Structural breaks, Cointegration and B Share Discount in Chinese Stock Market*

Dayong Zhang

Department of Economics, the University of Birmingham
Birmingham, UK B15 2TT
E-mail: dxz136@bham.ac.uk

David G. Dickinson

Department of Economics, the University of Birmingham
Birmingham, UK B15 2TT
E-mail: d.g.dickinson@bham.ac.uk

and

Marco Barassi

Department of Economics, the University of Birmingham
Birmingham, UK B15 2TT
E-mail: m.r.barassi@bham.ac.uk

Chinese Stock market has a special feature in that the stocks are diversified according to the type of investors. In most of the cases, these two types of shares have the same fundamentals that companies issue B shares also issue A shares. Therefore, we are expecting that these two share prices have the similar value and a long run relationship. However, empirical investigations do not support either of them. People find persistent discount of B share over A share price; standard cointegration analysis failed to prove the long run relationship. In this paper, we extend the current literature by allowing for structural breaks. We show there are two structural breaks exist, corresponding to the regulatory shift in 2001 and the Asian financial crisis. After corrections of structural breaks, we would be able to reconcile the long run relationship. Furthermore, we propose a noise-trading hypothesis in explaining the B share discount and the pattern of structural breaks.

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1. INTRODUCTION

The stock market in China has a special feature in the sense that it is divided not only geographically (there are two official stock exchange–Shanghai Stock Exchange and Shenzhen Stock Exchange); but also diversified according to the type of investor. Originally, the A share market is for domestic Chinese residence denominated in Chinese RMB Yuan, where as the B share is for foreign investors, denominated in US dollars. This situation was changed only recently in February 2001, when domestic investors were allowed to trade in the B share market. One company can issue A share as well as B share at the same time. For about 1250 listed companies in two exchanges, only 75 issued both A and B shares. A shares are traded more actively than B shares, where turnovers of A shares are much higher than B shares. A summary of key statistics relating to these two types of shares of Shanghai Stock Exchange [1](SSE thereafter)is provided in Table 1. Clearly, we can see there are much more accounts in A share market than B share market, which can be one of the reasoning for the following discussions.

TABLE 1.

Some basic statistics of A and B share in SSE

	A share	B share
Number of Listed	821	54
Total number of shares issued	4602.18	100.17
Number of non-institutional Investor accounts	37.41	0.9986

* Data source: Shanghai Stock Exchange, www.sse.com.cn, 2005; ** Number of shares are in 100 millions, whereas number of investor accounts are in millions

Since companies issuing B share normally also issue A share, A share and B share then have the same fundamentals, arguably, it suggests that they should be priced in the same level. However, empirical evidence does not support this argument. A great deal of literatures have found that B share prices are persistently discounted relative to A share prices.

[1]Shanghai Stock Exchange established in Dec. 19, 1990. It has 831 listed companies with total market capitalization around 2717 billions of RMB. Source: www.sse.com.cn

Earlier studies such as Bailey [3] provide evidence of price discounts on B shares relative to A shares. Fernald and Rogers [8] argue that the discounts on B shares are due to the fact that there are few domestic financial assets available in China. Bergstrom and Tang [4] also considered the problem of B share discounts. In a sample of 79 companies, the average daily price discount of B shares to A shares exceeded 69% during the period Jan. 1995 to Aug. 1999. They suggest a variety of reasons for this significant discount such as information asymmetry,liquidity effects and exchange risks.

Ma [12] uses cross sectional method to study share prices data for 38 companies that have both A and B shares listed in two exchanges. He found that the differences between prices of A and B shares are correlated with investors' attitudes toward risk. He also considered that regulatory changes might explain the variability of B shares' discounts. Chu [5] found prior price movements affect prices changes in A and B markets and the direction of information flow is mainly from B share markets to A share markets. Sjoo and Zhang [14] argue that this relationship holds only for Shanghai stock exchange. Groenewold et al. [10] explored weak and semi-strong efficiency for both A and B shares traded on both exchanges for the period 1992-2001. They find evidence of departures from weak efficiency in the form of predictability or returns on the basis of their own past values, and also the predictability from A to B returns in Shanghai but no cross causality in Shenzhen.

Almost all those literature acknowledged the phenomena of B share discount. However, their explanation are well diversified. Moreover, they overlooked one important feature of this problem, which could be very instructive, that is the possible structural changes in A share and B share long run relationships. B share discount is persistent, also it is varying. In this paper, our empirical analysis based on cointegration test has found no evidence of a stable long run relationship. As inspired by Ma [12], we investigate the possibility of structural changes in this relationship. Using the technique of Gregory and Hansen [9], we found two breaks over the last decades of SSE data. Apart from the regulatory changes also discussed in Ma [12], the Asian financial crisis played an important role in affecting A and B share relationship. Furthermore, by analyzing the properties of these breaks, we propose a Noise trading hypothesis to explain B share discount.

The organization of this paper is the follows: section 2 introduce the techniques applied; section 3 shows how we construct indices and statistical features of our dataset; section 4 outlines empirical results of the cointegration analysis; section 5 discuss the results and concludes.

2. METHODOLOGY

2.1. Residual based cointegration test with structural break

Gregory and Hansen [9] considered the idea of testing cointegration that allows for possible structural break. Their method is residual based technique. They suggest three models: level shifts, level and trend shifts and regime shifts. The statistics are designed to test the null of no cointegration against the alternative of cointegration in the presence of a possible regime shift. The shift point is assumed to be unknown and will be tested in the model.

