Nonparametric approach to portfolio diversification: the case of Australian equity market.

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NONPARAMETRIC APPROACH TO PORTFOLIO DIVERSIFICATION: THE CASE OF AUSTRALIAN EQUITY MARKET

1. Introduction

This paper examines diversification opportunities in the Australian equity market and its relationship with other international markets by means of nonparametric cointegration and principal component analysis (PCA). The rationale for the use of these methods is as follows. As noted by Jones and Nesmith (2007), standard cointegration method, such as one elaborated by Johansen (1988), is based on linear autoregressive model and assumes that underlying dynamics are in linear form or can be made linear by a simple transformation. However, it was proved on numerous occasions that most financial time series are non-linear. Also, standard cointegration assumes the existence of stationary linear combination of nonstationary time series. However, linear combination of nonlinear processes is non-linear itself. The use of Bierens nonparametric cointegration is preferable in this case, as no *apriori* assumption of linearity of stationary dynamics of the cointegrated system is made. Prior to conducting nonparametric test, the presence of nonlinear unit root should be established and the condition of the same order integration of time series should be satisfied. Regarding PCA, the presence of a large number of highly correlated variables in a sample can render bivariate cointegration method technically cumbersome (in our case 11 sectoral variables correspond to 55 bivariate relations in each period). PCA can bring a simplification to analysis, by reducing the dimensions of the data and reduce a number of variables to a small number of components.

The literature on the integration of equity markets is abundant, has covered a vast majority of markets, including Australia, but mostly focused on the relationships between countries' benchmark indexes (both on regional and global basis) and to a lesser extent between equity market sectors, size or investment style indexes. The use of parametric cointegration methods and principal component analysis has been common, while only few studies have employed nonparametric cointegration and assumed nonlinearity of the data.

For mature equity markets, Floros (2005), Taylor and Tonks (1989) and Kasa (1992) found long run relationships among the equity markets of the US, the UK, Japan, selected European economies and Canada. Rocca (1999), using Johansen cointegration technique, has discovered strong interlinks between Australian, the US and the UK markets. This result was confirmed by Kazi (2008), arguing that Australian market tends to move in concert with the Canadian, German and particularly the UK markets. In the case of emerging markets, interlinks were found between Indian, Latin American and East Asian markets on one hand and developed markets on the other (Choudhry, 1997; Wu and Su, 1998; Lamba, 2005; Saha and Bhunia, 2012). The international equity market linkages have also been investigated using PCA (Curto *et al*., 2006; Meric *et al*., 2009): the association between the markets was typically found on a regional basis or in terms of development stage (e.g. cointegration among emerging markets). Australian equity market was found to be cointegrated with developed economies rather than with Australia's neighbours in the South-East Asia (Valadkhani *et al*., 2008).

The analysis of size and style indexes has been scarce. The notable exceptions have been papers by Kang and Yoon (2011), examining causality linkages and transmission mechanisms among the portfolios composed of large, mid, and small cap stocks on the Korea Exchange (KRX). Based on bivariate Johansen cointegration test, no long-run relationship between three markets was found. The same results were obtained by Karmakar (2010) in the context of large and small cap indexes of the National Stock Exchange of India.

The research on sectoral cointegration has been performed in all cases using parametric cointegration (Engle-Granger, Johansen, and periodogram-based cointegration). Berument *et al*. (2005) examined relationships among services, industry and financial sectors on the Istanbul Stock Exchange, and found no cointegration among the respective sub-indexes. Al-Fayoumi *et al*. (2009) looked at causal linkages among general, financial, industrial and services indexes of the Jordanian stock market using multivariate Johansen cointegration and detected one cointegrating vector.

The applications of nonparametric cointegration methods included the analyses of diversification benefits in the ASEAN equity markets (Lim *et al.,* 2003), US and its trading partners' markets (Kanas, 1998; Chang and Tzeng, 2009), as well as Shanghai and Shenzhen markets in China (Chang *et al.,* 2010).

It should be noted, however, that despite ongoing financial globalization, cointegration of markets is by no means complete:

several studies (Errunza and Losq, 1985; Bekaert *et al.,* 2003) have discovered no stable relationship among the markets of Australia, Japan, Hong Kong, New Zealand and Singapore. Likewise, Nath and Verma (2003) looked at market indexes of India, Singapore and Taiwan and found no cointegration.

Importantly, in many cases inter-market cointegration was not constant over time due to structural changes and junctures in financial markets and fluid economic and political relations between countries. Jeon and Von-Furstenberg (1990) found stronger co-movement among international markets after October 1987 crash. Similarly, Jochum *et al.* (1999) found weakening cointegration among markets during 1997/98 financial crisis in emerging markets. Aggarwal and Kyaw (2003) discovered co-movement among the US, Canadian and Mexican market only in the aftermath of the NAFTA regional agreement, but not before it.

This study is innovative in the following respects. Firstly, the existing research on the presence of cointegrating relationships is inconclusive, partly attributed to structural changes in the equity market. Thereby, it is instructive to look at how relationships between Australian market and other international markets and within Australian market have changed during and in the aftermath of some major critical juncture, e.g. the recent global financial crisis. Secondly, the analysis of market integration using nonparametric and nonlinear methods is missing (particularly in Australian context as well as in terms of style and size indexes). It is therefore necessary to conduct nonlinear and nonparametric unit root tests and nonparametric cointegration in the Australian setting, the task not attempted previously. Thirdly, the principal components analysis was previously applied only in the international equity markets setting, but not for sectoral indexes, the gap that we intend to fill in this paper. Finally, from methodological standpoint, while previous studies provided only partial results about selected relations, we establish a comprehensive set of relations in the Australian market – in terms of size, style, sector and relations to other international markets.

2. Methodology

2.1 Data

For the purpose of nonparametric cointegration analysis we consider 7 Australian and international benchmark indexes (S&P/ASX 300 Accumulation Index, S&P 500 Index, FTSE 100 Index, Nikkei 225 Index, DAX 30 Index, Hang Seng Index and Shenzhen Composite Index), 3 Australian style indexes (Salomon Smith Barney Australian Equity Style neutral, growth and value accumulation indexes), as well as 3 Australian size indexes (S&P/ASX 50, S&P/ASX MidCap 50 and S&P/ASX Small Ordinaries), representing large, mid and small cap stocks.

To conduct principal component analysis we consider 11 sectoral S&P/ASX indexes, representing companies in the following industries: energy, utilities, information technologies, health care, consumer discretionary, materials, telecommunication services, financials, consumer staples, industrials and real estate. Companies are categorized for the inclusion in each index using the Global Industry Classification Standard (GICS) according to their primary sources of revenue and earnings as well as in accordance with the market's perception of the company.

