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Predictability of short-horizon returns in international equity markets

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Abstract

This paper examines the predictability of equity index returns for 18 developed countries. Based on the variance ratio test, the random walk hypothesis can be rejected at conventional significance levels for 11 countries with daily data and for 15 countries with weekly data. Monthly indices may well be characterized as a random walk for the majority of countries. The excess returns from buying past winners and selling past losers are positive and particularly striking for daily data, where they are not only statistically significant but also economically important in the absence of transaction costs. Imposing a reasonable transaction cost substantially reduces the profitability.

JEL classification: G15; G12
Keywords: International equity markets; Predictability; Variance ratio; Momentum strategies

1. Introduction

Whether security returns are predictable using their past history has been a focal point of research in the empirical finance literature. Tests for predictability have important implications for asset pricing and market efficiency. In an efficient capital market, equity prices reflect currently available information and one should not be able to predict future returns by using historical returns data. Therefore, if returns are predictable, it could imply market inefficiency unless the predictable variation can be reconciled with an equilibrium asset-pricing model. Over the past 2 decades, the extent of international investments has been steadily increasing. Investors (both institutional and individual) now allocate a substantially

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higher proportion of their financial wealth in international assets than 2 decades ago. However, our knowledge of predictability of security prices has primarily been drawn from studies on the U.S. market. As capital markets become more globally integrated, understanding the behavior of international equity prices is of increasing importance. In this paper, we employ the variance ratio test to investigate whether equity returns exhibit predictable variation for 18 developed countries over the period 1979–1998 and examine the implications of the results for international momentum strategies.

The theoretical underpinnings of tests for predictability are based on the idea that security prices follow a random walk, whereby price changes are unpredictable in an efficient market. A number of researchers study the predictability of U.S. equity returns at weekly or monthly horizons. These include, for example, Conrad and Kaul (1988), Lo and MacKinlay (1988, 1990), Jegadeesh and Titman (1993), and Chan et al. (1996), among others. Other researchers, such as DeBondt and Thaler (1985, 1987) and Kim et al. (1991), investigate the predictability of long-horizon (often including multiyear) U.S. equity returns.

Several researchers also examine the predictability of international equity returns. For example, Poterba and Summers (1988) study equity returns for the U.S. as well as 17 other countries and find positive serial correlation at medium horizons and negative serial correlation over longer horizons, although they cannot statistically reject the random walk hypothesis. Richards (1997) and Balvers et al. (2000) find evidence of mean reversion and return predictability across national equity markets. Chan et al. (2000), Griffin et al. (2003), Bhojraj and Swaminathan (2001), and Rouwenhorst (1998) document the profitability of international momentum investment strategies.

The above studies are mainly based on medium- to long-horizon returns. This paper focuses on the predictability of short-horizon returns (daily and weekly). To provide a comparison with previous studies using monthly data as well as with our own results, we also conduct the same tests using monthly returns. Apart from applying known techniques to new data, our paper has several interesting findings, which contributes to the literature on the behavior of international asset prices.

Firstly, we examine the predictability of short-horizon returns for 18 developed countries using the variance ratio test, which has not been pursued in previous research. This is a useful complement to the findings of Lo and MacKinlay (1988) for the U.S. We find that for daily equity returns, the null hypothesis of a random walk can be rejected at conventional significance levels in favor of positive serial correlations for 10 countries and in favor of negative serial correlation for one country. The null cannot be rejected for the other seven countries, including the United States. These results provide an interesting comparison to French and Roll (1986), who report that the average daily autocorrelations for all NYSE and AMEX stocks are positive for the first order and negative from the second to the 13th order. French and Roll (1986) employ data from 1963 to 1982, while our sample covers the period 1980 to 1998, almost nonoverlapped with their sample. Our results suggest that the U.S. market may be more efficient in the most recent 2 decades than 2 decades ago. Our findings of positive daily serial correlation for the other 10 countries are in contrast with French and Roll's (1986) results for the U.S.

Secondly, through simulations, we investigate the robustness of the variance ratio test. We find that inference on the random walk hypothesis is sensitive to currency denomination, return horizon, and distributional assumptions.

Finally, we examine the implications of predictability for international momentum strategies. We find that the excess returns from buying past winners and selling past losers are always positive at all horizons. The results are particularly striking for daily data, where the profitability is not only statistically significant but also economically important in the absence of transaction costs. We demonstrate that the excess returns are not greatly affected by potential biases due to nonsynchronous trading and cannot be simply explained as a compensation for bearing more systematic risks. We also find that both the winner and loser portfolios on average select smaller countries. These results complement recent findings on international momentum profitability by Chan et al. (2000), Rouwenhorst (1998), Griffin et al. (2003), and Bhojraj and Swaminathan (2001). These authors study momentum profitability at longer horizons while we focus more on the short-horizon predictability.

The remainder of the paper is organized as follows. Section 2 describes the empirical methodology. Section 3 discusses the data and presents some summary statistics. Results on the predictability using the variance ratio test are reported in Section 4. Section 5 presents the performance of international momentum strategies and discusses possible explanations. Section 6 offers some concluding remarks.

2. Empirical methodology

We use the variance ratio test as popularized by Lo and MacKinlay (1988) and Cochrane (1988) to examine the predictability of equity returns. This particular method is chosen over other methods because of its good finite-sample properties (see Lo and MacKinlay, 1989). Furthermore, this allows us to draw a close comparison of our findings for international data with those obtained for the U.S. data using the same methodology.

Suppose that there are $T+1$ time-series observations of a national stock price index. Let p_t represent the logarithm of stock price index at time t, where $t=0, 1, 2,\ldots T$. Then, its first difference, Δp_t, represents a one-period rate of return. Our maintained hypothesis is that p_t follows a random walk. That is, p_t is generated by the following process:

$$p_t = \mu + p_{t-1} + \varepsilon_t, \tag{1}$$

where μ is a drift parameter and ε_t is a disturbance term which follows an i.i.d. $N(0,\sigma^2)$.

The variance ratio test is based on the idea that if the logarithm of stock price follows a random walk, then the variance of the return over k periods must be equal to $k\sigma^2$. A test can be constructed by comparing the variance of the one-period return with that of the k-period return as follows:

$$\mathrm{VR}(k) = \frac{\sigma^2(r_t^k)}{\sigma^2(r_t^1)}\frac{1}{k}, \tag{2}$$

where $r_t^1 \equiv p_t - p_{t-1}$ is the one-period return and $r_t^k \equiv p_t - p_{t-k}$ is the k-period return.

The mean and variances can be estimated as follows:

$$\hat{\mu} = \frac{1}{T}\sum_{t=1}^{T}(p_t - p_{t-1}) = \frac{1}{T}(p_T - p_0), \tag{3}$$

$$\hat{\sigma}^2(r_t^1) = \frac{1}{T-1}\sum_{t=1}^{T}(p_t - p_{t-1} - \hat{\mu})^2, \tag{4}$$

$$\hat{\sigma}^2(r_t^k) = \frac{1}{m}\sum_{t=k}^{T}(p_t - p_{t-k} - k\hat{\mu})^2, \tag{5}$$

where,

$$m = k(T - k + 1)\left(1 - \frac{k}{T}\right). \tag{6}$$

Eq. (5) estimates the variance of the k-period return using overlapping kth difference of p_t and adjusts for the small-sample bias.

Under the null hypothesis that stock price follows a random walk so that returns are unpredictable, the variance ratio statistic VR(k) should not be significantly different from unity. On the other hand, under the alternative hypothesis that returns are predictable using past returns information, VR(k) will be different from unity. In particular, if VR(k) < 1, returns are negatively serially correlated and stock price is said to be mean reverting. If VR(k)>1, returns are positively serially correlated and the stock is said to have price continuation.

Lo and MacKinlay (1988) show that under the null hypothesis that the error term ε_t is i.i.d. with variance σ^2, the following standardized test statistic follows an asymptotic standard normal distribution:

$$Z(k) \equiv \sqrt{T}[\mathrm{VR}(k) - 1]\left[\frac{2(2k-1)(k-1)}{3k}\right]^{-1/2} \overset{a}{\sim} N(0,1). \tag{7}$$

On the other hand, if ε_t is heteroscedastic, the following modified test statistic also follows a standard normal distribution in large samples:

$$Z^*(k) \equiv \sqrt{T}[\mathrm{VR}(k) - 1]\hat{\theta}(k)^{-1/2} \overset{a}{\sim} N(0,1), \tag{8}$$

where,

$$\hat{\theta}(k) = \sum_{j=1}^{k-1}\left[\frac{2(k-j)}{k}\right]^2 \hat{\delta}(j), \tag{9}$$

$$\hat{\delta}(j) = \frac{\sum_{t=j+1}^{T}(p_t - p_{t-1} - \hat{\mu})^2(p_{t-j} - p_{t-j-1} - \hat{\mu})^2}{\left[\sum_{t=1}^{T}(p_t - p_{t-1} - \hat{\mu})^2\right]^2}. \tag{10}$$

We will calculate VR(k) for various values of k and the associated test statistics $Z(k)$ and $Z^*(k)$ to draw inference from the asymptotic standard normal distribution. Furthermore, to check for robustness of our results, inference will also be based on small-sample empirical distributions generated using three simulation methods: Monte Carlo simulation where the disturbance term is assumed to follow a normal distribution; randomization where return observations are resampled without replacement but no assumption about the distribution of the error term is made; and bootstrapping where return observations are resampled with replacement (see Kim et al., 1991).

3. The data

The data used in this study are returns on daily equity indices from Morgan Stanley Capital International (MSCI) for the period 1979–1998 for 18 developed countries and three regions.[1] The country indices are available from MSCI in both local currency and U.S. dollar terms while regional indices are available only in dollar terms. The observations are end-of-period value-weighted indices of a large sample of companies in each country. The indices do not include foreign companies and are computed consistently across markets, thereby allowing for a close comparison across countries. While monthly data for developed markets are available as early as December 1969, MSCI started reporting daily indices only from December 1979. Because the focus of this paper is on short-horizon returns, we use the complete history of daily data from December 31, 1979 to June 19, 1998. This gives us a sample of 4669 observations of daily returns, 963 observations of weekly returns, and 221 observations of monthly returns.[2]

Table 1 shows reports of some summary statistics. The returns for individual countries are in local currency terms, while those for the three regions are in dollar terms. All holidays are excluded. The weekly returns are the returns from Wednesday to Wednesday and the monthly returns are calculated using end-of-month index values from the daily index database.[3]

For most countries, the daily and weekly returns have a high kurtosis, suggesting that the return distributions are more fat-tailed than a normal distribution. For monthly data, however, except for Australia, Hong Kong, and Singapore, the sample kurtosis is not very different from the three, the kurtosis for the normal distribution. Furthermore, the

[1] 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 (SGP), Spain (SPN), Sweden (SWE), Switzerland (SWT), the United Kingdom (UK), and the United States (USA). The three regions are: developed markets in Europe (EUR), developed markets in Europe, Australasia and Far East (EAFE), and all developed markets in the world (WLD).

[2] The daily and weekly indices do not include dividends as MSCI provides indices with dividends only at the monthly frequency. To make the monthly results comparable with those from daily and weekly observations, we choose to use monthly indices without dividends as well. Therefore, the returns calculated in this paper are in fact capital gains yields. To check for robustness, we reproduce the results with monthly indices with gross dividends and find that they are very similar to those reported in this paper using monthly indices without dividends. These results are not reported and are available upon request.

[3] In constructing weekly observations, if a Wednesday is a holiday, we use Thursday's index value. If both Wednesday and Thursday are holidays, we use Tuesday's index value.

