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Exploitable cross autocorrelations among iShares

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Abstract

We extend the evidence on exploitable cross autocorrelations in equity returns by examining whether individual investors can exploit cross autocorrelations in Standard and Poor's Depository Receipts and iShares international index funds of 17 countries. Empirical testing reveals that iShares exhibit predictable elements that could be exploited by investors on a before transaction cost basis. We then compute bid-ask spreads and liquidity spreads to determine their affect on the risk-adjusted returns of the trading strategies. We find that transactions costs are generally high and that investors would need to be very cautious in placing trades to exploit returns patterns. © 2007 Academy of Financial Services. All rights reserved.

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1. Introduction

iShares are Exchange Traded Funds (ETFs) that are designed to track Morgan Stanley Capital International (MSCI) country indexes. These ETFs combine the benefits of diversification from index investing with the flexibility of investing in common stock. These investment vehicles are essentially index funds that are listed on an exchange, priced and

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traded intraday, and allow investors to buy or sell shares based on the collective performance of an entire portfolio. ETFs and iShares have become increasingly popular with investors because they are designed to replicate the holdings, performance, and yield of their underlying index.

ETFs and iShares are tax efficient because they generate few realized capital gains. Because ETFs and iShares are not actively managed, they only sell securities to reflect changes in the underlying index. Exchange trading further enhances their tax efficiency because investors who want to liquidate shares sell them in the secondary market. Because of this structure, ETFs and iShares, unlike mutual funds, are not required to sell securities to meet redemptions. Thus, this structure eliminates the generation of trading-related capital gains that would be taxable for remaining investors. ETFs and iShares also have significantly lower annual expense ratios than mutual funds which is due, in part, to passive management.[1] Additionally, because they are exchange traded, ETFs and iShares can be bought and sold at intraday market prices, purchased on margin, sold short, and traded using stop and/or limit orders.

The structure of ETFs and iShares makes them suitable for exploiting predictable patterns in security returns. Of particular interest in this study is the ability to exploit cross autocorrelations in returns. Hamao, Masulis and Ng (1990) report "spillover effects" between the United States and international markets. The practical significance of this finding is that markets behave in a predictably way and that a large positive (or negative) return in one market today could predict a large return in another market tomorrow. If this cross autocorrelation is found with iShares, it may be exploitable by individual investors.

Using 1,961 daily return observations of Standard and Poor's Depository Receipts and 17 iShare international index classes, we explore the potential exploitability of returns. Empirical testing uses cross autocorrelations and the Granger causality method to examine daily returns of iShares. We then develop a trading strategy that attempts to exploit statistical relationships. Finally, we test the trading strategy on a holdout sample to ascertain whether it dominates a buy-and-hold strategy in terms of raw and risk-adjusted returns. We contribute to existing literature by (1) examining whether the exploitable patterns observed among United States and foreign stocks are observed in the returns of the ETFs and iShares that represent equity indices in the United States and 17 foreign countries, (2) determining whether return patterns are exploitable on a before transaction cost basis, and (3) examining bid-ask spreads and liquidity spreads to ascertain whether return patterns are exploitable after considering transactions costs.

The next section discusses background literature, section three discusses our data and methodology, section four develops and tests our trading rules, and section five concludes.

2. Background

Hamao et al. (1990) report cross autocorrelations between United States and international stocks however, the cross autocorrelations were not exploitable because of large transactions costs associated with turning over a portfolio of individual stocks. In an effort to escape the trading costs of trading individual stocks, research concentrated on trading mutual funds/

variable annuities. The earliest research in this area is by Miller and Prather (2000) who report that TIAA/CREF retirement annuities exhibit predictable elements that could be exploited by informed traders. In addition, Chalmers, Edelen and Kadlec (2001) document that equity funds can be predicted from S&P 500 index futures and that bond funds can be predicted from futures contracts on the five-year T-note. Related research by Boudoukh, Richardson, Subrahmanyam and Whitelaw (2002) documents that European and Pacific funds can be predicted from their corresponding index futures and Greene and Hodges (2002) report a significantly higher average correlation between the lagged S&P 500 returns and international funds' returns. Zitzewitz (2003) reviews the size and scope of the stale pricing problem and finds substantial trading opportunities for international stock funds, convertibles, high yield bond, emerging market bond, and sector funds. Miller, Prather and Mazumder (2008) report similar return predictabilities using mutual fund investment objectives as asset class proxies. However, they also note that many mutual funds have made or are making changes to their prospectuses that prohibit frequent trading.[2] Thus, the opportunity to exploit knowledge of market movements has been or is being eliminated.

Despite the recently restricted ability to trade mutual funds to exploit cross autocorrelations, investors may be able to exploit these patterns by using ETFs and iShares. Studying iShares is beneficial for three reasons. First, iShares should exhibit cross autocorrelations similar to those reported by Hamao et al. (1990). Second, iShares provide an efficient way to examine any systematic cross autocorrelation effects in international portfolios. Third, the cost of trading iShares is much lower than the costs of trading a portfolio of individual stocks, thus, cross autocorrelations may be exploitable by investors.

3. Data and methodology

3.1. Data

Table 1 presents information on our sample. Daily return data for the Standard and Poor's Depositary Receipts (SPY) and iShares from 17 countries were extracted from CRSP for the period March 19, 1996 through December 31, 2003. Our sample consists of 1,961 returns for the SPY and each of the 17 iShares. These iShares track the stock market indices of Australia, Austria, Belgium, Canada, France, Germany, Hong Kong, Italy, Japan, Malaysia, Mexico, Netherlands, Singapore, Spain, Sweden, Switzerland, United Kingdom, and the United States.