Index values are quoted in respective national currencies and are not transformed to a common currency in order to avoid currency fluctuations affecting comparison of indexes and restrictions associated with relative purchasing power parity assumption. In addition, the index values represent solely capital gains and exclude dividend values, as the latter are not considered volatile enough to affect cointegrating relations.

The sample consists of monthly closing index prices of the benchmark and style indexes from May 31, 1992 through March 31, 2012. The data for size indexes is available on a monthly basis from February 28, 1995 through March 31, 2012. The dataset for sectoral indexes includes monthly data spanning period from June 30, 2001 through March 31, 2012. Taking into account the fact that cointegration relations among indexes may be disrupted (or significantly changed) in a post-GFC environment, we considered a smaller sample, including observations from October 31, 2007 through March 31, 2012. The starting observation in this sub-sample coincides with the highest price levels for the equity market indexes (the end of the bull rally). The monthly closing price data was obtained from Bloomberg database.

To avoid scaling problems and also to allow economic interpretation of the results, the index levels are converted to natural logarithms. Also to conduct principal component analysis, we standardize the data with zero mean and unit standard deviation in order to avoid the first principal component being dominated by the input variable with the greatest volatility. To perform PCA, the log differences are expressed in percentage terms – $\ln (P_t/P_{t-1}) \times 100$.

2.2 Stationarity Tests

Testing for stationarity is the first step in the analysis, as the requirements for cointegration technique are that time series are non-stationary and are also integrated of the same order. We use the combination of stationarity (unit root) tests in the event there are contradictions between their results.

The augmented Dickey-Fuller (ADF) test 'augments' the original Dickey Fuller test of stationarity by adding the lagged values of the dependent variable and by allowing for correlation of error terms. The ADF test has the following functional forms:

$$\Delta Y_t = \alpha + \psi Y_{t-1} + \lambda t + \sum_{j=1}^{k} d_j \Delta Y_{t-j} + \varepsilon_t \tag{1}$$

$$\Delta Y_t = \alpha + \psi Y_{t-1} + \sum_{j=1}^{k} d_j \Delta Y_{t-j} + \varepsilon_t \tag{2}$$

$$\Delta Y_t = \psi Y_{t-1} + \sum_{j=1}^{k} d_j \Delta Y_{t-j} + \varepsilon_t \tag{3}$$

where α is a constant, λ is a coefficient on a time trend, k is the lag order of the autoregressive process, and ΔY_{t-j} is a lagged first difference term. Lagged first difference terms are added until it is ensured that error term (ε_t) is not autocorrelated. The unit root test is carried under the null hypothesis $\psi = 0$ (non-stationarity of time series) and the alternative hypothesis $\psi < 0$ (stationarity). The null hypothesis is rejected if test statistic τ is smaller or equal than critical value statistic ($\tau \leq \tau_c$). If $\tau > \tau_c$, the null hypothesis of non-stationarity is not rejected. Equation 1 is tested if the original time series fluctuate around a linear trend. Equation 2 is tested if the original time series wander around non-zero mean. Equation 3 is tested if time series fluctuate around a zero mean.

The use of Phillips-Perron test (Phillips and Perron, 1988) is necessary, as ADF test may falsely report the unit root, when time series are subject to a structural break. In contrast to ADF test that controls autocorrelation by introducing lags of ΔY_t as regressors in the test equation, the Phillips-Perron test modifies the original Dickey-Fuller test equation[1] and makes a non-parametric correction to the t-test statistic by using autocorrelation and heteroskedasticity consistent estimates t_{pp}[2]. The test uses same critical values as

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[1] $\Delta Y_t = \alpha + \delta Y_{t-1} + \varepsilon_t$, where H_0: $\delta = 0$ (presence of unit root), and H_a: $\delta < 1$ (presence of stationarity).

[2] The relevant function form of the Phillips-Perron test is:

ADF test, and the same set of hypotheses (H_0: unit root, and H_a: stationarity).

In contrast to the above-mentioned unit root tests that rely on either parametric specification of the short-run dynamics or kernel type estimation of the nuisance process, Breitung (2002) nonparametric unit root test does not require such specification. It is also robust against structural breaks in the short-run components and is suitable for testing a range of nonlinear models. From technical viewpoint, Breitung test does not depend on the lag length and the inclusion of a trend or intercept (two factors that affect the Johansen test results). Breitung considers x_t process $x_t = \delta' d_t + \delta_t$, where $\delta' d_t$ is the deterministic part with $\delta' = [\delta_1 \delta_2]$ and $d_t = [1,t]$, and μ_t is the stochastic part. The former may include constant, time trend or dummy variables, while the latter is decomposed into a random walk component and component representing short-run dynamics of the process. If deterministic part is absent, x_t is consistent with stochastic part. The test contrasts null hypothesis of unit root H_0 against the alternative hypothesis of stationarity $H_a : x_t$ is $I(1)$, if $\mathrm{T} \rightarrow \infty$, $T^{-1/2} x_{[aT]} \Rightarrow \sigma W(a)$, where $\sigma > 0$ represents the constant (long-run variance), $W(a)$ is a Brownian motion and [] is the integer part. To avoid the specification of short-run dynamics to stationarity or computation of σ, Breitung suggests a variance ratio test statistic for unit root, similar to the one of Kwiatkowski (1992):

$$\hat{\rho}_T = \frac{T^{-2} \sum_{t=1}^{T} \hat{U}_t^2}{\sum_{t=1}^{T} \hat{u}_t^2} \tag{4}$$

where $\hat{u}_t$ is the OLS residuals such that $\hat{u}_t = x_t - \delta' d_t$ and $\hat{U}_t$ is the partial sum process such that $\hat{U}_t = \hat{u}_t + \ldots + \hat{u}_t$. If x_t is $I(0)$, the test statistic $\hat{\rho}_T$ converges to zero. The null hypothesis is rejected when the value of the variance ratio statistic is lower than the relevant critical values.

Both the ADF and PP tests take non-stationarity as a null hypothesis and test it against a stationary linear alternative. In contrast, Kapetanios *et al.* (2003) proposed a unit root test against a non-linear globally stationary exponentially smooth transition autoregressive (ESTAR) process that is more suitable (in terms of size and power

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$\Delta Y_t = \alpha_0 + \alpha_1 (t - T/2) + \alpha_2 Y_{t-1} \sum_{i=1}^{k} \Delta Y_{t-1} + \varepsilon_t$, where t is the trend variable, T is the number of observations.

properties) for the analysis of the financial time series than standard unit root tests. The ESTAR process for variable X_t is given as:

$$\Delta X_t = \lambda X_{t-1}[1-\exp(-\vartheta X^2_{t-1})]+\varepsilon_t \quad (5)$$

where X_t is de-meaned and de-trended series, ε_t is an i.i.d. error term with zero mean and constant variance, and $\vartheta \geq 0$ is the transition term of the ESTAR model that governs the speed of transition. The null hypothesis $H_0: \vartheta = 0$ is that series X_t follow a linear unit root process. The alternative $H_a: \vartheta > 0$ is that X_t follows nonlinear stationary ESTAR process. Since parameter λ is not defined under the H_0, it is not directly possible to test the hypotheses from the ESTAR equation.