Table 1
Summary statistics for international equity index returns

Country	Symbol	Daily returns (%)				Weekly returns (%)				Monthly returns (%)			
		Mean	S.D.	Skewness	Kurtosis	Mean	S.D.	Skewness	Kurtosis	Mean	S.D.	Skewness	Kurtosis
Australia	AUS	0.036	1.145	−2.879	64.112	0.168	2.671	−2.120	26.163	0.769	6.454	−2.818	22.372
Austria	AUT	0.030	1.073	−0.158	8.613	0.148	2.644	0.178	6.676	0.671	6.372	0.181	3.367
Belgium	BEL	0.050	0.999	−0.139	9.434	0.242	2.223	−0.234	3.341	1.037	5.293	−0.157	4.510
Canada	CAN	0.029	0.868	−0.753	13.179	0.143	2.088	−0.495	4.279	0.649	4.837	−0.948	4.990
Denmark	DEN	0.057	1.072	−0.208	5.254	0.282	2.303	−0.101	1.263	1.218	5.327	−0.188	0.286
France	FRA	0.052	1.175	−0.491	5.756	0.257	2.632	−0.960	5.658	1.100	5.927	−0.678	1.997
Germany	GER	0.046	1.161	−0.701	9.055	0.225	2.398	−1.026	5.421	0.965	5.603	−0.897	3.128
Hong Kong	HKG	0.045	1.870	−2.781	55.918	0.211	4.139	−1.313	10.751	0.982	9.540	−1.342	9.340
Italy	ITA	0.066	1.436	−0.342	4.347	0.321	3.314	−0.180	1.444	1.408	7.470	0.260	0.577
Japan	JPN	0.024	1.196	−0.262	14.693	0.113	2.528	−0.123	2.539	0.518	5.654	−0.323	1.552
Netherlands	NET	0.057	1.145	−0.235	7.567	0.278	2.201	−0.499	3.447	1.219	4.991	−0.818	4.207
Norway	NOR	0.035	1.439	−0.965	20.954	0.172	3.158	−0.416	3.736	0.759	7.358	−0.944	2.828
Singapore	SGP	0.015	1.270	−2.536	57.032	0.066	3.154	−2.811	38.153	0.351	7.527	−1.854	15.305
Spain	SPN	0.059	1.160	−0.072	6.111	0.292	2.765	−0.426	2.733	1.260	6.282	−0.456	2.789
Sweden	SWE	0.085	1.257	−0.123	4.293	0.414	2.981	−0.284	3.174	1.809	6.689	−0.267	2.374
Switzerland	SWI	0.049	1.021	−1.034	11.489	0.238	2.124	−1.421	9.371	1.046	4.865	−1.022	4.765
UK	UK	0.053	1.050	−0.631	9.018	0.261	2.191	−0.977	8.282	1.130	5.062	−1.386	6.678
USA	USA	0.050	0.966	−3.032	72.133	0.243	2.043	−0.802	5.487	1.042	4.219	−0.988	5.348
Europe	EUR	0.048	0.919	−0.630	7.796	0.232	2.045	−0.687	3.871	1.006	4.758	−0.802	2.434
EAFE	EAFE	0.044	0.939	−0.870	19.028	0.211	2.128	−0.424	2.270	0.926	5.020	−0.348	0.545
World	WLD	0.045	0.741	−0.856	18.272	0.218	1.808	−0.808	5.539	0.946	4.083	−0.736	2.447

The table shows summary statistics for daily, weekly, and monthly returns on MSCI equity indices for 18 countries and three regions from December 31, 1979 to June 19, 1998. The returns for individual countries are in local currencies, while those for the regional indices are in U.S. dollars. The sample includes 4669 daily observation, 963 weekly observations, and 221 monthly observations.

distributions all skew to the left, except for Austria's weekly and monthly returns. We carry out the formal Jarque–Bera test for normality (results not reported) and reject the null hypothesis of normal distribution at the 5% level for all series, except for Austria's monthly observations. These statistics indicate that equity returns in general do not follow a normal distribution and it is important to draw inference from finite-sample bootstrap distributions without the normality assumption.

4. Results from the variance ratio test

In this section, we report the variance ratio test results. Our primary interest will be in the indices in local currency terms. These results are relevant for local investors. We also report a set of results using the indices in dollar terms, which are more relevant for investors who care about returns in dollar terms such as the U.S. investors.

4.1. Variance ratios for country equity indices in local currency terms

Table 2 shows the variance ratio test results using daily returns in respective local currencies for 18 countries. We provide the point estimates of the variance ratios and the two normalized test statistics. The first statistic, $Z(k)$, with the assumption of homoskedasticity, follows a standard normal distribution in large samples under the null hypothesis that returns are unpredictable. The second statistic, $Z^*(k)$, is heteroskedasticity-robust and also follows the standard normal distribution asymptotically under the null. We implement the tests for different horizons, $k=2$, 4, 6, 8, and 10. As Table 1 shows, most returns do not follow a normal distribution, so the exact distribution of the variance ratio test will be in general unknown in finite samples, although its asymptotic distribution is normal as stated in Eq. (8). Kim et al. (1991) suggest the use of bootstrap (resampling with replacement) and randomization (resampling without replacement) methods to estimate the empirical distribution. We follow them to estimate the distribution using both methods. We also simulate the empirical distribution using Monte Carlo method under the normality assumption. As the three simulation methods produce similar results, we report only the results from randomization.

The randomization experiment is carried out as follows.

Step1: For each country, draw a random sample of T return observations from the historical data, r_t^1, one observation at a time without replacement (we use $T=4996$, 963, and 221 for daily, weekly, and monthly frequencies, respectively).

Step2: Calculate the variance ratio and test statistics $Z(k)$ and $Z^*(k)$ using Eqs. (7) and (8) with the simulated observations.

Step3: Repeat Steps 1 and 2 for 5000 times to produce the empirical distributions under the null hypothesis. This procedure is repeated for every country. We compute the p-value of each test statistic, defined as the percentage of the empirical distribution with values greater than the test statistic calculated with the data. With this definition, a p-value smaller than 0.05 means that the null hypothesis that an equity price index follows a random walk can be rejected at the 5% level in favor of the

Table 2
Variance ratio test for international equity index returns in local currencies using daily returns

	Variance ratios for number k of base observations aggregated					Homoscedastic test – statistic $Z(k)$ [randomization p-value]					Heteroscedastic test-statistic $Z^*(k)$ [randomization p-value]				
k	2	4	6	8	10	2	4	6	8	10	2	4	6	8	10
AUS	1.076	1.112	1.188	1.219	1.255	5.175	4.078	5.193	5.055	5.169	2.444	1.982	2.429	2.309	2.314
						[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.006]	[0.026]	[0.008]	[0.014]	[0.014]
AUT	1.066	1.174	1.244	1.308	1.369	4.489	6.343	6.751	7.112	7.462	2.435	3.640	3.958	4.250	4.554
						[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.006]	[0.000]	[0.000]	[0.000]	[0.000]
BEL	1.010	1.011	1.011	1.035	1.085	0.681	0.389	0.314	0.820	1.717	0.449	0.239	0.196	0.518	1.097
						[0.255]	[0.343]	[0.371]	[0.207]	[0.046]	[0.327]	[0.400]	[0.421]	[0.297]	[0.138]
CAN	1.154	1.230	1.276	1.314	1.336	10.490	8.404	7.641	7.262	6.806	3.714	3.164	3.027	2.997	2.912
						[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.002]	[0.002]	[0.003]
DEN	0.987	0.987	0.998	1.006	1.029	− 0.859	− 0.492	− 0.061	0.132	0.582	− 0.513	− 0.330	− 0.044	0.100	0.455
						[0.809]	[0.681]	[0.515]	[0.442]	[0.286]	[0.697]	[0.624]	[0.506]	[0.453]	[0.328]
FRA	1.031	1.057	1.063	1.070	1.090	2.135	2.086	1.745	1.623	1.814	1.333	1.291	1.103	1.047	1.187
						[0.019]	[0.021]	[0.041]	[0.053]	[0.036]	[0.095]	[0.102]	[0.133]	[0.146]	[0.118]
GER	0.963	0.920	0.922	0.927	0.949	− 2.547	− 2.911	− 2.143	− 1.683	− 1.038	− 1.370	− 1.627	− 1.235	− 0.996	− 0.627
						[0.996]	[0.998]	[0.987]	[0.963]	[0.851]	[0.917]	[0.956]	[0.900]	[0.838]	[0.739]
HKG	1.027	1.082	1.128	1.162	1.188	1.847	2.986	3.548	3.734	3.805	0.980	1.643	1.948	2.024	2.059
						[0.032]	[0.001]	[0.000]	[0.000]	[0.000]	[0.163]	[0.050]	[0.026]	[0.021]	[0.020]
ITA	1.095	1.147	1.197	1.204	1.207	6.502	5.378	5.446	4.703	4.190	4.076	3.430	3.535	3.099	2.791
						[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.000]	[0.001]	[0.003]

JPN	1.012	0.956	0.948	0.920	0.908	0.810	−1.620	−1.449	−1.849	−1.854	0.356	−0.793	−0.755	−1.006	−1.043
						[0.216]	[0.950]	[0.930]	[0.971]	[0.973]	[0.367]	[0.784]	[0.777]	[0.848]	[0.856]
NET	0.891	0.823	0.800	0.796	0.804	−7.417	−6.474	−5.528	−4.708	−3.967	−3.450	−3.038	−2.683	−2.362	−2.051
						[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[0.999]	[0.998]	[0.996]	[0.993]	[0.982]
NOR	1.073	1.068	1.043	1.042	1.066	5.000	2.491	1.182	0.970	1.346	1.830	1.045	0.543	0.474	0.685
						[0.000]	[0.008]	[0.110]	[0.157]	[0.083]	[0.033]	[0.145]	[0.287]	[0.308]	[0.234]
SGP	1.185	1.275	1.346	1.383	1.418	12.672	10.042	9.550	8.849	8.461	3.122	2.583	2.550	2.483	2.492
						[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.005]	[0.005]	[0.007]	[0.006]
SPN	1.098	1.180	1.232	1.252	1.282	6.6 74	6.589	6.404	5.829	5.712	3.980	4.056	4.027	3.731	3.709
						[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
SWE	1.089	1.133	1.169	1.183	1.207	6.093	4.867	4.659	4.216	4.186	3.774	3.140	3.049	2.788	2.789
						[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.002]	[0.003]
SWI	0.949	0.921	0.939	0.948	0.964	−3.483	−2.887	−1.689	−1.206	−0.723	−1.971	−1.530	−0.886	−0.636	−0.387
						[1.000]	[0.999]	[0.953]	[0.884]	[0.763]	[0.977]	[0.934]	[0.806]	[0.730]	[0.637]
UK	0.947	0.943	0.953	0.956	0.965	−3.629	−2.077	−1.289	−1.016	−0.718	−1.414	−0.888	−0.593	−0.496	−0.367
						[1.000]	[0.980]	[0.896]	[0.842]	[0.766]	[0.918]	[0.805]	[0.724]	[0.682]	[0.639]
USA	1.048	1.014	0.972	0.959	0.944	3.247	0.524	−0.776	−0.953	−1.126	1.114	0.173	−0.264	−0.335	−0.409
						[0.001]	[0.303]	[0.788]	[0.836]	[0.878]	[0.144]	[0.437]	[0.600]	[0.626]	[0.656]

The table shows results from the variance ratio test of the random walk hypothesis for daily MSCI country equity index returns, in local currencies, for the sample period December 31, 1979 to June 19, 1998. The columns show variance ratios for number k of base observations aggregated, homoscedastic test statistics, and heteroscedastic test statistics, respectively. The numbers inside the brackets are the p-values based on the empirical distribution from randomization with 5000 replications. A p-value smaller than 0.05 means that the null hypothesis that an equity price index follows a random walk can be rejected at the 5% level, in favor of the alternative hypothesis that the returns are positively serially correlated. On the other hand, a p-value greater than 0.95 indicates that the null hypothesis can be rejected at the 5% level, in favor of the alternative hypothesis that the returns are negatively serially correlated.

alternative hypothesis that the returns are positively serially correlated. On the other hand, a p-value greater than 0.95 indicates that the null hypothesis can be rejected at the 5% level, in favor of the alternative that the returns are negatively serially correlated.

Numbers inside the square brackets in Table 2 are p-values based on the empirical distribution from randomization. Inference from the asymptotic normal distribution is qualitatively similar and is therefore not reported to conserve space.

Several observations can be drawn from Table 2. Firstly, a broad view indicates that, for most countries, the variance ratios are greater than unity, implying positive serial correlation of daily local returns for these countries, with a few exceptions. These include Germany, Netherlands, Switzerland, and the United Kingdom, where the variance ratios are smaller than one, exhibiting negative correlation in daily returns. This implies mean reversion in daily returns for these countries.

Secondly, with respect to statistical inference, we find that the heteroskedastic-robust test statistic $Z^*(k)$ gives quite different results (in general, less significant) than those from the $Z(k)$ statistic whose distribution is valid only under homoskedasticity. Because it is well known that stock returns are nonnormal and heteroskedastic (see Campbell et al., 1997), the $Z^*(k)$ statistic is more appropriate for drawing inferences.

Thirdly, based on the randomization p-values for the $Z^*(k)$ statistic, we find that the null hypothesis of a random walk can be rejected (for all orders of k) at the 1% significance level in favor of positive serial correlation of returns for Austria, Canada, Italy, Singapore, Spain, and Sweden; and at the 5% level for Australia and Hong Kong (for $k>2$). France and Norway show significant positive correlation of returns only when $k=2$. On the other hand, Netherlands is the only country that can reject the null (for all orders of k) at the 5% level in favor of mean reversion. The null hypothesis cannot be rejected in general for the remaining seven countries, including the four largest capital markets of the world: the United States, Japan, Germany, and the United Kingdom.

Our results for the U.S. provide an interesting comparison to French and Roll (1986), who report that the equal-weighted average daily autocorrelations for all NYSE and AMEX stocks are positive for the first order and negative from the second up to the 13th orders. The first-order positive autocorrelation is particularly strong for large firms. Firstly, our results for the U.S. that $\mathrm{VR}(2)>1$ is consistent with French and Roll (1986) because it can be shown that $\mathrm{VR}(2)=1+2\rho(1)$, where $\rho(1)$ is the first-order serial correlation. Secondly, $\mathrm{VR}(k)$ decreases as the order k increases and becomes less than unity when $k\geq 6$ because higher-order negative autocorrelations play an important role and eventually become dominating. Thirdly, statistically, we cannot reject the null hypothesis that the variance ratios are equal to unity for the U.S. Because our sample covers the most recent 2 decades (1980 to 1998), which has little overlap with their sample (1963 to 1982), these results suggest that the U.S. market may be more efficient in the most recent 2 decades than in the past.