To conduct empirical investigation, we stratified the sample into two subsamples with an approximately equal number of observations. The first subsample contains 981 daily observations from March 19, 1996 through February 4, 2000 and is used for examining cross autocorrelations, testing lead and lag relationships, and developing trading rules. The holdout sample contains 980 daily observations from February 7, 2000 through December 31, 2003 and is used for testing the dominance of trading rules over a buy and hold strategy.

Table 1
iShares International Index Fund profiles

Time zone	Fund name	Ticker	Inception date
Asia Pacific	iShares MSCI Australia Index Fund	EWA	19960312
	IShares MSCI Japan Index Fund	EWJ	19960312
	iShares MSCI Hong Kong Index Fund	EWH	19960312
	iShares MSCI Malaysia Index Fund	EWM	19960312
	iShares MSCI Singapore Index Fund	EWS	19960312
Europe	iShares MSCI Austria Index Fund	EWO	19960312
	iShares MSCI Belgium Index Fund	EWK	19960312
	iShares MSCI Sweden Index Fund	EWD	19960312
	iShares MSCI Italy Index Fund	EWI	19960312
	iShares MSCI Netherlands Index Fund	EWN	19960312
	iShares MSCI Switzerland Index Fund	EWL	19960312
	iShares MSCI France Index Fund	EWQ	19960312
	iShares MSCI Spain Index Fund	EWP	19960312
	iShares MSCI United Kingdom Index Fund	EWU	19960312
	iShares MSCI Germany Index Fund	EWG	19960312
North America	iShares MSCI Canada Index Fund	EWC	19960312
	Standard and Poor's Depository Receipts Fund (U.S.)	SPY	19930129
	iShares MSCI Mexico Index Fund	EWW	19960312

Note: Column one through four list the time zones, iShares names, ticker symbols, and inception dates of the iShares, respectively.

3.2. Methodology

The most popular methodology used to ascertain lead-lag relationships is the Granger causality test. Granger's (1969) method is the only established method that permits testing whether one portfolio's returns are predictable by another portfolio's returns after controlling for autocorrelation. Therefore, it is useful in inferring relative predictability between stochastic variables to ascertain a lead-lag structure. The Granger approach to the question of whether X causes Y is to determine the amount of the current Y that can be explained by past values of Y and then to ascertain whether adding lagged values of X can improve the explanation. Y is said to be Granger-caused by X if X helps in the prediction of Y, or equivalently if the coefficients on the lagged Xs are statistically significant. The statement "X Granger causes Y" does not imply that Y is the effect or the result of X. Granger causality measures information content but does not indicate causality in the common use of the term. Because our objective is to determine whether past returns from one iShare are useful in predicting the future returns of another iShare, we follow Richardson and Peterson (1999), Miller and Prather (2000), and Miller et al. (2008), and use techniques based upon Granger causality.

Our test for return predictability uses Eqs. (1) and (2):

$$R_{x,t} = \alpha + \sum_{k=1}^{n} \beta_{x,k} R_{x,t-k} + \sum_{k=1}^{n} \beta_{y,k} R_{y,t-k} + \varepsilon_t \tag{1}$$

$$R_{y,t} = \delta + \sum_{k=1}^{n} \gamma_{x,k} R_{x,t-k} + \sum_{k=1}^{n} \gamma_{y,k} R_{y,t-k} + \nu_t \tag{2}$$

where n is the number of lags estimated; Rx,t is the return series for asset class x; $R_{y,t}$ is the return series for asset class y; α and δ are the estimated intercepts; $\beta_{x,k}$ and $\gamma_{x,k}$ are the coefficients for asset class x's return series lagged t-k periods; $\beta_{y,k}$ and $\gamma_{y,k}$ are the coefficients for asset class y's return series lagged t-k periods; and ε_t and ν_t are the normally distributed error terms.

The Granger causality tests consist of whether all the coefficients of the lagged Xs in Eq. (1) may be considered to be zero, and similarly whether the coefficients of the lagged Ys in Eq. (2) are zero. Thus, the null hypotheses being tested are that X does not Granger-cause Y and that Y does not Granger-cause X.

4. Empirical results of lead and lag relationships among asset classes

4.1. Correlation among asset classes

To assess the possibility of using returns from one asset class to foretell future returns of another asset class we examine instantaneous correlations. If instantaneous correlations are high, the impact of any trading strategy is mitigated. However, if instantaneous correlations are low, investors may be able to benefit from an asset reallocation strategy.

Table 2 provides instantaneous correlation matrices for the first subsample. The lowest correlation coefficient (0.1853) is between Austria and Malaysia and the highest (0.7110) is between France and Germany. The average correlation coefficient of the 153 possible test pairs is 0.4009 (median = 0.3787). Generally, correlations are low, suggesting substantial average daily differences in returns among countries. Thus, diversification between asset classes is possible and hope exists for uncovering exploitable cross autocorrelations.

One explanation for differing correlations among markets is that news is rapidly assimilated into prices; however, absorption of news is only possible during trading hours. Therefore, when news is released that affects a given market, or markets, that news impacts prices in the market(s). If the news has a broad impact, the news will affect many markets, but only when the market is open for trading. For markets that are closed to trading, the news will impact the market once it opens for trading. Conversely, news with a limited impact may affect only a select country's market. Thus, we would expect higher contemporaneous correlations within a time zone than between time zones.

