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Authors: Hui Hong, Naiwei Chen, Fergal O'Brien, James Ryan

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Stock Return Predictability and Model Instability: Evidence from Mainland China and Hong Kong[1]

Hui Hong[a], Naiwei Chen[b]*, Fergal O'Brien[c] and James Ryan[c]

[a] *International Institute for Financial Research, Jiangxi Normal University, Nanchang, China*

[b] *Business School, Changzhou University, Changzhou, China*

[c] *Kemmy Business School, University of Limerick, Ireland*

*Corresponding author. Tel: +86 791 88116582. Email: nwctw@yahoo.com.tw (N. Chen)

Highlights

- This paper examines the predictability of the Shanghai Composite, Shenzhen Composite and the Hang Seng China Enterprise index returns, with emphasis on whether considering structural breaks in model parameters improves the stock return predictability.
- Results are important for investors who are interested in investing in Mainland China and Hong Kong stock markets.
- Results indicate higher linear stock return predictability for the Hong Kong market than for the Chinese markets.
- Results differ when model instability is taken into consideration: the Shenzhen market is detected with structural breaks and its predictability varies across different subsamples defined by the breaks.

Abstract

This study examines the predictability of the Shanghai Composite, Shenzhen Composite and the Hang Seng China Enterprise index returns during the period 1993 to 2010, with emphasis on whether considering structural breaks in model parameters improves the stock return predictability. Results indicate higher linear stock return predictability for the Hong Kong market than for the Chinese markets. However, the results differ when model instability is considering. Specifically, using Bai and Perron's (1998, 2003) approach, the results indicate the presence of structural breaks particularly for the Shenzhen market, which appear to coincide with major economic events or political and institutional changes. The predictable component in stock returns is also time-varying when re-estimating the model over different subsamples defined by the break. Overall, results highlight the importance of considering breaks in forecasting stock returns, and suggest that the Hong Kong market is a relatively ideal haven to park wealth for risk-averse investors whereas the Shenzhen market offers enhanced opportunities for risk-seeking investors.

JEL Classification: G11; G14; C53

Keywords: Model instability; structural breaks; return predictability; China; Hong Kong

1. Introduction

Prior studies on stock return predictability generally use a time-invariant prediction model to predict stock returns based on lagged predictor variables. This approach has played an important role in the development of asset allocation strategies. However, recent studies indicate that predictions allowing for model instability can provide evidence suggesting more practical investment opportunities for investors (e.g., Henkel, Martin & Nardari, 2011; Kinnunen, 2013; Marfatia, 2014; Boamah et al, 2017a).

Structural breaks in the parameters that relate stock returns to predictor variables can occur for a number of reasons, including major changes in market sentiment as well as monetary policies and institutions. Macroeconomic shocks (e.g., unexpected inflation) that affect economic growth or risk premia may also contribute to these breaks. Additionally, if return predictability is partly a result of market inefficiency rather than mere time-varying risk premia, such a predictive relationship should disappear provided that sufficient capital is available to exploit the opportunity.[1] The presence of breaks is important because it fundamentally affects the extent of return predictability and introduces new sources of investment risk. As evidenced by Pettenuzzo and Timmermann (2011), model instability has a large effect on a long-run investor's optimal asset allocation. Failure to consider structural breaks in modeling stock returns could yield misleading results that incur significant losses for investors.

Despite its evident importance, model instability within a stock return forecasting context has received limited attention in the existing literature (Pettenuzzo & Timmermann, 2011). Instead of formal tests, instability is typically addressed by examining stock return prediction models across various subsamples, with the results showing time-varying predictable patterns. For example, Mohanty, Nandh and Bota (2010) uncover instability in return models, based on changes in oil prices, when data from the recent global financial crisis is added to the sample. Similarly, Fayyad and Daly (2011) detect the increased forecasting ability of oil prices for stock returns during the global financial crisis when considering structural breaks. Although econometric tests allowing for breaks (e.g., Chow, 1960; Brown et al., 1979; Andrews, 1993; Andrews et al., 1996; Bai & Perron, 1998, 2003; Elliott & Mueller, 2003) have been widely used in the existing literature, they have been rarely considered in examining stock return predictability.[2]

This paper aims to fill this research gap by examining the predictability of the Chinese and Hong Kong stock markets, the presence of structural breaks in prediction models, and to what extent breaks affect our analyses using monthly data. Emerging markets, China in particular, are more likely to experience shocks induced by regulatory changes and political crises (Bekaert et al., 1998), but have received minimal attention to date. Current studies (e.g.,

[1] More detailed explanations are provided in Pesaran and Timmermann (2002) and Paye and Timmermann (2006).
[2] Earlier work considers a single (unknown) break (e.g., Chow, 1960; Brown, Durbin & Evans, 1979; Andrews, 1993; Andrews et al., 1996) whereas more recent work allows for factors such as multiple breaks, unit root dynamics, heteroskedasticity and serial correlation (e.g., Bai & Perron, 1998, 2003; Elliott & Mueller, 2003).

Chen, Chen & Lee, 2013; Mensi et al., 2014; Beltratti et al., 2016) showing evidence of instability in China neither formally test for the presence of structural breaks in stock returns nor characterize the timing and the nature of these breaks.

This study focuses on the underlying dynamics for the Shanghai, Shenzhen and Hong Kong markets. More importantly, we investigate if any variations in the return generation process in these markets can be captured by candidate predictor variables. In other words, we examine if there is any evidence of investment opportunities that are predictable across the Chinese and the Hong Kong stock markets. Given the important differences between the Shanghai, Shenzhen and the Hong Kong markets, investment opportunities likely arise. Building on prior studies that found different pricing determinants in these markets due to the impact of factors such as geography, local influences, market structure and investor behavior (e.g., Sjoo & Zhang, 2000; Tan et al., 2008), this study assesses return predictability by accounting for instability in each market, with emphasis on the presence of breaks, estimation of break dates, and statistical analysis of the resulting estimators.

We provide evidence indicating greater predictability in the Hong Kong market and supporting a non-constant predictive model for the Shenzhen market. Although the precise timing of structural breaks is difficult to establish, their occurrence tends to be related to both national and international events, such as the Asian Financial Crisis, the Dot.com Bubble and a bull market period in Mainland China. Further, our results indicate that the relationships between stock returns and certain predictor variables may change significantly following a break. The results highlight the importance of considering structural breaks in the parameters in building reliable prediction models for the Shenzhen market.

The study thus contributes to the existing literature in two important ways. Firstly, it adds to the literature on fundamentals and stock returns by showing the ability of certain macroeconomic variables to predict Chinese and Hong Kong stock market returns, in contrast to prior studies that provide surprisingly little evidence on the role of fundamentals as drivers of stock prices in Mainland China (e.g., Eun & Huang, 2007; Chen et al., 2016). Secondly, structural breaks in stock return predictions have only recently been formally addressed, with most studies providing evidence for the US markets (e.g., Paye & Timmermann, 2006; Rapach & Wohar, 2006; Pettenuzzo & Timmermann, 2011). This study fills this gap by examining the existence, significance and characteristics of structural breaks in the relationships between stock returns and predictor variables using a more recent econometric methodology, thus providing unprecedented evidence that suggests practical investment opportunities in the Chinese and Hong Kong markets.

The reminder of this paper is structured as follows. We first describe our data and methodology. We then present our empirical results and discuss the principle findings. The final section concludes.

2. Data

The data consists of the three main stock indices for both the Chinese and Hong Kong markets (i.e., the Shanghai Composite index (SHCI), the Shenzhen Composite index (SZCI) from January 1993 to May 2010, and the Hang Seng China Enterprise index (HSCEI) from August 1993 to May 2010) and 10 primary predictor variables.[3]

The time period covered by this study was motivated by some limitations in the Bai and Perron (2003) multiple structural break model. According to Prodan (2008) heterogeneity in the data may lead to inconsistent test results. Therefore, we purposely exclude data from 1991 and 1992, the first two years of Chinese stock markets, because 1993 was the first year when a sizable number of A-shares were listed for trading purposes (Kang,

[3] The *HSCEI* is also called the H-share index, with shares issued by state-owned companies incorporated in Mainland China and listed on the Hong Kong Stock Exchange (HKSE).