Our findings of positive daily correlation for the other 10 countries are in contrast with French and Roll (1986). Recall that, in our sample, the MSCI index for a country is the value-weighted average index of the country's largest firms, whereas in French and Roll (1986), the reported autocorrelations are the equal-weighted averages for all NYSE and AMEX stocks. As French and Roll (1986) point out, measurement errors from bid–ask spread can lead to negative first-order autocorrelation, but measurement errors are more serious for small firms than large firms. The fact that we use MSCI indices may partly be responsible for the discrepancy between our findings for these 10 countries and those of French and Roll (1986) for the U.S. Our results may also indicate some fundamental differences in stock price behavior between the U.S. market and these 10 markets.

In summary, Table 2 shows that daily local returns exhibit significant positive serial correlation for most countries. For several countries, however, they appear to follow a random walk. We find that mean reversion is an exception.

For a close comparison, we also conduct the test using weekly and monthly observations and report the respective results in Tables 3 and 4. In general, the weekly results are stronger than the daily results against the random walk hypothesis in favor of positive correlation. In particular, for Belgium, Denmark, Germany, and Switzerland, while the null is not rejected using daily data, it can be strongly rejected using weekly data for $k>2$.[4] Furthermore, there is no significant evidence of mean reversion for a single country. Finally, the only countries whose indices can be classified as a random walk are the three largest markets, the United States, Japan, and the United Kingdom. Our results for the U.S. are in contrast with Lo and MacKinlay (1988) and Conrad and Kaul (1989), both of whom report positive correlation of weekly returns of CRSP value-weighted index and size-sorted portfolios for the period from 1962 to 1985. However, our findings are consistent with those of Campbell et al. (1997, page 69), who report that the random walk hypothesis cannot be rejected using weekly CRSP value-weighted index for the period 1978 to 1994.[5] These results suggest that the U.S. market may be more efficient in the recent 2 decades than in earlier periods.

Unlike the results for the weekly returns, our results reported in Table 4 for monthly data presents a quite different picture. Based again on the randomization p-values for the $Z^*(k)$ statistic, we find that most indices can be characterized as a random walk. Indeed, the null hypothesis can be comfortably rejected at the 5% level only for Italy (for $k>2$) and at the 10% level for Denmark (for $k>2$) and Sweden.

It is important to acknowledge two caveats of our findings at this point. Firstly, we have used the conventional significance levels (1% and 5%) for statistical inference for all sample sizes. Although this follows the literature, an alternative way can use the Schwarz criterion to select an appropriate significance level, which decreases with the sample size.[6]

[4] For daily data, we compute the variance ratio statistics for up to 10 days, whereas for weekly data, the significant variance ratios are those for 4 to 10 weeks for these four countries. It is possible for a time series to have near-zero correlations over the very short horizons and significant correlations over the relatively longer horizons. Therefore, our weekly results can be consistent with the daily results.

[5] Both Lo and MacKinlay (1988) and Campbell et al. (1997) use the CRSP value-weighted index for the U.S., which may not be fully comparable to the MSCI index that we use in this paper. Furthermore, their studies cover different sample periods. We have also used the CRSP index for our sample period and find the results very similar to those from the MSCI U.S. index reported in this paper. Therefore, the difference between Lo and MacKinlay (1988) and this paper can be primarily attributed to different sample periods covered.

[6] Specifically, consider the Schwarz criterion for a regression model: $SB=-2l(Y,X,\theta)+\ln(T)p/T$, where $l(Y,X,\theta)$ is the log likelihood value of the regression model; θ is the vector of parameters; T is the sample size; and p is the number of parameters. Then, the significance level can be set equal to the cumulative probability value of $\ln(T)p$ from a χ^2 distribution with p degrees of freedom. For the variance ratio test, because there is only one parameter to estimate, $p=1$. We are indebted to Rolf Tschernig for suggesting this criterion to select significance levels.

Table 3
Variance ratio test for international equity index returns in local currencies using weekly returns

	Variance ratios for number k of base observations aggregated					Homoscedastic test-statistic $Z(k)$ [randomization p-value]					Heteroscedastic test-statistic $Z^*(k)$ [randomization p-value]				
k	2	4	6	8	10	2	4	6	8	10	2	4	6	8	10
AUS	1.088	1.266	1.316	1.288	1.246	2.719	4.404	3.962	3.019	2.265	1.513	2.475	2.220	1.730	1.337
						[0.003]	[0.000]	[0.000]	[0.003]	[0.018]	[0.064]	[0.006]	[0.017]	[0.049]	[0.095]
AUT	1.097	1.306	1.422	1.514	1.575	2.997	5.083	5.298	5.395	5.281	1.793	3.129	3.270	3.336	3.280
						[0.003]	[0.000]	[0.000]	[0.000]	[0.000]	[0.038]	[0.001]	[0.001]	[0.001]	[0.002]
BEL	1.095	1.302	1.397	1.506	1.575	2.939	5.004	4.986	5.306	5.288	1.866	3.336	3.456	3.793	3.876
						[0.002]	[0.000]	[0.000]	[0.000]	[0.000]	[0.033]	[0.000]	[0.000]	[0.000]	[0.000]
CAN	1.083	1.191	1.204	1.189	1.171	2.580	3.160	2.562	1.984	1.570	1.473	1.954	1.696	1.382	1.134
						[0.003]	[0.001]	[0.007]	[0.028]	[0.061]	[0.066]	[0.027]	[0.049]	[0.083]	[0.125]
DEN	1.054	1.170	1.237	1.284	1.305	1.662	2.826	2.981	2.974	2.806	1.554	2.687	2.825	2.809	2.646
						[0.043]	[0.003]	[0.002]	[0.002]	[0.003]	[0.055]	[0.005]	[0.003]	[0.003]	[0.005]
FRA	1.013	1.183	1.242	1.290	1.310	0.418	3.037	3.037	3.043	2.853	0.264	1.871	1.893	1.947	1.872
						[0.346]	[0.002]	[0.003]	[0.003]	[0.005]	[0.403]	[0.032]	[0.029]	[0.029]	[0.034]
GER	1.076	1.251	1.307	1.311	1.325	2.356	4.165	3.852	3.263	2.991	1.458	2.496	2.383	2.093	1.977
						[0.010]	[0.000]	[0.000]	[0.002]	[0.005]	[0.073]	[0.009]	[0.013]	[0.028]	[0.035]
HKG	1.103	1.250	1.252	1.236	1.224	3.185	4.152	3.167	2.476	2.062	1.857	2.666	2.136	1.733	1.485
						[0.001]	[0.000]	[0.001]	[0.007]	[0.020]	[0.032]	[0.004]	[0.016]	[0.042]	[0.069]
ITA	1.063	1.201	1.273	1.286	1.309	1.944	3.336	3.426	2.998	2.840	1.579	2.745	2.809	2.460	2.343
						[0.029]	[0.001]	[0.001]	[0.002]	[0.004]	[0.066]	[0.004]	[0.004]	[0.009]	[0.013]

JPN	0.968	1.054	1.082	1.108	1.150	– 0.986	0.892	1.024	1.129	1.376	– 0.704	0.640	0.739	0.823	1.016
						[0.850]	[0.183]	[0.158]	[0.137]	[0.091]	[0.766]	[0.258]	[0.227]	[0.208]	[0.159]
NET	1.035	1.134	1.177	1.187	1.195	1.099	2.219	2.223	1.963	1.790	0.676	1.483	1.575	1.444	1.353
						[0.139]	[0.020]	[0.021]	[0.041]	[0.054]	[0.255]	[0.082]	[0.075]	[0.092]	[0.109]
NOR	1.052	1.237	1.331	1.365	1.366	1.603	3.937	4.151	3.834	3.368	1.047	2.696	2.912	2.769	2.495
						[0.054]	[0.000]	[0.000]	[0.000]	[0.001]	[0.151]	[0.006]	[0.002]	[0.006]	[0.012]
SGP	1.110	1.210	1.266	1.323	1.370	3.410	3.479	3.335	3.393	3.402	1.535	1.780	1.853	2.003	2.097
						[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.062]	[0.038]	[0.032]	[0.023]	[0.018]
SPN	1.083	1.219	1.304	1.358	1.373	2.567	3.636	3.811	3.754	3.429	1.666	2.512	2.759	2.812	2.630
						[0.004]	[0.000]	[0.000]	[0.000]	[0.001]	[0.048]	[0.007]	[0.005]	[0.005]	[0.008]
SWE	1.041	1.187	1.273	1.350	1.414	1.282	3.101	3.427	3.671	3.804	0.861	2.114	2.385	2.621	2.783
						[0.101]	[0.001]	[0.001]	[0.000]	[0.000]	[0.205]	[0.023]	[0.014]	[0.009]	[0.006]
SWI	1.083	1.244	1.301	1.349	1.394	2.584	4.042	3.774	3.665	3.619	1.245	2.108	2.117	2.182	2.260
						[0.005]	[0.000]	[0.001]	[0.001]	[0.001]	[0.108]	[0.019]	[0.019]	[0.020]	[0.019]
UK	1.050	1.133	1.141	1.100	1.035	1.559	2.199	1.764	1.054	0.322	0.690	1.150	1.039	0.671	0.216
						[0.061]	[0.020]	[0.048]	[0.154]	[0.367]	[0.250]	[0.136]	[0.158]	[0.253]	[0.407]
USA	0.998	0.998	0.963	0.969	0.973	– 0.074	– 0.034	– 0.464	– 0.330	– 0.251	– 0.041	– 0.021	– 0.305	– 0.228	– 0.180
						[0.545]	[0.506]	[0.661]	[0.612]	[0.575]	[0.533]	[0.500]	[0.603]	[0.568]	[0.547]

The table shows results from the variance ratio test of the random walk hypothesis for weekly (Wednesday-to-Wednesday) MSCI country equity index returns, in local currencies, for the sample period December 31, 1979 to June 19, 1998. The columns show variance ratios for number k of base observations aggregated, homoscedastic test statistics, and heteroscedastic test statistics, respectively. The numbers inside the brackets are the p-values based on the empirical distribution from randomization with 5000 replications. A p-value smaller than 0.05 means that the null hypothesis that an equity price index follows a random walk can be rejected at the 5% level, in favor of the alternative hypothesis that the returns are positively serially correlated. On the other hand, a p-value greater than 0.95 indicates that the null hypothesis can be rejected at the 5% level, in favor of the alternative hypothesis that the returns are negatively serially correlated.

Table 4
Variance ratio test for international equity index returns in local currencies using monthly returns

	Variance ratios for number k of base observations aggregated					Homoscedastic test-statistic $Z(k)$ [randomization p-value]					Heteroscedastic test-statistic $Z^*(k)$ [randomization p-value]				
k	2	4	6	8	10	2	4	6	8	10	2	4	6	8	10
AUS	0.982	0.852	0.853	0.821	0.822	− 0.268	− 1.180	− 0.882	− 0.900	− 0.785	− 0.383	− 1.342	− 0.915	− 0.908	− 0.785
						[0.611]	[0.893]	[0.819]	[0.822]	[0.786]	[0.637]	[0.904]	[0.806]	[0.802]	[0.760]
AUT	1.178	1.236	1.349	1.430	1.477	2.641	1.874	2.099	2.161	2.100	1.707	1.305	1.527	1.593	1.555
						[0.004]	[0.028]	[0.020]	[0.020]	[0.024]	[0.042]	[0.098]	[0.072]	[0.065]	[0.069]
BEL	1.170	1.168	1.102	1.045	1.068	2.524	1.333	0.613	0.227	0.301	2.163	1.257	0.553	0.200	0.265
						[0.006]	[0.098]	[0.262]	[0.391]	[0.362]	[0.014]	[0.119]	[0.289]	[0.403]	[0.376]
CAN	0.994	0.955	0.981	1.026	1.048	− 0.096	− 0.355	− 0.112	0.129	0.210	− 0.088	− 0.303	− 0.097	0.114	0.190
						[0.532]	[0.622]	[0.509]	[0.409]	[0.377]	[0.529]	[0.594]	[0.501]	[0.415]	[0.388]
DEN	1.029	1.198	1.382	1.580	1.738	0.437	1.573	2.295	2.917	3.249	0.424	1.549	2.278	2.910	3.244
						[0.338]	[0.066]	[0.019]	[0.005]	[0.003]	[0.346]	[0.070]	[0.020]	[0.006]	[0.003]
FRA	1.096	1.114	1.192	1.182	1.169	1.429	0.905	1.157	0.916	0.743	1.163	0.770	0.989	0.787	0.646
						[0.078]	[0.186]	[0.129]	[0.180]	[0.216]	[0.123]	[0.220]	[0.167]	[0.215]	[0.250]
GER	1.065	1.133	1.173	1.161	1.186	0.964	1.056	1.040	0.810	0.818	0.610	0.757	0.792	0.640	0.665
						[0.165]	[0.140]	[0.147]	[0.200]	[0.196]	[0.270]	[0.217]	[0.202]	[0.243]	[0.239]
HKG	1.018	0.970	0.844	0.805	0.760	0.272	− 0.241	− 0.940	− 0.981	− 1.057	0.316	− 0.269	− 1.013	− 1.042	− 1.116
						[0.389]	[0.585]	[0.835]	[0.844]	[0.866]	[0.378]	[0.591]	[0.844]	[0.852]	[0.868]
ITA	1.076	1.233	1.370	1.487	1.591	1.134	1.850	2.222	2.447	2.600	1.048	1.757	2.091	2.305	2.461
						[0.128]	[0.041]	[0.023]	[0.017]	[0.013]	[0.151]	[0.048]	[0.030]	[0.020]	[0.017]

