

Mean Reversion across National Stock Markets and Parametric Contrarian Investment Strategies

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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 18 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 one-half years. This result is robust to alternative specifications and data. Parametric contrarian investment strategies that fully exploit mean reversion across national indexes outperform buy-and-hold and standard contrarian strategies.

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 prewar data; and 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) summarize the debate concisely:

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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.

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. (p. 80)

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 generally lack the 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 indexes 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 indexes relative to a reference index. By considering stock price indexes relative to a reference index, the difficult task of specifying a fundamental or trend path can be avoided. Additionally, the panel format allows us to utilize the information on cross-sectional variation in equity indexes to increase the power of the test so that mean reversion can be more easily detected, if present.

Mean reversion has been examined most extensively for the U.S. stock market, though some researchers have investigated mean reversion in the context of international stock markets as well.² Kasa (1992) finds that national stock indexes 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 Kasa's results on the

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.

grounds that his use of asymptotic critical values 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 indexes. 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 one-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 one-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 those of 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. Section III reports the main test results for mean reversion and 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 and Section VII presents our concluding remarks.

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.

I. The Econometric Model and Empirical Methodology

A typical formulation of a stochastic process for the price of an asset displaying mean reversion is as follows:

$$P_{t+1}^i - P_t^i = \alpha^i + \lambda^i(P_{t+1}^{*i} - P_t^i) + \epsilon_{t+1}^i. \quad (1)$$

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

Empirically, to confirm mean reversion, a significant finding of $\lambda^i > 0$ 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, λ^i , across countries are equal and let this common value be λ . 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:

$$P_t^{*i} = P_t^{*r} + z^i + \eta_t^i, \quad (2)$$

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

⁴ Researchers have used various proxies for the fundamental. For example, Cutler et al. (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 λ . 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 λ is inconsistent and has a downward bias of unknown size.

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

$$R_{t+1}^i - R_{t+1}^r = \alpha^i - \lambda(P_t^i - P_t^r) + \omega_{t+1}^i \quad (3)$$

where the instantaneously compounded returns are defined as $R_{t+1}^i = P_{t+1}^i - P_t^i$. Furthermore, we define $\alpha^i = a^i - a^r + \lambda z^i$ and $\omega_t^i = \epsilon_t^i - \epsilon_t^r + \lambda \eta_t^i$, with α^i a constant and ω_t^i a stationary process with an unconditional mean of zero. Notice that the new disturbance term ω_t^i inherits the statistical properties of ϵ_t^i and η_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 λ , 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 toward 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 ω_t^i is serially uncorrelated, an ordinary least squares (OLS) regression of equation (3) can be run and the t -statistic for $\lambda = 0$ can be used to test for the null hypothesis of no mean

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.

reversion against the alternative of mean reversion ($\lambda > 0$). If ω_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:

$$R_{t+1}^i - R_{t+1}^r = \alpha^i - \lambda(P_t^i - P_t^r) + \sum_{j=1}^k \phi_j^i (R_{t+1-j}^i - R_{t+1-j}^r) + \omega_{t+1}^i. \quad (4)$$

For this formulation, the augmented Dickey–Fuller (ADF) unit root test can be employed to test for the sign and significance of λ (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 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 $\lambda = 0$ 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 λ . 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 ($\lambda = 0$) is based on the following two statistics: $z_\lambda = T\hat{\lambda}$ and $t_\lambda = \hat{\lambda}/s(\hat{\lambda})$, where $\hat{\lambda}$ is the SUR estimate of λ , $s(\hat{\lambda})$ is the standard error of $\hat{\lambda}$, and T is the sample size. It is well known that under the null hypothesis of $\lambda = 0$, $\hat{\lambda}$ is biased upward and these 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.

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.

II. Data and Summary Statistics

Annual data are obtained from Morgan Stanley Capital International (MSCI) for stock market price indexes 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 indexes of a large sample of companies in each country. Index prices in each market include reinvested gross dividends (i.e., before withholding taxes) and are available in both U.S. dollar and home-currency terms. Following related studies in this area, our main focus is on the indexes in dollar terms.

Since the primary interest of this paper is to examine mean reversion of equity indexes 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 (United States) and beta of 0.37 (Norway). The Jarque and Bera (1980) test indicates that the hypothesis that returns relative to the world or the United States follow a normal distribution cannot be rejected for most countries.

The correlations of the country indexes' 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 United States 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 in computing each correlation coefficient. We exploit this information in cross-country stock returns to further improve estimation efficiency.