Liu & Ni, 2002). Furthermore, in 2011 a significant change was announced[4] in the classification of the sectors that feed into the calculation of *Industrial Production*, one of our predictor variables. To avoid the use of inconsistent data and potentially inconsistent test results we truncated the sample period accordingly. However, the time span of the data employed in this study, which covers approximately seven market cycles, is a relatively long sample period in the history of the Chinese stock markets and is as broad, if not broader, than the sample periods used for stock return analysis in the related literature.

The testing procedure proposed by Bai and Perron (1998, 2003) is used to identify breaks as it allows us to determine the confidence intervals for the timing of break occurrence as well as the coefficients around the time of the breaks. We base our analysis on linear regression models estimated by least squares. In addition, we focus on *ex post* or full-sample predictability and examine the occurrence and significance of past breaks, instead of an ex ante approach which partitions data into estimation and testing subsamples (as is usually employed in the literature). The primary reason for using this approach is that it is deemed more powerful in detecting changes in model parameters given the nature of our data. Specifically, the history of stock indices in China-related markets is relatively short compared to that in developed markets in the sense that data suitable for use in this study is only available back to 1993. By using the full sample, we are able to gain more power when testing for model instability.

Monthly data for the stock market indices and predictor variables were gathered from *Thomson Reuters*' *DataStream* as the majority of the predictor variables are only available monthly. We calculate log returns for the SHCI, the SZCI and the HSCEI. To forecast market returns, we use predictor variables that have shown forecasting ability in the existing literature, including the inflation rate, money growth, industrial production growth, change in

[4] Classification for National Economic Activities (GB/T 4754-2011)

business cycle indices, change in sentiment indices and market volatility with lags of up to 2 months. Following French, Schwert and Stambaugh (1987), we measure market volatility using the sum of the squared daily returns plus twice the sum of the products of adjacent returns because of the autocorrelation in returns due to the general non-synchronous trading of securities. Tables 1a and 1b show the variable definitions for the stock market index returns and the predictor variables considered in this study, respectively.

[Insert Tables 1a and 1b Here]

2.1 Chinese and Hong Kong Stock Markets: An Overview

The establishment of the modern stock market in Mainland China commenced in the early 1990s, with the foundation of the Shanghai Stock Exchange (SHSE) at the end of 1990 and the Shenzhen Stock Exchange (SZSE) early in 1991 as non-profit self-disciplined membership institutions. Both stock exchanges are now under the control of the China Securities Regulatory Commission (CSRC), adopting similar microstructures, such as the clearance, settlement, and depository (CSD) facilities, and the same auction principles are utilized to discover stock prices (Xu, 2000). Dual listing is not allowed between the stock exchanges.[5] To reduce volatility and limit market speculation, a daily price movement limit system has been imposed on both exchanges since December 1996. In contrast, the Hong Kong Stock Exchange (HKSE) was established in 1980 with trading starting from 1986. It was essentially based on British rules and therefore adopted a trading system with a stronger infrastructure and a tighter regulatory regime although since the 1990s the mainland's economic and financial development has increasingly influenced the stock exchange (Johansson & Ljungwall, 2009).

[5] The Chinese government initially imposed a ban on dual listing on the two Chinese stock markets to encourage competition between the exchanges in the first instance. With the subsequent development of capital markets in China, the Shanghai Stock Exchange has now been re-designed as a platform for blue chip and international companies (large-cap shares) while the Shenzhen Stock Exchange is targeted at small and medium capitalization companies and designated as a Growth Enterprise Market (GEM).

There are also several other differences among the stock exchanges, for example, in their size and liquidity: the SHSE is comprised mainly of larger companies, many of which were formerly owned by the state and traditionally rely on the government for their financing, raw materials, and product distribution whereas the SZSE is composed mainly of smaller and export-oriented joint ventures (Tan et al., 2008). Companies listed on the HKSE are, however, more diverse with numerous small and large companies on the exchange. Based on the statistics from the Shanghai, Shenzhen and the Hong Kong stock exchanges, at the end of 2010 there were 894, 1,169 and 1,244 listed companies in the SHSE, SZSC and the HKSE, with stock market capitalization to GDP ratios of 47.30%, 22.80% and 1207.57%, respectively. The turnover rate for the HKSE was 58.63%, in contrast to 198.47% in the SHSC and 318.64% in the SZSC.

Summary statistics in Table 2 show that from January 1993 to May 2010 the kurtosis values for the returns of the *SHCI* and the *SZCI* were 11.75 and 2.25 respectively, indicating that extreme movements and large jumps were more prevalent in the Shanghai market, although the mean and the median values of those two index returns were close. In addition, the returns in the Shanghai market were more skewed to the right compared to those in the Shenzhen market as shown by their skewness values of 1.47 and 0.55 respectively for the returns of the *SHCI* and the *SZCI*. In contrast, both the kurtosis and skewness values were much smaller for the returns of the *HSCEI* within the period August 1993 to May 2010. The wide variations in summary statistics imply fundamental differences in the driving forces among these markets.

[Insert Table 2 Here]

Figure 1 presents a graph of the series for each market index returns. Of interest is that large movements in the Shanghai market seem to be clustered during the period from 1993 to 1994 whereas the volatility in the Shenzhen market is more evenly spread over the full sample period. This is supported by the kurtosis values during different time periods, which were 1.00 (11.75) and 1.58 (2.25) respectively for the returns of the *SHCI* and the *SZCI* when two-year period (1993-1994) data is excluded (included). The performance of the *HSCEI* is similar to the *SZCI* with the volatility being distributed in a relatively even pattern.

[Insert Figure 1 Here]

With respect to the predictor variables, the economy was characterized by uncertainty with considerable variability in market conditions and sentiment (Table 2). For example, the yearly industrial production growth (*YIPI*) ranged from 1.00% to 11.00% and averaged 5.61%. The average changes in all the business cycle indices were negative, implying that economic conditions were scarcely optimistic. Furthermore, extreme deviations were frequently observed in market sentiment, with the kurtosis values of the monthly changes of the three sentiment indices ranging from 11.78 to 21.58.

3. Methodology

3.1 Prediction Models and Model Estimation

Linear regression modeling is used for forecasting because it facilitates identification of breaks with relative ease when compared to non-linear approaches (e.g., Pesaran & Timmermann, 1995). We therefore build linear predictive regression models as follows:

$$y_t = \beta x_{t-n} + u_t, n = 1, 2 \qquad (1)$$

where y = the log of stock index returns as described in Table 1a; x (q*1) = the vector of the constant and predictor variables selected from Table 1b; u = the disturbance term with mean zero and variance σ^2; β (1*q) = the vector of corresponding coefficients (b_0, b_1,…b_q). Subscripts t and t-n are months t and t-n, respectively.

Suppose that the model is subject to m breaks occurring at times (T_1,…,T_m). This gives the following model

$$y_t = \begin{cases} \beta_0' + \beta_1' x_{t-n} + u_t & t = 1, \dots, T_1 \\ \beta_0' + \beta_2' x_{t-n} + u_t & t = T_1 + 1, \dots, T_2 \\ & \vdots \\ \beta_0' + \beta_{m+1}' x_{t-n} + u_t & t = T_k + 1, \dots, T \end{cases} \tag{2}$$

The model in Equation (2) is a pure structural change model if all the coefficients in the parameter vector β are subject to shifts (i.e. $\beta_0' = 0$) and is a partial structural change model if some components in the β are not subject to shifts (i.e. $\beta_0' \neq 0$) and are estimated with the entire sample.

