Strategy 2 except that $l$ is constrained to be zero, i.e. stock indices are assumed to follow random walks with drifts; Strategy 4 first calculates returns for all indices over a three-year period, and then constructs a portfolio to be held for the next three years. The portfolio consists of the one (three) stock(s) with the lowest return over the previous three-year period and short-selling the one (three) stock(s) with the highest return over that period. This is done for non-overlapping intervals for the entire sample. "Max1" denotes the highest expected return index, and "Max1-Min1" denotes the difference between the highest and the lowest returns; "Max3" denotes the average of three highest expected return indices and "Max3-Min3" the difference between the average of three highest and the average of three lowest returns. Note that significance is marked only for the "Max-Min" differences. Inference is based on the *t*-statistic calculated as $\overline{R}/[s(R)/(T - t_0)^{1/2}]$, where $T$- $t_0$ is the number of years in the forecasting period.

| Strategy | Type | Mean Return | *b* with World Index | Sharpe Ratio |
|---|---|---|---|---|
| 1. Buy and Hold | World | 0.137 | 1.000 | 0.447 |
| | U.S. | 0.150 | 0.602 | 0.644 |
| | E.W. Portfolio | 0.142 | 1.090 | 0.393 |
| 2. Rolling Regression | Max1 | 0.207 | 1.336 | 0.485 |
| | Max1-Min1 | 0.090* | -0.118 | 0.425 |
| | Max3 | 0.198 | 1.256 | 0.549 |
| | Max3-Min3 | 0.084** | 0.008 | 0.579 |
| 3. Random Walk Based (Fixing $l = 0$) | Max1 | 0.093 | 0.814 | 0.066 |
| | Max1-Min1 | -0.036 | -0.407 | -0.120 |
| | Max3 | 0.128 | 0.910 | 0.322 |
| | Max3-Min3 | -0.021 | -0.235 | -0.125 |
| 4. Contrarian (DeBondt-Thaler) | Max1 | 0.135 | 0.983 | 0.329 |
| | Max1-Min1 | 0.061 | -0.137 | 0.230 |
| | Max3 | 0.121 | 0.953 | 0.266 |
| | Max3-Min3 | 0.039 | -0.310 | 0.244 |

"*", "**", -- denote statistical significance at the five and one percent levels, respectively.

**Figure 1. Mean returns with alternative forecast points**. This figure presents the mean returns for the "Max1" portfolio under four investment strategies: rolling regression, DeBondt and Thaler (1985), random walk based, and buying-and-holding the world index, with alternative years to start forecasting.

**Figure 2. Mean excess returns of zero-net-investment portfolios with alternative forecast points**. This figure presents the mean excess returns of the zero-net-investment portfolio ("Max1-Min1") under four investment strategies: rolling regression, DeBondt and Thaler (1985), random walk based, and buying-and-holding the world index, with alternative years to start forecasting.

[1] As argued by Fama and French (1988a) and confirmed by general equilibrium models of Balvers, Cosimano, and McDonald (1990) and Cecchetti, Lam, and Mark (1990), mean reversion can be consistent with equilibrium in an efficiently functioning financial market.

[2] Mean reversion is equivalent to stationarity (in mean) -- shocks to prices are temporary so that returns are negatively autocorrelated at certain horizons. Mean reversion thus implies that returns are predictable based on lagged prices. Conversely, predictability of returns based on lagged prices need not imply mean reversion. For example, predictable explosive processes are not mean reverting. The more general predictability of international stock prices based on attributes other than price history has received growing attention. For instance, Ferson and Harvey (1993, 1998) use a conditional beta pricing model to explain the predictability of international equity returns. Cutler, Poterba, and Summers (1991) employ the dividend-price ratio to predict international equity returns.

[3] We use the term “contrarian strategy” in its general sense, as signifying buying (selling) assets that have performed poorly (well) in the past. The standard DeBondt and Thaler (1985) *zero-net-investment* strategy (short-selling assets that have performed well and using the proceeds to buy assets that have performed poorly) is in our usage of the term just a particular example of a contrarian strategy. The term “momentum strategy” correspondingly has the opposite meaning.

[4] Researchers have used various proxies for the fundamental. For example, Cutler, Poterba, and Summers (1991) estimate equation (1) for 13 countries (all included in our sample), using the logarithm of the dividend-to-price ratio as a proxy for the fundamental $p_t^{*i}$. Econometrically, incorrect specification of the fundamental contaminates the estimate of $l$. For instance, in the case of the dividend-to-price ratio, anticipated increases in the growth rate of dividends raise the fundamental value but not its proxy (which may actually fall). As the stock price typically increases with the anticipated increase in dividend growth rate, the estimate of $l$ is inconsistent and has a downward bias of unknown size.