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).

Table I
Summary Statistics of National Stock Index Returns

Summary statistics are reported 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 $\chi^2(2)$ 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	U.S. 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		

* and ** denote statistical significance at the 5 and 1 percent levels, respectively.

III. Empirical Results

Section I demonstrates that we can test for mean reversion by employing country indexes 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 indexes can serve as a legitimate candidate and we should obtain asymptotically equivalent estimates of the parameter λ . 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 generally obtain a different estimate of λ (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 it 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 indexes hold when we use Australia, Germany, and Japan as reference indexes. We find that our conclusions continue to hold for these reference indexes.

For 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 indexes are expressed in U.S. dollar terms, with the world index and the U.S. index serving as reference indexes. Critical values are obtained from Fuller (1976). It is observed that the null hypothesis of no mean reversion ($\lambda = 0$) cannot be rejected for most countries at conventional significance levels. In particular, at the 5 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, and they imply 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 SURs, 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_λ and t_λ , 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 λ are quite sizable and the null hypothesis of no mean reversion can be rejected at the 1 percent significance level based on the z_λ test using either reference index. Though the t_λ test appears to be somewhat less powerful (as demonstrated

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.

Table II
Augmented Dickey–Fuller Tests for Mean Reversion of Stock Indexes
Single-equation augmented Dickey–Fuller test results are reported for mean reversion in stock price indexes relative to a reference index. The model for the equity index of country i relative to a reference index is specified as

$$R_{t+1}^i - R_{t+1}^r = \alpha^i - \lambda^i (P_t^i - P_t^r) + \sum_{j=1}^k \phi_j^i (R_{t+1-j}^i - R_{t+1-j}^r) + \omega_{t+1}^i,$$

where $i = 1, \dots, N$. The superscript r denotes a reference index series. The null hypothesis is $H_0: \lambda^i = 0$ and the alternative hypothesis is $H_1: \lambda^i > 0$. The table reports the t -statistic defined as $\hat{\lambda}^i/s(\hat{\lambda}^i)$, where $\hat{\lambda}^i$ is the OLS estimate of λ^i and $s(\hat{\lambda}^i)$ is the standard error of $\hat{\lambda}^i$. 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 percent	2.63	2.63
5 percent	3.00	3.00
1 percent	3.75	3.75

* and ** denote statistical significance at the 5 and 1 percent levels, respectively.

numerically below, and similar to the single-equation findings reported in Schwert (1989)), the null hypothesis can nevertheless be rejected at the 5 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 λ to characterize the speed at which equity indexes revert to their fundamental or trend values following a one-time shock. As is well known, the point estimate of λ is biased upward. We therefore correct for the

Table III
Panel Tests for Mean Reversion of Stock Prices

Panel-based estimation results are reported for stock price indexes relative to a reference index. The model is specified as

$$R_{t+1}^i - R_{t+1}^r = \alpha^i - \lambda^i (P_t^i - P_t^r) + \sum_{j=1}^k \phi_j^i (R_{t+1-j}^i - R_{t+1-j}^r) + \omega_{t+1}^i,$$

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

	World Reference Index	U.S. Reference Index
Point estimate of λ	0.274	0.292
z_λ	7.407	7.894
p -value	0.002	0.000
t_λ	11.431	11.277
p -value	0.044	0.022
Median-unbiased estimate of λ	0.182	0.202
90 percent confidence interval of λ	[0.110, 0.250]	[0.135, 0.270]
Implied half-life (years)	3.5	3.1

small-sample bias under the alternative hypothesis, using Monte Carlo simulation described in the Appendix. The calculated median-unbiased estimates of λ equal 0.182 for the world reference index with a 90 percent confidence interval of (0.110, 0.250), and equal 0.202 for the U.S. reference index with a 90 percent confidence interval of (0.135, 0.270). These median-unbiased estimates of λ 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 et al. (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

¹⁰ As discussed previously, we consider three further reference indexes (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 indexes. Detailed results are available from the authors upon request.

mean reversion in this study with a half-life roughly one year shorter, which we believe results partly from 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 indexes are mean reverting, relative to a reference index, is largely in line with Kasa (1992) who reports that real national stock price indexes are cointegrated. Our results are based on national stock price indexes in nominal dollar terms rather than in real terms, and are somewhat stronger in that we impose, a priori, a cointegrating vector of $[1, -1]$. Though 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, $\lambda = 0.150, 0.100, 0.050$, and 0.182 . The first three values are typically adopted in the literature when researchers examine power properties of unit-root test procedures, and 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 λ and at all nominal sizes. Second, it is striking that when the observations are generated from the parameter estimated with the actual data ($\lambda = 0.182$), 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_λ) and 11 percent (t_λ) 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_λ statistic is in general more powerful than the t_λ statistic under all alternative specifications.