The key objective is to test for the presence of breaks and estimate the break dates ($T_1,\dots,T_m$), as well as the parameters around the time of the breaks, (β_1', β_2',…, β_{m+1}'). The variance of u_t does not need to be constant as long as breaks in the variance occur at the same dates as those in the parameters of the regression.

Bai and Perron (1998, 2003) propose a least-square approach to optimally determine the unknown break dates as well as the resulting size of changes in the parameter values. The principle involves searching over the possible m-partitions ($T_1,\dots T_m$) of the data to obtain the minimizer of the sum of squared residuals. For a set of m break dates, ($T_1,\dots T_m$) = $\{T_j\}$ = $[T\lambda_j]$, the coefficient estimates $\beta_{m,\{T_j\}}$ are chosen to minimize the sum of squared residuals:

$$S_T\left(\{T_j\}\right) = \sum_{j=1}^{m+1} \sum_{t=T_{j-1}+1}^{T_j} [y_t - x_t \hat{\beta}_{m,\{T_j\}}]^2 \tag{3}$$

The estimated break dates ($\hat{T}_1,\dots,\hat{T}_m$) are then determined to satisfy:

$$\left(\hat{T}_1, \dots, \hat{T}_m\right) = argmin_{T_1,\dots,T_m} S_T(T_1, \dots, T_m) \tag{4}$$

where the minimization is taken over all partitions ($T_1,\dots T_m$) such that $T_i - T_{i-1} \geq q$. Thus the break-date estimates are global minimizers of the objective function (3). Based on the work of Bai (1997), Bai and Perron (1998, 2003) also provide methods for obtaining confidence intervals for these estimated break dates.

3.2 Tests for Breaks

Several types of hypothesis tests are available when multiple breaks are allowed in stock return prediction models. The *Sup*F-type test developed by Bai and Perron (1998, 2003) considers the null hypothesis of no structural breaks against the alternative of $m= k$, where k is a specified number, using the following statistic:

$$F_T(\lambda_1, \ldots, \lambda_k) = \frac{1}{T}\left(\frac{T-2(k+1)}{2k}\right)\hat{\beta}'R'(R\hat{V}(\hat{\beta})R')^{-1}R\hat{\beta} \quad (5)$$

where R = the conventional matrix such that $(R\beta) = ({\beta_1}' - {\beta_2}', \ldots, {\beta_k}' - {\beta_{k+1}}')$; $V(\hat{\beta})$ = an estimate of the variance-covariance matrix of $\hat{\beta}$ that is robust to heteroskedasticity and serial correlation.

A type of maximum F-statistic corresponding to Equation (5) is then derived as:

$$SupF_T(k) = F_T(\hat{\lambda}_1, \ldots, \hat{\lambda}_k) \quad (6)$$

where $\hat{\lambda}_1, \ldots, \hat{\lambda}_k$ minimise the global sum of squared residuals. S_T $(T\lambda_1,\ldots,T\lambda_k)$ is under the restriction such that $(\hat{\lambda}_1, \ldots, \hat{\lambda}_k) \in \Lambda_\pi$, where $\Lambda_\pi = \{(\lambda_1,\ldots, \lambda_k); |\lambda_{j+1} - \lambda_j| \geq \pi, \lambda_1 \geq \pi, \lambda_k \leq 1 - \pi\}$ for some arbitrary positive number π (the trimming percentage).

Bai and Perron (1998, 2003) also develop two statistics, called 'the double maximum' statistics, to test the null hypothesis of no structural breaks against the alternative of an unknown number of breaks given an upper bound M:

$$UDmax = max_{1\leq m\leq M} SupF_T(\lambda_1, \ldots, \lambda_m) \quad (7)$$

$$WDmax = max_{1\leq m\leq M} \frac{c(q,\alpha,1)}{c(q,\alpha,m)} SupF_T(\lambda_1, \ldots, \lambda_m) \quad (8)$$

where $c(q, \alpha, m)$ = the asymptotic critical value of the test $Sup\mathrm{F}_T(\lambda_1,\ldots,\lambda_m)$ for a significance level α. The double maximum statistic in (8) applies different weights to the individual *UDmax* statistics in (7) such that the marginal p-values are equal across values of m. See Bai and Perron (1998, 2003) for more details.

Finally, a related test of l versus l+1 breaks, denoted as the $Sup\mathrm{F}_T(l+1|l)$ test, in Bai and Perron (1998, 2003) considers the null hypothesis of l breaks against the alternative that an additional break exists. It starts with the global minimized sum of squared residuals for a model with l breaks. Conditional on these break dates, the test is applied to each subsample for an additional break. Rejection in favor of a model with l+1 breaks occurs where the overall minimal value of the sum of the squared residuals (overall all subsamples where an additional break is included) is sufficiently smaller than the sum of squared residuals from the l breaks model. Therefore the break date selected is the one associated with this overall minimum. Bai and Perron (1998, 2003) derive asymptotic distributions for both the double maximum and the $Sup\mathrm{F}_{\mathrm{T}}(l+1|l)$ statistics and provide critical values for the values of π and M.

For each of three stock market indices we estimate predictive regression models as previously described and select predictor variables for each model using the widely-adopted stepwise methodology (e.g., Chang et al., 2009; Hsu, Hus & Kuan, 2010).[6] The procedure begins with an initial model, a constant only, and compares the explanatory power of incrementally larger and smaller models. At each step, the *p*-value for the *F*-statistic is computed to compare models with and without one of the candidate predictor variables and the predictor variable is added or removed from the model accordingly. This procedure terminates when the available improvement falls below the critical value at a 10% significance level

4. Empirical Results

4.1 Stock Return Predictions

Results for the market prediction models are presented in Table 3. To preserve space, we only report the estimation results of the final model throughout the rest of the paper, including the

[6] We use the stepwise procedure rather than the information criteria, such as the Akaike information criterion (AIC) and the Schwarz information criterion (SIC) because we assume that investors are looking for forecasting models with statistically significant coefficients and are interested in understanding whether the significance persists .

coefficients for the selected predictor variables and their standard errors (in brackets), *t*-statistics, *p*-values, R^2 and the root mean square error (RMSE).[7]

[Insert Table 3 Here]

Results suggest the inclusion of *MLDI* in the *SHCI* return model, *MLDI* and *MCEI* in the *SZCI* return model, and all monthly changes in business cycle indices (i.e., MLDI, MCI and MLGI) in the *HSCEI* return model. The estimated coefficients for these predictor variables are statistically significant at conventional levels. In addition, the regressions have also reached a local minimum of the RMSE. Other candidate predictor variables listed in Table 1b fail to satisfy the selection criteria of the stepwise regression and are therefore excluded from the final models.

The results reinforce those in prior studies that indicate the role of certain fundamental factors in explaining stock price behavior in China (e.g., Bondt et al., 2011; Narayan et al., 2014). They also highlight somewhat different dynamics for the three stock markets, which can be attributed to differences in market structure and investor behavior across markets. As previously discussed, both the Shanghai and the Hong Kong markets (especially the *HSCEI*) are comprised mainly of companies that were state-owned whereas the Shenzhen market is comprised mainly of joint ventures that are much smaller and less related to the government. The performance of the Shenzhen market is not only affected by macroeconomic influences but also by market sentiment, possibly because 1) investors tend to be less confident of government support and 2) investors tend to be less rational in investing activities, compared to those in the Shanghai and the Hong Kong markets.[8]

As is common in the literature, the R^2 statistics show that the predictable component in the Chinese stock returns tends to be relatively small even when the predictor variables significantly affect future stock returns. The R^2 values are 0.0314 and 0.0570 respectively for

[7] Estimation results of the stepwise regression at other steps are available upon request.
[8] See Chen et al. (2004) and Tan et al. (2008) for further discussion.

the *SHCI* and the *SZCI* return models. This is in sharp contrast with 0.1136 for the *HSCEI* return model. However, as evidenced by Kandel and Stambaugh (1996), even a relatively minor predictable component in stock returns can have important implications for asset-allocation decisions.