These models can be shown as:

Model I, Standard cointegration

$$y_t = \mu_1 + \alpha_1 x_t + \epsilon_t \tag{1}$$

Model II. Cointegration with level shift (CC)

$$y_t = \mu_1 + \mu_2 DB_t + \alpha_1 x_t + \epsilon_t \tag{2}$$

Model III. Cointegration with level shift and trend (CT)

$$y_t = \mu_1 + \mu_2 DB_t + \alpha_1 x_t + +\beta_t + \epsilon_t \tag{3}$$

Model IV. Cointegration with regime shift (CS)

$$y_t = \mu_1 + \mu_2 DB_t + \alpha_1 x_t + \alpha_2 x_t DB_t + \epsilon_t \tag{4}$$

The definition of dummy variable DB is that $DB_t = 1$ if $t > T_b$ and zero otherwise, here T_b is the breaking point.

Gregory and Hansen [9] constructed three statistics for those tests: ADF^*, Z_α^* and Z_t^*. They are corresponding to the traditional ADF test and Phillips type test of unit root on the residuals, but with all the possible breaking points considered over the sample. Then the test statistics are defined as the minimum value, and breaking points is where the minimum value is acquired. Alternatively, these can be written as:

$$ADF^* = \inf ADF(\tau) \tag{5}$$

$$Z_\alpha^* = \inf Z_\alpha(\tau) \tag{6}$$

$$Z_t^* = \inf Z_t(\tau) \tag{7}$$

These test statistics are not following standard distribution, thereby we cannot use standard critical values for residual based cointegration tests. Gregory and Hansen suggest to use response surface function to construct critical values, which will be applied in this paper.

2.2. Multiple breaks

Another technique applied in our paper is the recent contribution of Bai and Perron [1] and [2]. They considered both theoretical issues and empirical applications of multiple structural breaks in linear models. The existence of multiple structural breaks is attractive especially in long run time series analysis where different factors might affect the behaviour of tested data in different time period. Bai and Perron's model is obtained under a general framework of partial structural changes, which allows a subset of the parameters not to changes. It can be expressed as a compact matrix form:

$$\mathbf{Y} = \mathbf{X}\beta + \overline{\mathbf{Z}}\delta + \mathbf{U} \tag{8}$$

Here $\mathbf{Y} = (y_1, y_2, ..., y_t)'$, $\mathbf{X} = (x_1, x_2, ..., x_t)'$, $\mathbf{U} = (u_1, u_2, ..., u_t)'$, $\delta = (\delta_1, ...\delta_{m+1})'$, and $\overline{\mathbf{Z}}$is the matrix capture structural breaks, which diagonally partitions $\mathbf{Z}$ at $(T_1, T_2, ...T_m)$; or alternatively with m partitions, it can be written as: $\overline{\mathbf{Z}} = diag(\mathbf{Z_1}, \mathbf{Z_2}, ..., \mathbf{Z_m})$.

By minimizing the sum of squared residuals based on the least squares principle, we could get the break point estimators as global minimizes of the objective function. Since testing for multiple break may generate a great deal of computation burden, Bai and Perron use an algorithm based on the principle of dynamic programming to estimate general partial structural change models. A Gauss code performing this estimation is provided. They also provide several ways to test and confirm the number of breaks and discussed how to construct confidence intervals. In our estimation, due to the fact that these series are nonstationary, most of the test statistics proposed in Bai and Perron's original paper are not applicable. Thus, we do not intend to use this method to consider the issue of statistical tests or confidence intervals. However, by minimizing the sum of squared residuals and selecting results with information criteria, Bai and Perron's technique can provide a consistent estimation of possible breaks and thus provide useful information to our study here.

3. DATA DESCRIPTION

We collect data from Taiwan Economic Journal Asia Emerging Market Data Base. In order to have similar underlying features about A share and B shares, we construct our own indices. There are thirty stocks[2] have been selected based on the following criteria: stocks listed in SSE; data available for the full sample period; the underlying companies issuing both A and B share.

[2]See Table 2 for a full list of all stocks in the portfolio.

TABLE 2.
List of selected stocks

Name of the stock	A share Code	B share Code
Auto instrument	600848	900928
Baosight software	600845	900926
China Textile	600610	900906
Chlor-Alkali chemical	600618	900908
Dajiang	600695	900919
Daying	600844	900921
Dazhong Transportation	600611	900903
Erfangji	600604	900902
First pencil	600612	900905
Friendship	600827	900923
Haixin	600851	900917
Highly	600619	900910
Huaxin Cement	600801	900933
Jinjiang Investment	600650	900914
Jinqiao	600639	900911
Lianhua fibre	600617	900913
Lujiazui	600663	900932
Material Trading centre	600822	900927
Phoenix	600679	900916
SH. Sanmao	600689	900922
Sanjiu Development	600614	900907
Shanggong	600643	900924
Shanghai Diesel	600641	900920
SH Electric applicances	600835	900925
Shanghai forever	600618	900915
SH. Posts Telecoms	600680	900930
SVA electron	600602	900938
Tyre Rubber	600623	900909
Wingsung Data	600613	900904
Yaohua Pilkington Glass	600819	900918

* Data source: Taiwan Economic Journal Asia Emerging Market Data Base;

The full sample period is January 1995 to April 2005, which leaves totally 124 observations. We use January 1995 as base date to construct both equal weighted indices and value weighted indices. They are shown in Figure 1 and 2. There is a caveat that B share is denominated in US dollars. However, we do not explicitly include this into our data analysis. The reason is that due to foreign exchange policy in China, the exchange rate between US dollars and RMB Yuan is reasonably stable.

