Stochastic Dominance Tests for Momentum Strategies: A bootstrap versus Subsampling Approach

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Abstract

To compare the dominance of two return series, stochastic dominance tests can be implemented. In this paper, we test the dominance of country and industry momentum profits in developed countries using the stochastic dominance test by Linton, Maasoumi and Whang (2005). These authors implemented a subsample approach, rather than a bootstrap resampling method. They only use a full sample bootstrap to compare their subsampling results. A block bootstrap method, however, preserves the dependency of the return series and therefore improves the methodology. To test the merits of this block bootstrap, we compare the subsample and the block bootstrap's efficiency and show the strength of the block bootstrap in stochastic dominance tests.

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1. *Introduction*

In investments, a momentum strategy upholds that in the medium term, winners and losers confirm their performance. Believers therefore focus on the past performance of stocks and buy "winners" and sell "losers". The process computing the momentum returns at a certain point of time t consists of several steps. First of all, the stocks' cumulative (sometimes average) returns are sorted in past fixed-length periods of e.g. 6 months. Secondly, they are divided into groups (normally deciles) in ascending order. In a third step the difference between the contemporary returns in the top decile and the bottom decile at the time t is computed. Then the average returns of these time series momentum returns are tested for their statistically significance to prove the existence of a momentum effect.

The existence of the momentum effect has been well documented since Jegadeesh and Titman (1993). The extra profit from this stock return relationship is an anomaly to the efficient market theory, since the momentum effect cannot be explained by any standard asset pricing model supporting the efficient market hypothesis, such as the CAPM and Fama–French three-factor model (e.g. Jegadeesh and Titman, 1993, Grundy and Martin, 2001). Nonetheless, researchers still believe in the efficient market hypothesis and claim that existing models are inadequate, e.g. due to omitted risk factors. They therefore keep searching for more general asset pricing models.

Fong, Wong and Lean (2005) were the first to introduce the widely used econometric tests of stochastic dominance (see Hadar and Russell, 1969, Hanoch and Levy, 1969, Rothschild and Stiglitz, 1970, Whitmore, 1970) to momentum strategies on international stock market indices. Muga and Santamaria (2007) follow their approach and apply the same tests to the Emerging Latin-American markets. The authors test the explanatory power of asset pricing models on the momentum effect. They assume that if winner portfolios stochastically dominate loser portfolios then it is unlikely that the problem is due to omitted risk factors but more likely that momentum reflects market inefficiencies.

Their findings show that winners dominate losers on the second- and third-order level, implying that all investors with strictly concave utility functions would have preferred to buy winners and sell losers over the sample period. This result also implies that the traditional asset pricing models (based on the assumption of risk averse investors) do not explain the momentum effect. Moreover, they infer that the failure of existing asset pricing models to explain momentum may be determined by irrational aspects of momentum investors (e.g. Daniel et al., 1998; Hong and Stein, 1999) rather than by omitted risk factors. Fong, Wong and Lean (2005) use tests developed by Davidson and Duclous (2000) and Barrett and Donald (2003). They are actually an extended Kolmogorov-Smimov (KS) type of test for stochastic dominance.

Their research inspired us to examine the pattern of industry and country momentum. Since in diversified portfolios most firm-specific risks will have been eliminated, the common factor model should be able to explain the industry and country momentum. Under this assumption, no dominance pattern should exist. However, the tests Fong, Wong and Lean (2005) use make important assumptions about the independence of observations, drawn from a single normal distribution. We can improve this by introducing a mixture distribution of stock returns. This has been widely documented by Akgiray (1989), Davis and Mikosch (2000) and Engle (2001). Moreover, constructing the momentum strategy generates dependency across and within the compared series. That implies that the standard stochastic dominance tests used are not suitable for momentum scenarios. Fong, Wong and Lean (2005) noticed this problem. In their 2007 paper, they add the methodology by Linton, Maasoumi and Whang (2005, LMW) to allow for a mixture distribution.

To determine the critical value of the statistics, Fong, Wong and Lean (2005) used a subsampling approach with a grid of 100 winner and loser portfolio returns and assume its studentized maximum modules (SMM) distribution instead of the normal distribution. Studentized maximum modules is the maximum absolute value of a set of independent unite normal variates which is then Studentized by the standard deviation (Sahai and Ageel (2000))

$$m[n,v]=\frac{\max\left|X_i-\hat{X}\right|}{S},\ \hat{X}=\frac{1}{n}\sum_{i=1}^{n}X_i,\ S_j^2=\frac{1}{n-1}\sum_{i=1}^{n}(X_i-\hat{X})^2$$

To take the characteristic of momentum profit series into account, we use stochastic dominance tests that allow for a mixture distribution and for the dependency across and over the pair wised momentum series. We thereofer examine the efficiency of a block bootstrap approach in the LMW stochastic dominance test. Moreover, comparing to subsampling, a block bootstrap approache is used to determine the critical value: the circular block bootstrap (CBB).

The remainder of this report is arranged as follows. Section 2 describes our sample selection. Section 3 illustrates the basic definition of the stochastic dominance test and the methodology, (LMW test) we use. Section 4 presents the results. In the last section we conclude.

2. *Data*

We download country-specified industry indices from Datastream over the period January 1986 to October 2010. The sample contains monthly return indices of 26 developed countries and 116 industries[1].