Table 2 suggests that regional effects are consistent with the Efficient Market Hypothesis (EMH) and differences in trading hours. The average correlation coefficients between SPY and the Asian, European, and North America iShares are 0.3792, 0.4078, and 0.4884, respectively. Moreover, the average correlation coefficient is 0.4068 for iShares within the Asia-Pacific time zone and is 0.3249 for iShares between Asia-Pacific and other time zones. Homoscedastic t test results reveal that the difference in the averages is statistically significant (p-value = 0.0193). The average correlation coefficient is 0.5065 for iShares within the

Table 2
Instantaneous correlation among asset classes

iShare	Australia	Japan	Hong Kong	Malaysia	Singapore	Austria	Belgium	Sweden	Italy	Netherlands	Switzerland	France	Spain	UK	Germany	Canada	USA	Mexico
Australia	1	0.3827	0.4054	0.3193	0.3538	0.2557	0.2408	0.2837	0.3428	0.2972	0.2882	0.3789	0.2551	0.3332	0.3548	0.3787	0.3254	0.3760
Japan		1	0.4868	0.2803	0.4208	0.2410	0.3132	0.3236	0.3430	0.3528	0.3392	0.4031	0.3350	0.3376	0.3865	0.3333	0.3619	0.3768
Hong Kong			1	0.3735	0.6024	0.2326	0.3421	0.3184	0.3727	0.3892	0.3596	0.3944	0.3369	0.4515	0.4605	0.3469	0.5143	0.4642
Malaysia				1	0.4434	0.1853	0.2081	0.2450	0.2530	0.2451	0.1920	0.2846	0.2045	0.2654	0.2909	0.3114	0.2877	0.2933
Singapore					1	0.2032	0.3168	0.3035	0.3293	0.3243	0.3293	0.3485	0.3031	0.3642	0.3627	0.3245	0.4068	0.3961
Austria						1	0.3436	0.3156	0.3458	0.3331	0.3625	0.3377	0.3245	0.2982	0.3736	0.3390	0.2026	0.2194
Belgium							1	0.4633	0.4639	0.5633	0.5239	0.5305	0.5012	0.4357	0.5299	0.3206	0.3679	0.3123
Sweden								1	0.5180	0.5800	0.4764	0.5726	0.5579	0.4398	0.5514	0.4617	0.3736	0.3725
Italy									1	0.5556	0.5017	0.6456	0.6160	0.4744	0.6357	0.4024	0.4175	0.3904
Netherlands										1	0.5572	0.5951	0.6137	0.5130	0.6199	0.4420	0.4014	0.3967
Switzerland											1	0.5402	0.5583	0.5237	0.5654	0.3668	0.4098	0.3784
France												1	0.6075	0.5345	0.7110	0.4869	0.4840	0.4278
Spain													1	0.4989	0.6068	0.4251	0.4280	0.3960
UK														1	0.5775	0.4188	0.4629	0.4087
Germany															1	0.4969	0.5305	0.4185
Canada																1	0.4452	0.4143
USA																	1	0.5315
Mexico																		1

Note: Instantaneous correlations of the iShares are for the period March 19, 1996 through February 4, 2000.

European time zone and is 0.3448 for iShares between Europe and other time zones. Homoscedastic t test results reveal that the difference in the averages is statistically significant (p-value = 0.0000). The average correlation coefficient is 0.4637 for iShares within the North America time zone and is 0.3879 for iShares between North America and other time zones. Homoscedastic t test results reveal that the difference in the averages is statistically significant (p-value = 0.0719). Thus, the results reveal that average contemporaneous correlations of markets within a given geographic region (time zone) tend to be higher than the average contemporaneous correlations between different time zones. If news drives markets, the absorption of news may happen region by region.

4.2. Tests of granger causality

Because investors may be able to benefit from an asset reallocation strategy if returns in one country provide information about future returns in another country, we use Granger causality to ascertain whether returns patterns are exploitable. Table 3 presents F-statistics (p-values in parentheses) for Granger causality tests of the initial sample. Test statistics examine the null hypothesis that the asset class returns in the column do not Granger cause the asset class returns in the row for a one-day lag. Rejection of the null implies that knowing past returns of one asset class will help to determine future returns in another asset class.

For the 306 possible test pair combinations, 94 test pairs yield significant lead-lag relationships at the one-percent level (null hypothesis rejected), 50 additional test pairs are significant at the five-percent level, and 16 additional test pairs are significant at the ten-percent level. Combined, 160 of 306 test pairs (52%) show statistically significant lead-lag relationships. This is a powerful rejection of the EMH because only 3 to 4 rejections should have occurred by chance at the one-percent level if the EMH held. The United States has the most significant statistical relationships (15 of 17 countries), followed by Mexico (13 significant relationships). France, Hong Kong, Italy, Spain, Sweden, and Malaysia each have 11 significant statistical relationships. Among all test pair combinations, the ten most significant relationships are for: (1) United States leading Canada, (2) United States leading Sweden, (3) United States leading Netherlands, (4) Sweden leading Australia, (5) United States leading Australia, (6) Hong Kong leading Canada, (7) Germany leading Australia, (8) Sweden leading Canada, (9) Spain leading Australia, and (10) Mexico leading Australia. Results in Table 3 suggest that investors may exploit trading patterns.

4.3. Cross autocorrelation among asset classes

Because Granger F-statistics only show the strength of the relationship (not the direction), we verified that the cross autocorrelations among the iShare classes of interest was positive. Of the 324 test pair combinations, 49 pairs exhibit significant lead-lag directions at the one-percent level, 42 additional test pairs are significant at the five-percent level, and 24 additional test pairs are significant at the 10-percent level. Moreover, one-day lagged United States returns have a significant effect on the next day's returns in 12 countries at better than the ten-percent level. Mexico's market leads ten countries, and Australia, Hong Kong, and Spain lead eight countries.[3]