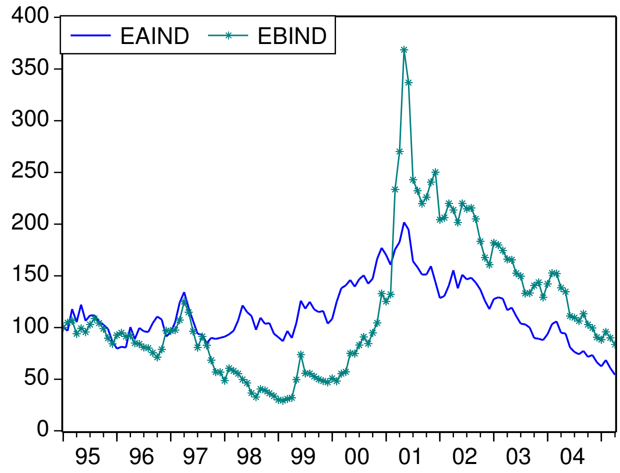

FIG. 1. Equal Weighted Indices

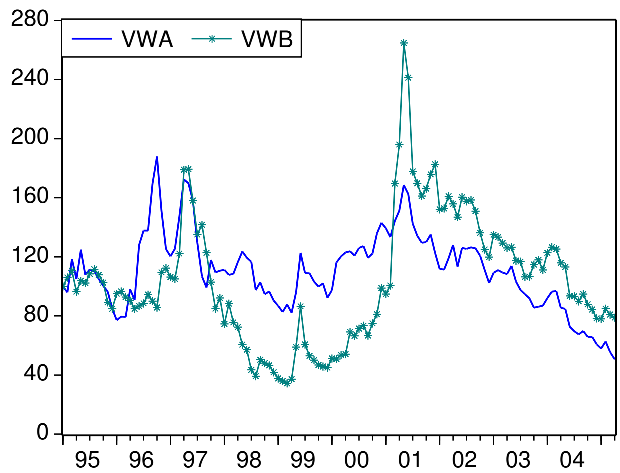

FIG. 2. Value Weighted Indices

We should be aware of the fact that in the diagrams, they are only indices and not suggesting the exact price differences. Direct observations from these diagrams of equal weighted and value weighted indices show that they are not likely to have those long run relations in full sample. However, it can be shown that two possible breakpoints around 30th and 74th observation might be the reason, which corresponding to the date June, 1997 and February 2001.

TABLE 3.

Descriptive statistics

Item	EWA index	EWB index	VWA index	VWB index
Mean	113.8867	115.1453	110.4417	103.6505
Median	106.4746	96.74705	109.8023	97.73975
Maximum	201.6682	368.579	187.9837	264.8024
Minimum	4.3308	29.3476	50.6033	34.448
Std. Dev.	29.15287	65.76468	25.90454	42.8546
Skewness	0.626471	1.206933	0.253819	0.807526
Kurtosis	3.11473	4.502971	3.329231	4.07038
Jarque-Bera	8.178966	41.77597	1.891462	19.39622
Number of observations	124	124	124	124

TABLE 4.

Results of Unit root tests

	ADF		PP	
	Level	First Difference	Level	First Difference
EW A Index	-1.32253	-10.8731***	-1.20715	-10.9945***
EW B Index	-1.98978	-8.76536***	-1.72687	-8.5446***
VW A Index	-2.39884	-9.70088***	-1.91366	-10.0178***
VW B Index	-2.48613	-8.91876***	-2.16172	-8.7166***

Note: ** represents significant at 5% level, *** represents significant at 1% level. Critical values are given by MacKinnon [13].

Table 3 and 4 show some descriptive statistics of the indices and standard unit root tests. A share indices have lower volatility than B share indices. All indices have some positive skewness over the full sample period. Based on ADF and PP test, we can conclude that all these indices are nonstationary or I(1) series.

4. EMPIRICAL RESULTS

4.1. Granger causality and Impulse response

In order to proceed to investigate the long run relationship between A and B indices, we may interested in finding out the causality structure between them. Additionally, for residual based cointegration analysis, it is necessary to determine which of the indices is treated as dependent variable. Since there are no explicit theory for us to decide the relation between A and B share prices, we need refers to the data themselves.

There are two ways of showing the causality structure: Granger causality and Impulse response. Based on a two variable VAR system, we found (See Table 5)that for Equal weighted indices (EA and EB), EA does Granger cause EB (only at 10% level) but not the opposite; for Value weighted indices (WA and WB), there is no Granger causality for both sides. However, since our series are nonstationary, standard Granger causality test may not be valid. So we may concentrate on the results of Impulse response (See Figure 3and 4).

TABLE 5.