Table 1. Descriptive Statistics of Developed Country Indices

	# Obs	Mean	Std	Skew	Kurt	Min	Median	Max	ACF1
AUSTRALIA	298	1.4%	4.6%	-1.7	14.5	-33.9%	2.1%	16.7%	16.0%
AUSTRIA	298	1.2%	5.5%	0.0	5.7	-20.3%	1.2%	25.1%	20.8%
BELGIUM	298	1.3%	5.1%	-0.6	5.7	-23.7%	1.5%	16.8%	24.9%
CANADA	298	1.5%	4.5%	-1.2	8.3	-24.0%	1.8%	12.5%	18.6%
DENMARK	298	1.4%	5.1%	-0.4	4.8	-18.4%	1.8%	20.1%	23.1%
FINLAND	271	1.5%	6.8%	0.4	4.8	-22.9%	1.2%	28.2%	22.7%
FRANCE	298	1.3%	5.7%	-0.4	4.5	-22.6%	1.4%	20.1%	19.0%
GERMANY	298	1.1%	4.9%	-0.6	4.7	-20.1%	1.5%	14.5%	19.5%
GREECE	273	2.0%	9.2%	0.9	6.0	-22.4%	1.4%	48.2%	22.5%
HONG KONG	298	2.3%	8.6%	-0.7	6.8	-47.4%	2.5%	29.4%	16.1%
IRELAND	298	1.9%	7.4%	0.4	6.9	-25.1%	2.1%	38.5%	26.8%
ISRAEL	297	1.3%	11.8%	-1.6	14.5	-77.2%	1.8%	52.7%	4.9%
ITALY	298	1.2%	7.2%	1.5	11.8	-19.3%	0.5%	51.2%	13.2%
JAPAN	298	0.6%	5.9%	-0.1	4.5	-23.7%	0.7%	21.4%	12.6%
SOUTH KOREA	298	2.1%	9.1%	1.1	7.4	-21.7%	1.4%	57.4%	10.3%
LUXEMBOURG	225	1.2%	3.9%	1.2	11.4	-12.1%	1.2%	27.3%	7.3%
NETHERLANDS	298	1.1%	5.6%	-1.0	5.9	-27.8%	1.7%	16.0%	27.4%
NEW ZEALAND	297	1.4%	7.2%	1.1	10.5	-27.4%	1.4%	42.9%	-5.7%
NORWAY	298	1.9%	7.9%	-0.3	4.2	-25.6%	2.0%	26.4%	16.0%
PORTUGAL	273	1.0%	6.2%	1.1	8.2	-18.8%	0.4%	36.1%	22.2%
SINGAPORE	298	1.7%	8.0%	0.4	9.4	-39.4%	1.6%	48.0%	20.0%
SPAIN	284	1.2%	6.5%	-0.3	5.0	-28.0%	1.4%	21.7%	21.0%
SWEDEN	298	2.0%	7.3%	0.2	5.1	-22.6%	2.5%	32.7%	20.6%
SWITZERLAND	298	1.0%	5.5%	-1.1	6.3	-26.7%	1.4%	14.6%	32.2%
UK	298	1.3%	5.1%	-0.8	6.2	-25.8%	1.8%	16.4%	16.2%
US	298	1.2%	5.2%	-0.7	7.1	-25.2%	1.6%	19.2%	8.9%

Note: The table provides the descriptive statistics of the monthly returns for the developed country indices. The columns from left to right are the number of observations, means, standard deviations, skewness, kurtosis, minimum return, median returns, maximum returns, and autocorrelation of lag1.

[1] We use level 4 industry classification of Datastream (Industry Classification Benchmark, ICB). We eliminate the series with less than 24 monthly observations; the dead observations; the extremely high or low return rates, the boundary is, 200% to -200% per month)

The descriptive statistics of the country and industry indices are shown in table 1 and 2. Most country indices have 298 observations. The average monthly return across countries (or industries) is 1.4% (or 1.6%), while the average standard deviation is 6.5% (or 5.2%). All 22 industries have 298 observations.

Table 2. Descriptive Statistics of Industry Indices in Developed Countries

Level 2 Industry	Level 3 Industry	# Obs	Mean	Std	Skew	Kurt	Min	Median	Max	ACF1
Oil & Gas	Oil & Gas	298	1.9%	5.5%	-0.6	6.3	-23.3%	2.1%	20.6%	18.0%
Basic Materials	Chemicals	298	1.3%	5.2%	-0.5	5.4	-21.6%	1.4%	19.3%	19.0%
	Basic Resource	298	2.1%	5.9%	-0.2	7.8	-26.1%	2.1%	28.9%	19.0%
Industrials	Construction & Materials	298	1.8%	5.6%	-0.8	6.7	-26.8%	2.3%	21.5%	29.0%
	Industrial Goods & Services	298	1.6%	4.5%	-1.1	6.6	-22.1%	1.9%	14.2%	27.5%
Consumer Goods	Automobiles & Parts	298	1.7%	6.0%	-0.1	6.3	-25.8%	1.5%	26.0%	29.9%
	Food & Beverage	298	1.9%	3.8%	-0.5	8.0	-18.0%	2.1%	17.3%	25.7%
	Personal Household Goods	298	1.7%	4.4%	-1.0	7.0	-22.4%	1.9%	14.0%	30.5%
Health Care	Health Care	298	1.6%	4.4%	-1.1	8.4	-25.6%	2.1%	15.7%	22.4%
Consumer Services	Retail	298	1.6%	3.9%	-1.2	8.2	-22.2%	1.9%	11.3%	21.9%
	Media	298	1.5%	5.5%	-0.5	6.2	-26.8%	1.7%	20.6%	31.0%
	Travel & Leisure	298	1.6%	4.5%	-0.9	7.0	-21.7%	1.8%	19.3%	26.2%
Telecomunications	Telecomunications	298	1.7%	6.0%	-0.1	4.0	-19.4%	2.0%	20.0%	20.6%
Utility	Utility	298	1.5%	3.9%	-1.2	8.9	-23.2%	1.6%	12.6%	17.6%
Financials	Banks	298	1.5%	5.3%	-0.4	6.7	-20.5%	1.5%	20.4%	26.4%
	Insurance	298	1.5%	4.7%	-0.8	5.8	-21.1%	1.9%	14.6%	24.6%
	Real Estate	298	1.3%	4.9%	-0.9	10.3	-30.4%	1.5%	18.4%	22.7%
	Real Estate InvestmentTrust	298	1.2%	4.2%	-1.2	9.8	-22.9%	1.5%	17.2%	30.8%
	Financial Services	298	2.0%	5.9%	0.5	10.2	-24.9%	1.8%	39.4%	17.6%
	Equity Investment Instruments	298	1.9%	5.8%	0.7	6.9	-18.4%	1.6%	32.2%	14.9%
	Nonequity Investment Instruments	298	1.1%	6.3%	-0.8	5.9	-26.7%	1.7%	18.6%	11.8%
Technology	Technology	298	1.7%	7.2%	0.5	7.4	-25.7%	1.8%	41.8%	33.2%

Note: The table provides the descriptive statistics of the monthly returns of the industry indices that we created based on the level 5 Datastream country-specified industry indices. The columns from left to right are the number of observations, means, standard deviations, skewness, kurtosis, minimum return, median returns, maximum returns, and autocorrelation of lag1.

The average minimum country return (-27%) is lower than that of industry return (-23%) while the maximum country return (29%) is lower than that of industry return (21%). The deviation across the countries is larger than the deviation over the industries. The average first lag autocorrelation for countries is 17.6%, or 23.6% for industries.

From the descriptive statistics above, we can see that generally, industry indices have relative higher returns but less volatility. We could therefore imagine that a risk averse investor might prefer industry momentum to country momentum portfolios.