Luukkonen *et al.* (1988) computed a first-order Taylor series approximation to the $1-\exp(-\vartheta X^2_{t-1})$ under $\vartheta = 0$ and derived the following auxiliary regression:

$$\Delta X_t = \delta X^3_{t-1} + \varepsilon_t \quad (6)$$

or in augmented form:

$$\Delta X_t = \xi + \delta X^3_{t-1} + \sum_{i=1}^{k} b_i \Delta X_{t-i} + \varepsilon_t \quad (7)$$

It is then possible to apply a t_{NL} statistic ('*t* non-linear') to test whether X_t is a unit root process ($H_0: \delta = 0$) or is a stationary process ($H_a: \delta < 0$).

Similarly to ADF test, $t_{NL} = \dfrac{\hat{\delta}}{s.e.(\hat{\delta})}$, where $\hat{\delta}$ is the OLS estimate for δ and $s.e.(\hat{\delta})$ is the standard error of $\hat{\delta}$. The null hypothesis is accepted, when *t* value exceeds the critical values of *t* simulated by Kapetanios *et al.* (2003).

2.3 Bierens (1997) Nonparametric Cointegration

The two rationales for using Bierens nonparametric cointegration method rather than standard parametric Johansen-Juselius cointegration test is that the latter is inferior in detecting cointegration relations when error correction mechanism is non-linear and is based on the assumption of the linear nature of time series' dynamics. The ample evidence (Hsieh, 1991; Opong *et al.,* 1999) exists, however, suggesting that financial time series, including stock prices, exhibit non-linear dependencies. In this regard, it is essential to test for the existence of these dependencies in the data, e.g. by BDS test (Brock *et al.,* 1996), and to account for the possibility of non-linear data generation (by means of nonparametric unit root test) prior to conducting nonparametric cointegration test.

For the purpose of conducting Bierens's nonparametric cointegration we consider the following general framework:

$$x_t = \pi_0 + \pi_1 t + y_t \tag{8}$$

where x_t is an unobservable q-variate process for $t = 1,2,\ldots,T$; $\pi_0(q\times 1)$ is optimal mean term; $\pi_1(q\times 1)$ is the trend term; y_t is the zero-mean unobservable process such that Δy_t is ergodic and stationary.

While similarly to Johansen (1988, 1991) cointegration method the cointegration estimates are based on the solution to a generalized eigenvalue problem, no specification of the data-generating process for x_t is needed and therefore the cointegration test is completely nonparametric (Maghyereh, 2006).

Specifically, two matrices A_m and $(B_m + cT^{-2}A_m^{-1})$ are constructed, where A_m and B_m are defined as:

$$A_m = \frac{8\pi^2}{T}\sum_{k=1}^{m} k^2 (\frac{1}{T}\sum_{t=1}^{T}\cos(2k\pi(1-0.5)/T)x_t)(\frac{1}{T}\sum_{t=1}^{T}\cos(2k\pi(t-0.5)/T)x_t)' \tag{9}$$

$$B_m = 2T\sum_{t=1}^{m}(\frac{1}{T}\sum_{t=1}^{T}\cos(2k\pi(t-0.5)/T)\Delta x_t)(\frac{1}{T}\sum_{t=1}^{T}\cos(2k\pi(t-0.5)/T)\Delta x_t)' \tag{10}$$

To ensure invariance of the test statistic to drift terms, the weighted functions of $\cos(2k\pi(t-0.5)/T)$ are suggested. The ordered generalized eigenvalues $\hat{\lambda}_{1,m} \geq \ldots \geq \hat{\lambda} q,m$ of the nonparametric test are obtained as a solution to the characteristic equation $\det[P_t - \lambda Q_T] = 0$, when the pair of random matrices $P_T = A_m$ and $Q_T = (B_m + cT^{-2}A_m^{-1})$ are defined. These eigenvalues have similar properties as eigenvalues in Johansen-Juselius likelihood ratio test and therefore can be used to test the cointegration rank r.

For this purpose, two statistic are proposed. The first is λ_{min} (lambda min) test statistic $\hat{\lambda}_{q-r0,m}$, corresponding to the Johansen-Juselius maximum likelihood procedure, and testing the $H_0: r = r_0$ against $H_a: r = r_0 + 1$. Parameter m is provided for different levels of significance and for various levels of q and r_0 in such a way that the lower end of the power of the test is maximized.

The second test statistic $g_m(r_0)$ is computed from the Bierens generalized eigenvalues as follows:

$$\hat{g}_m(r_0) = \left(\prod_{k=1}^{q}\hat{\lambda}_{k,m}\right)^{-1}, \quad \text{if} \quad r_0 = 0 \tag{11}$$

$$\hat{g}_m(r_0) = \left(\prod_{k=1}^{q-r_0}\hat{\lambda}_{k,m}\right)^{-1}\left(T^{2r_0}\prod_{k=q-r_0+1}^{q}\hat{\lambda}_{k,m}\right)^{-1}, \quad \text{if} \quad r_0 = 1,\ldots q-1 \tag{12}$$

$$\hat{g}_m(r_0) = T^{2q} \prod_{k=1}^{q} \hat{\lambda}_{k,m} \tag{13}$$

This statistic employs tabulated values for m, when $q > r_0$ and $m = q$ is chosen when $r_0 = q$. $g_m(r_0)$ converges in probability to infinity if $r \neq r_0$ (i.e. the true number of cointegrating vectors is not equal to r; if $r = r_0$, $g_m(r_0) = O_p(1)$. A consistent estimate of r is thus given by $\hat{r}_m = \arg\min_{r0 \leq q} \left\{ \hat{g}_m(r_0) \right\}$. The test statistic is considered as a tool to double check the determination of r.

2.4 Principal Component Analysis

Principal component analysis is a multivariate statistical technique that reduces a large number of variables to a smaller set of factors (principal components) that summarize essential information contained in variables and account for most of their variance (Stevens, 1986; Alexander, 2008). In the context of equity market sub-sectors, PCA determines whether sub-sectors can be combined into principal component clusters in terms of similarities of their contemporaneous movements, thereby hampering portfolio diversification within each cluster.