Test for Granger Causality

Null Hypothesis:	F-Statistic	Probability
EB does not Granger Cause EA	2.4434	0.12065
EA does not Granger Cause EB	3.26679	0.0732
Null Hypothesis:	F-Statistic	Probability
WB does not Granger Cause WA	2.16925	0.11884
WA does not Granger Cause WB	1.19346	0.30683

Note: VAR lag structural is selected using information criteria

Twelve months period forward response in shown and a twice-standard error bonds is provided in the diagrams. We may notice that the shocks to those series are not die out quickly even after 12 months. This is reasonable result since the series we are

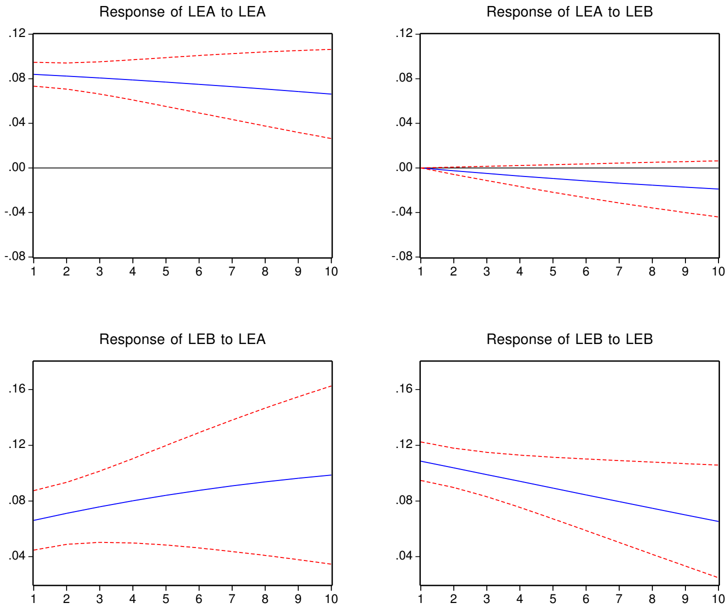

FIG. 3. Impluse for Log Value Weighted Indices

dealing with are nonstationary. Shocks to those series tend to persist. For both equal weighted and value weighted indices, we found similar results that B share indices are responding to the shocks on A share, where the opposite statement is not true. The response of A share indices to the shocks on B share indices is statistically not significant. Thereby we could conclude from this evidence that B share indices should be dependent variable in our residual based cointegration test and A share indices should be exogenous variable. The reason for this situation will be further examined in the last section.

4.2. Standard Cointegration Analysis

We perform standard cointegration analysis for A share indices and B share indices in this subsection for the full sample period. Table 6 shows that neither the residual based nor the Johansen VAR based technique could reject the null of no cointegration between these indices. The results here are just a

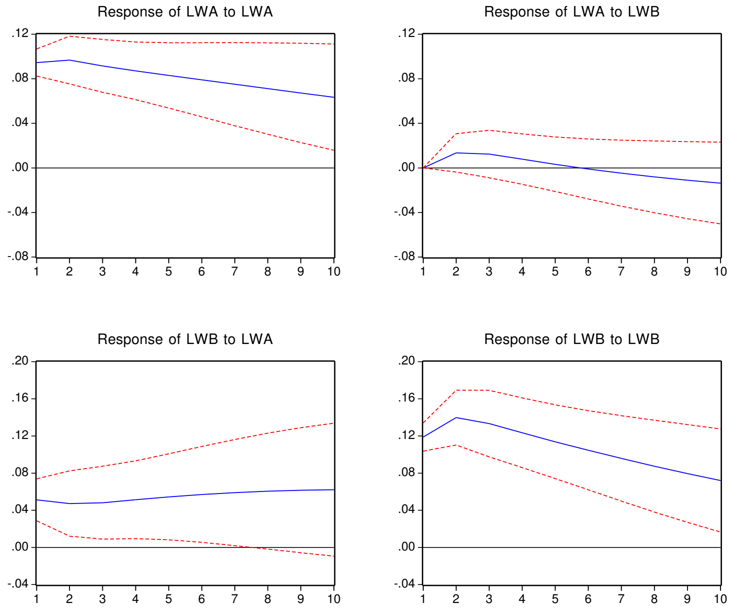

FIG. 4. Impulse for Log Value Weighted Indices

confirmation of what we saw in the diagram plots. No long run relations present in A share and B share indices even they share the same fundamentals is interesting. Either market is not efficient because of regulations, government control, market segmentation and other possible reasons mentioned earlier by other researchers, or there might be some other information haven't been revealed.

4.3. Cointegration test with structural break

Consider the possibility of structural breaks within the full sample period, one of the major events would be 28th of February 2001, when Chinese government change the trading rules. Domestic investors are then allowed to trade on B shares. This would be a quite significant event during our sample period. As we saw from the diagrams in Figure 1 and Figure 2, both equal weighted and value weighted indices of B share prices have a significant increase around the early stage of 2001. This can be an

TABLE 6.
Standard cointegration test results

Panel A	Residual based test		
	Deterministic trend	ADF	PP
	Intercept	-0.98555	-1.08813
Equal weighted	Intercept and trend	-1.63386	-1.72839
	None -0.99218	-1.09478	
	Intercept	-1.59285	-1.59285
Value weighted	Intercept and trend	-1.92238	-1.92238
	None	-1.60023	-1.60023
Panel B	Johansen test		
	Number of CE	Max-eigenvalue	Trace statistics
Equal weighted	None	5.988237	9.161201
	At most 1	3.172964	3.172964
Value weighted	None	4.847163	7.861862
	At most 1	3.014699	3.014699

Note: Critical values for residual based cointegration test are nonstandard critical values for ADF and PP tests.

important evidence of possible break in the long run relations between A and B shares. Furthermore, Asian financial crisis happened in 1997 will also have important impact on this relation especially B share market. Since B share is denominated in US dollars. Financial crisis cause a big capital loss in many Southeast Asian countries and international capital market as well, not surprisingly, a downward impact on international investment.