JPN	1.033	1.080	1.148	1.195	1.251	0.490	0.632	0.889	0.979	1.104	0.385	0.500	0.723	0.810	0.923
						[0.311]	[0.248]	[0.178]	[0.158]	[0.135]	[0.348]	[0.298]	[0.224]	[0.199]	[0.174]
NET	1.027	1.041	1.013	0.971	0.944	0.400	0.323	0.081	− 0.145	− 0.247	0.273	0.251	0.068	− 0.128	− 0.224
						[0.344]	[0.360]	[0.434]	[0.519]	[0.556]	[0.402]	[0.390]	[0.438]	[0.512]	[0.543]
NOR	1.117	1.093	1.051	1.013	0.976	1.745	0.739	0.305	0.068	− 0.104	1.352	0.620	0.270	0.062	− 0.098
						[0.043]	[0.222]	[0.355]	[0.435]	[0.505]	[0.097]	[0.263]	[0.372]	[0.438]	[0.500]
SGP	1.060	1.052	1.065	1.014	0.944	0.898	0.415	0.391	0.071	− 0.246	0.921	0.441	0.400	0.072	− 0.247
						[0.169]	[0.313]	[0.314]	[0.425]	[0.553]	[0.179]	[0.316]	[0.320]	[0.427]	[0.547]
SPN	1.138	1.192	1.177	1.203	1.240	2.058	1.523	1.062	1.021	1.056	1.742	1.385	0.987	0.962	1.006
						[0.018]	[0.069]	[0.144]	[0.156]	[0.150]	[0.042]	[0.093]	[0.169]	[0.172]	[0.166]
SWE	1.151	1.282	1.337	1.387	1.404	2.245	2.244	2.027	1.946	1.780	1.791	1.875	1.728	1.698	1.588
						[0.012]	[0.016]	[0.029]	[0.039]	[0.059]	[0.038]	[0.036]	[0.054]	[0.063]	[0.079]
SWI	1.105	1.192	1.192	1.184	1.203	1.556	1.527	1.156	0.926	0.893	1.032	1.132	0.904	0.750	0.746
						[0.061]	[0.068]	[0.121]	[0.167]	[0.174]	[0.157]	[0.133]	[0.174]	[0.212]	[0.209]
UK	0.946	0.779	0.713	0.640	0.579	− 0.807	− 1.756	− 1.727	− 1.809	− 1.854	− 0.622	− 1.405	− 1.451	− 1.580	− 1.671
						[0.794]	[0.966]	[0.968]	[0.976]	[0.980]	[0.725]	[0.908]	[0.923]	[0.945]	[0.958]
USA	1.004	0.957	0.919	0.927	0.901	0.065	− 0.342	− 0.485	− 0.365	− 0.436	0.050	− 0.283	− 0.423	− 0.329	− 0.404
						[0.483]	[0.621]	[0.664]	[0.614]	[0.638]	[0.491]	[0.593]	[0.636]	[0.596]	[0.622]

The table shows results from the variance ratio test of the random walk hypothesis for monthly MSCI country equity index returns, in local currencies, for the sample period December 1979 to May 1998. The columns report variance ratios for number k of base observations aggregated, homoscedastic test statistics, and heteroscedastic test statistics, respectively. The numbers inside the brackets are the p-values based on the empirical distribution from randomization with 5000 replications. A p-value smaller than 0.05 means that the null hypothesis that an equity price index follows a random walk can be rejected at the 5% level, in favor of the alternative hypothesis that the returns are positively serially correlated. On the other hand, a p-value greater than 0.95 indicates that the null hypothesis can be rejected at the 5% level, in favor of the alternative hypothesis that the returns are negatively serially correlated.

This criterion selects significance levels of 0.021, 0.009, and 0.0036 for our monthly, weekly, and daily sample sizes, respectively. However, even with these much more conservative significance levels, the null hypothesis can be rejected for Austria, Canada, Italy, Spain, and Sweden with daily data; for Austria, Belgium, Denmark, and Spain with weekly data; and for Denmark and Italy with monthly data.[7]

Secondly, Lo and MacKinlay (1988) show that infrequent trading can induce artificial autocorrelation of security returns, making returns appear to be predictable even if they are in fact independent. The equity markets of smaller countries are less liquid and the infrequent trading issue may be more of a problem for smaller countries than for large countries, such as the U.S. This can make smaller markets spuriously more predictable than large markets. To check whether serial correlation is related to market size, we plot in Fig. 1 the variance ratios (at $k=2$ and 10) against the countries ranked by average market capitalization in U.S. dollars (from smallest to largest).[8] The VR(2) statistic simply reflects the first-order serial correlation of returns because $\mathrm{VR}(2)=1+2\rho(1)$ where $\rho(1)$ is the first-order serial correlation, while VR(10) captures autocorrelation of returns at higher orders. As shown in Fig. 1, there is no clear relation between size and variance ratio. This is also borne out by statistically testing the correlation between the two. We also find no significant relation between market capitalization and variance ratio at other orders ($k=4$, 6, and 8). The results are similar and are not reported. Therefore, it does not seem that predictability is merely attributed to small countries.

In summary, the findings in this subsection indicate significant evidence of return continuation at daily and weekly horizons for the majority of the countries in our sample. However, the random walk hypothesis is generally not rejected using monthly data.

4.2. Variance ratios for country equity indices in U.S. dollar terms

The results of the preceding section are based on the indices denominated in local currencies, which are of most relevance to local investors. In this subsection, we investigate the importance of exchange rate fluctuations in affecting the predictability of returns by using indices in dollar terms. In addition, as regional indices in dollar terms are also available, we include three more indices, Europe, EAFE, and the World index in the analysis. These results will be of more relevance to an investor residing in the U.S. who is interested in global asset allocation and global diversification.

Panel A of Table 5 shows a summary of the results for daily dollar returns. For inference, we report only the $Z^*(k)$ test statistic with p-values from randomization in order to conserve space. Compared to Table 2, we find that the evidence against random walk in favor of positive correlation in returns is stronger for dollar indices than for local-currency

[7] The same caveat should apply to all results throughout the paper as well, namely, using the sample size-dependent significance levels, the significance levels of the variance ratio tests will be weaker in general. We will, however, follow the tradition by using the conventional significance levels when discussing the results in the remaining sections.

[8] The monthly market capitalization data are obtained from MSCI. We average these monthly observations for the same sample period used to calculate the variance ratios for each country.

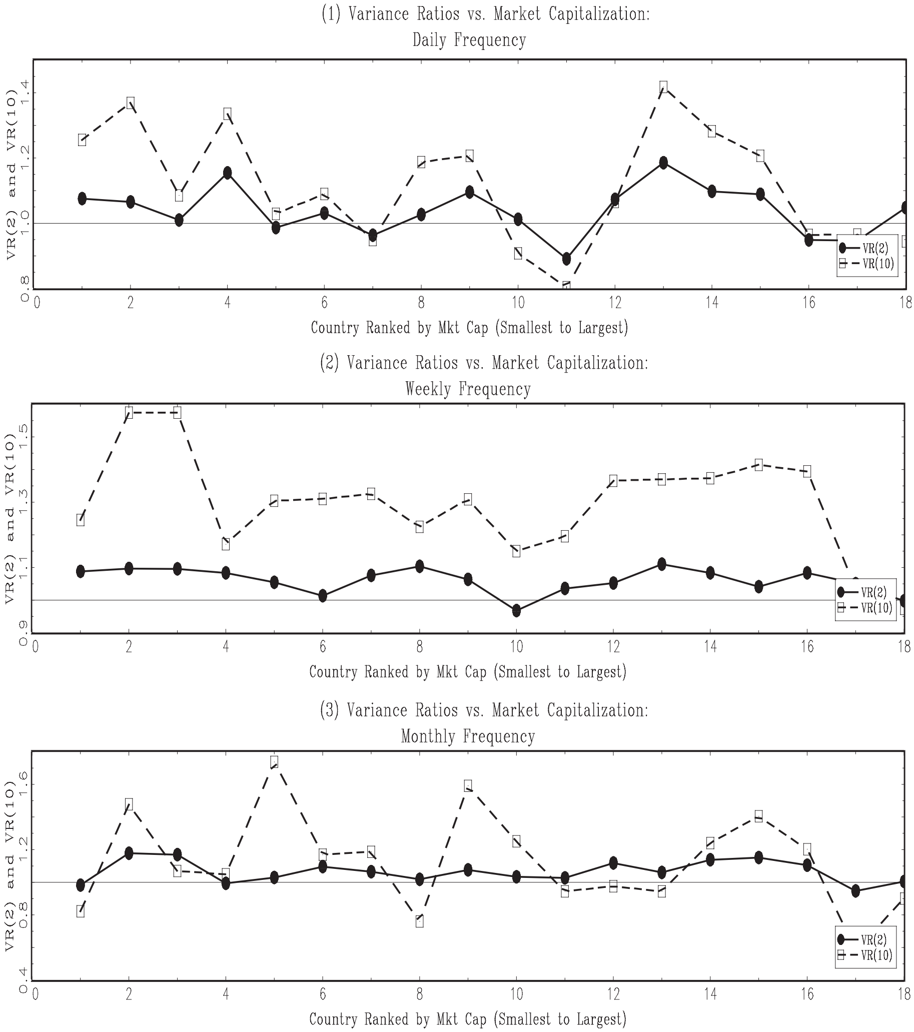

Fig. 1. (1) Variance ratios vs. market capitalization: daily frequency. VR(2) and VR(10). Country ranked by market capitalization (smallest to largest). (2) Variance ratios vs. market capitalization: weekly frequency. VR(2) and VR(10). Country ranked by market capitalization (smallest to largest). (3) Variance ratios vs. market capitalization: monthly frequency. VR(2) and VR(10). Country ranked by market capitalization (smallest to largest).

indices. We can reject the null hypothesis at the 1% level for 11 series, and at the 5% level for two series. In particular, for Japan, the index in Japanese yen roughly follows a random walk, but the returns in dollar terms show significant positive correlation at the 5% level. Furthermore, the null can be rejected at the 1% level for the world index, at the 5% level for the EAFE index, and at the 10% level for the European index. On the other hand, similar to the results for local currency indices, the indices in dollar terms also follow a random walk for Germany, Netherlands, Switzerland, and the United Kingdom. These

Table 5
Variance ratio for international equity index returns in U.S. dollars

	Variance ratios for number *k* of base observations aggregated					Heteroscedastic test-statistic $Z^*(k)$ [randomization *p*-value]				
k	2	4	6	8	10	2	4	6	8	10
Panel A. Daily data										
AUS	1.122	1.186	1.261	1.305	1.353	4.473	3.627	3.671	3.489	3.451
						[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
AUT	1.154	1.269	1.337	1.392	1.437	6.642	6.141	5.796	5.721	5.710
						[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
BEL	1.074	1.112	1.129	1.142	1.167	3.857	2.995	2.619	2.449	2.541
						[0.000]	[0.001]	[0.004]	[0.007]	[0.006]
CAN	1.178	1.286	1.355	1.410	1.445	4.202	3.907	3.896	3.943	3.896
						[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
DEN	1.073	1.108	1.122	1.118	1.119	3.471	2.933	2.629	2.179	1.968
						[0.000]	[0.002]	[0.004]	[0.015]	[0.025]
FRA	1.095	1.162	1.192	1.216	1.231	4.052	3.737	3.456	3.330	3.197
						[0.000]	[0.000]	[0.000]	[0.000]	[0.001]
GER	1.003	0.985	0.995	1.001	1.012	0.135	− 0.332	− 0.085	0.009	0.168
						[0.446]	[0.630]	[0.534]	[0.496]	[0.433]
HKG	1.031	1.091	1.143	1.182	1.210	1.145	1.867	2.210	2.314	2.333
						[0.126]	[0.026]	[0.013]	[0.014]	[0.015]
ITA	1.130	1.179	1.207	1.206	1.201	6.010	4.429	3.912	3.302	2.848
						[0.000]	[0.000]	[0.000]	[0.000]	[0.002]
JPN	1.078	1.096	1.111	1.108	1.113	2.672	1.955	1.821	1.535	1.451
						[0.004]	[0.025]	[0.034]	[0.062]	[0.073]
NET	0.952	0.911	0.900	0.893	0.881	− 1.447	− 1.504	− 1.349	− 1.253	− 1.269
						[0.926]	[0.934]	[0.911]	[0.895]	[0.898]
NOR	1.097	1.117	1.106	1.107	1.127	2.503	1.868	1.409	1.266	1.377
						[0.006]	[0.031]	[0.079]	[0.103]	[0.084]
SGP	1.183	1.275	1.346	1.383	1.413	3.291	2.742	2.701	2.624	2.599
						[0.000]	[0.002]	[0.006]	[0.007]	[0.010]
SPN	1.126	1.223	1.287	1.315	1.335	4.991	4.886	4.928	4.642	4.411
						[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
SWE	1.118	1.146	1.176	1.175	1.179	5.617	3.748	3.460	2.905	2.614
						[0.000]	[0.000]	[0.000]	[0.002]	[0.004]
SWI	1.039	1.056	1.076	1.085	1.092	1.555	1.187	1.226	1.168	1.130
						[0.060]	[0.118]	[0.110]	[0.121]	[0.129]
UK	1.059	1.078	1.091	1.086	1.079	1.788	1.389	1.323	1.106	0.932
						[0.037]	[0.082]	[0.093]	[0.134]	[0.176]
USA	1.048	1.014	0.972	0.959	0.944	1.114	0.173	− 0.264	− 0.335	− 0.409
						[0.133]	[0.431]	[0.604]	[0.631]	[0.659]
EUR	1.066	1.086	1.110	1.123	1.130	2.080	1.564	1.586	1.559	1.496
						[0.019]	[0.059]	[0.056]	[0.059]	[0.067]
EAFE	1.087	1.128	1.163	1.176	1.178	2.287	2.070	2.164	2.070	1.918
						[0.011]	[0.019]	[0.015]	[0.019]	[0.028]
WLD	1.199	1.276	1.315	1.328	1.327	4.023	3.235	3.009	2.777	2.554
						[0.000]	[0.001]	[0.001]	[0.003]	[0.005]
Panel B. Weekly data										
AUS	1.107	1.306	1.369	1.343	1.300	1.754	2.804	2.615	2.100	1.667
						[0.040]	[0.003]	[0.004]	[0.018]	[0.048]