3. *Methodology*

In this section we compare the difference between the subsample and block bootstrap's efficiency and show the relative strength of the block bootstrap in the SD test. Politis, Romano and Wolf (1999) document that subsampling can be used in many cases where the bootstrap fails. However, if the bootstrap is valid, then the bootstrap approximation is often better.[2] It is remarkable that the conditions for subsampling are so weak. Essentially, all that is required is that the root has a limiting distribution, and that the subsample size b is not too large (but still going to infinity). On the other hand, we notice that the main disadvantage of the SD approach is that stochastic dominance test may lack power compared to well-specified asset pricing tests. In addition, stochastic dominance rankings are sensitive to outliers that may undermine the power of the statistical tests (see Fong, Wong and Lean, 2005)). Especially, Kläver (2006) shows that some SD tests, including LMW test, might not be useful when the sample size is less than 1000. It therefore makes sense to introduce a block bootstrap approach to increase the sample size.

[2] See Politis, Romano and Wolf (1999) for the proof.

(1) Stochastic Dominance Test Concept

The two most commonly used stochastic dominance decision rules, first and second order stochastic dominance (we call SD1 and SD2) are applied in the all branches of economics, e.g. finance and social welfare theory (Davidson and Duclous (2000), Levy and Levy (2000), Fong et al. (2005), etc.) .

More specifically, if *X* and *Y* are random variables representing certain payoffs of relative decisions, and *F* is the cumulative distribution function then *X* dominates *Y* in the sense of SD1 if every individual preferring more over less prefers *X*, i.e. $F_X(x) \le F_Y(x)$ for a strict inequality for at least one *x*. This is the most strict stochastic dominance condition since the two decisions' cumulative probability function cannot cross at any point. SD2 has more restriction because its dominance requires that the individual who prefers more over less is risk averse, i.e. $\int_{-\infty}^{x} F_X(t)dt \le \int_{-\infty}^{x} F_Y(t)dt$ with a strict inequality for at least one *t*. It implies that at least one cross point is allowed. Naturally, SD1 embodies SD2.

Since the SD test is non-parametric test, it contains several advantages for applications in finance. First, it provides a general framework to assess portfolio choices without the requirement of asset pricing benchmarks. Second, it makes no strict assumptions about the distribution of asset returns and minimal assumptions about investors' utility functions.

Statistical tests for stochastic dominance vary from different empirical distribution or quantile functions. When determining the critical region, many tests assume contemporaneous and serial independence in the distribution of the test statistic under the null hypothesis (e.g. Schmid and Trede, 1996,1998). However, the observations do not satisfy these constraints under some circumstances. Particularly, financial data are usually cross-correlated and conditional heteroskedasticity is often present within the sample. Due to the dependence of the sample series, we therefore employ the SD test of Linton, Maasoumi and Whang (2005, referred to as LMW).

(2) LMW test specification

Linton, Maasoumi and Whang (2005) developped a test for the first and second degree of stochastic dominance. For a set of random variables $X_1, \ldots, X_n$, they test

$$H_0 : \exists i, j \in \{1, \ldots, n\}, i \neq j : X_i \succeq_k X_j,$$

i.e. whether there is one random variable which is dominated, against the alternative hypothesis of absence of dominance. The test statistic

$$T_k = \min_{i \neq j} \sup_{x \in \mathbb{R}} \sqrt{n}(\hat{F}^{(k)}_{X_i,n}(x) - \hat{F}^{(k)}_{X_j,n}(x))$$

Kläver (2006) modifies this statistic by omitting the minus operator in the case of test that

$$H^i_0 : F_X(x_n) \leq F_Y(x_n) \; or \; X \succeq_i Y$$
$$H^i_1 : not \; H^i_0 \; .$$

for $i = 1; 2$ order, and the test statistic

$$T_{n,i} = \sup_{x \in \mathbb{R}} \sqrt{n}(\hat{F}^{(i)}_{X,n}(x) - \hat{F}^{(i)}_{Y,n}(x))$$

where n is the size of variables X and Y, and

$$\hat{F}_X^{(1)}(x) = \frac{1}{n}\sum_{t=1}^{n} 1(X_t \leq x), \quad \hat{F}_Y^{(1)}(x) = \frac{1}{n}\sum_{t=1}^{n} 1(Y_t \leq x)$$

$$\hat{F}_X^{(2)}(x) = \frac{1}{n}\sum_{t=1}^{n} \frac{1}{(2-1)!}(x - X_t)^{2-1} 1(X_t \leq x), \quad \hat{F}_Y^{(1)}(x) = \frac{1}{n}\sum_{t=1}^{n} \frac{1}{(2-1)!}(x - Y_t)^{2-1} 1(Y_t \leq x)$$

$$\hat{F}_X^{(i)}(x) = \frac{1}{n}\sum_{t=1}^{n} \frac{1}{(i-1)!}(x - X_t)^{i-1} 1(X_t \leq x), \quad \hat{F}_Y^{(i)}(x) = \frac{1}{n}\sum_{t=1}^{n} \frac{1}{(i-1)!}(x - Y_t)^{i-1} 1(Y_t \leq x)$$

LMW use a subsampling procedure for determining the critical value. The advantage of this test is that it can be applied to strongly mixed processes because the subsampling captures the dependency of nearby observations. Moreover, they also briefly introduce the possibility of a bootstrap approach: a full-sample bootstrap approach for the SD test,[3] in which the precondition is that the data series are cross-sectionally correlated but independent over time; a non-overlapped block bootstrap; and the overlapped block bootstrap (or moving block bootstrap). However, they argue that "the subsampling works in many cases where the standard bootstrap fails: in heavy tailed distribution, in unit root cases, in cases where the parameter is on the boundary of its space, etc."[4] As they only use a fully random sample bootstrap to compare with subsampling result, it is not surprising that the results from subsampling outperform that from this bootstrap approach, since the requirement of the series dependency is not matched by the data in the random bootstrap approach. To preserve the dependency of the data series, a block bootstrap would be more suitable for the SD test.

The procedure for the test of SD1 in LMW subsampling is below. Let

$$W_k = (X_k, Y_k), \quad k = 1, \ldots, n$$

[3] Linton, Maasoumi and Whang (2005) p. 749.
[4] Linton, Maasoumi and Whang (2005) p. 744.

$$d_n(W_1, \ldots, W_n) = \frac{1}{\sqrt{n}} T_{n,1}$$

and $d_{n,b,k} = d_b(W_k, W_{k+1}, \ldots, W_{k+b-1})$ for $k = 1, \ldots, n-b+1$ be the transformed test statistic for the subsample $(W_k, W_{k+1}, \ldots, W_{k+b-1})$ of size b. We follow Linton, Maasoumi and Whang (2005) and suppose that $g_{n,b}$ is the empirical quantile function of $\{\sqrt{b} d_{n,b,k} : k = 1, \ldots, n-b+1\}$ and g the quantile function of the asymptotic distribution of $T_{n,1}$ under H_0^1 .

Assume that $b(n) \underset{n\to\infty}{\longrightarrow} \infty$ and $\frac{b(n)}{n} \underset{n\to\infty}{\longrightarrow} 0$, then the subsample size goes to infinity when the entire sample size becomes infinite, but the subsample size is always less than the entire sample size and that the mixing condition holds.