Technically, if structural changes are ignored where they are indeed presence, the standard cointegration tests are biased. To consider this potential problem of standard cointegration analysis, we first look at Gregory and Hansen test with possible one break in the cointegrating relation. Test results are presented in Table 7. None of these tests provide significant evidence in favour of a cointegration relation even allowing for structural breaks between A and B indices. The reason for this situation might be explained by observing the graphic results of this test, see Figure 5 and Figure 6, in which we present only Phillips type test of Z_a. We observe two local minimums instead of one, which suggests two breaks might make more sense in this situation, thereby only allow one break cannot solve the problem.

TABLE 7.

Gregory and Hansen test results for full sample

		EW Indices		VW Indices	
	Model type	Test statistics	Break date	Test statistics	Break date
ADF	CC	-2.6261	2000.12	-3.31988	2001.07
	CT	-4.39566	2000.11	-4.40506	2000.11
	CS	-2.8638	2000.12	-3.3126	2000.11
Z_a	CC	-12.6031	2000.12	-17.6733	2001.06
	CT	-32.7209	2000.12	-34.9486	2000.12
	CS	-14.8444	2000.12	-18.606	2001.06
Z_t	CC	-2.67211	2000.12	-3.07708	2001.06
	CT	-4.2783	2000.12	-4.39286	2000.12
	CS	-2.88845	2000.12	-3.19886	2001.06

Note: we obtain critical values from Gregory and Hansen [9] Table 1. For significant level 1%, we give a ***, level 5% with ** and 10% a *.

4.4. Multiple breaks

Graphic views of Gregory and Hansen tests provide the indication of existing two breaks in the whole sample period, we now exploit this situation based on Bai and Perron [1] and [2] (BP thereafter). The series in considering are nonstationary, so there might be some problems in traditional regression analysis. In BP, we consider a linear regression, instead of looking at some standard inference, we concentrate on two criteria: SSR (Sum of Squared Residuals) and Information criteria. As mentioned in BP, these criteria are consistent even the series are nonstationary. BP's model allow us to consider partial structural break as well as full structural break. We consider a simple case with only mean shifts in a linear regression between A and B indices, where we allow maximum 5 breaks and a trimming value of 0.15. With the assistant of information criteria, we conclude

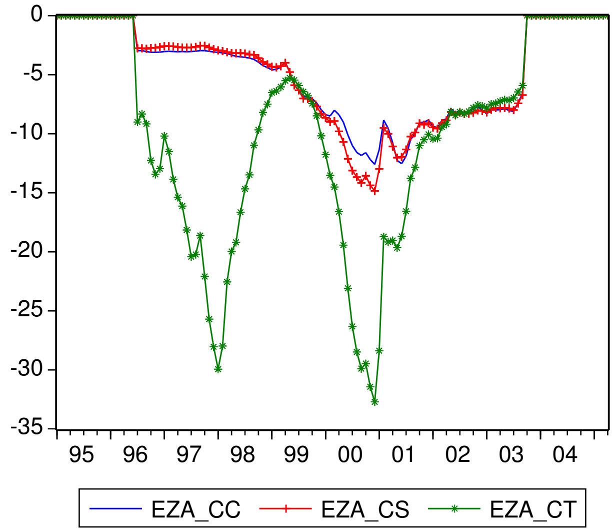

FIG. 5. Z_a **statistics for the model of CC, CT and CS: Equal weighted indices**

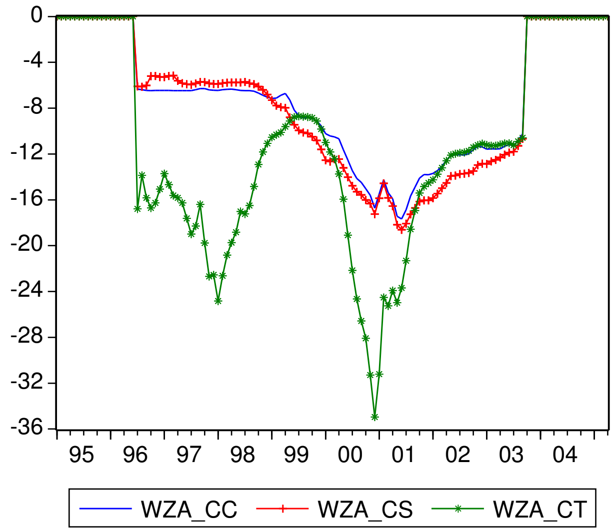

FIG. 6. Z_a **statistics for the model of CC, CT and CS: Value weighted indices**

that two breaks are preferred in both cases, see Table 8 and Table 9. They are roughly consistent with the indication from earlier analysis. Break points are corresponding to the time of the 1997 Financial crisis and the regulatory changes in 2001.