The first step in PCA methodology is consideration of its appropriateness. Four criteria are identified. Firstly, it is agreed by convention that the number of observations in the sample should substantially exceed (at least in five-to-one or, better, ten-to-one proportion) the number of the variables, if meaningful results are to be obtained. Secondly, as the main assumption of PCA is that variables that share common components are strongly correlated, it is essential to examine the correlation strength, measured by correlation coefficient, by Kaiser-Meyer-Olkin (KMO) test, and by Bartlett test of sphericity (Kaiser, 1974; Leech *et al.,* 2005). If bivariate correlation coefficient is small (e.g. lower than 0.3), then PCA is not appropriate, as variables do not share common components. KMO test compares observed correlation coefficients with partial correlation coefficients. If the KMO index level is between 0.6 and 1, the sum of squared partial correlation coefficients between all pairs of variables is small relative to the sum of squared correlation coefficients, indicating that the data is appropriate for the purpose of principal component analysis. The purpose of Bartlett test is to accept/reject the null hypothesis that non-zero correlation coefficients between variables are due to sampling errors. If null hypothesis is not rejected, then variables are not significantly different from a ‘spherical’ (totally uncorrelated) set of variables, and thus there is little point in doing PCA.

The next step is determination of a number of principal components to be retained. According to Kaiser criterion (Kaiser, 1960), any component with eigenvalue greater than 1 should be retained, as such component accounts for a meaningful amount of variance of at least a single variable[3]. This criterion is complemented by the scree test (Cattell, 1966) that identifies breaks between the components with large eigenvalues and ones with small eigenvalues. The components that appear before the break are retained. Also, the components that account for a specified proportion of variance in the data set (usually at least 5% to 10%) are retained. Alternatively, the components that contribute to a specified level of cumulative variance (at least 70%) are retained.

Once the components representing returns of 10 sub-indexes are extracted it becomes possible to relate returns to components in component loadings matrix. The rows of the matrix represent variables analyzed, the columns represent the retained components, and the entries in the matrix are factor loadings (bivariate correlations between the observed variables and the components).

The matrix indicates how much weight is assigned to each component. The components with the largest loading for a variable (in this study – equity sub-index) are more closely related to that variable (sub-index). The proportion of the variance of the returns (communality of returns) can then be calculated as the sum of squared loadings. Communalities can range from 0 to 1, with 0 indicating that common factors don’t explain any variance and 1 indicating the opposite.

The final step in PCA is interpretation of the components by means of factor rotation methods. This is needed due to the difficulties in interpreting unrotated component loadings matrix, when more than one component has been retained. While several methods can be used (quartimax, oblimin etc.), in this study we perform varimax orthogonal rotation. The interpretation of a rotated matrix may involve:

1) establishing statistical significance of each component loading,
2) visualization of component loadings (correlations) with the help of correlation circle, or
3) interpretation of squared cosines data.

[3] Jolliffe (2002) argues that Kaiser criterion tends to under-select the right number of principal components. In order to incorporate the effect of sample variance Jolliffe suggests retaining components whose eigenvalues exceed 0.7.

Following Stevens (1986), the statistically significant loading should have absolute value of no less than 0.4. The correlation circle shows a projection of the initial variables in the components space. The further variables are from the centre of the circle, the more significant loading is in statistical sense. In this case, if variables are close to each other, the correlation coefficient is positive and close to 1. If they are on the opposite side of the centre, the correlation coefficient is negative and close to -1. If variables are orthogonal, they are not correlated. The proximity of variables to the centre may pose difficulties in establishing correlation relations between variables.

3. Empirical results

3.1 Stationarity Tests

As a first step, stationarity of time series has been examined. To ensure appropriateness of the stationarity (unit root) tests for the nonlinear financial data we first conducted the KSS nonlinear unit root test. Its results (Table 1) clearly indicate that all index time series in the level form contain unit root and are integrated of order 1. We note that in a longer study period (1992-2012) the test

Table 1 - *Nonlinear Unit Root Test Results*

Variable	t_{NL} statistic	
	Sample 1	Sample 2
S&P/ASX 300 Acc	-1,326	-2,204
S&P 500	-2,026	-1,461
FTSE 100	-2,065	-1,832
Nikkei 225	-1,549	-2,657
DAX 30	-1,645	-1,918
Hang Seng	-2,054	-2,227
Shenzhen Composite	-1,074	-1,625
SSB Australian Equity Neutral	-1,37	-2,214
SSB Australian Equity Growth	-1,103	-2,254
SSB Australian Equity Value	-1,618	-2,089
S&P/ASX 50	-1,767	-2,235
S&P/ASX MidCap 50	-1,508	-2,378
S&P/ASX Small Ordinaries	-1,465	-2,134

Note: The critical values for the KSS test are 2.82, 2.22 and 1.92 respectively at the 1%, 5% and 10% significance levels.
Source: (Kapetanios *et al.,* 2003)

statistics well exceed KSS test critical values, while in the post- and during-GFC period (2007-2012) they are only marginally greater than critical values (especially for Nikkei index).

For comparison we also applied two conventional unit root techniques (ADF and PP) as well as nonparametric Breitung unit root test (Table 2). For the ADF test the number of lags was

Table 2 - *Unit Root Test Results*

Variable	ADF test level	ADF test first difference	Phillips-Perron test level	Phillips-Perron test first difference	Breitung test level	Breitung test first difference
Sample 1 (31 May 1992 - 31 March 2012)						
S&P/ASX 300 Acc	-1,277	-14,697	-1,2543	-14,824	0,09556	0,00058
S&P 500	-1,9214	-13,906	-1,9142	-14,008	0,05861	0,00113
FTSE 100	-2,0301	-14,464	-2,0618	-14,476	0,04305	0,00075
Nikkei 225	-1,5558	-14,218	-1,7316	-14,234	0,05351	0,00021
DAX 30	-1,5704	-14,602	-1,6327	-14,653	0,05959	0,00049
Hang Seng	-2,0588	-14,613	-2,0899	-14,615	0,06697	0,00022
Shenzhen Composite	-1,0927	-14,37	-1,3836	-14,534	0,06299	0,00035
SSB Australian Equity Neutral	-1,2751	-14,509	-1,2421	-14,655	0,09623	0,00064
SSB Australian Equity Growth	-1,0276	-15,246	-1,0354	-15,289	0,09609	0,00038
SSB Australian Equity Value	-1,4995	-13,907	-1,4049	-14,129	0,09556	0,00096
S&P/ASX 50	-1,7477	-13,602	-1,6924	-13,685	0,0934	0,00103
S&P/ASX MidCap 50	-1,4704	-12,405	-1,4408	-12,633	0,09076	0,00103
S&P/ASX Small Ordinaries	-1,5711	-11,635	-1,5576	-11,826	0,08228	0,00055
Sample 2 (31 October 2007 - 31 March 2012)						
S&P/ASX 300 Acc	-2,4301	-5,4046	-2,4099	-5,3966	0,01226	0,00721
S&P 500	-1,8203	-5,3092	-1,8148	-5,2465	0,01004	0,00865
FTSE 100	-1,8184	-6,1919	-1,8901	-6,2023	0,0202	0,00535
Nikkei 225	-2,4755	-5,9326	-2,7026	-5,9346	0,03417	0,00468
DAX 30	-1,9703	-3,0983	-2,0256	-5,9611	0,01873	0,00534
Hang Seng	-2,2032	-6,0964	-2,3928	-6,1027	0,0871	0,00434
Shenzhen Composite	-1,6117	-7,2118	-1,8063	-7,2487	0,01885	0,00293
SSB Australian Neutral	-2,2161	-5,3892	-2,3875	-5,3879	0,01189	0,0074
SSB Australian Growth	-2,2489	-5,8883	-2,427	-5,9186	0,01119	0,00587
SSB Australian Value	-2,26	-5,232	-2,2896	-5,1708	0,01259	0,00762
S&P/ASX 50	-2,1173	-5,4759	-2,4145	-5,4724	0,01239	0,00746
S&P/ASX MidCap 50	-1,8277	-3,6112	-2,4729	-5,7982	0,01284	0,00672
S&P/ASX Small Ordinaries	-2,4137	-2,727	-2,3396	-5,1434	0,01004	0,0071