Then under the subcase $P_X = P_Y$ of H_0^1 , we have

$g_{n,b}(1-\alpha) \xrightarrow{p} g(1-\alpha)$ and

$$P(T_{n,1} > g_{n,b}(1-\alpha)) \underset{n\to\infty}{\longrightarrow} \alpha$$

Under H_1^1 the test is consistent, i.e. $P(T_{n,1} > g_{n,b}(1-\alpha)) \underset{n\to\infty}{\longrightarrow} 1$

The process for the SD2 test is analogous.

(3) LMW Circular Subsampling and Bootstrap Procedure

The modification of the subsampling method of LMW is analogous. The distribution of $T_{n,i}$ under H_0^i is approximated by $\sqrt{b} d_{n,b,k}$ where

$$d_{n,b,k} = \begin{cases} d_b(W_k, W_{k+1}, \ldots, W_{k+b-1}) & \text{for} \quad k = 1, \ldots, n-b+1, \\ d_b(W_k, \ldots, W_n, W_1, \ldots, W_{k+b-n-1}) & \text{for} \quad k = n-b+2, \ldots, n. \end{cases}$$

The collection of blocks from which it is resampled consists of the blocks $B_1, \ldots, B_{n-b+1}$ of the moving block bootstrap, MBB) and additionally of the blocks $B_{n-b+2}, \ldots, B_n$ of the form $B_k =$, $x_k, \ldots, x_n, x_1, \ldots, x_{k+b-n-1}$). Lahiri (1999) investigates the asymptotic behavior of some block bootstrap methods and found that MBB and circular block bootstrap (CBB) are asymptotically equivalent. We apply CBB to the LMW test and investigate by simulation whether this improves the size of the test.

(4) Construction of momentum profit

We construct the Jegadeesh and Titman (1993) momentum portfolios, based on the industry indices we downloaded from Thompson Datastream.

Our momentum strategy is built based on a ranking period, J= 6 months, a holding period, K= 1 month; and a skipping period, S_k= 0 months. We use 30% deciles to distinguish the winner and looser portfolios.

Based on the previous ranking period: J months' (cumulative, arithmetic or geometric) returns of the stocks, or indices) $[t\text{-}J\text{: } t\text{-}1]$, we sort them into deciles by ascending order. The cross-sectional (equally/value weighted) average returns of the first or last three deciles at time t are returns of "Losers", or "Winners" at time or month t. The momentum profit at time t equals the return of winner portfolio minus the return of loser portfolio at time t. Then we will generate a momentum return series which length is $n=T-(J+K+S_k)+1$, where T is the number of observation in a raw data series. Therefore, we can generate the mean and variance (or std) of this momentum profit, e.g at the jth replication.

On the other hand, in order to examine the significance of the momentum profit, we apply the *t*-test corrected for heteroskedasticity and autocorrelations (up to eight lags) based on the adjustments outlined in Newey and West (1987)' (see e.g. Pan, Liano and Huang (2004), Chordia and Shivakumar (2002), Chen and De Bondt (2004) and Gallant (1987)). As a complement, the sign test is used to measure the deviations of percentage of positive profit from 50 percent are given in parentheses below the percentage positive. In addition, we use the normality test, the Kolmogorov–Smirnov D-statistic) for testing the normality of momentum series. Then, we apply the stochastic dominance tests to compare the dominance of the industry and the country momentum, and the dominance of winner and loser portfolios across industries and countries.

4. Results

Table 3 shows the descriptive statistics and t-test for the country and industry momentum portfolio returns. The average momentum returns of "winners minus losers" are 0.79% and 0.54% for countries and industries, respectively. The t-test, that corrected for autocorrelation, and corrected for heteroskedasticity and autocorrelation are all significant for both country and industry momentum portfolios. The Sharpe ratio test (Jobson and Korkie (1981)) comparing the Sharpe ratios between different portfolios does not show the difference between the country momentum and industry momentum (z-value is -0.01). Moreover, the Kolmogorov–Smirnov D-statistic shows that the null hypotheses of normality are all rejected for momentum returns. In addition, we notice a higher autocorrelation in industry momentum returns (14.5%) than in country momentum portfolio returns (-0.7%).

Table 3. Descriptive Statistics and Tests for Developed Country Momentum Returns

		Country momentum strategy			Industry momentum strategy		
Panel A : Descriptive Statistics		Winner	Loser	**W - L**	Winner	Loser	**W - L**
Average Return		1.89%	1.10%	0.79%	1.86%	1.33%	0.54%
Average Std		5.17%	4.81%	3.60%	4.43%	4.90%	2.45%
Newey West T-test		5.28	3.39	3.77	5.94	3.95	3.48
ACF(1)		25%	26%	-1%	28%	29%	14%
Sharpe ratio = Prtf return/Prtf Std		0.36	0.229	0.2181	0.42	0.27	0.2185
% of returns (>0)		69%	64%	60%	73%	66%	62%
Sign test (p-value)		0.0%	0.1%	1.7%	0.0%	0.0%	1.4%
Panel B: Sharpe ratio test (Z-\ p-value)							
Country momentum strategy	Winner	1	0.2%	1.9%	10.4%	1.3%	9.5%
	Loser	3.15	1	91.1%	0.0%	10.3%	91.7%
	W-L	2.34	0.11	1	1.0%	53.7%	99.6%
Industry momentum strategy	Winner	-1.62	-5.01	-2.58	1	0.0%	1.2%
	Loser	2.49	-1.63	-0.62	4.76	1	59.9%
	W-L	1.67	0.10	-0.01	2.50	0.53	1
Panel C: Normality test (Kolmogorov–Smirnov D-statistic)							
KS-stat		0.44	0.44	0.45	0.45	0.44	0.47
KS-p		0.00%	0.00%	0.00%	0.00	0.00	0.00

Note: This table shows the descriptive statistics of the country and industry indices momentum returns in developed countries. "Winner" shows the winner portfolio returns; "Loser"the loser portfolio returns; "W-L" the difference in returns between the winner and loser portfolio. Panel A shows descriptive statistics with Sharpe ratios. Panel B displays the Sharpe ratio test (Jobson and Korkie (1981)) that compares the Sharpe ratios between different portfolios. The upper triangular indicates the p-values of the test, while the lower triangular shows the z-statistics. Panel C uses the Kolmogorov–Smirnov D-statistic for testing normality of momentum series. KS-stat is its statistic value, and KS-p is the p-value of the test. When the KS-p is less than 5%, we can reject the null hypothesis of normality at the significance level of 5%.

The sign test in table 4 shows that there is no significant difference between the countries' winners minus losers (and winner) portfolio returns and the industries' version. However, the country losers have a lower rank (or returns) than the industry losers.