TABLE 8.
Multiple breaks test for Equal weighted indices

No. of Breaks	SSR	Break point	BIC	LWZ
0	31.40099	N/A	-1.3734	-1.3653
1	11.4016	2001.02	-2.3088	-2.2309
2	3.2497	1998.01 2001.02	-3.4862	-3.3383*
3	2.9899	1998.01 2001.02 2003.09	-3.4918	-3.2735
4	2.6848	1996.06 1998.03 2001.02 2003.09	-3.5217	-3.2328
5	2.4706	1996.06 1998.02 1999.08 2001.02 2003.09	-3.5271*	-3.1672

Note: Optimum SSR selected on information criteria are shown with a *

4.5. Sub-sample evaluation

With the results of above structural breaks analysis, we now proceed to consider sub-sample properties. Two sub-samples are considered: 1995:01 to 2001:01 and 1998:03 to 2005:04 with sample size of 73 and 86 respectively. The first one covers Asian financial crisis but excluding policy changes, and the second one excluding the crisis but including policy changes.

Since the sample size is relatively small, it is not proper to use the asymptotic critical values provided by Gregory and Hansen in their original paper. We work out exact critical values with a simple Monte Carlo simulation similar to them based on re-

TABLE 9.

Multiple breaks test for Value weighted indices

No. of Breaks	SSR	Break point	BIC	LWZ
0	19.67168	N/A	-1.8411	-1.833
1	8.9456	2001.02	-2.5514	-2.4735
2	3.2227	1998.03 2001.02	-3.4946*	-3.3466*
3	3.0031	1996.06 1998.03 2001.02	-3.4874	-3.2691
4	2.9639	1996.06 1998.03 2001.02 2003.09	-3.4228	-3.1339
5	2.949	1996.06 1998.02 1999.08 2001.02 2003.09	-3.3501	-2.9902

Note: Optimum SSR selected on information criteria are shown with a *

sponse surface to solve this problem. The results of our sub-sample tests are presented in Table 10.

It is clear that for the second sub-sample, we found consistent and significant evidence that those two series are cointegrated with one single break happens at February 2001. The break point is right the time that policy change happens. Further diagram illustration is provided in the appendix. On the other hand, the evidence from first sub-sample test is not that conclusive. Some test statistics are not significant; some are only marginally be able to reject the null of no cointegration against the alternative of cointegrated with a single break.

4.6. Cointegration test with dummy variables

In this step of analysis, we construct two dummy variables and according to our analysis about multiple breaks and then

TABLE 10.

Gregory and Hansen test results for sub-samples

		Panel A	**Sample I**		
		EW Indices		VW Indices	
	Model type	Test statistics	Break point	Test statistics	Break point
	CC	-4.83962*	1998:02	-4.27211	1998:01
ADF	CT	-4.74469	1998:02	-4.50921	1998:01
	CS	-5.72678*	1998:01	-4.97725	1998:03
	CC	-34.6539*	1998:01	-25.9374	1998:01
Z_a	CT	-34.0865	1998:01	-27.4172	1998:01
	CS	-40.5427**	1998:01	-32.3964	1998:01
	CC	-4.53622*	1998:01	-3.75177	1998:01
Z_t	CT	-4.47239	1998:01	-3.90581	1998:01
	CS	-5.06478*	1998:01	-4.42923	1998:01
		Panel B	**Sample II**		
		EW Indices		VW Indices	
	Model type	Test statistics	Break point	Test statistics	Break point
	CC	-5.42337**	2001:02	-6.27126***	2001:02
ADF	CT	-6.36525***	2001:02	-6.15276***	2001:02
	CS	-7.06112***	2001:02	-6.27633***	2001:02
	CC	-43.3553**	2001:01	-48.1196***	2001:02
Z_a	CT	-47.5665**	2001:02	-47.0772**	2001:02
	CS	-56.5921***	2001:02	-53.2042***	2001:02
	CC	-5.28933**	2001:01	-5.75882***	2001:02
Z_t	CT	-6.40302***	2001:02	-5.91025***	2001:02
	CS	-7.10722***	2001:02	-6.27584***	2001:02

Critical values are calculated through a simple Monte Carlo simulation with 10000 experiments. They are available upon request. For significant level 1%, we give a ***, level 5% with ** and 10% a *.

perform the standard residual based cointegration test. The dummy variables are corresponding to the date of March 1998 and Feburary 2001. It is worth to note that including two dummy variables in the system might affect the distribution and critical values in cointegration test. We then construct exact critical values with Monte Carlo simulation, where two dummy variables are considered. Table 11 shows all the test statistics. In all three situations considered, we are able to reject the null of no cointegration. A further confirmation is made by Johansen type test, where we including two dummy variables as exogenous regressors in the VAR. Both maximum eigenvalues and trace statistics are significantly rejecting the null or no cointegration in favour of one cointegration relationship.

TABLE 11.

Residual based cointegration test with dummy variables

ADF statistics	T1	T2	T3
Equal weighted	-5.73817***	-5.90544***	-7.19458***
Value weighted	-5.45765***	-5.45619***	-5.73564***

Note: 1. We perform cointegration test for three alternatives: T1 represents break in the intercept without time trend, T2 represents break in the intercept with time trend and T3 represents break in the intercept as well as cointegrating relationship. Critical values are calculated with 50000 experiments for out sample size and dummy variables.;
2. For T1, critical values are: -4.8894446 -4.2721604 -3.9746529 for 1%, 5% and 10% respectively. For T2, critical values are: -5.2491579 -4.6214992 -4.3004059 or 1%, 5% and 10% respectively. For T3, critical values are: -5.5905692 -4.9154111 -4.5760866 for 1%, 5% and 10% respectively.;
3. The ADF statistics are performed to OLS residuals with only intercept considered. Optimal lag order for the tests is selected with the help of BIC

TABLE 12.