¹¹ One interesting question to ask is: By how much can the power of the single-equation test be improved if a longer series is available? To get a rough idea, we compute the empirical power under the alternative $\lambda = 0.182$ 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_λ is 67.2 percent, and that of t_λ is 46.6 percent. Though 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.

Table IV
Power Comparison of Test Procedures

Empirical power is reported for both the single-equation and panel-based test procedures under alternative values of λ . 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 λ . Analogously, for the panel test, 18 mutually independent price series with 28 observations each are generated for each replication. A nominal size is a prespecified 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 λ . The test statistics are defined as: $z_\lambda = T\hat{\lambda}$ and $t_\lambda = \hat{\lambda}/s(\hat{\lambda})$, where $\hat{\lambda}$ is the OLS estimate of λ , T is the time periods in the sample, and $s(\hat{\lambda})$ is the standard error of $\hat{\lambda}$.

Test Procedure	Nominal Size = 1 percent for Alternative Values of λ				Nominal Size = 5 percent for Alternative Values of λ				Nominal Size = 10 percent for Alternative Values of λ			
	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_λ 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_λ 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_λ 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_λ 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

IV. Robustness of the Mean Reversion Results

Based on our panel estimation by SURs 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 indexes 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. Although the SUR estimation in principle improves the efficiency of the estimates, it requires the estimation of the 18×18 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 λ is significantly positive at the 1 percent level for both the z_λ and t_λ tests, with p -values *lower* than the corresponding values in the SUR case. The median-unbiased estimate of λ 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 United States, 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_λ test and 0.051 for the t_λ test). The median-unbiased estimate of λ 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_λ test yields a p -value of 0.004 and the t_λ 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.

Table V
Further Tests for Mean Reversion of Stock Prices

Panel-based estimation results are reported for stock indexes relative to a reference index for alternative specifications: (1) estimation with a diagonal error covariance matrix (OLS); (2) estimation by excluding the United States; (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 indexes 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:

$$R_{t+1}^i - R_{t+1}^r = \alpha^i - \lambda^i(P_t^i - P_t^r) + \sum_{j=1}^k \phi_j^i(R_{t+1-j}^i - R_{t+1-j}^r) + \omega_{t+1}^i,$$

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

	Alternative Specifications								
	(1) OLS	(2) Without the U.S.	(3) Without Japan	(4) Only OECD Countries	(5) Without Outliers	(6) Local Currency	(7) Post-Bretton Woods	(8) 1949–97 <i>IFS</i> Data	(9) <i>IFS</i> with Dummy Variable
Point estimate of λ	0.235	0.267	0.280	0.241	0.251	0.294	0.311	0.140	0.291
z_λ	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_λ	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 λ	0.140	0.174	0.187	0.143	0.145	0.204	0.198	0.090	0.195
90 percent confidence interval of λ	[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

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*.¹² Though 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_λ test p -value of 0.006 and a t_λ test p -value of 0.001. The median-unbiased estimate of λ , 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_λ and t_λ tests, and a median-unbiased λ 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 indexes 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

¹² Our *IFS* sample includes the following countries: Austria, Denmark, Finland, France, Ireland, Italy, Japan, the Netherlands, Norway, Sweden, and the United States. 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 indexes are not as comprehensive, do not include dividends, and are period averages rather than end-of-period observations.

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 one-third of the sample (year 1978) to ensure that a reasonable number of observations are 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 indexes.

We first consider the Max1 *rolling regression* strategy based on estimating the panel equations (4) with λ 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

¹³ Here we estimate the system using OLS rather than SURs 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.