Table 3

Pairwise Granger causality tests for a one-day lag

iShare	Australia	Japan	Hong Kong	Malaysia	Singapore	Austria	Belgium	Sweden	Italy	Netherlands	Switzerland	France	Spain	UK	Germany	Canada	USA	Mexico
Australia		12.479	20.159	2.0862	4.1244	4.3715	11.412	37.788	13.151	18.559	15.535	12.290	27.179	14.551	28.395	13.594	32.064	26.203
		(0.00)	(0.000)	(0.149)	(0.043)	(0.037)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Japan	1.1670		0.0465	0.7324	0.4330	0.1914	0.1582	0.6962	0.6163	0.0174	1.8496	0.8955	2.3230	0.0400	0.1197	0.6985	0.2524	0.5086
	(0.280)		(0.829)	(0.392)	(0.511)	(0.662)	(0.691)	(0.404)	(0.433)	(0.895)	(0.174)	(0.344)	(0.128)	(0.841)	(0.729)	(0.403)	(0.616)	(0.476)
Hong Kong	3.9268	0.0644		4.7776	0.1166	1.8373	2.3227	0.1749	0.0913	2.7789	3.0892	0.0831	0.0062	0.4187	1.6616	0.5400	4.1310	3.1184
	(0.048)	(0.800)		(0.029)	(0.733)	(0.176)	(0.128)	(0.676)	(0.763)	(0.096)	(0.079)	(0.773)	(0.937)	(0.518)	(0.198)	(0.463)	(0.042)	(0.078)
Malaysia	0.0105	5.6060	11.975		2.6665	1.5594	4.4606	3.5124	1.2843	3.2670	6.4492	6.5021	3.3118	3.8595	4.2112	1.2709	9.4939	6.4153
	(0.919)	(0.018)	(0.001)		(0.103)	(0.212)	(0.035)	(0.061)	(0.257)	(0.071)	(0.011)	(0.011)	(0.069)	(0.050)	(0.040)	(0.260)	(0.002)	(0.011)
Singapore	0.4955	0.6885	19.947	22.740		0.2538	0.0139	1.1902	0.8946	1.1487	0.0305	2.5105	5.5659	1.5992	1.3220	0.9459	0.1314	1.9241
	(0.482)	(0.407)	(0.000)	(0.000)		(0.615)	(0.906)	(0.276)	(0.344)	(0.284)	(0.861)	(0.113)	(0.019)	(0.206)	(0.251)	(0.331)	(0.717)	(0.166)
Austria	0.2290	5.2477	10.476	3.1671	3.7264		16.041	23.072	12.922	14.414	10.277	10.514	21.405	6.1175	15.328	4.8711	12.556	5.9881
	(0.632)	(0.022)	(0.001)	(0.075)	(0.054)		(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.014)	(0.000)	(0.028)	(0.000)	(0.015)
Belgium	0.0500	4.8332	1.8909	6.0292	1.6241	0.4155		6.4564	12.182	5.8626	7.9378	6.3829	11.366	0.0363	21.095	2.1690	16.007	7.5520
	(0.823)	(0.028)	(0.169)	(0.014)	(0.203)	(0.519)		(0.011)	(0.001)	(0.016)	(0.005)	(0.012)	(0.001)	(0.849)	(0.000)	(0.141)	(0.000)	(0.006)
Sweden	0.0441	0.5236	18.556	14.683	3.3187	0.6618	0.1895		18.150	4.8858	6.3269	19.332	8.3734	1.8406	17.057	7.4784	56.163	14.383
	(0.834)	(0.469)	(0.000)	(0.000)	(0.069)	(0.416)	(0.663)		(0.000)	(0.027)	(0.012)	(0.000)	(0.004)	(0.175)	(0.000)	(0.006)	(0.000)	(0.000)
Italy	4.0491	4.1721	0.1921	2.0351	0.5769	0.7469	0.1687	4.9445		0.2542	0.2535	0.7783	1.1772	0.3483	0.0002	0.0773	7.7387	6.9271
	(0.044)	(0.041)	(0.661)	(0.154)	(0.448)	(0.388)	(0.681)	(0.026)		(0.614)	(0.615)	(0.378)	(0.278)	(0.555)	(0.989)	(0.781)	(0.006)	(0.009)
Netherlands	0.2133	0.5764	8.9254	6.8205	6.7164	0.3748	1.9391	10.968	12.182		5.3748	22.296	15.932	1.5859	19.857	6.8097	54.217	23.547
	(0.644)	(0.448)	(0.003)	(0.009)	(0.010)	(0.541)	(0.164)	(0.001)	(0.001)		(0.021)	(0.000)	(0.000)	(0.208)	(0.000)	(0.009)	(0.000)	(0.000)
Switzerland	1.0536	1.0294	2.2493	4.0261	0.5357	0.1435	2.6553	6.5797	9.4697	7.9586		9.2864	14.598	0.0515	12.597	2.2506	8.3044	4.5112
	(0.305)	(0.311)	(0.134)	(0.045)	(0.464)	(0.705)	(0.104)	(0.010)	(0.002)	(0.005)		(0.002)	(0.000)	(0.821)	(0.000)	(0.134)	(0.004)	(0.034)
France	1.2764	0.1788	5.2566	5.4446	0.4904	1.3597	0.6206	4.1565	5.6883	0.7034	2.4431		4.0353	0.4853	2.9913	1.4460	17.454	12.128
	(0.259)	(0.672)	(0.022)	(0.020)	(0.484)	(0.244)	(0.431)	(0.042)	(0.017)	(0.402)	(0.118)		(0.045)	(0.486)	(0.084)	(0.229)	(0.000)	(0.001)
Spain	0.0047	0.0164	5.0373	3.4280	2.6314	0.0009	0.8332	5.5487	11.945	0.6151	0.4471	7.8544		0.2870	3.3273	3.3678	25.666	23.355
	(0.945)	(0.898)	(0.025)	(0.064)	(0.105)	(0.976)	(0.362)	(0.019)	(0.001)	(0.433)	(0.504)	(0.005)		(0.592)	(0.068)	(0.067)	(0.000)	(0.000)
UK	0.5861	4.6902	12.440	6.9161	4.5537	0.0012	1.5598	14.459	16.474	7.3308	1.7401	8.5203	10.186		3.6815	1.5829	16.569	10.190
	(0.444)	(0.031)	(0.000)	(0.009)	(0.033)	(0.972)	(0.212)	(0.000)	(0.000)	(0.007)	(0.187)	(0.004)	(0.001)		(0.055)	(0.209)	(0.000)	(0.001)
Germany	5.8870	0.0011	0.1938	7.1446	0.0000	0.0004	1.7057	13.414	9.1565	1.3568	2.7629	5.5580	14.487	1.9004		1.4009	13.899	5.4447
	(0.015)	(0.973)	(0.660)	(0.008)	(0.997)	(0.984)	(0.192)	(0.000)	(0.003)	(0.244)	(0.097)	(0.019)	(0.000)	(0.168)		(0.237)	(0.000)	(0.020)
Canada	0.7575	7.1207	29.049	5.2022	5.6131	0.3397	13.775	27.304	20.243	11.221	10.935	21.848	21.524	5.2998	24.367		102.26	23.231
	(0.384)	(0.008)	(0.000)	(0.023)	(0.018)	(0.560)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.022)	(0.000)		(0.000)	(0.000)
USA	4.1805	0.9086	1.8482	4.9946	0.6366	0.6525	0.0634	0.2116	2.1705	0.2318	1.5745	0.2030	0.2918	1.4625	0.0001	0.2162		0.6836
	(0.041)	(0.341)	(0.174)	(0.026)	(0.425)	(0.419)	(0.801)	(0.646)	(0.141)	(0.630)	(0.210)	(0.652)	(0.589)	(0.227)	(0.990)	(0.642)		(0.409)
Mexico	0.7468	0.0788	3.8736	0.6608	3.6081	0.0316	0.2145	1.5772	2.3869	0.9689	0.1558	0.4253	0.3400	0.5991	1.3987	0.0389	6.2024	
	(0.388)	(0.779)	(0.049)	(0.416)	(0.058)	(0.859)	(0.643)	(0.209)	(0.123)	(0.325)	(0.693)	(0.514)	(0.560)	(0.439)	(0.237)	(0.844)	(0.013)	