Johansen test with dummy variables as exogenous variables

	Number of CE	Max-eigenvalue	Trace statistics
Equal weighted	None	29.29809***	30.12533***
	At most 1	0.827233	0.827233
Value weighted	None	34.60031***	38.07972***
	At most 1	3.479413	3.479413

Note: For significant level 1%, we give a ***, level 5% with ** and 10% a *. For Johansen test, we consider a structural break in constant only for T1 (Breaks in the intercept without trend), which means there are two intercept shift at associated break points.

4.7. Error Correction Model (ECM) representation

For a two-step cointegration analysis procedure proposed by Engle and Granger [7], since we found cointegration relationship allowing for structural breaks, then we can estimate an

ECM equation. Table 13 presents the ECM from residual based analysis. For a simple ECM, we are estimating the following equation:

$$\Delta y_t = \beta_0 + \beta 1 \Delta x_t + \beta_2 ECM_t + \epsilon_t \tag{9}$$

TABLE 13.

ECM Representation with two dummy variables

Panel A: ECM for Equal weighted indices
$ECM_t = y_t + 0.88 + 0.69 * dum1 - 1.16 * dum2 - 1.16x_t$
$\Delta y_t = 0.002 + 0.832\Delta x_t - 0.215ECM_{t-1} + \epsilon_t$ (0.248)[0.243]; (7.393)[5.801]; (-3.83)[-2.378] $R^2 = 0.351$, Adjusted $R^2 = 0.340$, $Q(30) = 50.664$ ($Pvalue = 0.01$)
Panel B: **ECM for Value weighted indices**
$ECM_t = y_t - 0.64 + 0.57 * dum1 - 0.89 * dum2 - 0.84x_t$
$\Delta y_t = 0.001 + 0.602\Delta x_t - 0.238ECM_{t-1} + \epsilon_t$ (0.118)[0.090]; (5.646)[2.770]; (-4.954)[-4.203] $R^2 = 0.296$, Adjusted $R^2 = 0.284$, $Q(30) = 30.415$ ($Pvalue = 0.165$)

Note: numbers in parentheses are t-statistics and numbers in square brackets are t-statistics with Newey-west HAC covariance matrix.

Here the ECM term contains two dummy variables defined in subsection 4.6. And we consider a shift on intercept only. The error correction term in both equal weighted and value-weighted estimation is significant. The speeds of adjustment of these two ECMs are essentially the same. Two dummy variables have different sign, which correctly reflect the dynamics of the relations between A and B indices.

5. DISCUSSIONS AND CONCLUSION

5.1. Structural changes with a noise-trading model

As we discussed in section 1, there are many proposals to explain the B share discount but not much about structural changes. The fact that regulatory changes, market segmentation may play an important role in this process, however, it is necessary to consider what is the real driving force for the price difference. Here we propose a noise trader approach to explain the market behavior based on the model of De Long et al. [6].

It quite plausible to assume that investors who trade in B share markets tend to have more experience and more sophisticated, where on the contrary, investors in A share market are likely to be less experienced noise traders. If this is true, combining with the fact that there are much more individual investors accounts in A share market than in B share market (See Table 1), then we can assume that the proportion of noise traders in A market are higher than the proportion of noise traders in B market. We introduce μ_a and μ_b to represent proportions of noise traders in A and B market respectively, where $\mu_a > \mu_b$.

First of all, we need to refer this analysis to De Long et al. [6](DSSW thereafter). Their model is an overlapping generations model with two period-lived agents. There are no first-period consumption, no labour supply decision and no bequest. The agents have an exogenous wealth w_0 to invest and the only decision they need to make is to choose a portfolio when they are young to maximize expected utility. There are two kinds of identical agents: noise trader (N), measured by μ and misperceives the expected price of risky asset by an normal random variable ρ distributed as $iidN(\rho^*, \sigma_\rho^2)$. The constant mean of this misperceiving ρ^* is a measure of the average attitude or sentiment of the noise traders. We assume the future investor sentiment is unpredictable; Arbitrageurs (A), measured by $1-\mu$ and correctly perceives the distribution of returns from holding the risky asset. Arbitrageurs have a limited risk bearing capacity. There are only two assets in the economy with identical dividends: perfectly elastic supply of safe asset s with dividend r and a unit price; fixed supply (normalize to one) of risky asset u with same dividend of r but a price of p_t. If the price of each asset were equal to its fundamentals (the net present value of its future dividends), they should have same price in each period. However, with the existence of noise trader, they are not perfect substitute.

DSSW assume a constant absolute risk aversion function of wealth:

$$U = -e^{-2\gamma w} (where\ U' > 0 > U'') \tag{10}$$

w is the end period wealth. If it is normally distributed, then maximizing expected value of utility is equivalent to maximizing $E(w) - \gamma\delta_w^2$.