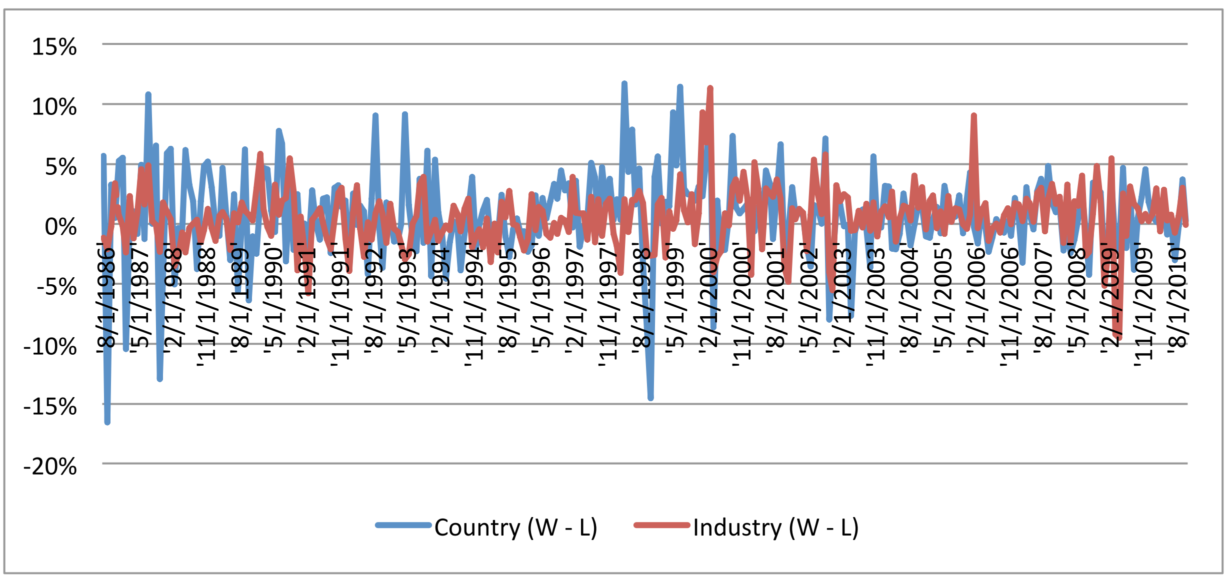
Table 4. Sign Test of Country vs. Industry Portfolio Returns

Sign Test of Country vs. Industry	W-L	Winner	Loser
p (two tails)	61%	49%	4%
p (one tails)	31%	24%	2%
Sign of difference	+	-	-

Note: The sign test here used is the Wilcoxon signed-rank test. That is suitable for the case of two related samples and non-normal distributions. The null hypothesis is that the common central point of both samples that come from a continuous population should be zero. The significance level is 5%. The difference is computed from country portfolio returns minus industry portfolio returns. This table shows the p-values with two tails (non direction) and one tail (one direction).

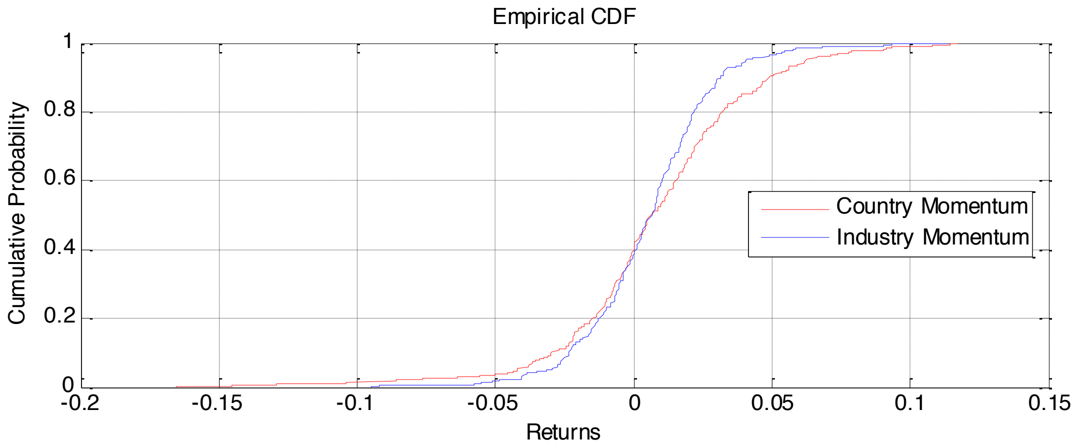
Figure 1 shows the time series of country and industry momentum returns. The results show that country returns were higher than industry returns before 2000, while the situation reversed after 2000. We also can see the change in figure 2 looking at the cumulative probability of both momentum returns.

Figure 1: Time series of country and industry momentum returns



Note: This figure displays the evolution of the country and industry momentum returns over the sample period, in which "(W-L)" means "winners minus losers". The momentum strategy is built based on 6-month ranking period, 1-month holding period without skipping period. We use 30% deciles to distinguish the winner and looser portfolios.

Figure 2. The Cumulative Probability of the Country and Industry Momentum Return Series



Note: This figure shows the cumulative probability of country and industry momentum returns. The momentum strategy is built based on 6-month ranking period, 1-month holding period without skipping period. We use 30% deciles to distinguish the winner and looser portfolios.

Table 5 displays the LMW SD1 and SD2 test results. Two hypotheses are tested. The first one ($H_0(1)$) verifies whether country momentum returns dominate industry returns. The second hypothesis ($H_0(2)$) has the opposite specification. The block length ranges from 12 months (or 1 year) to 48 months (or 4 years). When the *p*-values in table 5 are more than 95% then we can reject the null hypothesis at the 5% significance level. For the SD1 tests, the *p*-values decrease when the block length is extended.

We cannot reject the null hypothesis that country momentum dominates industry momentum ($H_0(1)$) for all block sizes. However, we can reject the hypotheses that industry momentum dominates country momentum ($H_0(2)$) when the block length is 12 months. Moreover, there is no significant difference between the subsampling and the circular subsampling results. However, it is clear that the results from the circular bootstrap are more significant, as $H_0(1)$ stays significant at 10% significance level.

The SD2 results show a similar pattern, however, no significant rejections of the null hypotheses occur for most blocks. One exception being the country dominance hypotheses (H_0(*1*)) based on the results from the subsamping approach when the block size is larger than 11 years (141 months). However, in the SD2 test, neither the circular subsampling nor the circular bootstrap can provide significant rejections.