Note: The critical values for the ADF and Phillips-Perron tests for 1%, 5% and 10% significance levels are -3.4578, -2.8735 and -2.5732 for the test with constant. The critical values for Breitung test are 0.00536, 0.01046 and 0.01473 at 1%, 5% and 10% significance level for the sample of 500 observations. Optimal lag orders were chosen by Schwartz information criterion for the ADF test, and by Newey-West automatic truncation lag for the Phillips-Perron test.

selected in order to minimize Schwartz Information Criterion. The truncation lag of the ADF test is firstly set at $p = cn^r$, where $c = 5$, $r = 0.25$; a Wald test is then employed to reduce the number of lags only to those that are significant at the 5% level. All time series in log form were tested with one deterministic component (constant, but no trend) for both sample periods. For the PP test the truncation lag for the Newey-West estimator was set using the same formula as for the ADF. Regarding ADF and PP tests, it was shown that null hypothesis of a unit root could not be rejected for any of the variables and hence one can conclude that series are non-stationary in levels at 5% level of significance ($\tau > \tau_c$). The same test applied to the first differences showed that time series are stationary at 5% level of significance ($\tau < \tau_c$), and therefore are integrated of order 1, I(1). The nonparametric Breitung unit root test statistics are above critical values for the time series in levels and below critical values for the series in first differences, thereby confirming that series are I(1), the result consistent with ADF and PP tests' outcomes. Thus, we conclude that all time series are integrated of the same order and hence the use of Bierens nonparametric cointegration methodology is justified.

3.2 Bierens Nonparametric Cointegration

Table 3 reports the results of the Bierens' cointegration test for pairs of benchmark, size and style indexes in two periods. In addition, in order to confirm whether international markets become more (or less) integrated in the post- and during-GFC period and whether Australian equity market becomes more (less) detached, we also provide empirical evidence regarding possible cointegrating relations between pairs of international benchmark indexes, excluding Australia. Overall, 27 relationship pairs are examined. For each pair, λ_{min} is performed in two steps: in the first we hypothesize the absence of cointegration against the presence of one cointegrating relation; in the second we hypothesize one cointegrating relation against the two. $g(r)$ statistic is also provided for three cases: no cointegration ($r = 0$), one relationship ($r = 1$), two relationships ($r = 2$).

We found that during 1992-2012 period Australian equity market was cointegrated with FTSE and Shenzhen Composite indexes, the result that partially contradicts Kazi (2008), who argued that over 1945-2002 period significant overseas markets for Australia were the UK, Germany and Canada (no cointegration with German DAX

TABLE 3 - *Bierens Nonparametric Cointegration Results*

Relation	Hypotheses	λ min	λ min (5%)	ghat(r) r=0	ghat(r) r=1	ghat(r) r=2
			Sample 1 (31 May 1992 - 31 March 2012)			
Aus-US	H0: r=0 Ha: r=1	0,18067	(0,0.017)	**53.40×10^{-1}**	13.22×10^{2}	60.07×10^{7}
	H0: r=1 Ha: r=2	2,8319	(0,0.054)			
Aus-UK	H0: r=0 Ha: r=1	0,00797	(0,0.017)	15.25×10^{1}	**11.01×10^{1}**	20.89×10^{6}
	H0: r=1 Ha: r=2	1,82986	(0,0.054)			
Aus-Japan	H0: r=0 Ha: r=1	0,04131	(0,0.017)	**26.75×10^{-1}**	13.5×10^{1}	11.99×10^{8}
	H0: r=1 Ha: r=2	12,5207	(0,0.054)			
Aus-Germ	H0: r=0 Ha: r=1	0,07128	(0,0.017)	**13.98×10^{1}**	44.98×10^{1}	22.93×10^{6}
	H0: r=1 Ha: r=2	0,94877	(0,0.054)			
Aus-HK	H0: r=0 Ha: r=1	0,03871	(0,0.017)	**20.54×10^{0}**	22×10^{1}	15.61×10^{7}
	H0: r=1 Ha: r=2	3,54008	(0,0.054)			
Aus-Ch	H0: r=0 Ha: r=1	0,00441	(0,0.017)	15.29×10^{3}	**32.28×10^{0}**	20.97×10^{4}
	H0: r=1 Ha: r=2	0,33866	(0,0.054)			
			Sample 2 (31 October 2007 - 31 March 2012)			
Aus-US	H0: r=0 Ha: r=1	0,00335	(0,0.017)	48.97×10^{1}	**13.96×10^{0}**	14.92×10^{3}
	H0: r=1 Ha: r=2	0,62875	(0,0.054)			
Aus-UK	H0: r=0 Ha: r=1	0,00018	(0,0.017)	16.91×10^{3}	**10.6×10^{-1}**	43.23×10^{1}
	H0: r=1 Ha: r=2	0,3882	(0,0.054)			
Aus-Japan	H0: r=0 Ha: r=1	0,00003	(0,0.017)	70.05×10^{3}	**97.63×10^{-3}**	10.43×10^{1}
	H0: r=1 Ha: r=2	0,62873	(0,0.054)			
Aus-Germ	H0: r=0 Ha: r=1	0,00159	(0,0.017)	20.47×10^{2}	**13.38×10^{0}**	35.7×10^{2}
	H0: r=1 Ha: r=2	0,31413	(0,0.054)			
Aus-HK	H0: r=0 Ha: r=1	0,00164	(0,0.017)	48.59×10^{4}	**24.43×10^{-3}**	15.04×10^{0}
	H0: r=1 Ha: r=2	0,47723	(0,0.054)			
Aus-Ch	H0: r=0 Ha: r=1	0,14775	(0,0.017)	43.91×10^{1}	**22.71×10^{0}**	16.65×10^{3}
	H0: r=1 Ha: r=2	0,52071	(0,0.054)			
			Sample 1 (31 May 1992 - 31 March 2012)			
Large-mid	H0: r=0 Ha: r=1	0,00018	(0,0.017)	10.82×10^{3}	**39.08×10^{-1}**	16.31×10^{4}
	H0: r=1 Ha: r=2	0,99666	(0,0.054)			
Mid-small	H0: r=0 Ha: r=1	0,0004	(0,0.017)	62.12×10^{2}	**20.85×10^{0}**	28.39×10^{4}
	H0: r=1 Ha: r=2	0,5692	(0,0.054)			
Large-small	H0: r=0 Ha: r=1	0,00433	(0,0.017)	14.68×10^{1}	**11.51×10^{1}**	12.02×10^{6}
	H0: r=1 Ha: r=2	1,57624	(0,0.054)			
			Sample 2 (31 October 2007 - 31 March 2012)			
Large-mid	H0: r=0 Ha: r=1	0,0001	(0,0.017)	22.13×10^{3}	**49.77×10^{-2}**	35.65×10^{1}
	H0: r=1 Ha: r=2	0,50498	(0,0.054)			
Mid-small	H0: r=0 Ha: r=1	0,00003	(0,0.017)	11.42×10^{7}	**61.9×10^{-6}**	69.08×10^{-3}
	H0: r=1 Ha: r=2	0,63032	(0,0.054)			
Large-small	H0: r=0 Ha: r=1	0,00028	(0,0.017)	23.31×10^{3}	**38.92×10^{-2}**	33.84×10^{1}
	H0: r=1 Ha: r=2	0,55635	(0,0.054)			