We further examine the extent to which the ordinary least square (OLS) estimates in Table 3 might be affected by general data problems and present the results in Table 4. We evaluate the robustness of our results by testing whether model parameter estimates change substantially after considering the effects of outliers, heteroskedasticity and serial correlation, with emphasis on whether the coefficients remain statistically significant under such circumstances.

[Insert Table 4 Here]

Table 4 highlights that the performance of all predictive regression models stays robust after considering potential data issues. The coefficients (i.e., β_1^{SHCI}, β_1^{SZCI}, β_2^{SZCI}, β_1^{HSCEI}, β_2^{HSCEI} and β_3^{HSCEI}) remain significant at the same or higher level and the RMSE associated with each model is smaller, suggesting that our OLS estimates are not influenced by outliers. As for the heteroskedasticity and serial correlation, the performance of the Shanghai market return models is more affected. That is, the heteroskedasticity-and-serial-correlation robust standard error is 1.7222 for β_1^{SHCI}, consequently leading to an increase in the corresponding *p*-value from 0.0102 to 0.0530. However, the model remains competitive in forecasting according to the criteria established.[9] In contrast, robust standard errors are 1.5170 (1.2580), 1.0818 (0.3080) and 1.0575 respectively for β_1^{HSCEI} (β_1^{SZCI}), β_2^{HSCEI} (β_2^{SZCI}) and β_3^{HSCEI} in the *HSCEI* (*SZCI*) return model, which are generally smaller than those based on the OLS approach, rendering both coefficients as significant or more significant compared to those in Table 3.

[9] We consider conventional significance levels when deciding whether the forecasting model is appropriate for use throughout the paper.

Overall, the results based on both *p*-values and RMSE suggest that the predictive regression models derived are appropriate for forecasting returns in both the Chinese and Hong Kong markets using the full sample data, with statistically significant coefficients robust to the potential data problems. The question that therefore arises is whether model parameters have undergone structural breaks such that return predictability varies over different subperiods.

4.2 Presence of Breaks

In our empirical specification, we assume that all of the three prediction models are subject to partial structural changes. That is, only the constants are not subject to shifts and are estimated using the entire sample. This is necessary because: 1) the constants are insignificant and fail to improve the explanatory power of the entire model when we run stepwise regression. It follows that there is no need to impose any identifying restrictions on our models in doing so; and 2) a partial structural change model allows efficient estimation of the regression parameters and greater degrees of freedom (Bai & Perron, 1997).[10]

Table 5 presents the results of various tests for structural breaks. We set the trimming percentage, π, to 15% and 20% of the entire sample, allowing for 5 breaks (m = 5) and 3 breaks (m = 3) respectively.[11] These correspond to a minimum window of 2.7 years and 3.5 years between breaks for our dataset beginning in January 1993.

[Insert Table 5 Here]

The results of the *Sup*F-type test, double maximum tests, and the $Sup\mathrm{F}_{\mathrm{T}}(l+1|l)$ test are insignificant irrespective of the choice of π, suggesting no structural breaks for the parameters in the return models of the *SHCI* and the *HSCEI* using the stepwise regression. Together with

[10] We also consider pure structural change models. However, the results are similar and therefore are not reported for brevity.
[11] The selection of trimming percentages may significantly affect the results when detecting structural breaks since a small trimming of the total sample can lead to tests with substantial size distortions when allowing for heteroskedasticity and serial correlation whereas increasing the trimming can sharply reduce the combinations of break dates allowed (Bai & Perron, 1998). We therefore use trimming percentages of 15% and 20% that are the most widely used in literature (e.g., Bai & Perron, 2003; Paye & Timmermann, 2006; Rapach &Woha , 2006).

the findings in Section 4.1, we conclude that investors can use these models to forecast stock returns in both the Shanghai and the Hong Kong markets.

We reach a different conclusion for the return model of the S*ZCI*. For the case π = 15% with up to 5 breaks, both the $Sup\mathrm{F}_T(5)$ and the double maximum test statistics are significant at the 1% or 5% level (although the $Sup\mathrm{F}_T(l+1|l)$ test is not). For the case π = 20% with up to 3 breaks, both the $Sup\mathrm{F}_T$ (3) and the double maximum test statistics are significant. Results in both cases suggest the presence of breaks in the model of the *SZCI*.

In summary, the results suggest instability for the *SZCI* return model based on $MLDI_{t-1}$ and $MCEI_{t-1}$ with at least 3 breaks evident.[12] For these predictor variables, both the *Sup*F and the double maximum statistics provide strong evidence indicating multiple breaks. However, the results suggest the non-existence of breaks for the *SHCI* and the *HSCEI* return models based on $MLDI_{t-2}$. The potential reason for the difference might be that listed companies in the SZSE are more volatile, smaller export-oriented firms that are more susceptible to changes in domestic and international economic conditions and in investor sentiment leading to instability in the predictive ability of our model. By contrast, those listed in the SHSE and HKSE are mostly state-owned and more diverse, respectively, and as such are potentially exhibit greater immunity to economic shocks. This finding together with those in Section 4.1 suggest that the *SHCI* and the *HSCEI* return models are effective in forecasting returns in the Shanghai and Hong Kong markets respectively whereas the *SZCI* return model performs poorly over the time period under investigation.

The finding of structural breaks using the *SZCI* data is consistent with the results from studies using international data. For example, Rapach and Wohar (2006) examine predictive regression models of U.S. aggregate stock returns and find strong evidence of breaks in most

[12] We use the Bayesian Information Criterion and the modified Schwarz Criterion (Yao, 1988; Liu, Wu & Zidek, 1997) to decide upon the number of breaks (i.e., 3 versus 5 breaks in our case) in the model. However due to a non-significantly high R^2 value, these criteria do not provide useful information for selecting the appropriate number of breaks. Therefore, we focus on the minimum of 3 breaks detected for the *SZCI* return model.

regressions. When testing return models in 10 countries of the Organisation for Economic Cooperation and Development (OECD), Paye and Timmermann (2006) also find evidence supporting model instability for the vast majority of countries.

4.3 Robustness Check

One might argue that our results are affected by 'over-fitting', i.e., spuriously finding breaks when truly none exists. As discussed in Paye and Timmermann (2006), this may occur when persistent lagged endogenous predictor variables are used. Consider the following data generation process:

$$y_t = \alpha + \beta x_{t-1} + \varepsilon_t; \;\; \varepsilon_t \sim N(0, \sigma_\varepsilon^2) \qquad (9)$$

$$x_t = \theta + \varphi x_{t-1} + v_t; \;\; v_t \sim N(0, \sigma_v^2); \;\;\; E(\varepsilon_t) = E(v_t) = 0; \;\; \frac{E(\varepsilon_t v_t)}{\sigma_\varepsilon \sigma_v} = \rho \qquad (10)$$

Here assume y_t (i.e., r_t^{SZCI}) is generated as a linear function of lagged x_t (i.e., $MLDI_{t-1}$ and $MCEI_{t-1}$) with a Gaussian white noise error term. The variables x_t follow a first order auto-regressive process with φ governing the persistency of the process. Shocks to y_t and x_t have correlations given by the parameter ρ. When $\rho = 0$, the predictor variable x_{t-1} is strictly exogenous and predetermined otherwise. Our break tests will have a severe problem with both correlated disturbances and high persistency.

To address this concern, we estimate the parameter governing the persistency of the process for each predictor variable and the correlation between shocks to stock returns and the predictor variables in the *SZCI* return model as a robustness check that guards against the 'over-fitting' problem in our analysis. In terms of $MLDI_{t-1}$, the autocorrelation for its historical time series is 0.4168 whereas this is 0.2397 for $MCEI_{t-1}$. Figure 2 further plots the autocorrelations for both predictor variables, as a function of the time lag of up to 12 months over the entire sample period, which largely fluctuate around zero and therefore indicates data randomness. In addition, the scaled correlations between shocks of both series to stock returns ρ are close to zero.[13] Given that both the persistency and the correlation between shocks are not significantly high, the break results based on the *Sup*F and the double maximum tests are reliable.