Table 5 (*continued*)

	Variance ratios for number k of base observations aggregated					Heteroscedastic test-statistic $Z^*(k)$ [randomization p-value]				
k	2	4	6	8	10	2	4	6	8	10
Panel B. Weekly data										
AUT	1.088	1.229	1.298	1.357	1.420	1.779	2.587	2.573	2.576	2.659
						[0.038]	[0.005]	[0.005]	[0.005]	[0.004]
BEL	1.068	1.220	1.303	1.384	1.454	1.638	2.911	3.114	3.360	3.524
						[0.051]	[0.002]	[0.001]	[0.000]	[0.000]
CAN	1.108	1.234	1.249	1.235	1.217	2.049	2.531	2.166	1.781	1.483
						[0.020]	[0.006]	[0.015]	[0.037]	[0.069]
DEN	1.019	1.050	1.040	1.014	0.973	0.522	0.749	0.449	0.131	− 0.225
						[0.301]	[0.227]	[0.327]	[0.448]	[0.589]
FRA	1.059	1.162	1.209	1.234	1.262	1.249	1.872	1.857	1.771	1.772
						[0.106]	[0.031]	[0.032]	[0.038]	[0.038]
GER	1.076	1.184	1.190	1.162	1.170	1.780	2.315	1.840	1.336	1.241
						[0.038]	[0.010]	[0.033]	[0.091]	[0.107]
HKG	1.111	1.265	1.267	1.246	1.236	2.025	2.820	2.247	1.787	1.549
						[0.019]	[0.002]	[0.018]	[0.038]	[0.058]
ITA	1.030	1.133	1.194	1.181	1.190	0.882	2.012	2.177	1.686	1.544
						[0.189]	[0.022]	[0.015]	[0.046]	[0.061]
JPN	1.047	1.166	1.228	1.265	1.300	1.194	2.241	2.320	2.259	2.254
						[0.116]	[0.013]	[0.010]	[0.012]	[0.012]
NET	1.027	0.982	0.961	0.946	0.947	0.601	− 0.233	− 0.400	− 0.469	− 0.408
						[0.274]	[0.592]	[0.655]	[0.680]	[0.658]
NOR	1.061	1.212	1.284	1.297	1.298	1.359	2.639	2.723	2.434	2.176
						[0.087]	[0.004]	[0.003]	[0.007]	[0.015]
SGP	1.113	1.210	1.259	1.302	1.339	1.739	1.943	1.945	1.999	2.034
						[0.038]	[0.023]	[0.030]	[0.031]	[0.026]
SPN	1.076	1.176	1.226	1.242	1.241	1.793	2.297	2.299	2.093	1.852
						[0.036]	[0.011]	[0.011]	[0.018]	[0.032]
SWE	1.035	1.103	1.131	1.145	1.166	0.828	1.311	1.280	1.203	1.222
						[0.204]	[0.095]	[0.100]	[0.114]	[0.111]
SWI	1.104	1.205	1.232	1.248	1.265	2.046	2.351	2.139	1.997	1.924
						[0.020]	[0.009]	[0.016]	[0.023]	[0.027]
UK	1.020	1.030	1.011	0.954	0.908	0.406	0.364	0.104	− 0.392	− 0.699
						[0.342]	[0.358]	[0.459]	[0.652]	[0.758]
USA	0.998	0.998	0.963	0.969	0.973	− 0.041	− 0.021	− 0.305	− 0.228	− 0.180
						[0.516]	[0.508]	[0.620]	[0.590]	[0.571]
EUR	1.070	1.145	1.164	1.144	1.144	1.248	1.569	1.441	1.115	1.004
						[0.106]	[0.058]	[0.075]	[0.132]	[0.158]
EAFE	1.072	1.175	1.219	1.231	1.254	1.645	2.204	2.125	1.908	1.873
						[0.050]	[0.014]	[0.017]	[0.028]	[0.031]
WLD	1.057	1.136	1.142	1.148	1.170	1.048	1.449	1.215	1.102	1.144
						[0.147]	[0.074]	[0.112]	[0.135]	[0.126]
Panel C. Monthly data										
AUS	0.971	0.855	0.819	0.764	0.747	− 0.456	− 1.167	− 1.086	− 1.173	− 1.093
						[0.676]	[0.878]	[0.861]	[0.880]	[0.863]
AUT	1.128	1.221	1.433	1.636	1.765	1.198	1.213	1.912	2.404	2.555
						[0.115]	[0.113]	[0.028]	[0.008]	[0.005]

(continued on next page)

Table 5 (*continued*)

	Variance ratios for number k of base observations aggregated					Heteroscedastic test-statistic $Z^*(k)$ [randomization p-value]				
k	2	4	6	8	10	2	4	6	8	10
Panel C. Monthly data										
BEL	1.111	1.214	1.287	1.368	1.508	1.379	1.543	1.564	1.663	2.010
						[0.084]	[0.061]	[0.059]	[0.048]	[0.022]
CAN	0.993	0.917	0.907	0.914	0.934	−0.098	−0.558	−0.476	−0.375	−0.259
						[0.539]	[0.712]	[0.683]	[0.646]	[0.602]
DEN	0.908	0.941	1.022	1.125	1.186	−1.271	−0.459	0.132	0.632	0.827
						[0.898]	[0.677]	[0.447]	[0.264]	[0.204]
FRA	1.060	1.076	1.204	1.295	1.371	0.681	0.496	1.032	1.270	1.426
						[0.248]	[0.310]	[0.151]	[0.102]	[0.077]
GER	0.960	0.997	1.097	1.196	1.294	−0.456	−0.021	0.498	0.860	1.141
						[0.676]	[0.508]	[0.309]	[0.195]	[0.127]
HKG	1.029	0.981	0.857	0.828	0.793	0.453	−0.157	−0.870	−0.875	−0.921
						[0.322]	[0.535]	[0.785]	[0.781]	[0.793]
ITA	1.058	1.182	1.354	1.511	1.652	0.733	1.310	1.987	2.425	2.729
						[0.232]	[0.095]	[0.023]	[0.008]	[0.003]
JPN	1.071	1.083	1.152	1.197	1.287	0.911	0.577	0.820	0.896	1.150
						[0.181]	[0.282]	[0.206]	[0.185]	[0.125]
NET	0.936	0.859	0.859	0.875	0.913	−0.801	−1.021	−0.804	−0.612	−0.379
						[0.788]	[0.846]	[0.789]	[0.730]	[0.648]
NOR	1.075	1.053	1.046	1.035	1.010	0.895	0.365	0.252	0.166	0.044
						[0.185]	[0.358]	[0.401]	[0.434]	[0.482]
SGP	1.031	0.998	1.027	1.007	0.966	0.463	−0.019	0.158	0.033	−0.145
						[0.337]	[0.498]	[0.415]	[0.462]	[0.520]
SPN	1.076	1.067	1.092	1.201	1.312	0.887	0.441	0.480	0.899	1.246
						[0.188]	[0.330]	[0.316]	[0.184]	[0.106]
SWE	1.042	1.042	1.069	1.127	1.168	0.514	0.291	0.371	0.581	0.688
						[0.304]	[0.386]	[0.355]	[0.281]	[0.246]
SWI	1.046	1.068	1.152	1.203	1.297	0.559	0.491	0.859	0.988	1.293
						[0.288]	[0.312]	[0.195]	[0.162]	[0.098]
UK	0.905	0.757	0.725	0.680	0.654	−1.486	−1.856	−1.573	−1.535	−1.465
						[0.931]	[0.968]	[0.942]	[0.938]	[0.929]
USA	1.004	0.957	0.919	0.927	0.901	0.050	−0.283	−0.423	−0.329	−0.404
						[0.480]	[0.611]	[0.664]	[0.629]	[0.657]
EUR	0.965	0.943	1.009	1.066	1.145	−0.460	−0.422	0.054	0.320	0.626
						[0.677]	[0.663]	[0.478]	[0.374]	[0.266]
EAFE	1.021	0.979	1.028	1.068	1.171	0.264	−0.140	0.148	0.309	0.681
						[0.396]	[0.556]	[0.441]	[0.379]	[0.248]
WLD	1.027	0.985	0.985	1.000	1.042	0.363	−0.112	−0.087	0.000	0.179
						[0.358]	[0.545]	[0.535]	[0.500]	[0.429]

The table shows results from the variance ratio test of the random walk hypothesis for MSCI country equity index returns, in U.S. dollars for the sample period December 31, 1979 to June 19, 1998. The columns report variance ratios for number k of base observations aggregated and heteroscedastic test statistics, respectively. The numbers inside the brackets are the p-values from randomization with 5000 replications. A p-value smaller than 0.05 means that the null hypothesis that an equity price index follows a random walk can be rejected at the 5% level, in favor of the alternative hypothesis that the returns are positively serially correlated. On the other hand, a p-value greater than 0.95 indicates that the null hypothesis can be rejected at the 5% level, in favor of the alternative hypothesis that the returns are negatively serially correlated.

results suggest that the choice of measurement currency plays an important role in drawing statistical inferences.[9]

Panels B and C of Table 5 shows results using weekly and monthly data in dollar terms, respectively. We find that these results are much in agreement with those of Tables 3 and 4 for local currency indices. That is, weekly returns primarily exhibit positive correlation while monthly indices basically follow a random walk. In particular, using monthly data, all three regional indices can be characterized as a random walk. In general, we do not find evidence of mean reversion.

5. International momentum strategy

The results reported in the preceding section show some evidence of predictability in international equity returns. In particular, at the daily and weekly horizons, equity returns exhibit substantial positive autocorrelation for the majority of the markets. In this section, we investigate the economic significance of the positive correlation. If returns are positively correlated over time, then a high (low) return in this period should imply a high likelihood that returns in the following periods will also be high (low). Therefore, investors may be able to take advantage of this information to improve their portfolio positions. Namely, they can buy stocks that have recently performed well (winners) and sell short stocks that have recently performed poorly (losers) to make an excess profit. This so-called momentum strategy has been studied by previous researchers, including Jegadeesh and Titman (1993) and Chan et al. (1996), who use U.S. data, and Richards (1997), Rouwenhorst (1998), Chan et al. (2000), and Griffin et al. (2003) using international data.

5.1. Profitability of momentum strategy

We study the profitability of momentum strategy using 18 country indices in dollar terms. Our strategy is designed in a way similar to Jegadeesh and Titman (1993) and Rouwenhorst (1998). Specifically, at the end of each period, we calculate the average return of the past J periods for each of the 18 country indices and rank them in descending order. We assign the top three indices (with the highest average returns) to the "winner portfolio" and the bottom three indices to the "loser portfolio." These portfolios are equally weighted at formation. We then buy the winner portfolio, simultaneously sell short the loser portfolio, and hold the position for L periods without rebalancing. When the holding horizon L is longer than one period, this creates an overlap in the holding period return. We follow Jegadeesh and Titman (1993) and Rouwenhorst (1998) to compute the period average return of L strategies, each starting one period apart. In other words, this return is equivalent to the return of a composite portfolio in which $1/L$ of the holdings is updated each period and the remaining from the previous period is carried over.

[9] The predictability of international equity indices in dollar terms may in part be driven by the predictability of exchange rates. However, we do not take this as a convincing explanation because the literature suggests that exchange rates are largely unpredictable at least over the short horizons. See, for example, Qi and Wu (2003) and the related references cited in that paper.