Relation	Hypotheses	λ min	λ min (5%)	ghat(r) r=0	ghat(r) r=1	ghat(r) r=2
Sample 1 (31 May 1992 - 31 March 2012)						
Neutral-growth	H0: r=0 Ha: r=1	0,00676	(0,0.017)	20.34×10^{1}	**11.53×10^{1}**	15.76×10^{6}
	H0: r=1 Ha: r=2	1,55321	(0,0.054)			
Growth-value	H0: r=0 Ha: r=1	0,06301	(0,0.017)	**16.46×10^{0}**	10.77×10^{2}	19.48×10^{7}
	H0: r=1 Ha: r=2	1,78703	(0,0.054)			
Neutral-value	H0: r=0 Ha: r=1	0,00238	(0,0.017)	34.46×10^{1}	**35.73×10^{0}**	93.09×10^{5}
	H0: r=1 Ha: r=2	2,14458	(0,0.054)			
Sample 2 (31 October 2007 - 31 March 2012)						
Neutral-growth	H0: r=0 Ha: r=1	0,00001	(0,0.017)	40.52×10^{5}	**55.51×10^{-4}**	19.47×10^{-1}
	H0: r=1 Ha: r=2	0,35336	(0,0.054)			
Growth-value	H0: r=0 Ha: r=1	0,00012	(0,0.017)	24.32×10^{4}	**59.65×10^{-3}**	32.44×10^{0}
	H0: r=1 Ha: r=2	0,43998	(0,0.054)			
Neutral-value	H0: r=0 Ha: r=1	0,00001	(0,0.017)	33.63×10^{5}	**31.86×10^{-4}**	23.45×10^{-1}
	H0: r=1 Ha: r=2	0,51192	(0,0.054)			

Note: The values in bold indicate cointegrating relationships.

was detected in our study). Similarly to Kazi, Australian market was not integrated with Japan and the US. Regarding linkages between Australia and China and Hong Kong, cointegration was detected for Australia-China pair, but not for Australia-Hong Kong pair, which is consistent with results by Paramati *et al*. (2012).

Also, as shown in Table 4, international benchmark indexes are principally cointegrated on a regional basis, driven by economic integration forces: the UK market co-moves in the long run with Germany, as was previously suggested by Kasibhatla *et al*. (2006). Asian markets have been integrated with each other (Japan-China, China-Hong Kong, and China-Hong-Kong), presumably through trade and investment linkages and complementarities between the respective economies. Over 1992-2012 period, US appears to be a stand-alone market. The latter result confirms findings by Westermann (2002) and Kanas (1998), and importantly, the nonparametric cointegration analysis by Chang and Tzeng (2009) for 2000-2008 period. We note that the absence of a common trend between the US and other markets in the long run does not necessarily prevent the S&P 500 from Granger-causing other markets in the short run.

In Australia, large, mid and small cap stocks were integrated over 1992-2012. Style-wise, growth stocks were not cointegrated with value stocks, suggesting diversification benefits.

Table 4 - *Bierens Nonparametric Cointegration (International Benchmark Indexes)*

Relation	λ min	ghat(r)	λ min	ghat(r)
	Sample 1		Sample 2	
US-UK	r=0	r=0	r=1	r=1
US-Japan	r=0	r=0	r=1	r=1
US-Germany	r=0	r=0	r=1	r=1
US-Hong Kong	r=0	r=0	r=0	r=0
US-China	r=0	r=0	r=0	r=0
UK-Japan	r=0	r=0	r=1	r=1
UK-Germany	r=1	r=1	r=1	r=1
UK-Hong Kong	r=0	r=0	r=1	r=1
UK-China	r=0	r=0	r=0	r=0
Japan-Germany	r=0	r=0	r=1	r=1
Japan-Hong Kong	r=1	r=1	r=1	r=1
Japan-China	r=1	r=1	r=0	r=0
Germany-Hong Kong	r=0	r=0	r=1	r=1
Germany-China	r=0	r=0	r=0	r=0
China-Hong Kong	r=1	r=1	r=1	r=1

In the post- and during-GFC period the degree of integration of Australian and overseas markets has increased. In 2007-2012 the S&P/ASX 300 was cointegrated with all indexes (of both developed markets and China) included in this study. The co-movement between size indexes continued and cointegration was also detected between growth and value indexes.

The degree of integration of international benchmarks has also increased in the post- and during-GFC period, in particular between developed economies' markets. New relationships were detected between the US and the UK, Japan and Germany, between the UK and Japan, Germany and Hong Kong, and between Japan, Germany and Hong Kong. This stronger co-movement of asset returns across developed markets during and after GFC is likely to support the hypotheses of global financial fragility and excessive financial globalization advanced to explain severity of the recent GFC.