[Insert Figure 2 Here]

4.4 Timing of Breaks and Changes in Return Predictability

The tests outlined above suggest that structural breaks may be an important feature of our stock return regression model. While these tests show that instability is statistically significant, they alone cannot justify the economic significance of breaks. It is therefore worthwhile to go one step further by timing and characterizing the breaks to see if they are linked to any market events or changes in policies and institutions.

To this end, we re-estimate the *SZCI* return model over different subsamples partitioned based on breaks identified in the previous section, and present the results (i.e., estimated coefficients and the standard errors) in Table 6. Caution should be exercised when interpreting the coefficient estimates owing to potential small sample bias for some of the subsamples. To investigate the nature of the breaks, we also include the estimated break dates and a 90% confidence interval (in brackets) for each break.

[Insert Table 6 Here]

The regressions show several interesting results. Most notably, both the regression coefficients and the R^2 values change substantially following a break. Although sometimes this is clearly due to sampling variations such as small or large standard errors, the breaks in the regression model are nonetheless sufficiently large to be of economic interest. For π = 15%, β_1^{SZCI}, for example, was almost 2.5 times smaller with the R^2 value decreasing

[13] The full results for both the autocorrelations for $MLDI_{t-1}$ and $MCEI_{t-1}$ and the shocks of the two series to stock returns are not presented here but are available for the authors available upon request.

substantially from 0.1188 to 0.0068 after the first break (July 1995). The coefficient was around 4 times as high in the subsample after the second break (April 1998) and was accompanied by a significant increase in the R^2 value to 0.1833. Both β_1^{SZCI} and the R^2 value declined again to close to zero after the third break (March 2001). The coefficient β_1^{SZCI} which had been positive in all prior subsamples became negative with an increase in the R^2 value to 0.0504 after the fourth break (July 2004). This was followed by a positive coefficient again and a further increase in the R^2 value to 0.1244 after the fifth break (March 2007). Similar results apply for π = 20%. The significant change in return predictability as measured by R^2 across subsamples highlights the importance of considering the possibility of breaks since the expected economic value of any prediction model would reduce dramatically if there is a high likelihood of the model subsequently breaking down.

Although breaks may significantly affect return predictability, their exact timing is not readily discernible. As shown in Table 6, the breaks cannot be correctly estimated when π = 15% because the procedure to get critical values has reached the upper bound on the number of iterations. The same is true when we increase the bound until it is extremely large. For π = 20%, the second and the third break dates have a relatively large confidence intervals, i.e., February 1998 to November 2005 and July 2004 to May 2010 respectively when we set the significance level to 10%. The first date is, however, more precisely estimated since the 90% confidence interval covers a much smaller number of months before and after. This is not in itself surprising given that confidence intervals may contain true values, particularly when breaks are large, but are quite wide leading to a conservative assessment of the estimate accuracy (Bai & Perron, 2001).

However, the picture becomes much clearer when we attempt to study these break dates against market events or political and institutional changes. In the case of π = 15%, the first break (July 1995) corresponds to the treasury bond futures suspension in China, consistent with Poon et al.'s (1998) finding that the liquidity of both A- and B-shares greatly increased after the suspension of trading.[14] The second break (April 1998) occurred around the middle of the Asian financial crisis which negatively affected the efficiency and the integration of Chinese stock markets (Cheng & Glascock, 2006). The third break (March 2001) was close to the end of the Dot.com bubble (Kenourgios et al., 2011). The fourth break (July 2004) corresponds to the Split Share Structure Reform (SSSR) in the Chinese capital market, consistent with Huang, Su and Chong's (2008) finding of a structural change in the Chinese stock-price level after the SSSR.[15] The most recent break (March 2007) occurred in the latter half of a long bull market period in China (Ahmed, Rosser & Uppal, 2010).

In contrast, in the case of π = 20%, the first break (April 1997) was around the beginning of the Asian financial crisis. The second break took place in March 2001, which is exactly the same as that indicated based on π = 15%. The third break (June 2006) corresponds to the middle of the bull market period in Mainland China. In summary, the results suggest that the break occurrences for the *SZCI* return model are related at least to the Asian financial crisis, the Dot.com bubble and the bull market period in Mainland China.

The results clearly demonstrate the transitory nature of the predictive accuracy of our model of Shenzhen market returns, with frequent shifts in the model's predictive ability after the identified break dates. The identified breaks can be linked to changes in the domestic market environment and to global financial events. The market is dominated by domestic individual investors (Tan et al., 2008), who tend to seek speculative profits as shorter-term traders (Eun and Huang, 2007) resulting in the high volumes of turnover evident in the market. As such, it would appear that the degree of predictability of market returns is susceptible to changes in individual investor sentiment especially during bull market periods

[14]After the bond market had soared, the short side of treasury bond future contracts deliberately violated transaction rules by generating a large number of sell orders to suppress the price resulting in a large fall in market value. The trading of the bond futures was suspended on the 17th May 1995.

[15] SSSR is defined as the process to eliminate the existence of a large volume of non-tradable state-owned and legal person shares via a negotiation mechanism to balance the interests of non-tradable and tradable shareholders.

and around local market reforms. Furthermore, a growing literature examines the relationship between emerging market returns and global financial events, and the identification of break dates in the predictability of the Shenzhen market returns adds to this evidence as it highlights the impact of international events on the market. In particular, it has been shown that the global effects are time-varying and can lead to surges in the global influence on emerging market returns (Boamah, 2017; Boamah *et al*., 2017b), with financial and trade linkages being the key channels of transmission (Neaime, 2016). As export-oriented firms dominate the Shenzhen market the linkage to global events is potentially through these trade links. Overall, the results further corroborate the findings of previous studies that the Chinese stock markets respond to both local and global market shocks (e.g., Nikkinen et al., 2006; Dooley & Hutchison, 2009).

5. Conclusion

This paper examines stock return forecastability using the *SHCI*, *SZCI* and the *HSCEI* from 1993 to 2010 as the study sample, with an emphasis on whether considering structural breaks in the model parameters improves forecasting performance using the Bai and Perron (1998, 2003) approach. Results based on a constant model indicate greater predictability for the Hong Kong market whereas a non-constant model gains support for the Shenzhen market. This is unsurprising given that the listed companies in the SZSE are mostly smaller joint ventures that are more susceptible to changes in economic conditions. In addition, despite difficulty in timing these breaks, their occurrences appear to coincide with major market events or changes in policies and institutions. More specifically, the break dates for the *SZCI* return model can be attributed to the Asian financial crisis, the Dot.com bubble and the bull market period in Mainland China. Overall, we show that the relationships between the predictor variables and stock returns change substantially following a break. That is, the stock market predictability varies overtime, with the predictability being weaker after both the Asian financial crisis (April 1997) and the Dot.com bubble (March 2001) but stronger after the bull market period (June 2006).

Important implications are provided. The results highlight the much higher risks associated with predictive models when investing in the Shenzhen market relative to the Shanghai and the Hong Kong markets as the Shenzhen market is most affected by changes in economic conditions. Hence, such investors when seeking to invest in the Shenzhen market should be more aware of international events as this market appears to be more integrated with the world market. By contrast, the presented results highlight the relative security of forecasting models in the Hong Kong market given the higher predictability than the Shanghai market. In sum, for risk-averse investors, the Hong Kong market is seen as more appropriate market through which to channel their investment. For risk-takers, the Shenzhen market offers a clearer opportunity to gain additional returns if the investor can intelligently time their trades.