Table VI
Results of Portfolio Switching Strategies

The table reports means, β 's, and Sharpe ratios for the returns based on various portfolio switching strategies. The Sharpe ratio is defined as $(\bar{R} - R_f)/s(R)$, where \bar{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 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 one-third 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-weight portfolio of all 18 country indexes in the sample; Strategy 2 uses rolling regressions to estimate model parameters for each period where the parameter λ is constrained to be identical across countries; Strategy 3 is similar to Strategy 2 except that λ is constrained to be zero (i.e. stock indexes are assumed to follow random walks with drifts); Strategy 4 first calculates returns for all indexes 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 nonoverlapping 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 indexes and Max3 – Min3 is the difference between the average of the three highest and the average of the three lowest returns. Note that significance is marked only for the Max – Min differences. Inference is based on the t -statistic calculated as $\bar{R}/[s(R)/(T - t_0)^{1/2}]$, where $T - t_0$ is the number of years in the forecasting period.

Strategy	Type	Mean Return	β with World Index	Sharpe Ratio
1. Buy and hold	World	0.137	1.000	0.447
	United States	0.150	0.602	0.644
	Equal weight 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 $\lambda = 0$)	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 1985)	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

* and ** denote statistical significance at the 5 and 1 percent levels, respectively.

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 $\lambda = 0$. If country indexes are not mean reverting, this strategy should outperform the previous strategies. The reason is that it would simply pick those country indexes 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 nonparametric 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 indexes 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).

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 and the Max1 – Min1 difference equals 20.5 percent with a t -value of 3.33, which is statistically significant at the 1 percent level.

¹⁵ Using monthly CRSP files, DeBondt and Thaler (1985) calculate stock returns for all U.S. firms over a three-year period, and then construct a zero-net-investment portfolio to be held for the following three years. The portfolio consists 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 demonstrate that this strategy delivers significantly positive excess returns.

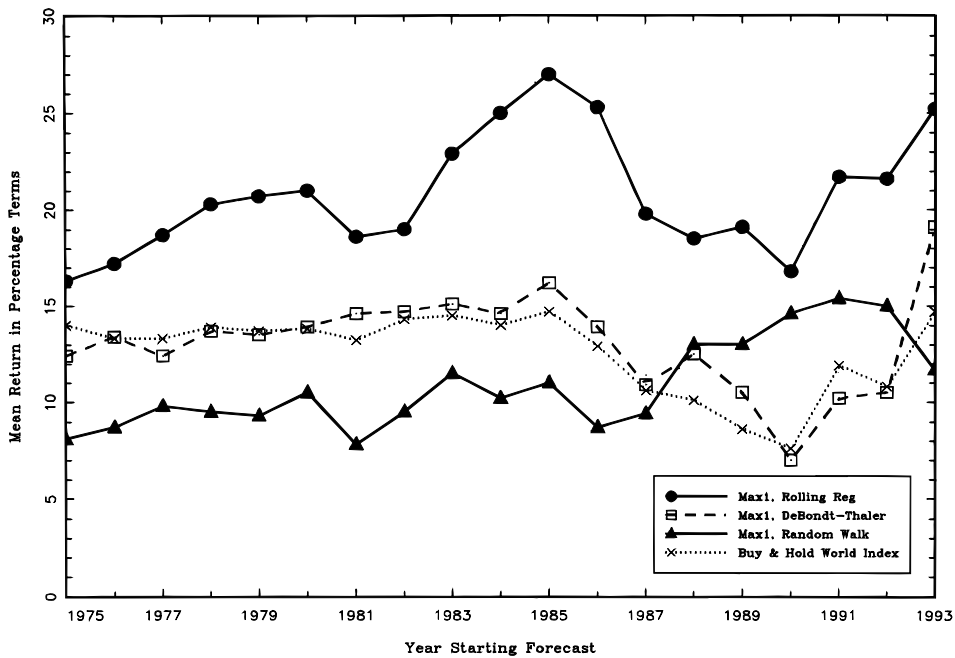


Figure 1. Mean returns with alternative forecast points. This figure presents the mean returns for the Max1 portfolio under four investment strategies: rolling regression, DeBondt and Thaler (1985), random-walk based, and buying-and-holding the world index, with alternative years to start forecasting.

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—that is, 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 one-third of the sample to estimate the first rolling regression and by starting forecasting onward. We reproduce all results by starting the rolling regression at different points in the 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.

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.