Note: A matrix of the *F*-statistic (*p*-value in parenthesis) for the Granger causality test of lead and lag relationships is presented for 981 trading days (March 19, 1996 through February 4, 2000). Test statistics are for testing the null hypothesis that the asset class returns in the column do not Granger cause the asset class returns in the row for a one-day lag.

4.4. Exploitation of return predictability

Data in Table 3 and cross autocorrelation results are consistent with the findings of Hamao et al. (1990). Because iShare returns closely approximate returns on the market it tracks, investors could monitor iShare returns, make decisions based on observed patterns, and immediately reposition the iShare during any given day. Exploiting information provided by Granger causality tests requires moving assets based on the strength of the statistical relationship. Therefore, we examine the Granger F-statistic (p-value) to find the strongest statistical relationship as the starting point for the selection of combination pairs used in our trading strategy. To test the predictabilities among iShares, we select SPY and one iShares fund for each of the three time zones in our sample as the leading asset classes. These four leading funds provide more significant statistical relationships than with other funds. For each of the leading funds, we then select a corresponding lagged fund for each of the three time zones based on the significance of Granger F-statistics (Table 3). This selection process results in 12 test pair combinations that will be used to test proposed trading strategies.

Preliminary regression tests examine magnitudes of predictable components to determine potential gains from trading. Results suggest that all 12 test pairs have positive estimates of regression coefficients and 10 of the 12 test pairs are statistically significant at greater than the 5% level. The average coefficient estimate is 0.0803, suggesting that a positive 1% return by the leading funds on day t should lead to an average positive return on the lagged funds of about 0.08% return on day t+1, which is the equivalent of 20% annualized return.[4]

For comparison purposes, we use only the lagged returns from an iShare to predict future returns. The returns of the four selected leading funds (dependent variables) are regressed on their own one-day lagged returns (independent variables). The regression coefficients of the four selected leading funds all are negative and two are statistically significant at the one percentage level, suggesting that using only lagged returns for the same iShare does not provide high returns.

4.5. Risk and return of trading strategies

Our trading strategy is based on a one-day lag and requires moving assets from the leading iShare to the lagged iShare when a highly positive return in the leading iShare occurs. The investor stays in the lagged iShare until the leading iShare has a large negative return.

To reduce transactions costs, our trading strategy is to trade only on highly positive returns in the leading iShare, not any positive return. As a starting point, we selected a return slightly higher than the top 20% of past daily returns as the trigger point for moving into the lagged iShare (and a trigger point of a bottom 20% of past daily returns to move back into the leading iShare based on negative return in the leading iShare).[5]

To measure portfolio performance, the Sharpe (1966) measure (S) is computed as

$$S = [R_p - R_f]/\sigma_p, \tag{3}$$

where R_p is the portfolio return, R_f is the risk-free rate, and σ_p is the standard deviation of the portfolio returns. Daily returns of three-month Treasury bills proxy the risk-free rate. The returns, risks, and Sharpe measures for both buy-and-hold strategies and the proposed trading