Table 6

Excess returns of momentum strategies for international equity indices

Ranking period (*J*)		Daily frequency holding period (*L*)					Weekly frequency holding period (*L*)					Monthly frequency holding period (*L*)				
		L = 1	*L* = 3	*L* = 6	*L* = 9	*L* = 12	*L* = 1	*L* = 3	*L* = 6	*L* = 9	*L* = 12	*L* = 1	*L* = 3	*L* = 6	*L* = 9	*L* = 12
J = 1	Winners – losers	0.576	0.217	0.100	0.074	0.086	0.093	0.088	0.029	0.033	0.023	0.075	0.037	0.043	0.036	0.021
	t-stat	(13.295)	(8.171)	(5.358)	(4.744)	(6.346)	(2.349)	(3.633)	(1.611)	(2.015)	(1.720)	(1.791)	(1.332)	(1.880)	(1.915)	(1.225)
	β	− 0.088	− 0.096	− 0.079	− 0.074	− 0.057	− 0.066	− 0.030	− 0.020	− 0.025	− 0.008	− 0.102	− 0.020	0.037	0.073	0.073
	t-stat (β)	(− 3.906)	(− 7.024)	(− 8.163)	(− 9.200)	(− 8.093)	(− 1.575)	(− 1.187)	(− 1.029)	(− 1.476)	(− 0.602)	(− 1.195)	(− 0.346)	(0.785)	(1.916)	(2.133)
J = 3	Winners – losers	0.368	0.154	0.042	0.067	0.078	0.183	0.120	0.039	0.033	0.035	0.021	0.041	0.035	0.055	0.045
	t-stat	(8.652)	(4.500)	(1.499)	(2.828)	(3.701)	(4.408)	(3.548)	(1.420)	(1.362)	(1.710)	(0.440)	(0.991)	(1.032)	(2.055)	(1.809)
	β	− 0.172	− 0.117	− 0.116	− 0.113	− 0.096	− 0.110	− 0.122	− 0.051	− 0.038	− 0.025	− 0.005	0.106	0.144	0.152	0.182
	t-stat (β)	(− 7.844)	(− 6.602)	(− 8.115)	(− 9.237)	(− 8.881)	(− 2.512)	(− 3.414)	(− 1.766)	(− 1.497)	(− 1.124)	(− 0.055)	(1.254)	(2.115)	(2.868)	(3.692)
J = 6	Winners – losers	0.229	0.079	0.062	0.088	0.093	0.131	0.081	0.028	0.029	0.041	0.106	0.082	0.091	0.081	0.062
	t-stat	(5.248)	(2.030)	(1.810)	(2.917)	(3.417)	(3.196)	(2.167)	(0.837)	(0.964)	(1.538)	(2.012)	(1.744)	(2.397)	(2.365)	(1.997)
	β	− 0.190	− 0.162	− 0.154	− 0.144	− 0.132	− 0.048	− 0.059	− 0.022	− 0.005	0.016	0.074	0.217	0.237	0.296	0.258
	t-stat (β)	(− 8.440)	(− 8.111)	(− 8.805)	(− 9.201)	(− 9.403)	(− 1.095)	(− 1.500)	(− 0.629)	(− 0.148)	(0.561)	(0.682)	(2.258)	(3.094)	(4.342)	(4.172)
J = 9	Winners – losers	0.231	0.144	0.129	0.127	0.118	0.095	0.044	0.018	0.033	0.044	0.096	0.111	0.108	0.088	0.076
	t-stat	(5.309)	(3.608)	(3.521)	(3.780)	(3.836)	(2.246)	(1.136)	(0.508)	(1.012)	(1.458)	(1.799)	(2.333)	(2.523)	(2.323)	(2.235)
	β	− 0.241	− 0.187	− 0.168	− 0.157	− 0.142	− 0.087	− 0.052	− 0.007	0.018	0.026	0.269	0.297	0.349	0.307	0.231
	t-stat (β)	(− 10.809)	(− 9.076)	(− 8.939)	(− 9.080)	(− 8.953)	(− 1.933)	(− 1.247)	(− 0.195)	(0.503)	(0.813)	(2.492)	(3.102)	(4.134)	(4.080)	(3.399)
J = 12	Winners – losers	0.253	0.176	0.157	0.147	0.134	0.089	0.058	0.041	0.045	0.050	0.126	0.118	0.095	0.091	0.073
	t-stat	(5.796)	(4.332)	(4.165)	(4.142)	(4.042)	(2.046)	(1.445)	(1.103)	(1.270)	(1.465)	(2.242)	(2.285)	(2.152)	(2.375)	(2.089)
	β	− 0.190	− 0.177	− 0.180	− 0.162	− 0.149	− 0.040	− 0.039	0.015	0.035	0.039	0.319	0.364	0.318	0.224	0.157
	t-stat (β)	(− 8.441)	(− 8.425)	(− 9.261)	(− 8.896)	(− 8.719)	(− 0.850)	(− 0.906)	(0.368)	(0.930)	(1.085)	(2.830)	(3.526)	(3.631)	(2.924)	(2.227)

The difference between winners and losers is computed as follows. At the end of each ranking period (*J*), the 18 countries are ranked in descending order. The top three countries are assigned to the winner portfolio and the bottom three are assigned to the loser portfolio. The portfolios are equally weighted and are held for *L* periods. The table reports the difference of the annualized average returns of the winners and losers. β is the slope coefficient from a simple OLS regression of the excess returns of the portfolio on the excess returns on the MSCI world market portfolio. The *t*-stats for the difference in returns and the β are reported below them. The *t*-stats greater than 1.96 and 1.65 in absolute value indicate significance at the 5% and 10% levels, respectively, using a two-sided test.

Table 6 shows a summary of the results. For each data frequency, we choose the portfolio ranking periods (J) and holding periods (L) to be 1, 3, 6, 9, and 12. We report the difference of the average excess returns (annualized) between the winner portfolio and the loser portfolio. This is an excess return from a zero-net investment strategy. The associated t-statistic tests whether the excess return is statistically different from zero.[10] We also compute the beta of this winner – loser portfolio with the world index as the market portfolio. This beta gives us a rough idea on whether the excess return of the momentum strategy can simply be explained by the increase in market risk. We make several remarks.

Firstly, the average excess returns are positive for all ranking periods (J), holding periods (L), and data frequencies. These return measures are in general relatively large in magnitude and in many cases have significant t-ratios.

Secondly, compared across three data frequencies, it is clear that the results for daily data are the strongest. For example, when the ranking period is 12 days, the average excess returns are 25.3%, 17.6%, 15.7%, 14.7%, and 13.4% per annum if the portfolio is held for 1, 3, 6, 9, and 12 days, respectively. Each of these return measures is statistically significant at the 1% level using a two-sided test. Returns for daily data with other ranking horizons are somewhat lower but are statistically significant in most cases. Indeed, among all return measures for daily data, only two of them are not significant at the 5% level ($J=3$ with $L=6$, and $J=6$ with $L=6$). These results show strong momentum effects at short-horizon returns. They are not only statistically significant, but also economically important. These results complement those from the variance ratio test reported in the preceding section and suggest that information on the positive serial correlation in returns may potentially be exploitable.

Thirdly, results from weekly data are in general weaker than those from daily data. Nevertheless, we find that many return measures are substantial in magnitude and statistically significant. For example, when the holding horizon is one period ($L=1$), all weekly return measures are significant at the 5% level, and these returns average to 11.8% per annum. When the holding horizon is three periods ($L=3$), three out of the five return measures ($J=1$, 3, 6) are significant. The average excess return for $L=3$ is 7.8% per annum. Returns from other ranking or holding periods are smaller and in general statistically insignificant.

Fourthly, the excess returns from monthly data are somewhat stronger than weekly data with 14 out of 25 return measures statistically significant at the 5% level. These large excess returns primarily occur to the longer ranking and holding periods. In particular, the returns are significant for all combination of 6 to 12 months ranking and holding periods. Compared with the weekly results, these results show that momentum profitability is strong for intermediate horizons (6–12 months), consistent with findings in the literature. For monthly data, average excess returns per annum for different holding periods are 8.5% ($L=1$), 7.8% ($L=3$), 7.4% ($L=6$), 7.0% ($L=9$), and 5.5% ($L=12$), some of which are economically significant.[11]

[10] We follow the literature (e.g., Jegadeesh and Titman (1993) and many others) to compute the usual t-statistics without taking into account the potential heterosecedasticty and correlation due to the overlapping of returns.

[11] Our results on momentum profits from weekly and monthly data seem to be inconsistent with those from the variance ratio test where we find significantly positive correlation for weekly data and insignificant correlation for monthly data. However, as Lo and MacKinlay (1990) demonstrate, the sources of momentum profits can be decomposed into own serial correlation, cross-sectional serial correlation, and cross-sectional differences in expected returns. Positive serial correlation is neither a necessary nor a sufficient condition for momentum profitability.

In summary, the results on the profitability of international momentum strategies are fairly significant.[12] In particular, those obtained from daily data are new and are a useful addition to the literature. Our monthly results reconfirm recent findings on international momentum profits, including Rouwenhorst (1998), Richards (1997), Bhojraj and Swaminathan (2001), and Griffin et al. (2003). Furthermore, our findings from weekly data complement those of Chan et al. (2000), who use weekly market indices for 23 countries and report significant momentum profitability. Our momentum profitability using weekly data is somewhat less significant for lower orders J's and K's than Chan et al. (2000, compared to their Table 2), and this can be attributed to the following reasons. Firstly, their sample includes 17 developed markets and six emerging markets, while our sample consists only of the homogeneous 18 developed markets. More countries and heterogeneity expand their investment opportunity set and may in part be responsible for their higher profitability. Secondly, they use the popular market indices, each of which consists of a relatively small number of firms in the respective country. We use the MSCI indices, which have much wider market coverage and are more diversified. The MSCI indices are computed consistently across markets, thereby allowing for a direct comparison across countries.

5.2. Robustness of results

While the results shown above are quite strong, they should be interpreted with caution because they could be driven by potential biases associated with asynchronous trading, infrequent trading, and/or transactions costs. These excess returns could also be a compensation for exposures to systematic risks. In this subsection, we conduct a number of robustness checks of our findings.

Firstly, there is a fundamental problem of asynchronous trading due to different time zones of the countries under investigation. The bias can be especially severe for daily data. To deal with this issue, we introduce a 1-day gap between portfolio ranking and portfolio formation. That is, portfolios are formed 1 day after they are ranked. The results are reported in Table 7. The excess returns at the daily frequency with a 1-day gap are indeed smaller than those reported in Table 6 when portfolios are formed immediately after ranking. Especially, when the holding period is short ($L=1$, 3, and 6), the excess returns are much lower. Nevertheless, these average returns are positive except for two cases ($J=1$, 3 and $L=9$). Furthermore, 14 of them are significant at the 1% level. The results at the weekly horizon are quite similar to those without the 1-day gap, and those at the monthly horizons are indeed somewhat stronger. These results suggest that the problem of asynchronous trading is relatively serious at daily horizon but is not as important at weekly and monthly horizons. The excess returns generated by the momentum strategy cannot be primarily attributed to the bias due to asynchronous trading.

Secondly, we study the duration and the persistence of momentum effect. To this end, we examine the performance of the momentum portfolio in event time. We ask the

[12] Our inference is based on the conventional 5% and 1% significance levels. As noted in Section 4.1, if the more conservative significance levels based on the Schwarz criterion are used, our momentum profitability will appear weaker statistically.