Table 5. P-value of LMW First and Second Order Stochastic Dominance Tests

	Block length	Subsampling		Circular Subsampling		Circular Bootstrap	
	(year)	H0 (1)	H0 (2)	H0 (1)	H0 (2)	H0 (1)	H0 (2)
SD1	1	97.9%	49.8%	97.9%	50.3%	99.5%	55.9%
	2	91.4%	50.6%	92.1%	52.1%	98.4%	70.4%
	3	87.2%	42.0%	87.7%	41.1%	94.9%	53.4%
	4	87.8%	53.1%	88.4%	51.7%	92.1%	50.6%
SD2	1	78.6%	86.5%	79.5%	83.6%	83.3%	87.2%
	2	75.8%	88.5%	77.7%	83.6%	77.5%	84.6%
	3	70.8%	87.9%	73.3%	82.9%	72.2%	83.0%
	4	65.7%	84.5%	71.2%	80.5%	72.6%	76.8%

Note: The LMW Subsampling approach is compared to a circular subsampling and a circular block bootstrap with 5000 replications. The null hypothesis $H_0(1)$: the country momentum returns dominates the industry returns; null hypothesis of $H_0(2)$ is industry momentum returns dominate country momentum returns. The block length is 12 months to 48 months. p-value more than 95% imply that we can reject the null hypothesis with 5% significance level.

As the validity of the three approaches depends on the stability of their critical values, we compute the distribution of the quantiles. As an example of the first order dominance (i=1), the null hypothesis $F_{X,n}^{(1)}(x) \le F_{Y,n}^{(1)}(x)$ means that the random variable X dominates Y. Under this hypothesis, $F_{X,n}^{(1)}(x) - F_{Y,n}^{(1)}(x)$ should be small. If the $F_{X,n}^{(1)}(x) - F_{Y,n}^{(1)}(x)$ is large so that the probability of $T_{n,1} > g_{n,b}(1-\alpha)$ is larger than 95% (α =5%), then, we can reject the null hypothesis. Therefore, checking the distribution of the quantile, $g_{n,b}(1-\alpha)$ is very important. If the distribution of the quantile $g_{n,b}(1-\alpha)$ is biased, then the non-rejection or the rejection of the null hypothesis is not valid.

Table 6. Distribution of the Quantile under First Order Stochastic Dominance Test with Circular Subsample Approach

Panel A: $H_0(1)$ that the country momentum returns dominates the industry returns. (T=0.82)

Block length					Quantile						
(year)	Mean	Std	Skewness	Kurtosis	Min	5%	25%	Median	75%	95%	Max
1	0.78	0.44	0.44	2.71	0	0.29	0.58	0.58	1.15	1.73	2.02
2	0.86	0.41	-0.09	2.36	0	0.20	0.61	0.82	1.22	1.43	1.84
3	0.88	0.48	0.23	2.45	0	0.17	0.50	0.83	1.17	1.67	2.00
4	0.88	0.44	0.28	2.11	0	0.29	0.58	0.72	1.30	1.59	1.88
5	0.88	0.43	0.49	2.09	0.26	0.39	0.52	0.77	1.29	1.68	1.81
6	0.90	0.41	0.59	2.43	0.35	0.35	0.59	0.82	1.06	1.65	1.89
7	0.92	0.41	0.57	2.43	0.33	0.33	0.55	0.87	1.09	1.75	1.85
8	0.94	0.43	0.60	2.44	0.31	0.31	0.51	0.87	1.12	1.74	1.94
9	0.93	0.43	0.58	2.22	0.38	0.38	0.48	0.87	1.20	1.73	1.92
10	0.93	0.43	0.48	2.14	0.37	0.37	0.46	0.91	1.19	1.73	1.83
11	0.91	0.42	0.31	2.01	0.26	0.35	0.44	0.87	1.18	1.65	1.74
12	0.90	0.40	0.17	2.04	0.25	0.33	0.50	0.92	1.25	1.58	1.75
13	0.90	0.36	0.08	2.03	0.32	0.40	0.56	0.96	1.12	1.52	1.68
14	0.90	0.34	0.10	1.91	0.39	0.39	0.58	0.93	1.16	1.47	1.62
15	0.90	0.34	0.27	1.97	0.37	0.38	0.60	0.89	1.19	1.42	1.64
16	0.90	0.33	0.45	2.21	0.36	0.37	0.65	0.79	1.15	1.44	1.66
17	0.89	0.31	0.62	2.56	0.35	0.49	0.63	0.84	1.19	1.47	1.68
18	0.89	0.29	0.76	2.93	0.41	0.48	0.68	0.82	1.02	1.50	1.63
19	0.87	0.26	0.93	3.12	0.46	0.53	0.70	0.79	0.93	1.46	1.52
20	0.87	0.22	1.05	3.27	0.52	0.58	0.71	0.77	0.90	1.36	1.42

Panel B: H_0 (2) that the industry momentum returns dominates the country returns. (T=2.11)

Block length					Quantile						
(year)	Mean	Std	Skewness	Kurtosis	Min	5%	25%	Median	75%	95%	Max
1	0.92	0.56	0.59	2.49	0.00	0.29	0.58	0.87	1.44	2.02	2.31
2	1.07	0.65	0.49	2.09	0.20	0.20	0.61	0.92	1.63	2.25	2.45
3	1.13	0.69	0.42	2.10	0.00	0.18	0.50	1.17	1.67	2.33	2.83
4	1.20	0.71	0.17	1.86	0.14	0.14	0.51	1.30	1.88	2.31	2.74
5	1.27	0.72	-0.11	1.62	0.13	0.26	0.52	1.42	1.94	2.32	2.45
6	1.34	0.70	-0.29	1.67	0.12	0.24	0.59	1.47	1.94	2.24	2.36
7	1.38	0.68	-0.45	1.79	0.22	0.22	0.65	1.53	1.96	2.18	2.29