Table 4
Risk and return of sample portfolios

Leading asset class	Asset class	Return	Standard deviation	Sharpe
U.S. leading others	Australia (Asia Pacific)	0.000472	0.014979	0.026190
	RULE (U.S. & Australia)	0.001228	0.015267	0.075220
	Sweden (Europe)	−0.000192	0.024160	−0.011247
	RULE (U.S. & Sweden)	0.000756	0.020166	0.033550
	Canada (North America)	0.000137	0.016689	0.003451
	RULE (U.S. & Canada)	0.001061	0.016106	0.060940
Hong Kong leading others	Australia (Asia Pacific)	0.000472	0.014979	0.026190
	RULE (Hong Kong & Australia)	0.001828	0.017816	0.098150
	Sweden (Europe)	−0.000192	0.024160	−0.011247
	RULE (Hong Kong & Sweden)	0.001335	0.021631	0.058040
	Canada (North America)	0.000137	0.016689	0.003451
	RULE (Hong Kong & Canada)	0.001654	0.018431	0.085425
Spain leading others	Australia (Asia Pacific)	0.000472	0.014979	0.026190
	RULE (Spain & Australia)	0.001326	0.015982	0.077993
	Austria (Europe)	0.000728	0.014722	0.044050
	RULE (Spain & Austria)	0.001171	0.016182	0.067449
	Canada (North America)	0.000137	0.016689	0.003451
	RULE (Spain & Canada)	0.000783	0.016558	0.042490
Mexico leading others	Australia (Asia Pacific)	0.000472	0.014979	0.026190
	RULE (Mexico & Australia)	0.000880	0.017795	0.044981
	Spain (Europe)	0.000217	0.016674	0.008244
	RULE (Mexico & Spain)	0.000933	0.018802	0.045391
	Canada (North America)	0.000137	0.016689	0.003451
	RULE (Mexico & Canada)	0.000847	0.019289	0.039772
U.S. leading	U.S. (North America)	−0.000099	0.013982	−0.012781
Hong Kong leading	Hong Kong (Asia Pacific)	−0.000020	0.019536	−0.005111
Spain leading	Spain (Europe)	0.000217	0.016674	0.008244
Mexico leading	Mexico (North America)	0.000229	0.019610	0.007642

Note: Columns one through five are the leading asset class, lagging asset class (either a buy-and-hold strategy or a portfolio that applies the proposed trading rule), average daily return, standard deviation of returns, and the Sharpe measure. The upper panel shows the trading strategy results for the 12 pairs selected and the lower panel shows the results for the leading iShares only. The sample period is from February 7, 2000 through December 31, 2003.

rules are presented in Table 4. The results confirm exploitable effects among international stock markets as all trading rules outperform buy-and-hold strategies.

Additionally, trading rules generally yield smaller standard deviations. The higher returns and lower risks of the trading rules make their Sharpe measure exceed that of a buy-and hold strategy. The highest average daily return is 0.183% (45.75% annualized) is for the case of Hong Kong leading Australia, and it also has the highest Sharpe measure of 0.0982.

As a test of robustness, we computed the Jensen (1968) measure to determine whether positive risk-adjusted returns are statistically significant. The Jensen measure is computed as

$$R_p - R_f = \alpha + \beta_p(R_m - R_f) + \epsilon, \tag{4}$$

where β_p is the systematic risk of the trading rule portfolio and R_m is the market return. We perform ordinary least squares regression (OLS) from the perspective of an investor based in a given country. We use the daily returns of the leading iShare and Treasury bills as the

Table 5
Risk-adjusted return of trading rule portfolios

Portfolio	α	t-statistic	p-value	β	R^2	N
U.S. & Australia	0.001283 (0.00035)	3.620569	0.000309	0.750913 (0.02535)	0.472993	980
U.S. & Sweden	0.000854 (0.00047)	1.831994	0.067256	0.995523 (0.03337)	0.476438	980
U.S. & Canada	0.001129 (0.00036)	3.153991	0.001660	0.827502 (0.02562)	0.516152	980
Hong Kong & Australia	0.001814 (0.00039)	4.609544	0.000005	0.658851 (0.02016)	0.522082	980
Hong Kong & Sweden	0.001331 (0.00050)	2.644235	0.008319	0.758956 (0.02578)	0.469800	980
Hong Kong & Canada	0.001644 (0.00040)	4.111824	0.000043	0.692947 (0.02047)	0.539522	980
Spain & Australia	0.001154 (0.00036)	3.187203	0.001482	0.676450 (0.02171)	0.498074	980
Spain & Austria	0.000999 (0.00037)	2.675422	0.007588	0.671468 (0.02241)	0.478685	980
Spain & Canada	0.000604 (0.00036)	1.670316	0.095177	0.725189 (0.02169)	0.533334	980
Mexico & Australia	0.000704 (0.00040)	1.762413	0.078312	0.646273 (0.02037)	0.507246	980
Mexico & Spain	0.000747 (0.00040)	1.855791	0.063784	0.712144 (0.02053)	0.551661	980
Mexico & Canada	0.000659 (0.00042)	1.567789	0.117254	0.719123 (0.02146)	0.534517	980

Note: Column one through seven present the portfolio trading rules, risk-adjusted return (α), t-statistic, p-value (for the two-tailed hypothesis tests that risk-adjusted returns equal zero), systematic risk (β), coefficients of determination (R^2), and number of observations (N), respectively. Standard errors are in parentheses beside the coefficient estimates. The sample period is from February 7, 2000 through December 31, 2003.

market returns and risk-free rates, respectively. Table 5 shows that the risk-adjusted returns of the trading rule portfolios are all positive and statistically significant at better than the ten-percent level, except for the case of Mexico leading Canada. The highest risk-adjusted daily return is 0.181% (45.25% annualized) for the case of Hong Kong leading Australia. The lowest risk-adjusted daily return is 0.06% (15.0% annualized) is for the case of Spain leading Canada. The superior Sharpe and Jensen performance measures confirm that investors could exploit the predictabilities in the iShares international index funds.

4.6. Explanation of return predictability

One explanation for this exploitability is an asynchronous pricing problem (e.g., Chalmers et al., 2001; Goetzmann, Ivković & Rouwenhorst, 2001; Varela, 2002). This explanation suggests that because of time differences across markets, changes in security prices in one market may not be reflected in other markets on the same calendar day. Moreover, changes in price volatility in one market are probably related to changes in the price volatility observed in the next market to trade.