Table 7
Excess returns of momentum strategies for international equity indices portfolio formed 1 day after ranking

Ranking period (J)		Daily frequency holding period (L)					Weekly frequency holding period (L)					Monthly frequency holding period (L)				
		$L=1$	$L=3$	$L=6$	$L=9$	$L=12$	$L=1$	$L=3$	$L=6$	$L=9$	$L=12$	$L=1$	$L=3$	$L=6$	$L=9$	$L=12$
$J=1$	Winners – losers	0.039	0.035	– 0.003	0.029	0.039	0.068	0.093	0.033	0.034	0.024	0.088	0.038	0.045	0.038	0.024
	t-stat	(0.931)	(1.373)	(– 0.149)	(1.873)	(2.940)	(1.683)	(3.748)	(1.788)	(2.095)	(1.719)	(2.155)	(1.414)	(1.969)	(2.039)	(1.403)
	β	– 0.126	– 0.049	– 0.073	– 0.066	– 0.053	– 0.114	– 0.059	– 0.032	– 0.036	– 0.012	– 0.114	– 0.028	0.034	0.077	0.086
	t-stat (β)	(– 5.864)	(– 3.716)	(– 7.643)	(– 8.434)	(– 7.802)	(– 2.645)	(– 2.260)	(– 1.603)	(– 2.112)	(– 0.846)	(– 1.381)	(– 0.516)	(0.727)	(2.036)	(2.530)
$J=3$	Winners – losers	0.065	0.013	– 0.012	0.041	0.052	0.157	0.113	0.030	0.027	0.033	– 0.001	0.033	0.041	0.058	0.050
	t-stat	(1.537)	(0.380)	(– 0.434)	(1.736)	(2.503)	(3.867)	(3.473)	(1.133)	(1.212)	(1.708)	(– 0.021)	(0.798)	(1.229)	(2.185)	(1.972)
	β	– 0.079	– 0.088	– 0.106	– 0.100	– 0.093	– 0.026	– 0.076	– 0.022	– 0.013	– 0.002	– 0.082	0.048	0.085	0.099	0.137
	t-stat (β)	(– 3.611)	(– 5.004)	(– 7.402)	(– 8.202)	(– 8.623)	(– 0.600)	(– 2.219)	(– 0.776)	(– 0.525)	(– 0.088)	(– 0.833)	(0.573)	(1.243)	(1.865)	(2.711)
$J=6$	Winners – losers	0.028	0.010	0.048	0.075	0.079	0.098	0.054	0.019	0.028	0.042	0.111	0.084	0.091	0.082	0.070
	t-stat	(0.648)	(0.273)	(1.422)	(2.524)	(2.947)	(2.379)	(1.465)	(0.603)	(0.990)	(1.641)	(2.099)	(1.810)	(2.414)	(2.396)	(2.223)
	β	– 0.144	– 0.148	– 0.148	– 0.135	– 0.127	– 0.030	– 0.063	– 0.024	– 0.010	0.010	0.018	0.171	0.194	0.271	0.227
	t-stat (β)	(– 6.468)	(– 7.572)	(– 8.522)	(– 8.795)	(– 9.217)	(– 0.684)	(– 1.618)	(– 0.700)	(– 0.320)	(0.367)	(0.168)	(1.791)	(2.524)	(3.940)	(3.614)
$J=9$	Winners – losers	0.113	0.102	0.111	0.113	0.100	0.048	0.016	0.007	0.022	0.031	0.111	0.117	0.114	0.092	0.078
	t-stat	(2.630)	(2.578)	(3.089)	(3.413)	(3.274)	(1.141)	(0.410)	(0.200)	(0.672)	(1.046)	(2.061)	(2.427)	(2.647)	(2.405)	(2.297)
	β	– 0.176	– 0.152	– 0.153	– 0.141	– 0.132	– 0.084	– 0.050	– 0.011	0.024	0.033	0.266	0.285	0.347	0.309	0.232
	t-stat (β)	(– 7.963)	(– 7.415)	(– 8.249)	(– 8.236)	(– 8.449)	(– 1.879)	(– 1.215)	(– 0.307)	(0.687)	(1.031)	(2.434)	(2.928)	(4.050)	(4.065)	(3.415)
$J=12$	Winners – losers	0.135	0.145	0.134	0.133	0.118	0.057	0.041	0.034	0.038	0.045	0.114	0.117	0.092	0.089	0.072
	t-stat	(3.102)	(3.638)	(3.587)	(3.794)	(3.592)	(1.310)	(1.037)	(0.904)	(1.075)	(1.349)	(2.074)	(2.293)	(2.096)	(2.352)	(2.075)
	β	– 0.162	– 0.166	– 0.161	– 0.151	– 0.140	– 0.021	– 0.015	0.026	0.045	0.050	0.292	0.348	0.305	0.217	0.156
	t-stat (β)	(– 7.191)	(– 8.084)	(– 8.375)	(– 8.337)	(– 8.308)	(– 0.459)	(– 0.363)	(0.647)	(1.219)	(1.402)	(2.630)	(3.433)	(3.509)	(2.864)	(2.220)

The difference between winners and losers is computed as follows. At the end of each ranking period (J), the 18 countries are ranked in descending order. The top three countries are assigned to the winner portfolio and the bottom three are assigned to the loser portfolio. Portfolio formation occurs 1 day after the ranking takes place. The portfolios are equally weighted and are held for L periods. The table reports the difference of the annualized average returns of the winners and losers. The β is the slope coefficient from a simple OLS regression of the excess returns of the portfolio on the excess returns on the MSCI world market portfolio. The t – stats for the difference in returns and the β are reported below them. The t-stats greater than 1.96 and 1.65 in absolute value indicate significance at the 5% and 10% levels, respectively, using a two-sided test.

following question: for portfolios ranked based on past 12 periods ($J=12$), what is the average excess return on buying the winners and selling the losers in the Lth period after portfolios are formed? Fig. 2(1)–(3) display the average returns of the momentum portfolio for three data frequencies. We can see that for daily data, the average excess returns are positive for the first 16 days, and then turn negative thereafter. For weekly data, the mean excess returns are uniformly positive for $L=1$ to 36. For monthly data, the momentum effect lasts for about 11 months, which is consistent with Rouwenhorst (1998), who uses firm-level data for 12 European countries.

Thirdly, the evidence presented thus far suggests that the international momentum strategy predicated on positive serial correlation in short-horizon returns yield excess returns that are economically important. But these returns could be a compensation for systematic risks.[13] To study whether the excess returns we obtain can be explained by exposure to risk factors, we first look at the simple covariance risk with the world index as the market portfolio. From Table 6, we find that, for daily data, the beta from the winner – loser portfolio is negative and significant at the 1% level for all cases. These results show that the winner portfolio not only produces a higher average return but also bears a smaller systematic risk than the loser portfolio. The weekly results show a similar pattern. In most cases, the betas are negative, and in the few cases where the betas are positive, they are statistically insignificant. Overall, these beta values suggest that the higher returns of the strategies exploiting momentum cannot be easily explained by simple beta risk. For monthly data, we do find that the beta for the winner portfolio is larger than that for the loser portfolio in most cases and the difference is in general statistically significant. However, as to be presented in Table 8 below, the beta risk only explains a small portion of the momentum profitability, leaving the excess return after adjusting for beta risk and size risk still significant.

Fama and French (1996) argue that the differences in returns between small and big firms (SMB) and between high and low book-to-market value ratios can be additional risk factors in explaining cross-sectional U.S. stock returns. To further examine whether the excess returns from momentum strategies are a compensation for systematic risks, we estimate a two-factor model with the small-minus-big (SMB) factor as an additional source of risk. We construct the SMB factor for U.S. firms using data from CRSP. As daily or weekly observations on book-to-market ratios are unavailable, we do not consider the third Fama–French factor. The results reported in Table 8 for the case of $J=12$ and $L=12$ are somewhat mixed. At the daily frequency, we find that the momentum portfolio has significant negative loadings on both factors, making the risk-adjusted excess return (the alpha) larger than the unadjusted return. While the unadjusted excess return for weekly data is not significant, the SMB factor has a significant positive loading. Finally, the beta coefficient for the SMB factor is positive but insignificant and the risk-adjusted excess return is nearly significant at the 5% level for monthly data. We also perform the same analysis for the case of $J=6$ and $L=6$ (not reported) and find that the SMB factor is insignificant.

The above results demonstrate that exposure to the market risk factor or the SMB factor does not provide a simple explanation for the excess returns on momentum

[13] Conrad and Kaul (1998) argue that profitability of momentum strategies for U.S. stocks reflect cross-sectional variations in mean returns of the stocks.

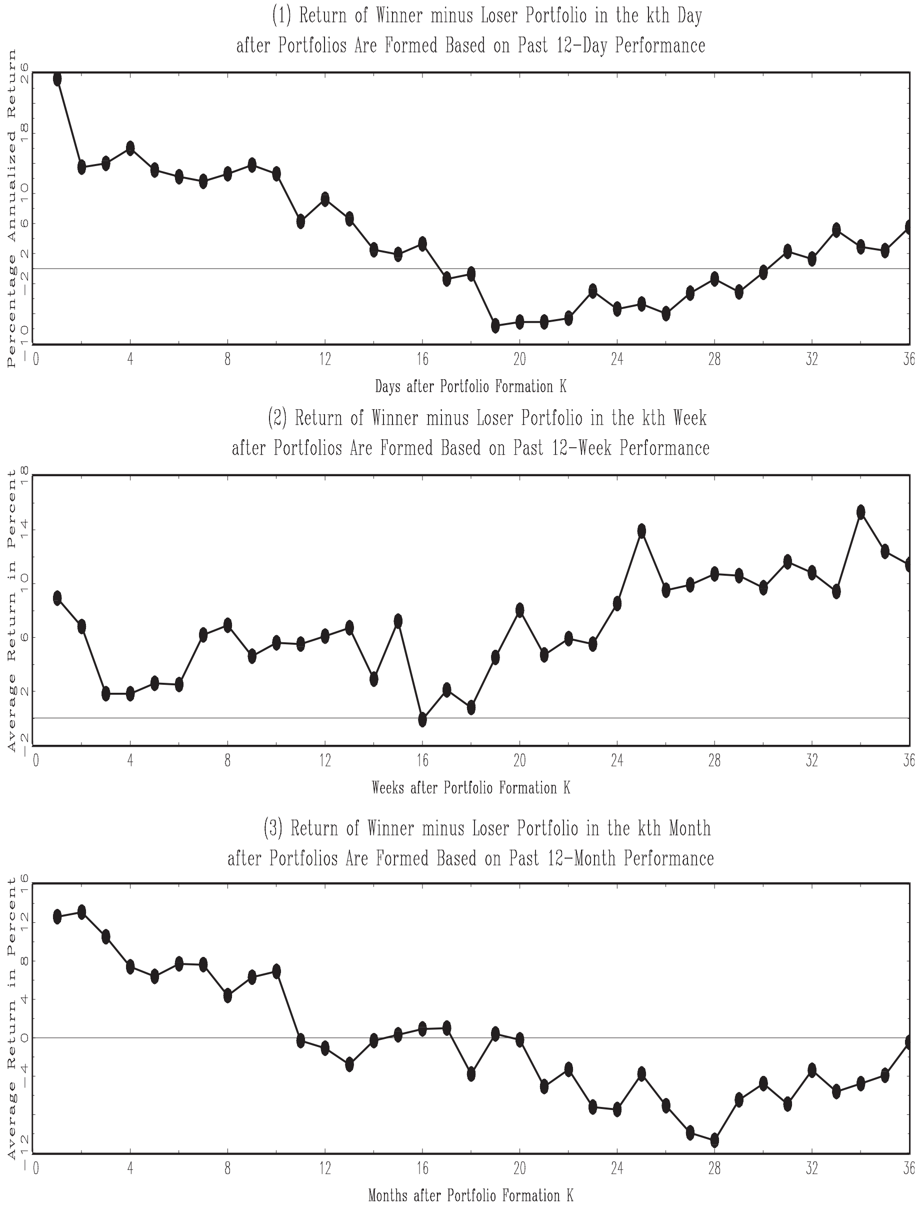

Fig. 2. (1) Return of winner – loser portfolio in the *k*th day after portfolios are formed based on past 12-day performance. Percentage annualized return. Days after portfolio formation *k*. (2) Return of winner – loser portfolio in the *k*th week after portfolios are formed based on past 12-week performance. Percentage annualized return. Weeks after portfolio formation *k*. (3) Return of winner – loser portfolio in the *k*th month after portfolios are formed based on past 12-month performance. Percentage annualized return. Months after portfolio formation *k*.

Table 8
Risk-adjusted excess returns

Portfolio	Mean return	t-ratio	α	t-ratio	β_{WLD}	t-ratio	β_{SMB}	t-ratio	Percentage switches in portfolio
Daily frequency									
Winner	0.179	5.421	0.066	2.677	0.870	60.902	0.272	23.220	6.57
Loser	0.046	1.187	− 0.074	− 2.673	1.042	64.645	0.315	23.842	6.59
Winner − loser	0.134	4.042	0.141	4.279	− 0.172	− 9.049	− 0.043	− 2.767	6.58
Weekly frequency									
Winner	0.123	3.304	0.006	0.236	0.964	32.407	0.224	8.230	6.72
Loser	0.073	2.024	− 0.040	− 1.562	0.887	29.562	0.140	5.096	6.63
Winner − loser	0.050	1.465	0.046	1.360	0.077	1.946	0.084	2.321	6.68
Monthly frequency									
Winner	0.142	3.356	0.035	1.238	0.948	16.081	0.115	2.547	6.39
Loser	0.069	1.862	− 0.032	− 1.204	0.779	14.116	0.066	1.545	6.43
Winner − loser	0.073	2.089	0.067	1.946	0.168	2.348	0.050	0.904	6.41

This table shows results from regressing returns of winner and loser portfolios on the excess return on the MSCI world index and the return on the Fama–French small-minus-big portfolio:

$$r_{i,t} - r_{f,t} = \alpha + \beta_{\mathrm{WLD}}(r_{\mathrm{WLD},t} - r_{f,t}) + \beta_{\mathrm{SMB}} r_{\mathrm{SMB},t} + \varepsilon_t$$

and the results from regressing returns of winner − loser portfolio on the same two factors:

$$r_{\mathrm{winner},t} - r_{\mathrm{loser},t} = \alpha + \beta_{\mathrm{WLD}}(r_{\mathrm{WLD},t} - r_{f,t}) + \beta_{\mathrm{SMB}} r_{\mathrm{SMB},t} + \varepsilon_t.$$

The winner and loser portfolios are as defined in Table 6 with ranking period $J = 12$ and holding period $L = 12$. The Eurodollar deposit rates are used as the risk-free rate and the α values are annualized. The last column reports the number of switches (as a percentage of sample size) that the respective portfolio incurs.

strategies at short horizons. We do not intend here to fully explore the possibilities of explaining the excess returns as a compensation for bearing more systematic risks. As Adler and Dumas (1983) and Stulz (1995) show, strong assumptions are 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 returns across markets.[14]

Fourthly, another important caveat is that we have not considered transactions costs. In reality, costs of international funds transactions may be substantial, especially when short selling is involved and stock index futures contracts do not exist.[15] The costs can be

[14] We also examine whether exchange rate risk is another common factor that can explain the excess return from momentum strategies. We run the excess return from momentum strategies on the market factor, the size factor, as well as three exchange rate factors as measured by the percentage changes in the Japanese yen, the British pound, and the German mark exchange rates. We find that these exchange rate factors do not provide more explanatory power for the momentum profits. The results are not reported to conserve space but are available from the authors upon request.