In 2007-2012 China's market was detached from all markets except for Hong Kong. This can be attributed to diverging economic growth trajectories of China and other large economies (Japan, USA), faster recovery path and more active stimulus policies. The surprising result (that warrants further investigation) of missing cointegration relation between China and Japan in the post-crisis period is confirmed by Kim (2011).

3.3 Principal Component Analysis

Principal component analysis assumes that series are stationary: therefore we used equity returns rather than equity prices in the analysis (the results are not reported here but available upon request).

With regard to PCA appropriateness we note that the number of observations in the first (2001-2012) and second (2007-2012) samples exceed the number of variables by factors 11.8 and 4.9 respectively. Correlation and anti-image correlation coefficients are presented in Table 5. Out of 55 correlation coefficients only 5 are not statistically significant at the 5% significance level (0.164 for df=100 in the first sample and 0.231 for df=50 in the second sample) in each sample. This implies that all variables have correlation with at least one of other variables and hence principal components analysis is appropriate.

The anti-image correlation coefficients on the main diagonal of the matrix are above the acceptable level of 0.5 in both periods, pointing to the sampling adequacy of the individual variables. Also, the results from KMO test (Table 6) show that for all variables KMO measure of sampling adequacy is above 0.7 (0.860 for sample 1 and 0.798 for sample 2), and thus the data is appropriate for PCA. The observed and p-values from the Bartlett sphericity tests are 765.731 and 0.00 for sample 1 and 365.540 and 0.000 for sample 2, indicating that at least one of the correlations between the variables is significantly different from 0. The risk to reject the null hypothesis of no correlation is lower than 0.01%.

Eleven components have been extracted. In the sample 1, the eigenvalues associated with the first, second, third and fourth components equal 5.539, 1.096, 1.000 and 0.753, are greater than 0.7 and therefore Jolliffe criterion is satisfied and these four components must be retained. The third component's eigenvalue is 0.626, which is well below 0.7. However, the scree test identifies substantial break between the first and second components, indicating that only first component should be retained. Based on the scree test two components should be retained. We note, however, that two retained components contribute only to 60.315% of the total variance, while third and fourth components that contribute 9.094% and 6.848% of the total variance would be missed. We therefore make subjective decision to retain four components, amounting to 76.25% of the total variance. The retention issue in our study demonstrates frequent conflicts between retention tests and inevitable subjective judgments.

TABLE 5 - *Correlation and Anti-image Correlation Coefficients Matrix*

Sample 1 (30 June 2001 - 31 March 2012)

	Energy	Utilities	Inform Tech	Health Care	Consumer Disc	Materials	Telecom Services	Financials	Consumer Staples	Industrials	Real Estate
Energy	.794	.310	.495	.391	.498	.753	.118	.494	.376	.555	.401
Utilities	.310	.832	.378	.391	.381	.406	.252	.557	.450	.580	.476
Inform Tech	.495	.378	.835	.446	.673	.480	.186	.505	.406	.563	.219
Health Care	.391	.391	.446	.941	.497	.359	.250	.443	.498	.461	.367
Consumer Disc	.498	.381	.673	.497	.856	.536	.236	.667	.524	.713	.507
Materials	.753	.406	.480	.359	.536	.801	.136	.470	.334	.538	.354
Telecom Services	.118	.252	.186	.250	.236	.136	.794	.111	.256	.204	.157
Financials	.494	.557	.505	.443	.667	.470	.111	.897	.540	.738	.703
Consumer Staples	.376	.450	.406	.498	.524	.334	.256	.540	.930	.505	.443
Industrials	.555	.580	.563	.461	.713	.538	.204	.738	.505	.913	.669
Real Estate	.401	.476	.219	.367	.507	.354	.157	.703	.443	.669	.825

Sample 2 (1 October 2007 - 31 March 2012)

	Energy	Utilities	Inform Tech	Health Care	Consumer Disc	Materials	Telecom Services	Financials	Consumer Staples	Industrials	Real Estate
Energy	.717	.360	.624	.325	.603	.823	.156	.510	.404	.545	.470
Utilities	.360	.760	.553	.432	.562	.516	.372	.586	.532	.637	.480
Inform Tech	.624	.553	.807	.335	.735	.525	.197	.595	.532	.626	.342
Health Care	.325	.432	.335	.891	.461	.252	.286	.464	.560	.397	.460
Consumer Disc	.603	.562	.735	.461	.826	.573	.217	.813	.688	.860	.660
Materials	.823	.516	.525	.252	.573	.727	.203	.457	.381	.570	.435
Telecom Services	.156	.372	.197	.286	.217	.203	.827	.150	.296	.228	.228
Financials	.510	.586	.595	.464	.813	.457	.150	.901	.578	.799	.755
Consumer Staples	.404	.532	.532	.560	.688	.381	.296	.578	.856	.521	.498
Industrials	.545	.637	.626	.397	.860	.570	.228	.799	.521	.861	.724
Real Estate	.470	.480	.342	.460	.660	.435	.228	.755	.498	.724	.851

Note: 5% critical value for one tail testing the significance of Pearson's correlation coefficient with n=100 is 0.163, and with n=50 is 0.231. The anti-image correlation coefficient as a measure of sampling adequacy is MSAi = $\sum_{i\neq j} r_{ij}^2 / (\sum_{i\neq j} r_{ij}^2 + \sum_{i\neq j})$, where r_{ij}^2 is a simple correlation coefficient between two variables, and a_{ij}^2 is a partial correlation coefficient.

TABLE 6 - *KMO and Bartlett Tests*

Sample 1			Sample 2		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,860	Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,798
Bartlett's Test of Sphericity	Approx. Chi-Square	765,731	Bartlett's Test of Sphericity	Approx. Chi-Square	365,540
	Sig.	,000		Sig.	,000

In the sample 2, using same retention methods four components are retained with eigenvalues equal to 6.089, 1.164, 0.962 and 0.704, accounting to 80.993% of the cumulative variance.

Regarding communality of returns, the initial communalities are set equal to one, meaning that the common factors explain all of the variance in equity market returns among sub-indexes. Also, the extracted communalities indicate that the variances of returns of all equity market segments are relatively well explained (for sample 1, over 80% of the variance of energy, materials, financials and real estate, and approximately 60% of utilities, health care, and consumer staples; for sample 2, over 70% of the variance of all variables, and over 60% of the variance of utilities).