Maximizing agents' expected utility generates the demands for the risky asset for arbitrageurs and noise traders. They are proportional to perceived expected returns and inversely proportional to the perceived variance of returns. Denote λ^A as the amount of risky asset held by an arbitrageur and λ^N as the amount of risky asset held by noise trader. They can be written as:

$$\lambda^A = \frac{E_t(R_{t+1})}{2\gamma_t \sigma^2_{p_{t+1}}} \tag{11}$$

$$\lambda^N = \frac{E_t(R_{t+1})}{2\gamma_t \sigma^2_{p_{t+1}}} + \frac{\rho_t}{2\gamma_t \sigma^2_{p_{t+1}}} \tag{12}$$

Where $E(R_{t+1}) = r + E_t(p_{t+1}) - (1 + r)p_t$ represents the conditional expected return and $\sigma^2_{p_{t+1}} = E_t\{[p_{t+1} - E_t(p_{t+1}]^2\}$ is the conditional variance of next period price.

In equilibrium, the old generation sell their holdings to the young generation and must sum to one as the assumption of risky asset is fixed and normalized to one. Therefore, the equilibrium price is determined by the following equation:

$$(1 - \mu)\lambda^A + \mu\lambda^N = 1 \tag{13}$$

Work out the pricing function as:

$$p_t = 1 + \frac{\mu(\rho - \rho^*)}{1 + r} + \frac{\mu\rho^*}{r} - \frac{2\gamma\mu^2\sigma^2_\rho}{r(r+1)^2} \tag{14}$$

To make the problem simple, we assume the volatility of noise trader's sentiment is zero, and then pricing function reduce to

$$p_t = 1 + \frac{\mu(\rho - \rho^*)}{1 + r} + \frac{\mu\rho^*}{r} \tag{15}$$

The price of underlying stocks is equal to fundamental values plus noise traders' effects. Since we normally assume discount rate is constant over time, than price is affected by two main factors: shares of noise traders and their sentiments. Remember here the second term are generally small compare to the third term.

In our example, there are three stages in the full sample period shown in the graphs. In the first stage, A share index is slightly above B index, which may represents higher proportion of noise traders in A market. Testing results above show us two major breaks corresponding to Asian financial crisis and regulation changes in 2001. We can see Asian financial crisis in 1997 does affect both A and B share indices in the early stage, then B share index fall further away from A index. Since there are not much changes in A share markets, there are two possible reasons for this to happen: first of all, Financial crisis reduce the confidence of international investors, thereby the sentiment in B share markets is generally lower, thereby price getting lower; second, many noise traders in B market are driven out by the crisis, which reduce the share of noise traders in B market further.

The third stage is related to the fact that Chinese government change the regulation rules that allow domestic investors trading on B share market. The first impact from this rule change is we have more noise traders in B share market. Suppose there is X_A amount of extra domestic investors join the trading in B share market and the proportion of noise traders are μ_A and noise traders are generally positive in the market. A simple calculation suggest now in B market, proportion of noise traders increased to $\mu_B^* = \frac{\mu_A X_A + \mu_B N_B}{X_A + N_B} > \mu_B$, thereby price of B index increase. Furthermore, there maybe more than average of proportions of noise traders in domestic market join B markets, which suggest an even higher proportion of noise trader in B market after open to domestic. Since more investors in B market, then their confidence also has been boosted; we could have $\rho_t \uparrow$, but as a short run process, then B share index shoots up right after the policy changes, then fall back again into the long run value.

5.2. Why B share price indices respond to the Shock on A share indices?

Another interesting result in our empirical applications found that B share indices respond to shocks on A share indices significantly, where the opposite is not true. Turn back to our assumption about the experience of investors in those two markets. If investors in B share market is indeed more sophisticated and acting as arbitrageurs. They should trade on information rather than trend. The price movements in A share market caused at least partly by noise trading should not be reproduced in B share market. However, we observe even after 12 month period, the responds of B share indices to the shock on A share indices are still significant. This phenomenon is a challenge to EMH, where arbitrageurs should act to correct mispricing generated by irrational trading. In this case, some behavioral models can be reintroduced to explain, for example, De Long et al.'s [11] positive feedback trading model. They found arbitrageurs might benefit from positive feedback trading. At least in the short run, they would like to further increase those mispricing rather than trying to correct them. In this sense, arbitrageurs may deliberately create certain levels of mispricing.

5.3. Conclusion

In this paper, we analyzed the relationship between SSE A and B share price indices. Extending from standard cointegration framework, we allow structural breaks in the full sample period. Even though single break model by Gregory and Hansen [9] do not reject the null of no cointegration after considering structural break in the underlying model, we do find some evidence that our sample may subject not one, but two breaks. In our full sample period, two major events happened: Asian financial crisis and allowing B share to be traded by domestic investors. They are roughly consistent with the results we observed from our empirical tests.

Based on this finding, we then consider the possibility of multiple breaks. Using BP's [1] technique, we successfully identified two break points, which are quite consistent with those two events. After dating the break point, we extend the standard cointegration test with two dummy variables. It is arguable that including dummy variables in the system may changes the distribution, thus the standard cointegration critical values is not applicable. We solve this problem by using Monte Carlo simulation to find exact critical value for our test. All three tests suggest the existence of a long run relationship between A and B share indices if we account for those two breaks identified.

Another part of work is to seek for explanation on these empirical findings. DSSW [6] and [11] noise trading model and positive feedback trading model seems to provide some reasonable explanation. However, more investigation is required since they are mainly based on our assumption about the feature of investors in each market and they are hardly examined formally. Furthermore, we are investigating indices in this study, which may lose some information of how A share price and B share prices are related. It may be idea of further research on the price level of each individual companies.

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