Although "stale price problems" based on NAV computation processes are used to explain the cross autocorrelation in mutual funds, it fails to explain the pattern in stock returns found by Hamao et al. (1990) or the two-day lag reported by Miller et al. (2008). However, "stale prices" cannot be avoided for stocks trading in different time zones even without a NAV computation issue. For example, if good macro news is released in the United States during normal trading hours that has implications for both United States and foreign stocks, U.S. stock prices can respond immediately. However, even though foreign stock price *should* react, they cannot until the foreign market begins to trade. Once trading begins, prices of the foreign stocks should adjust to reflect the new information. iShares compute NAVs based on Indicated Optimized Portfolio Values (IOPV) that is the last price on the country/exchange where the underlying securities were last traded. Although the IOPV is updated in every 15 seconds, it is sometimes based on stale prices because foreign iShares are traded in U.S. when their underlying markets are closed. However, all iShares in this study trade in the United States. Therefore, if new information is released during the U.S. trading day that is expected to affect foreign markets, traders may adjust the prices of the iShares immediately to reflect their expectations. Thus, the reaction of investors to news is crucial in determining how return patterns will emerge.

Curcio, Lipka and Thornton (2004), Jares and Lavin (2004), Simon and Sternberg (2005), and Zhong and Yang (2005) document that iShare returns are correlated more closely with U.S. returns than with their corresponding NAVs' returns and the explanation for this is the overreaction hypothesis. Thus, observed lead-lag relationships may have a behavioral finance explanation. Kahneman and Tversky (1979) suggest that investors use mental accounting or framing in making risky financial decisions and evaluating outcomes and those investors make systematic errors, termed cognitive bias, because they do not correctly adjust for new information. Tversky and Kahneman (1981) document that mental framing may produce predictable shifts in preferences when the same problem is framed in different ways. De Bondt and Thaler (1985) show that people systematically over react to recent past news and under react to base information. Barberis, Shleifer and Vishny (1998) show that investors are motivated by two judgment biases: (1) *conservatism bias* that leads investors to update their beliefs slowly after the arrival of new information (i.e., under reaction) and (2) *representative heuristics bias* or *optimism bias* that leads investors to over react.

Durand and Scott (2003) examine short-run inefficiency between iShares Australia (EWA) and the S&P 500 and find that EWA investors overreact to (1) the contemporaneous and lagged returns of the S&P; (2) the current exchange rate between United States and Australia and (3) the lagged iShares returns. The contemporaneous and lagged relationship between EWA and S&P is consistent with the over reaction hypothesis. However, EWA investors under react to the current exchange rate movements and the lagged iShares returns.

Madura and Richie (2004) investigate ETFs (including iShares) and find that ETFs overreact. They show that daily winners and losers experience price reversals after hours and the after hours winners and losers experience price reversals the following day. However, the degree of over reaction is more pronounced for daily winners and losers than after-hours winners and losers. Moreover, over reactions are greater for less liquid ETFs and more volatile ETFs.

Simon and Sternberg (2005) report that European iShares trade at discounts or premiums to their NAVs and that the next-day NAV returns tend to be one-third of the observed discounts or premiums. This suggests that European iShares over react to late day U.S. market developments and correct the next day when the movement in the home market is observed.

4.7. Transactions costs

Results excluding transactions costs suggest that active trading is beneficial; however, it is worthwhile to examine the effects of trading costs. Because most discount brokerage firms allow unlimited iShare transactions for $8 to $11 commissions, the commission percentage will be negligible for those trading large quantities. Thus, we exclude those costs. However, two costs need to be examined. First, bid-ask spreads are unavoidable and may be material. Secondly, a liquidity spread may exist if iShares are not traded throughout the entire day. In this case, there may be a significant difference between the price of the last trade (upon which daily return is based) and the last bid or ask price quote a trading day. We define the liquidity spread as the percentage difference between the last trade during normal trading hours and the last quote during normal trading hours.

Using the actual number of round-trip trades, the average total spread required to remove any profitable opportunities under our trading rule are: United States leading Australia (0.18%), United States leading Sweden (0.23%), United States leading Canada (0.22%), Hong Kong leading Australia (0.30%), Hong Kong leading Sweden (0.33%), Hong Kong leading Canada (0.33%), Spain leading Australia (0.20%), Spain leading Austria (0.10%), Spain leading Canada (0.15%), Mexico leading Australia (0.18%), Mexico leading Spain (0.31%), and Mexico leading Spain (0.31%). This implies that a combined bid-ask and liquidity spread of approximately 0.35% removes profits generated by the trading rule.

To investigate actual spreads, we acquired iShare transaction-by-transaction data from TickData to compute bid-ask and liquidity spreads. After screening the data for outliers, we computed bid-ask spreads as [ask-bid]/ask.

Columns three through seven in Table 6 present the average bid-ask spread percentages (in decimal) for the entire holdout period, the trading days only, the last hour of trading days, the last five minutes of the trading day, and the last trade of the trading day. Results suggest that the SPY has spreads of 32 to 59 basis points for trades placed during the final hour of trading. Spreads of other iShares are much larger, thus, the average spreads remove the exploitable component.