The rotated component loadings matrix is finally presented (Table 7). The highest component loadings in each component (i.e. the loadings with value above 0.5) are indicated in bold. The variables (equity market segments) that have high component loadings in each principal component and that fall within specified range move closely together and hence provide little diversification benefits. The second highest component loadings that have value above 0.4 (and satisfy significance condition proposed by Stevens) but less than 0.5 are indicated in italics.

Regarding sample 1, the highest loadings in the first component belong to utilities, financials, industrials and real estate, indicating that these sectors are highly correlated and are bad diversifiers to one another. The highest loadings in the second component are attributed to information technologies, health care, consumer discretionary and consumer staples (0.771, 0.702, 0.684 and 0.604). The highest loadings in the third component are materials and energy (0.872 and 0.845), while the only highest loading in the fourth component belongs to telecommunications (0.950). The diversification benefits are therefore maximized if the following pairs of sectoral stocks are included into the portfolio: energy and telecommunication services, materials and utilities, or industrials and health care. Thus, three clusters of highly correlated variables can be identified, corresponding to three broad economic sectors in Australia ('finance and industry', 'consumer goods economy', and 'resource economy'), while telecommunication services are an outlier.

Table 7 - *Rotated Component Matrix*

	Sample 1				*Sample 2*			
Component	1	2	3	4	1	2	3	4
Energy	,239	,241	**,845**	,027	,243	**,877**	,146	,031
Utilities	**,662**	,211	,174	,285	*,478*	,331	,334	*,427*
Inform Tech	,063	**,771**	*,420*	,012	,285	**,676**	*,419*	,020
Health Care	,248	**,702**	,106	,203	,225	,065	**,818**	,173
Consumer Disc	,384	**,684**	,364	,020	**,671**	*,483*	*,420*	,021
Materials	,236	,200	**,872**	,082	,270	**,864**	,025	,184
Telecom Services	,080	,149	,057	**,950**	,066	,071	,161	**,943**
Financials	**,748**	*,419*	,267	-,087	**,821**	,288	,337	-,009
Consumer Staples	*,461*	**,604**	,030	,189	,334	,260	**,754**	,136
Industrials	**,672**	*,425*	,389	,037	**,808**	*,407*	,203	,116
Real estate	**,885**	,109	,163	,021	**,858**	,145	,185	,140

Note: The highest component loadings are indicated in bold. The second highest component loadings for the relevant variables that satisfy significance condition proposed by Stevens (i.e. the value greater than 0.4) are indicated in italics.

In sample 2, the highest loadings in the first component included financials, industrials and real estate, and also consumer discretionary, while the highest loadings in the second component also included information technologies. Telecommunication services continued to be a good diversifier. Thus additional pairs could diversify portfolio in the post-GFC period: consumer staples and consumer discretionary, or health care and information technologies. We can argue however that GFC did not cause substantial havoc in sectoral index relations and financial and economic structure of Australia in general, with principal relations in each cluster (e.g. high correlation of financials and industrials, or energy and materials) remaining unchanged.

Rotated component matrix also shows the relative impact of other sectoral indexes on the return of a particular index. For instance, in sample period 1 the returns of information technologies firstly depended on health care and consumer goods (0.771) and secondly on energy and materials (0.420), with the values of the first and second highest loadings being statistically significant. In sample period 2 the relative impacts reversed – information technologies firstly depended on energy and materials (0.676), and secondly on health care (0.419).

4. Conclusion

The results of nonparametric Bierens cointegration lend credence to the presence of a greater number of cointegrating relations in the during- and post-GFC period, suggesting that diversification opportunities dwindle for Australian (but not necessarily international) investors. Specifically, Australian investors could diversify away from S&P/ASX 300 index towards the S&P 500, Nikkei 225, DAX 30 and Hang Seng indexes or between Australian growth and value stocks during 1992-2012 period, whereas after October 2007 such strategies were no longer viable. European, US and Asian investors could diversify between the US index and other indexes and between European and the US indexes and Shenzhen Composite during 1992-2012, while after October 2007 diversification was possible between Shenzhen Composite and developed economies' indexes, and between S&P 500 and Hang Seng. Australian sectoral indexes formed three distinct clusters, roughly representing major economic sectors, in both sample periods, while telecommunication services index was an outlier (and hence a perfect diversifier).

The analysis performed in this paper can be extended in four directions. Firstly, the consistency should be ensured and contradictions identified between parametric (Johansen and Engle-Granger) and nonparametric methods in the Australian equity market context. Secondly, the nonparametric cointegration of Australian and international size and style indexes can be examined (e.g. between small cap stocks). Thirdly, a greater number of markets can be included in the analysis (e.g. ASEAN and NZ indexes). Finally, principal component analysis of sectoral indexes can be performed for other countries' markets or in the ETF context.

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ABSTRACT

This study investigates the portfolio diversification possibilities among Australian sectoral, size and style indexes and between Australian aggregate equity index and selected international indexes. Two analytical methods are used – nonparametric cointegration that appears to be the most appropriate for the financial data analysis, and principal component analysis (PCA) that is suitable for detecting relations among a large number of variables and for clustering co-moving variables. Having identified linear and non-linear unit roots in the time series data we show that based on Bierens' nonparametric cointegration the number of cointegrating relations between respective indexes increases (and the portfolio diversification opportunities diminish) in the post-GFC period (2007-2012) relative to the historic average (1992-2012). Regarding sectoral diversification, the PCA results suggest that sectoral relations underwent minor changes in the post-GFC period with few additional diversification opportunities appearing.

Keywords: Nonparametric Cointegration, Principal Component Analysis, Portfolio Diversification, Non-linear Unit Root

JEL Classification: C14, C58, G11, G15

RIASSUNTO

Un approccio non-parametrico alla diversificazione del portafoglio: il caso del mercato azionario australiano

In questo studio si esaminano le possibilità di diversificazione del portafoglio tra indici australiani settoriali, dimensionali e di stile di gestione e tra indici aggregati australiani e indici internazionali. Vengono usati due metodi – la cointegrazione non-parametrica, che sembra essere la più appropriata per l'analisi dei dati finanziari, e l'analisi delle componenti principali (PCA) che consente di individuare le relazioni esistenti tra numerose variabili e di individuare gruppi di variabili mobili. Dopo aver identificato le radici unitarie lineari e non lineari nei dati *time series* lo studio mostra che sulla base della cointegrazione non-parametrica di Bierens il numero di relazioni cointegrate tra i rispettivi indici aumenta (e le opportunità derivanti dalla diversificazione del portafoglio diminuiscono) nel periodo post-GFC (2007-2012) relativamente alla media storica (1992-2012). Per quanto riguarda la diversificazione settoriale, i risultati della PCA suggeriscono che relazioni settoriali hanno subito cambiamenti modesti nel periodo post-GFC con poche opportunità ulteriori di diversificazione.