[5] Barro (1991) finds *conditional* convergence for a larger group of 98 countries in that real per capita GDP in these countries converges to the same steady state after adjusting for differences in human capital. The absolute convergence findings of Barro and Sala-i-Martin (1995) and conditional convergence findings of Barro (1991) may be reconciled when we consider that differences in human capital across OECD countries are relatively minor.

[6] Levin and Lin (1993) have formally studied the asymptotic and finite-sample properties of the panel-based tests for a unit root. Abuaf and Jorion (1990), Frankel and Rose (1996), and Wu (1996), among others, have implemented the panel tests to study long-run dynamics in cross-country time series.

[7] Perron (1989, 1991) has pointed out that the power of unit root tests is primarily affected by the time span of the sample, rather than the actual number of observations used. In other words, one gains little power by using more frequently sampled data which cover the same time frame.

[8] These countries are: Australia (AUS), Austria (AUT), Belgium (BEL), Canada (CAN), Denmark (DEN), France (FRA), Germany (GER), Hong Kong (HKG), Italy (ITA), Japan (JPN), the Netherlands (NLD), Norway (NOR), Singapore (SIG), Spain (SPN), Sweden (SWE), Switzerland (SWT), the United Kingdom (UKM), and the United States (USA).

[9] Another popular selection criterion, the Akaike information criterion (AIC), also selects $k = 1$ here. We have experimented with longer lags (up to three) and found that the overall results were not sensitive to the choice of lag length.

[10] As discussed previously, we consider three further reference indices (Australia, Germany and Japan), one from each geographical region, and find that the test results are robust, with a half-life of 3.1 years when Australia is the reference index and 2.7 years when the other two countries are the reference indices. Detailed results are available from the authors upon request.

[11] One interesting question to ask is by how much the power of the single-equation test can be improved if a longer series is available. To get a rough idea, we compute the empirical power under the alternative $l = 0.182$ with 70 observations, which is approximately the sample size had we started the

sample in 1926 as in Fama and French (1988a, 1988b). We find that at the five percent nominal size, the power of $z_l$ is 67.2 percent, and that of $t_l$ is 46.6 percent. While these numbers are substantially higher than those obtained with 28 observations, they are probably not high enough for a researcher with 70 annual observations to comfortably reject the null hypothesis of no mean reversion.

[12] Our *IFS* sample includes the following countries: Austria, Denmark, Finland, France, Ireland, Italy, Japan, the Netherlands, Norway, Sweden, and the U.S. These are all the countries with complete data from 1949 to 1997. Many of the time series start in 1948 but we would have to drop three countries if we started in 1948. Belgium was dropped because the IMF stopped reporting its share prices after 1995. In spite of the longer sample period, these data are less desirable than the MSCI data for several reasons. In particular, the price indices are not as comprehensive, do not include dividends, and are period averages, rather than end-of-period observations.

[13] Here we estimate the system using OLS rather than SUR because too few effective observations are available for use in the early rolling regressions. In order to conduct a feasible SUR, the innovation covariance matrix across countries must be estimated from the first step single-equation regressions. To guarantee that this estimated covariance matrix is positive definite and hence invertible, the number of observations must be at least as large as the number of countries in the panel.

[14] Note that this strategy employs only prior information. If we use information from the full sample to estimate the panel regression, and use the fixed set of parameters from this regression to form portfolios, the “Max1” return equals 23.3 percent while the “Max1-Min1” difference equals 20.5 percent, with a *t*-value of 3.33 which is statistically significant at the one percent level.

[15] Using monthly CRSP files, DeBondt and Thaler (1985) calculated stock returns for all U.S. firms over a three-year period, and then constructed a zero-net-investment portfolio to be held for the following three years. The portfolio consisted of a long position in the 35 stocks with the lowest cumulative return over the previous three-year period and a short position in the 35 firms with the highest cumulative return over that same period. They demonstrated that this strategy delivered significantly positive excess returns.

[16] We choose $t_0$ to be no earlier than 1974 so that four observations are available to run the first rolling regression, and no later than 1992, so that four years are available for out-of-sample forecasting.

[17] As an example, in Table VI, the "Max1" with the rolling regression strategy requires only nine switches among countries over the forecasting period (18 years).