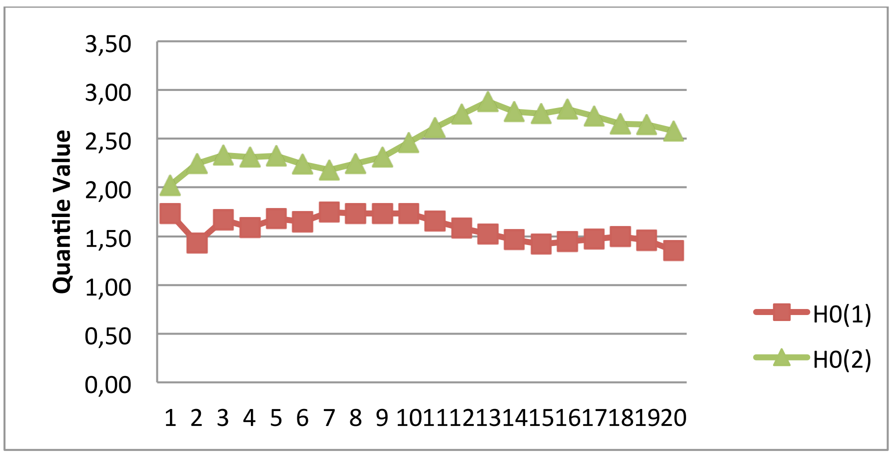
8	1.42	0.68	-0.58	1.92	0.10	0.20	0.77	1.63	1.94	2.25	2.25
9	1.48	0.67	-0.51	2.07	0.10	0.29	0.96	1.64	2.02	2.31	2.50
10	1.56	0.65	-0.38	2.16	0.27	0.37	1.19	1.55	2.10	2.46	2.65
11	1.60	0.66	-0.26	2.32	0.26	0.35	1.31	1.57	2.09	2.61	2.70
12	1.65	0.64	0.02	2.53	0.33	0.50	1.25	1.58	2.00	2.75	3.00
13	1.70	0.61	0.46	2.52	0.56	0.72	1.28	1.68	2.00	2.88	3.04
14	1.73	0.57	0.76	2.43	0.93	1.00	1.31	1.54	2.04	2.78	3.09
15	1.76	0.53	0.85	2.45	1.04	1.19	1.34	1.57	2.20	2.76	3.06
16	1.80	0.51	0.79	2.41	1.08	1.23	1.44	1.59	2.24	2.81	3.03
17	1.83	0.47	0.58	2.04	1.12	1.26	1.47	1.68	2.24	2.73	2.87
18	1.88	0.45	0.38	1.91	1.22	1.29	1.50	1.77	2.25	2.65	2.79
19	1.91	0.41	0.26	2.06	1.26	1.39	1.52	1.92	2.25	2.65	2.85
20	1.95	0.37	0.00	2.06	1.29	1.36	1.61	2.00	2.26	2.58	2.71

Note: This table shows the descriptive statistics and distribution of the statistic of the circular subsample approach under the first-order stochastic dominance test. In Panel A the null hypothesis is that country momentum returns dominates the industry returns. And the test statistic of the sample, T=0.82. In Panel B the null hypothesis is that industry momentum returns dominates the country returns. And the test statistic of the sample, T=2.11.

The distribution of the statistic of the circular subsample approach under the first-order (second-order) stochastic dominance test is shown in table 6 (table 7). Panel A shows the descriptive statistics and the distribution of the statistic under the null hypothesis, $H_0(1)$, that country momentum returns dominate the industry returns. The test statistic of the sample under this hypothesis is 0.82. Panel B shows similar results from the null hypothesis, $H_0(2)$, that industry momentum returns dominate the country returns. The test statistic of the sample under $H_0(2)$ is 2.11.

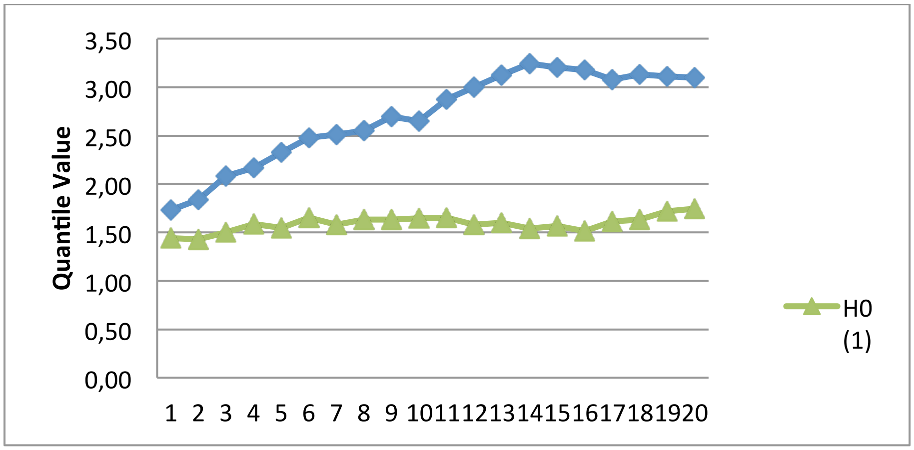
The distribution in Panel A is more stable than that in Panel B. For instance, the interval of the 95% quantile under $H_0(1)$ is [1.36, 1.75], while the interval of the same quantile in $H_0(2)$ is [2.02, 2.88]. On the other hand, it is obvious that the quantile under $H_0(2)$ increases along with the increased resample block size (see figure 3). This is the main reason why the test statistic is significant when the block size is shorter than 2 years (24 months), while it becomes insignificant after that. In contrast, the quantile in $H_0(1)$ is quite stable and the test statistic always remains insignificant. The circular block bootstrap results show a similar but more stable pattern compared to the distribution generated from the circular subsample approach. First of all, the interval of the 95% quantile is narrowed to [1.44, 1.74] under $H_0(1)$, and the quantile under this hypothesis shows more stability. Moreover, the increasing pattern of the quantile under $H_0(2)$ is clearer in Figure 4 than in figure 3. The interval expands to [1.73, 3.24]. The significant statistic appears in the block size from 1 year to 3 years.

Figure 3. Comparison of 95% Quantile under Two Hypotheses with Circular Subsample Approach



Note: This figure shows the evolution of 95% quantile under two hypotheses with a circular subsample approach under the first order stochastic dominance test along with the block length from 1 to 20 years. The first hypothesis, "H0(1)" is that the country momentum dominates the industry momentum, while the second hypothesis, "H0(2)" is contrast to the first hypothesis.

Figure 4. Comparison of 95% Quantile under Two Hypotheses with Circular Block Bootstrap Approach



Note: This figure shows the evolution of 95% quantile under two hypotheses with circular block approach under the first order stochastic dominance test along with the block length from 1 to 20 years. The first hypothesis, "H0(1)" is that the country momentum dominates the industry momentum, while the second hypothesis, "H0(2)" is opposite of the first hypothesis.

Looking at the quantile distribution, we can see that the circular block bootstrap can provide a more stable critical value under the first null hypothesis. Moreover, it gives a clearer tendency of the quantile under the second null hypothesis, a complemented null hypothesis of the first one.