[15] In practice, investors can use exchange-traded funds called the World Equity Benchmark Shares (WEBS), which are part of the iShares family. These funds represent the MSCI country equity indices and are traded on the American Stock Exchange. Currently, there are 25 iShares MSCI series for 20 countries and five regions, including iShares for EAFE and the European Monetary Union.

especially high for daily data when transactions are intensive and can much lower the actual returns. Furthermore, a few countries were subject to some degree of capital controls in the early part of the sample, which may have limited international speculation. To examine the effect of transactions costs, the last column of Table 8 reports the frequencies at which the winner and loser portfolios switch over the sample period. Consider the daily frequency case with $J = 12$ and $L = 12$, the winner and loser portfolios switch 6.57% and 6.59% of the time in sample, respectively. Assume a half percentage transaction cost per one-way transaction, the 6.57% switching frequency implies 17 trades per year, which translates into an average transactions cost of 8.54% per year ($0.0657 \times 260 \times 0.5 = 8.54$) for the winner portfolio. The momentum strategy involves buying the winner portfolio and short-selling the loser portfolio, and therefore incurs a round-trip transactions cost. This makes the average transactions cost for the momentum portfolio as high as 17.08% per year, eliminating the raw excess return. On the other hand, for monthly data, a 6.41 percentage switching frequency only translates into a 0.38% transactions cost per year ($0.0641 \times 12 \times 0.5 = 0.38$). This produces an *after-cost* excess return of $7.3 - 0.38 \times 2 = 6.54$% per year, which remains an economically significant figure. Nevertheless, our results may not necessarily be viewed as profitable strategies in practice. They should be interpreted as providing complementary support for our results on short-horizon predictability using the variance ratio test. Notice that as Grundy and Martin (2001) point out, establishing that one cannot actually profit from momentum does not imply that momentum does not exist. It is still a peculiar feature of financial markets.

Lastly, we examine whether market size plays a role in the momentum strategies. In particular, we investigate whether large countries appear in the winner and loser portfolios as often as small countries. To this end, in Fig. 3, we plot the average market capitalization (in natural logarithm) against the 18 portfolios (1 being the winner and 18 being the loser).[16] Interestingly, these graphs show an inverse "U"-shaped pattern, indicating that the winner and the loser portfolios often comprise countries with lower market capitalization. These results suggest that the profitability of momentum strategies should be interpreted with caution. These strategies may not be feasible in practice because small countries are more subject to infrequent trading and microstructure biases, and may not have sufficient liquidity.

In sum, the results presented in this subsection suggest that the profitability of momentum portfolios may partially be accounted for by several factors. These strategies may not be feasible in practice. Nevertheless, these results provide additional evidence on the predictability of international equity returns and complement those from the variance ratio test.[17]

[16] Because daily or weekly data on market capitalization are not available, we approximate the daily and weekly market capitalization by the observation at the end of the previous month.

[17] Recently, several searchers propose alternative explanations for momentum profitability. Hong and Stein (1999) attribute stock market underreaction to bounded rationality of investors. Moskowitz and Grinblatt (1999) suggest that momentum in industry factors may explain the profitability of momentum trading strategies for U.S. firms. However, Grundy and Martin (2001) cast doubt on the ability of industry momentum in explaining the profitability of momentum strategies.

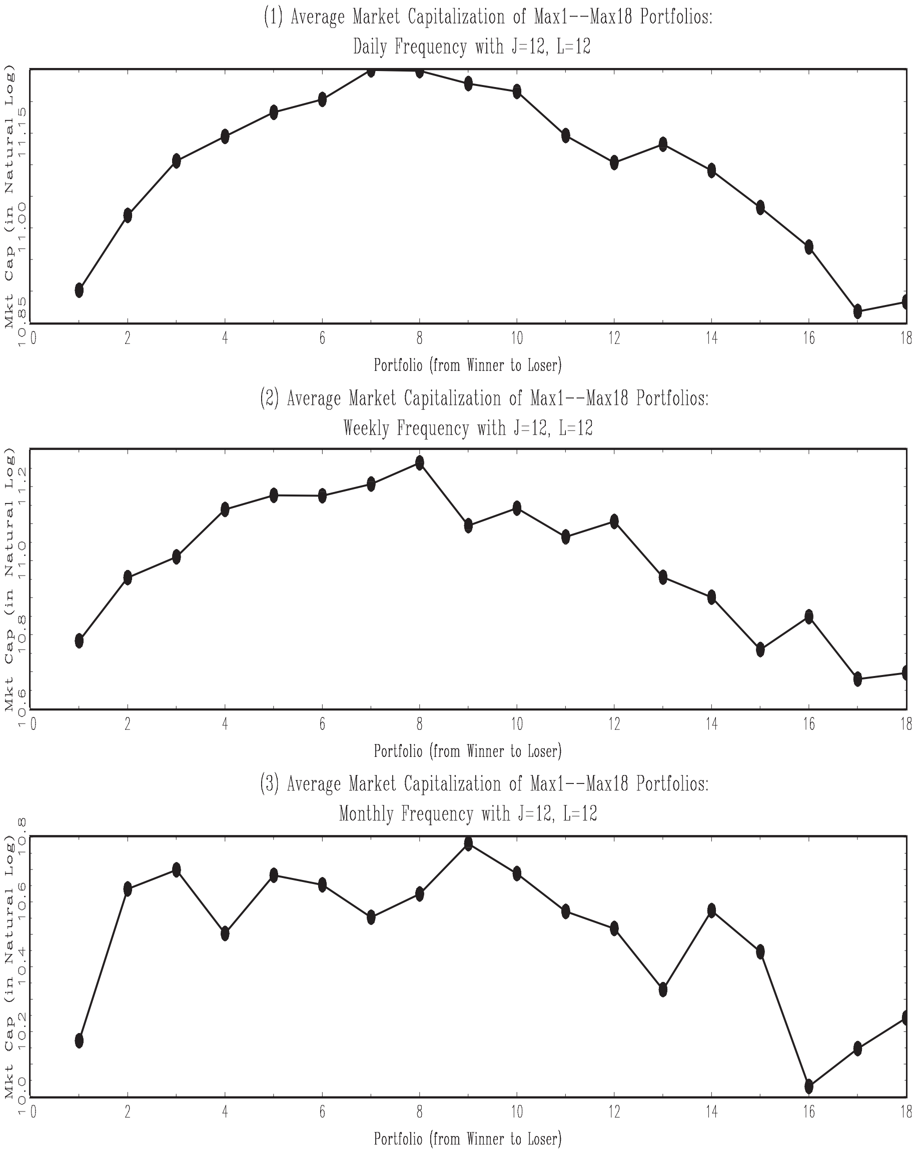

Fig. 3. (1) Average market capitalization of Max1–Max18 portfolios: daily frequency with $J=12$, $L=12$. Market capitalization (in natural log). Portfolio (from winner to loser). (2) Average market capitalization of Max1–Max18 portfolios: weekly frequency with $J=12$, $L=12$. Market capitalization (in natural log). Portfolio (from winner to loser). (3) Average market capitalization of Max1–Max18 portfolios: monthly frequency with $J=12$, $L=12$. Market capitalization (in natural log). Portfolio (from winner to loser).

6. Conclusions

This paper examines the predictability of short-horizon equity returns of 18 developed countries for the period 1979–1998. Using the variance ratio test and conventional significance levels, we find that the random walk hypothesis can be rejected for daily and weekly data for the majority of countries and that equity indices exhibit significant return continuation at short horizons. For monthly data, most markets may well be characterized as a random walk.[18] Our results show that inference on the random walk hypothesis is sensitive to currency denomination, return horizon, and distributional assumptions.

We also investigate the profitability of international momentum strategies. We find that the excess returns from buying past winners and short selling past losers are always positive. The results are particularly striking for daily data, where the momentum profits are not only statistically significant but also economically important in the absence of transaction costs. They complement those from the variance ratio test and provide further support for the predictability of short-horizon international equity returns.

We provide a number of robustness checks for the profitability of momentum strategies. We find that the excess returns are not greatly biased by nonsynchronous trading. Furthermore, they cannot be simply explained as a compensation for bearing more market risk. A two-factor model with the Fama–French size portfolio as a second factor does not explain the results better. Imposing a reasonable transactions cost substantially reduces momentum profits, especially for the daily data. We also show that both the winner and the loser portfolios, on average, tend to select smaller countries.

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[18] It will be interesting to investigate if there are time series models that can produce these required correlation patterns. Answering this question would require detailed model searching through simulations and it is beyond the scope of this paper. In a recent paper, Balvers and Wu (2002) propose a simple time series model to generate momentum over the short horizons and mean reversion over the long-term horizons across national equity markets. The model is built on the assumption that industrial production converges across countries so that relative equity prices have long-term reversal across countries.

References

Adler, M., Dumas, B., 1983. International portfolio choices and corporation finance: a synthesis. Journal of Finance 38, 925–984.

Balvers, R., Wu, Y., 2002. Momentum and mean reversion across national equity markets. mimeo, Rutgers University.

Balvers, R., Wu, Y., Gilliland, E., 2000. Mean reversion across national stock markets and parametric contrarian investment strategies. Journal of Finance 55, 745–772.

Bhojraj, S., Swaminathan, B., 2001. Macromomentum: evidence of predictability in international equity markets. mimeo. Cornell University.

Campbell, J., Lo, A., MacKinlay, A., 1997. The Econometrics of Financial Markets. Princeton Univ. Press, Princeton.

Chan, L., Jegadeesh, N., Lakonishok, J., 1996. Momentum strategies. Journal of Finance 51, 1681–1713.

Chan, K., Hameed, A., Tong, W., 2000. Profitability of momentum strategies in the international equity markets. Journal of Financial and Quantitative Analysis 35, 153–172.

Conrad, J., Kaul, G., 1988. Time-variation in expected returns. Journal of Business 61, 409–425.

Conrad, J., Kaul, G., 1989. Mean reversion in short-horizon in expected returns. Review of Financial Studies 2, 225–240.

Conrad, J., Kaul, G., 1998. An anatomy of trading strategies. Review of Financial Studies 11, 489–519.

Cochrane, J., 1988. How big is the random walk in GNP? Journal of Political Economy 96, 893–920.

DeBondt, W., Thaler, R., 1985. Does the stock market overreact? Journal of Finance 40, 793–805.

DeBondt, W., Thaler, R., 1987. Further evidence on investor overreaction and stock market seasonality. Journal of Finance 42, 557–581.

Fama, E., French, K., 1996. Multifactor explanations of asset pricing anomalies. Journal of Finance 51, 55–84.

French, K., Roll, R., 1986. Stock return variances: the arrival of information and the reaction of traders. Journal of Financial Economics 17, 5–26.

Griffin, J., Ji, S., Martin, S., 2003. Momentum investing and business cycle risk: evidence from pole to pole. Journal of Finance 58, 2515–2547.

Grundy, B., Martin, J., 2001. Understanding the nature of the risks and the source of the rewards to momentum investing. Review of Financial Studies 14, 29–78.

Hong, H., Stein, J., 1999. A unified theory of underreaction, momentum trading, and the overreaction in asset markets. Journal of Finance 54, 2143–2184.

Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: implications for stock market efficiency. Journal of Finance 48, 65–91.

Kim, M., Nelson, C., Startz, R., 1991. Mean reversion in stock prices? A reappraisal of the empirical evidence. Review of Economic Studies 58, 515–528.

Lo, A., MacKinlay, A., 1988. Stock market prices do not follow random walks: evidence from a simple specification test. Review of Financial Studies 1, 41–46.

Lo, A., MacKinlay, A., 1989. The size and power of the variance ratio tests in finite samples? Journal of Econometrics 40, 203–238.

Lo, A., MacKinlay, A., 1990. When are contrarian profits due to stock market overreaction? Review of Financial Studies 3, 175–205.

Moskowitz, T., Grinblatt, M., 1999. Do industries explain momentum? Journal of Finance 54, 1249–1290.

Poterba, J., Summers, L., 1988. Mean reversion in stock prices: evidence and implications. Journal of Financial Economics 22, 27–59.

Qi, M., Wu, Y., 2003. Nonlinear prediction of exchange rates with monetary fundamentals. Journal of Empirical Finance 10, 623–640.

Richards, A., 1997. Winner–loser reversals in national stock market indices: can they be explained? Journal of Finance 52, 2129–2144.

Rouwenhorst, G., 1998. International momentum strategies. Journal of Finance 53, 267–284.

Stulz, R., 1995. International portfolio choice and asset pricing: an integrative survey. In: Jarrow, R., Maximovich, M., Ziemba, W. (Eds.), Handbook of Modern Finance. North-Holland-Elsevier, Amsterdam, pp. 201–223.