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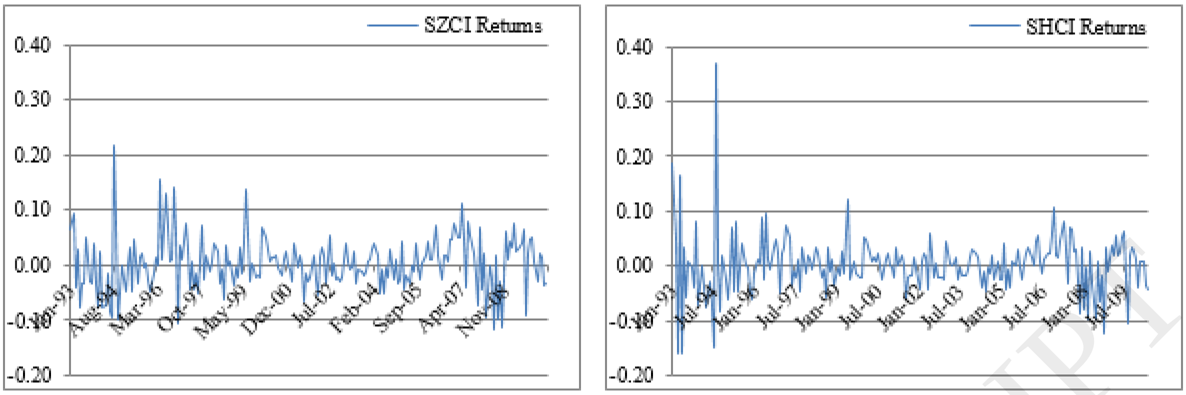
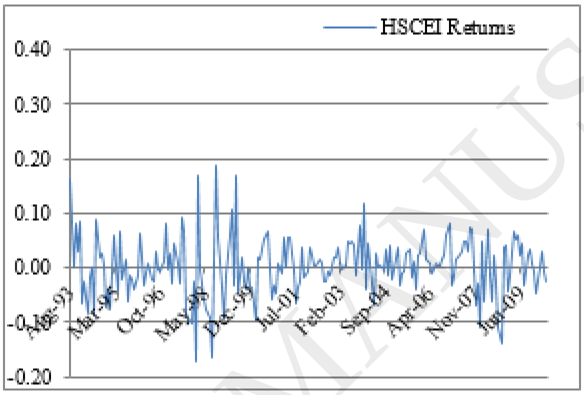
Figure 1. Monthly Stock Market Index Returns



Period: 01.1993 – 05.2010



Period: 08.1993 – 05.2010

Figure 2. Autocorrelations (0-12 months) for Predictor Variables in the *SZCI* Return Model

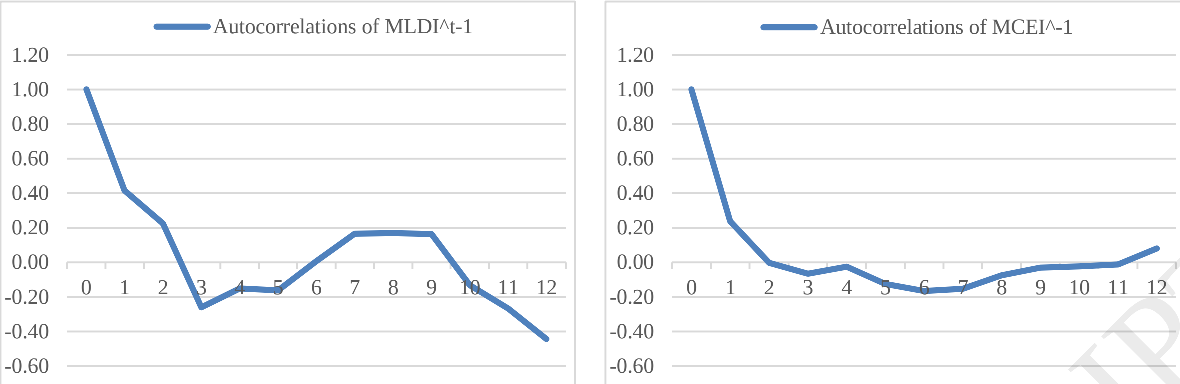


Table 1a
Stock Market Index Returns

Symbol	Variable	Definition
r_t^{SHCI}	Shanghai Composite index (*SHCI*) return	$\log[PI_t^{SHCI}/PI_{t-1}^{SHCI}]$
r_t^{SZCI}	Shenzhen Composite index (*SZCI*) return	$\log[PI_t^{SZCI}/PI_{t-1}^{SZCI}]$
r_t^{HSCEI}	Hang Seng China Enterprise index (*HSCEI*) return	$\log[PI_t^{HSCEI}/PI_{t-1}^{HSCEI}]$

Notes: *PI* = the net share price index. Subscripts *t* and *t-1* are months *t* and *t-1*, respectively.

Table 1b

Predictor Variables

Symbol	Variable	Definition
$YIR_{t-1,\ t-2}$	Yearly inflation rate	$\log[CPI_{t-12}/100]$, $\log[CPI_{t-24}/100]$
$MMS_{t-1,\ t-2}$	Monthly money growth	$\log[M_{1,t-1}/M_{1,t-2}]$, $\log[M_{1,t-2}/M_{1,t-3}]$
$YMS_{t-1,\ t-2}$	Yearly money growth	$\log[M_{1,t-12}/M_{1,t-24}]$, $\log[M_{1,t-24}/M_{1,t-36}]$
$YIPI_{t-1,\ t-2}$	Yearly industrial production growth	$\log[IPI_{t-1}/100]$, $\log[IPI_{t-2}/100]$
$MLDI_{t-1,\ t-2}$	Monthly change in the leading index	$\log[LDI_{t-1}/LDI_{t-2}]$, $\log[LDI_{t-2}/LDI_{t-3}]$
$YLDI_{t-1,\ t-2}$	Yearly change in the leading index	$\log[LDI_{t-12}/LDI_{t-24}]$, $\log[LDI_{t-24}/LDI_{t-36}]$
$MCI_{t-1,t-2}$	Monthly change in the coincidence index	$\log[CI_{t-1}/CI_{t-2}]$, $\log[CI_{t-2}/CI_{t-3}]$
$YLI_{t-1,\ t-2}$	Yearly change in the coincidence index	$\log[CI_{t-12}/CI_{t-24}]$, $\log[CI_{t-24}/CI_{t-36}]$
$MLGI_{t-1,\ t-2}$	Monthly change in the lagging index	$\log[LGI_{t-1}/LGI_{t-2}]$, $\log[LGI_{t-2}/LGI_{t-3}]$
$YLGI_{t-1,t-2}$	Yearly change in the lagging index	$\log[LGIt_{.12}/LGI_{t-24}]$,$\log[LGI_{t-24}/LGI_{t-36}]$
$MCCI_{t-1,t-2}$	Monthly change in the consumer confidence index	$\log[CCI_{t-1}/CCI_{t-2}]$, $\log[CCI_{t-2}/CCI_{t-3}]$
$YCCI_{t-1,t-2}$	Yearly change in the consumer confidence index	$\log[CCI_{t-12}/CCI_{t-24}]$, $\log[CCI_{t-24}/CCI_{t-36}]$
$MCEI_{t-1,\ t-2}$	Monthly change in the consumer expectation index	$\log[CEI_{t-1}/CEI_{t-2}]$, $\log[CEI_{t-2}/CEI_{t-3}]$
$YCEI_{t-1,t-2}$	Yearly change in the consumer expectation index	$\log[CEI_{t-12}/CEI_{t-24}]$, $\log[CEI_{t-24}/CEI_{t-36}]$
$MCSI_{t-1,\ t-2}$	Monthly change in the consumer satisfaction index	$\log[CSI_{t-1}/CSI_{t-2}]$, $\log[CSI_{t-2}/CSI_{t-3}]$
$YCSI_{t-1,\ t-2}$	Yearly change in the consumer satisfaction index	$\log[CSI_{t-12}/CSI_{t-24}]$, $\log[CSI_{t-24}/CSI_{t-36}]$
$MV_{t-1,\ t-2}$	Market Volatility	$\sigma_{t-1}^2 = \sum_{i=1}^{N_{t-1}} r_{it}^2 + 2\sum_{i=1}^{N_{t-1}-1} r_{it}r_{i+1,t}$, $\sigma_{t-2}^2 = \sum_{i=1}^{N_{t-2}} r_{it}^2 + 2\sum_{i=1}^{N_{t-2}-1} r_{it}r_{i+1,t}$