Table 7. Distribution of the Quantile under First Order Stochastic Dominance Test with Circular Bootstrap Approach

Panel A: $H_0(1)$ that the country momentum returns dominates the industry returns. (T=0.82)

Block length					Quantile						
(year)	Mean	Std	Skewness	Kurtosis	Min	5%	25%	Median	75%	95%	Max
1	0.69	0.41	0.50	3.12	0	0.00	0.29	0.58	0.87	1.44	2.60
2	0.74	0.40	0.57	3.35	0	0.20	0.41	0.61	1.02	1.43	2.86
3	0.75	0.38	0.60	3.39	0	0.17	0.50	0.67	1.00	1.50	2.50
4	0.83	0.39	0.59	3.40	0	0.29	0.58	0.72	1.01	1.59	2.74
5	0.88	0.40	0.55	3.36	0	0.26	0.65	0.77	1.16	1.55	3.10
6	0.88	0.40	0.66	3.67	0	0.35	0.59	0.82	1.06	1.65	2.71
7	0.88	0.39	0.59	3.49	0	0.33	0.55	0.87	1.09	1.58	2.73
8	0.95	0.39	0.52	3.29	0	0.31	0.71	0.92	1.22	1.63	2.86
9	0.96	0.39	0.57	3.71	0	0.38	0.67	0.96	1.15	1.64	3.08
10	0.99	0.39	0.44	3.20	0	0.37	0.73	1.00	1.28	1.64	2.74
11	0.99	0.39	0.52	3.43	0	0.44	0.70	0.96	1.22	1.65	3.05
12	0.93	0.37	0.47	3.30	0	0.42	0.67	0.92	1.17	1.58	2.67
13	0.97	0.36	0.50	3.45	0.08	0.40	0.72	0.96	1.20	1.60	2.64

14	0.96	0.34	0.46	3.41	0.08	0.46	0.69	0.93	1.16	1.54	2.62
15	0.93	0.34	0.57	3.88	0	0.45	0.67	0.89	1.12	1.57	3.06
16	0.92	0.35	0.53	3.47	0	0.36	0.65	0.87	1.15	1.52	2.45
17	0.97	0.35	0.54	3.58	0	0.42	0.70	0.91	1.19	1.61	2.94
18	1.00	0.36	0.55	3.62	0.07	0.48	0.75	0.95	1.22	1.63	2.86
19	1.04	0.37	0.52	3.42	0.13	0.46	0.79	0.99	1.26	1.72	2.65
20	1.07	0.38	0.60	3.68	0.06	0.52	0.77	1.03	1.29	1.74	3.10

Panel B: $H_0(2)$ that the industry momentum returns dominates the country returns. (T=2.11)

Block length					Quantile						
(year)	Mean	Std	Skewness	Kurtosis	Min	5%	25%	Median	75%	95%	Max
1	0.89	0.44	0.41	3.03	0	0.29	0.58	0.87	1.15	1.73	2.60
2	1.08	0.46	0.39	3.11	0	0.41	0.82	1.02	1.43	1.84	3.06
3	1.27	0.47	0.31	2.88	0	0.50	1.00	1.17	1.50	2.08	3.00
4	1.39	0.48	0.29	3.05	0	0.58	1.01	1.30	1.73	2.17	3.46
5	1.48	0.49	0.23	2.88	0.13	0.65	1.16	1.42	1.81	2.32	3.23
6	1.57	0.50	0.25	2.98	0.24	0.82	1.18	1.53	1.89	2.47	3.54
7	1.68	0.50	0.23	2.97	0.22	0.87	1.31	1.64	1.96	2.51	3.49
8	1.76	0.49	0.19	2.97	0.31	0.92	1.43	1.74	2.04	2.55	3.57
9	1.81	0.49	0.17	2.86	0.19	1.06	1.44	1.83	2.12	2.69	3.75
10	1.83	0.49	0.23	3.01	0.18	1.00	1.46	1.83	2.10	2.65	3.83
11	1.98	0.50	0.24	3.10	0.52	1.22	1.65	2.00	2.26	2.87	4.00
12	2.15	0.51	0.12	2.99	0.42	1.33	1.83	2.17	2.50	3.00	4.25
13	2.28	0.50	0.14	3.03	0.56	1.44	1.92	2.24	2.64	3.12	4.32
14	2.35	0.51	0.12	3.02	0.77	1.54	2.01	2.31	2.70	3.24	4.32
15	2.31	0.50	0.18	3.06	0.60	1.49	1.94	2.31	2.61	3.21	4.47
16	2.32	0.51	0.13	2.87	0.72	1.52	1.95	2.31	2.67	3.18	4.19
17	2.26	0.49	0.20	2.94	0.70	1.47	1.89	2.24	2.59	3.08	4.34
18	2.32	0.49	0.20	3.06	0.82	1.56	1.97	2.31	2.65	3.13	4.42
19	2.28	0.49	0.17	3.07	0.79	1.52	1.92	2.25	2.58	3.11	4.30
20	2.30	0.50	0.11	2.96	0.65	1.48	1.94	2.26	2.65	3.10	4.20

Note: This table shows the descriptive statistics and distribution of the statistic of the circular bootstrap approach under the first-order stochastic dominance test. In Panel A the null hypothesis is that country momentum returns dominates the industry returns. And the test statistic of the sample, T=0.82. In Panel B the null hypothesis is that industry momentum returns dominates the country returns. And the test statistic of the sample, T=2.11.

Since Linton, Maasoumi and Whang (2005) use a one-block subsample and Kläver (2006) uses a one-block circular subsample, we apply a one-block circular bootstrap approach in this test. This will remain consistent with the above-mentioned authors' research and allow a comparison of three approaches. The results from the circular bootstrap with more than one block show a similar pattern to that for the one-block bootstrap. Increasing the number of blocks in the resample approach does not significantly improve the stability of the test[5].

Since the SD test is not very stable, we have to be very careful to use this test. Firstly, it is better to implement more than one test statistic. Then we can compare the test result from them and check the robustness of the SD test. Secondly, we can compare the stochastic dominance result with traditional mean-variance methodology if we want to make the portfolio choice. Thirdly, as a possible solution, the circular block bootstrap is suitable for computing the critical value of the SD test statistic in small samples. Nonetheless, a proper block size should be determined based on statistical experience and economic sense. On the other hand, we should notice the significance of the stochastic dominance test in momentum research. The normal distribution under the null hypothesis is rejected for all series. Therefore, it can be a valuable complement for the traditional methods.

5. Conclusion

This chapter presents an approach to improve the methodology determining the critical value of the LMW stochastic dominance test. We propose to add a bootstrap to this test when comparing the country and industry momentums. Stochastic dominance tests offer a different perspective to compare the portfolio performance rather than merely looking at the value of the portfolio return.

In our sample, the average momentum returns are 0.79% and 0.54% for countries and industries. Over the last 10 years the industry momentum returns were higher than the country momentum returns. This change is reflected in the SD test as well. We can reject the null hypothesis that

[5] The results of resampling more than one block are available upon request.

country momentum dominates industry momentum. On the other hand, we cannot reject the hypotheses that industry momentum dominates country momentum.

Moreover, we compare the results of the three critical value determinations of SD test from an empirical point of view. When checking the results using different block sizes and their critical value distribution, we notice that the circular block bootstrap approach can provide more stable and significant results than previous subsampling and circular subsampling approaches put forward. However, the choice of the block size is still an issue that deserves attention in future research.

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