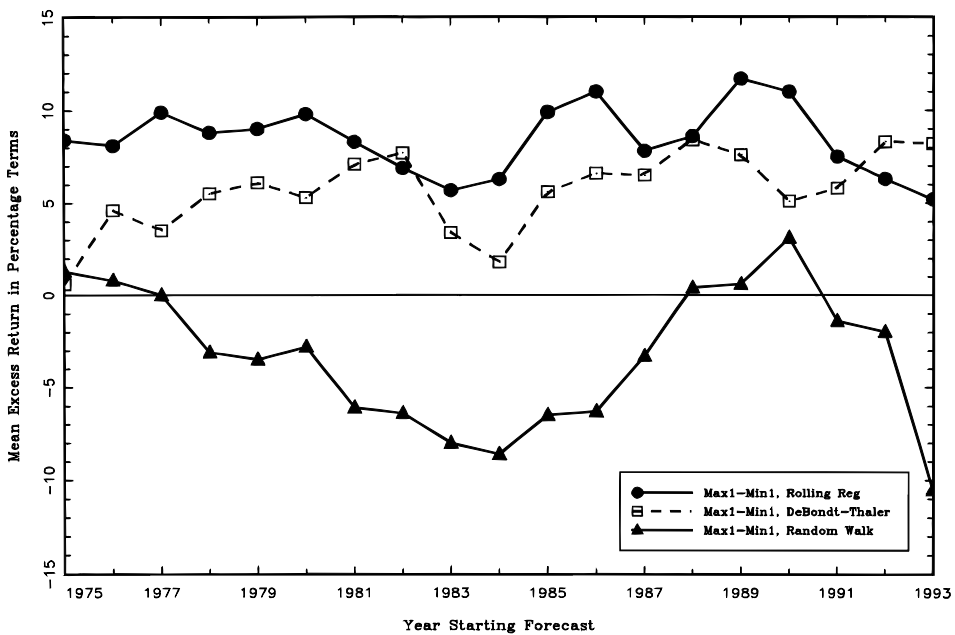


Figure 2. Mean excess returns of zero-net-investment portfolios with alternative forecast points. This figure presents the mean excess returns of the zero-net-investment portfolio (Max1 – Min1) under four investment strategies: rolling regression, DeBondt and Thaler (1985), random-walk based, and buying-and-holding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

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 and 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 indexes 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 indexes 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, nonsystematic (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 toward those countries (like the United States) 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

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 generally 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 5 percent level.

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 indexes 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 indexes 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 microstructure biases that 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 et al. (1990) show, U.S. equity returns are positively correlated over short horizons and negatively correlated over longer horizons. We present next an explanation that, 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 et al. (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.

Although our study differs substantially from the above studies—in its basic methodology, its focus on mature national markets, and its 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. Conclusions

We believe our paper contributes to the finance literature generally 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 more efficiently utilizing information 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 5 or 1 percent significance level, thereby firmly establishing the occurrence of mean reversion among stock indexes. Furthermore, this finding is reconfirmed with the

IFS data set. This is a key result because 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 and 20 percent per year. This implies that following a one-time shock to stock prices, it takes approximately three to three and one-half years for these prices to revert halfway to their fundamental values.

Third, the simple parametric contrarian investment strategies, which 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 nonsystematic (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 indexes 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; for the *IFS* data, N is 10 and T is 49.

(1) *Testing for no mean reversion* $\lambda = 0$. This involves three 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 λ^i are equal, and calculate the two statistics, z_λ and t_λ . 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 $\lambda = 0$. 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 $\hat{\lambda}$* . Similar to the above experiment, we first use equation (3) to simulate N price series with T observations each, with a specific value of λ , and then obtain an estimate $\hat{\lambda}$. Replicating this process 1,000 times yields the empirical distribution of $\hat{\lambda}$ under this

particular value of λ . We conduct the experiment for various values of λ , ranging from 0.00 to 0.50, in increments of 0.01. Using interpolation, we estimate the values of λ that equate the median and the five and 95 percent fractiles of the simulated $\hat{\lambda}$'s to our historical $\hat{\lambda}$. This yields the median-unbiased estimate of λ 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 λ . As the cross-country error covariance matrix under an alternative value of λ 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 i.i.d. $N(0,1)$ distributions. Four alternative values, $\lambda = 0.150, 0.100, 0.050$, and 0.182 , are considered. For the equation-by-equation test, a price series of 28 observations is generated, and for the panel-based test, a panel of 18 series with 28 observations each is simulated. Step 2: Compute the test statistics z_λ and t_λ . Determine whether the hypothesis of no mean reversion can be rejected at the prespecified significance levels, 1, 5, and 10 percent, respectively, with corresponding critical values obtained under the null hypothesis of $\lambda = 0$. Step 3: Under each alternative value of λ , 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 $\lambda = 0$ as a percentage of the total number of replications (5,000).

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