[18] Consider the "Max1" strategies. The average returns and the betas in Table VI do in general correlate positively, but the variation in the betas is not large enough to explain a large part of the excess returns. Specifically, given that over the full sample period, the average three-month T-bill rate equals 6.9 percent and the average return on the world index is 11.2 percent, the estimated equity premium for the world index is 4.3 percent. The value of beta equal to 1.34 (0.34 higher than the world portfolio) for the rolling regression strategy would then explain an excess return of 1.4 percent, which is only 20 percent of the actual excess return of 7.0 percent. More strikingly, for the "Max1-Min1" (zero net investment) portfolio, the beta for the rolling regression strategy is slightly below zero, yet this strategy produces an excess return of 9.0 percent, which is significantly positive at the five percent level.

Figure 1. Mean Returns with Alternative Forecast Points

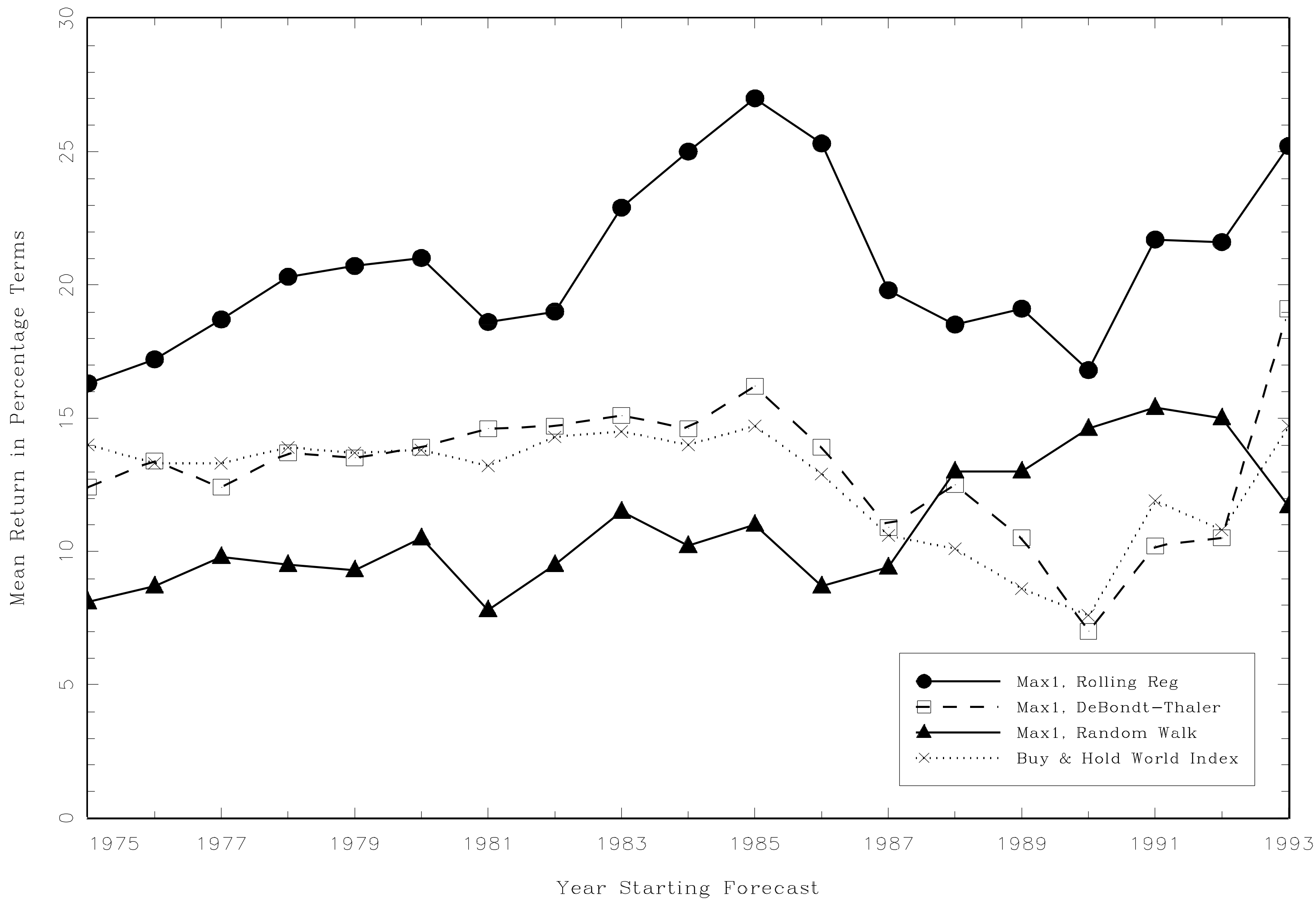

Figure 2. Mean Excess Returns of Zero Net Investment Portfolios with Alternative Forecast Points