Notes: *CPI* = the consumer price index; $M_1 = M_1$ money supply; *IPI* = the industrial production index; *LDI* = the leading index; *CI* = the coincidence index; *LGI* = the lagging index; [16]*CCI* = the consumer confidence index; *CEI* = the consumer expectation index; *CSI* = the consumer satisfaction index; [17]*N* = the number of daily returns in the month. The denominators in the yearly inflation rate and the yearly industrial production growth are 100 because the indices at the same period of the previous year are set to 100. Market volatility is measured using the returns of the market indices included in the paper (i.e. r^{SHCI}, $r^{SZIC}$and r^{HSCEI}). Subscripts *t-1, t-2, t-3, t-12, t-24* and *t-36* are month*st -1, t-2, t-3, t-12, t-24* and *t-36*, respectively

Table 2

[16]The leading, coincident and the lagging indices are business cycle indices named after the timing of their movement relative to the business cycle. In particular, the leading index (*LDI*) contains economic series of the share turnover-value of the Shanghai stock exchange, rate of sales value to gross output value, money supply – M_2,investment of new stated project, freight traffic, cargo handle at major seaports, consumer expectation index, and difference of national debt interest rates, which tends to shift direction in advance of the business cycle. The coincidence index (CI) is a series of industrial production, employment, social demands including investment consumption and foreign trades, and social incomes including the government tax revenue, profits of enterprises and income of residents, which measures current aggregate activities in the economy. Finally, the lagging index (*LGI*) tends to change directions after the business cycle. The index is composed of indicators of government expenditure, financial institution – industrial and commercial loans, financial institution – household savings deposit, consumer price index, and enterprise finished products – industrial enterprises.

[17]The consumer confidence, consumer expectation and the consumer satisfaction indices are sentiment indices released each month by the China Economic Monitoring and Analysis Centre of National Bureau of Statistics of China. In particular, the consumer confidence index (*CCI*) is a composite index covering the consumer expectation and the consumer satisfaction indices and could describe the consumer's degree of satisfaction with the current economic situation and expectation for the future economic trend. Of which, the consumer expectation index (*CEI*) indicates the expectation of consumers for the household's economic situation and the overall economic trend; the satisfactory index (*CSI*) reflects the estimation of consumers for the current overall economic situation and the purchasing time for major durable consumer goods.

Monthly Summary Statistics

Notes: The sample for the *SHCI* and the *SZCI* is from January 1993 to May 2010 and is from August 1993 to May 2010 for the *HSCEI*.

	Mean (%)	Median (%)	St.Dev (%)	Min	Max	Skewness	Kurtosis	*N*
Panel A: Stock Market Index Returns								
r^{SHCI}	0.25	0.31	5.33	-0.16	0.37	1.47	11.75	209
r^{SZCI}	0.30	0.29	4.79	-0.12	0.22	0.55	2.25	209
r^{HSCEI}	0.25	0.23	5.43	-0.17	0.19	0.10	1.61	202
Panel B: Predictor Variables								
YIR	1.96	0.77	2.83	-0.01	0.11	1.49	1.34	209
MMS	0.62	0.64	1.07	-0.03	0.05	0.35	3.04	209
YMS	7.66	7.26	2.78	0.03	0.18	1.36	2.63	209
YIPI	5.61	5.58	1.78	0.01	0.11	0.10	0.59	209
MLDI	-0.01	0.01	0.28	-0.01	0.01	-0.72	4.39	209
YLDI	-0.12	0.06	1.30	-0.05	0.04	-0.78	2.55	209
MCI	-0.01	0.00	0.32	-0.01	0.01	-0.08	0.77	209
YCI	-0.10	0.00	1.72	-0.04	0.05	-0.01	0.60	209
MLGI	-0.01	0.01	0.34	-0.01	0.01	-0.47	0.99	209
YLGI	-0.26	-0.17	2.31	-0.07	0.03	-0.79	0.40	209
MCCI	-0.02	0.04	0.53	-0.04	0.02	-2.68	18.49	209
YCCI	-0.27	-0.04	2.16	-0.06	0.05	-0.41	-0.05	209
MCSI	-0.02	0.04	0.46	-0.03	0.02	-1.87	11.78	209
YCSI	-0.24	-0.18	1.86	-0.05	0.04	-0.29	-0.03	209
MCEI	-0.02	0.04	0.84	-0.06	0.03	-2.99	21.58	209
YCEI	-0.47	0.09	2.58	-0.08	0.04	-0.81	0.36	209
MV^{SHCI}	0.17	0.08	0.39	0.00	0.04	7.35	62.02	209
MV^{SZCI}	0.19	0.08	0.33	0.00	0.03	5.04	31.74	209
MV^{HSCEI}	0.29	0.15	0.41	0.00	0.03	3.38	13.95	202

Table 3
Return Prediction Model Estimation

	Coefficient	*t*-Stat	*p*-Value	R^2	RMSE
Model I: $r_t^{SHCI} = \beta_0^{SHCI} + \beta_1^{SHCI} MLDI_{t-2} + \mu_t,$					
β_0^{SHCI}	0.0028 (0.0036)	0.7713	0.4414	0.0314	0.0526
β_1^{SHCI}	3.3552 (1.2943)	2.5923	0.0102**		
Model IV: $r_t^{SZCI} = \beta_0^{SZCI} + \beta_1^{SZCI} MLDI_{t-1} + \beta_2^{SZCI} MCEI_{t-1} + \mu_t,$					
β_0^{SZCI}	0.0031 (0.0032)	0.9556	0.3404	0.057	0.0467
β_1^{SZCI}	3.8315 (1.8017)	3.2452	0.0014***		
β_2^{SZCI}	-0.8007 (0.3912)	-2.0470	0.0419**		
Model V: $r_t^{HSCEI} = \beta_0^{HSCEI} + \beta_1^{HSCEI} MLDI_{t-1} + \beta_2^{HSCEI} MCI_{t-2} + \beta_3^{HSCEI} MLGI_{t-2} + \mu_t,$					
β_0^{HSCEI}	0.0024 (0.0036)	0.6708	0.5032	0.1136	0.0515
β_1^{HSCEI}	6.6092 (1.4042)	4.7067	0.0005***		
β_2^{HSCEI}	-2.6759 (1.2378)	-2.1618	0.0318**		
β_3^{HSCEI}	2.9986 (1.1033)	2.7177	0.0072***		

Notes: Model I, Model II and Model III are the return prediction models for the *SHCI*, *SZCI* and the *HSCEI*, respectively. The sample for the *SHCI* and the *SZCI* is from January 1993 to May 2010 and is from August 1993 to May 2010 for the *HSCEI*. Standard errors are provided in the bracket. ** and *** indicate significance at the 5% and 1% levels, respectively.