Liquidity is also a potential issue for iShare traders. The liquidity spread is computed as [last trade price – closing bid (ask) price] / [closing bid (ask) price]. The SPY is highly liquid and average liquidity spreads on the bid side on trading days is 13 basis points whereas the average liquidity spread on the ask side of the SPY is −0.57%. Thus, on average, closing bid prices are lower and closing ask prices are higher than the last trade prices. Foreign iShares are not as liquid and spreads are considerably higher. For example, the largest average spread on the bid side is for Mexico (EWW) at 9.31% and the largest spread on the ask side is for Canada (EWC) at −7.58%. Although these results highlight the importance of liquidity, it is important to realize that this effect can be determined before placing a trade. Because traders may choose not to place a given trade if the liquidity spread is an issue for that transaction it is not possible to quantify the precise effect of liquidity spreads on our results. However, there is no question that liquidity spreads would have a negative impact.[6]

5. Conclusion

Recent evidence suggests that asset class returns possess a predictable component that is exploitable by informed investors. We contribute to the literature by (1) examining whether the observed patterns among United States and foreign stocks are observed in the returns of iShares, (2) determining whether observed patterns among iShares are exploitable on a

Table 6
Bid-ask spreads of trading rule portfolios

Portfolio	Ticker	Entire holdout periods	Average Bid-Ask Spreads			
			Trading days	Last hour of trading days	Last five minutes of trading days	Last trade of trading days
U.S. & Australia	SPY	0.0033265	0.0035851	0.0032216	0.0056283	0.0059423
	EWA	0.0977375	0.1008308	0.0838433	0.0780338	0.0548311
U.S. & Sweden	SPY	0.0033265	0.0035851	0.0032216	0.0056283	0.0059423
	EWD	0.0873069	0.0779823	0.0737248	0.0759338	0.0552402
U.S. & Canada	SPY	0.0033265	0.0035851	0.0032216	0.0056283	0.0059423
	EWC	0.0896702	0.0924494	0.0789720	0.0886676	0.0762911
Hong Kong & Australia	EWH	0.0560798	0.0538804	0.0444394	0.0425189	0.0374312
	EWA	0.0977375	0.0954082	0.0868872	0.0824799	0.0476617
Hong Kong & Sweden	EWH	0.0560798	0.0538804	0.0444394	0.0425189	0.0374312
	EWD	0.0873069	0.0755115	0.0738525	0.0822134	0.0534998
Hong Kong & Canada	EWH	0.0560798	0.0538804	0.0444394	0.0425189	0.0374312
	EWC	0.0896702	0.0875450	0.0778246	0.0965879	0.0811838
Spain & Australia	EWP	0.0762044	0.0728842	0.0419291	0.0477586	0.0400006
	EWA	0.0977375	0.0992090	0.0875625	0.0829949	0.0609453
Spain & Austria	EWP	0.0762044	0.0728842	0.0419291	0.0477586	0.0400006
	EWO	0.1091311	0.1210229	0.0908644	0.0854583	0.0788267
Spain & Canada	EWP	0.0762044	0.0728842	0.0419291	0.0477586	0.0400006
	EWC	0.0896702	0.0929928	0.0785324	0.0820776	0.0548607
Mexico & Australia	EWW	0.0661231	0.0610525	0.0436385	0.0466613	0.0561230
	EWA	0.0977375	0.0922895	0.0748290	0.0654727	0.0545382
Mexico & Spain	EWW	0.0661231	0.0610525	0.0436385	0.0466613	0.0561230
	EWP	0.0762044	0.0723193	0.0368407	0.0353462	0.0459611
Mexico & Canada	EWW	0.0661231	0.0610525	0.0436385	0.0466613	0.0561230
	EWC	0.0896702	0.0865284	0.0744953	0.0882116	0.0536552

Note: Column one through seven list the trading rule portfolios, ticker symbols, average bid-ask spread percentages (in decimal) for the entire holdout period, the trading days only, the last hour of trading days, the last five minutes of the trading day, and the last trade of the trading day, respectively.

before transaction cost basis, and (3) examining bid-ask and liquidity spreads to ascertain whether observed patterns are exploitable on an after transaction cost basis.

Our sample consists of 1,961 daily returns on the Standard and Poor's Depository Receipts (SPY) and 17 iShares international index funds. To avoid data mining effects, we divided the sample into two subsamples with an approximately equal number of observations. The first subsample contains 981 daily observations from March 19, 1996 through February 4, 2000 and is used for examining cross autocorrelations, testing lead and lag relationships between pairs of asset classes, and developing trading rules. A sample containing 980 daily observations from February 7, 2000 through December 31, 2003 is used to test the trading rules.

Granger causality tests find that iShare returns are predictable. Using the return patterns observed, we develop and test a trading strategy on a holdout sample. Examination of risks and returns of the trading rules and buy-and-hold strategies shows that the trading rule has superior Sharpe and Jensen measures compared with the buy-and-hold strategy.

Once average bid-ask and liquidity spreads are considered, the trading rules are no longer profitable on average. Average bid-ask spreads on iShares start at about 36 basis points for the SPY and increase for the foreign iShares. Liquidity spreads may also be important to active traders and the average spreads start at about 13 basis points and go as high as 11%. However, it is important to realize that traders can observe these spreads a priori and that the spreads will differ for each transaction. Therefore, traders can decide not to place a trade if they are unable to get satisfactory terms. Thus, the trading rule may or may not work for a given trade. Moreover, traders need to be very cautious when attempting to exploit return patterns using trading rules and scrutinized the spreads.

Notes

1. Morningstar's Barclays Global Investors Analysis (May 2003) reports that iShares have expense ratios of about 60 basis points compared to 106 to 192 basis points for index and actively managed funds, respectively.
2. The Securities and Exchange Commissions (SEC) adopted new rules and amended existing regulations to eliminate market timing and late trading problems which arise from stale pricing problems. These include (1) rule 22c-2 of the Investment Company Act that recommends a redemption fee of up to 2% if fund shares are redeemed within seven business days of initial purchase; (2) all mutual fund transaction orders should be received and executed by 4:00 pm EST; and (3) more transparent market disclosures for mutual funds. The SEC left the issue of redemption fee policies as matter for the mutual fund boards to determine (see http://www.sec.gov/rules/final/2006/ic-27504.pdf). However, redemption fees are a standard practice, except for money market funds and funds designed for market timers.
3. Complete results are available from the corresponding author.
4. Complete results are available from the corresponding author.
5. We also employ 10% trigger points and find similar results.
6. Complete results are available from the corresponding author.

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