Table 4
Robustness of Model Parameter Estimates

	Outlier Robust Statistics[1]					Heteroskedasticity and Serial Correlation Robust Statistics[2]				
	Estimate	*t*-Stat	*p*-Value	R^2	RMSE	Estimate	*t*-Stat	*p*-Value	R^2	RMSE
Model I: $r_t^{SHCI}= \beta_0^{SHCI} + \beta_1^{SHCI} MLDI_{t-2} + \mu_t$,										
β_0^{SHCI}	0.0023 (0.0027)	0.8548	0.3936	0.0327	0.0394	0.0028 (0.0032)	0.8800	0.3800	0.0314	0.0526
β_1^{SHCI}	2.5409 (0.9684)	2.6238	0.0093***			3.3552 (1.7222)	1.9500	0.0530*		
Model II: $r_t^{SZCI}= \beta_0^{SZCI} + \beta_1^{SZCI} MLDI_{t-1} + \beta_2^{SZCI} MCEI_{t-1} + \mu_t$,										
β_0^{SZCI}	0.0018 (0.0029)	0.6238	0.5335	0.0668	0.0422	0.0031 (0.0032)	0.9400	0.3470	0.0570	0.0467
β_1^{SZCI}	3.7744 (1.0655)	3.5424	0.0049***			3.8315 (1.2580)	3.0500	0.0030***		
β_2^{SZCI}	-0.7602 (0.3530)	-2.1535	0.0324**			-0.8007(0.3080)	-2.6000	0.0100***		
Model III: $r_t^{HSCEI}= \beta_0^{HSCEI} + \beta_1^{HSCEI} MLDI_{t-1} + \beta_2^{HSCEI} MCI_{t-2} + \beta_3^{HSCEI} MLGI_{t-2} + \mu_t$,										
β_0^{HSCEI}	0.0013 (0.0033)	0.3820	0.7029	0.1340	0.0464	0.0024 (0.0034)	0.7109	0.4780	0.1136	0.0515
β_1^{HSCEI}	6.6433 (1.2762)	5.2056	0.0000***			6.6092 (1.5170)	4.3567	0.0000***		
β_2^{HSCEI}	-2.4295 (1.1249)	-2.1597	0.0320**			-2.6759 (1.0818)	-2.4735	0.0142**		
β_3^{HSCEI}	2.8473 (1.0027)	2.8396	0.0050***			2.9986 (1.0575)	2.8355	0.0050***		

Notes: Model I, Model II and Model III are the return prediction models for the *SHCI*, *SZCI* and the *HSCEI*, respectively. The sample for the *SHCI* and the *SZCI* is from January 1993 to May 2010 and is from August 1993 to May 2010 for the *HSCEI*.[1] Iteratively reweighted least squares with a bi-square weighting function is used to obtain outlier robust statistics. [2] The Newey-West test statistic is used as the heteroskedasticity and serial correlation robust statistic, where the lag $4(\frac{n}{100})^{2/9}$ is included to correct for serial correlation. Standard errors are provided in the bracket. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 5

Tests for the Presence of Breaks

Specifications: π = 15%, m = 5 Break Tests										
*Sup*F$_T$(1)	*Sup*F$_T$(2)	*Sup*F$_T$(3)	*Sup*F$_T$(4)	*Sup*F$_T$(5)	*UD*max	*WD*max	*Sup*F$_T$(2|1)	*Sup*F$_T$(3|2)	*Sup*F$_T$(4|3)	*Sup*F$_T$(5|4)
Model I: $r_t^{SHCI} = \beta_0^{SHCI} + \beta_1^{SHCI} MLDI_{t-2} + \mu_t$,										
3.4753	1.3194	1.0084	3.1523	1.9627	3.4753	5.0323(10%)	0.7449	0.5162	0.3557	0.0018
Model II: $r_t^{SZCI} = \beta_0^{SZCI} + \beta_1^{SZCI} MLDI_{t-1} + \beta_2^{SZCI} MCEI_{t-1} + \mu_t$,										
1.9013	2.7920	2.4659	4.1490	10.5233***	10.5233***	26.3404***	0.9289	0.5071	0.1626	0.0000
Model III: $r_t^{HSCEI} = \beta_0^{HSCEI} + \beta_1^{HSCEI} MLDI_{t-1} + \beta_2^{HSCEI} MCI_{t-2} + \beta_3^{HSCEI} MLGI_{t-2} + \mu_t$,										
0.6731	1.3225	1.3060	1.5234	1.0548	1.5234	2.4319 (10%)	0.6610	0.8892	0.1233	0.0000
Specifications: π = 20%, m = 3 Break Tests										
*Sup*F$_T$(1)	*Sup*F$_T$(2)	*Sup*F$_T$(3)	*UD*max	*WD*max	*Sup*F$_T$(2|1)	*Sup*F$_T$(3|2)				
Model I: $r_t^{SHCI} = \beta_0^{SHCI} + \beta_1^{SHCI} MLDI_{t-2} + \mu_t$,										
2.8661	1.1496	3.4776	3.4776	5.3477(10%)	0.2210	0.0312				
Model IV: $r_t^{SZCI} = \beta_0^{SZCI} + \beta_1^{SZCI} MLDI_{t-1} + \beta_2^{SZCI} MCEI_{t-1} + \mu_t$,										
1.9013	3.6222	7.4958***	7.4958***	11.5268**	0.2890	0.3420				
Model V: $r_t^{HSCEI} = \beta_0^{HSCEI} + \beta_1^{HSCEI} MLDI_{t-1} + \beta_2^{HSCEI} MCI_{t-2} + \beta_3^{HSCEI} MLGI_{t-2} + \mu_t$,										
0.673	1.246		1.2462	1.8422	0.2377	0.3192				

Note: Model I, Model II and Model III are the return prediction models for the *SHCI*, *SZC*I and the *HSCEI*, respectively. The sample for the *SHC*I and the *SZCI* is from January 1993 to May 2010 and is from August 1993 to May 2010 for the *HSCEI*. The *Sup*F tests allow for the possibility of heteroskedasticity and serial correlation in the errors. The heteroskedasticity and serial correlation consistent covariance matrix is constructed following Andrew (1991) and Andrews and Monahan (1992) using a quadratic kernel with automatic bandwidth selection based on a first order auto-regression (AR (1)) approximation. The residuals are pre-whitened using a first order vector auto-regression (VAR (1)).*, ** and ***indicate significance at the 10%, 5% and 1% levels, respectively.

Table 6

Return Prediction Model Estimation under Instability for the *SZCI* Return Model

Specifications: π = 15%, m = 5												
	Subsample 1 (01.93 - 06.95, N = 30)			Subsample 2 (07.95 - 03.98, N = 33)			Subsample 3 (04.98 - 02.01, N = 35)			Subsample4 (03.01 - 06.04, N = 40)		
	Estimate	R^2	Break Date	Estimate	R^2	Break Date	Estimate	R^2	Break Date	Estimate	R^2	Break Date
$\beta_0^{SZ}{}_{CI}$	-0.0077 (0.0122)	0.1188	07.95(/)[1]	0.0146 (0.0102)	0.0068	04.98 (/)	0.0053 (0.0056)	0.1833	03.01 (/)	-0.0057 (0.0049)	0.0006	07.04 (/)
$\beta_1^{SZ}{}_{CI}$	3.2833 (2.2982)			1.3519 (4.6355)			5.3695 (2.4726)**			0.3595 (3.8693)		
$\beta_2^{SZ}{}_{CI}$	-1.1830 (0.7897)			-0.6271 (1.6427)			0.9139 (1.0013)			-0.0929 (0.6057)		
	Subsample 5 (07.04 - 02.07, N = 32)			Subsample 6 (03.07 - 05.10, N = 39)								
	Estimate	R^2	Break Date	Estimate	R^2	Break Date						
$\beta_0^{SZ}{}_{CI}$	0.0125 (0.0062)	0.0504	03.07(/)	0.0011 (0.0089)	0.1244							
$\beta_1^{SZ}{}_{CI}$	-1.8543 (5.4833)			6.8780 (3.3129)**								
$\beta_2^{SZ}{}_{CI}$	-1.9794 (1.9107)			-1.6001 (1.6331)								
Specifications: π = 20%, m = 3												
	Subsample 1 (01.93 – 03.97, N = 51)			Subsample2 (04.97 - 02.01, N = 47)			Subsample3 (03.01 - 05.06, N = 63)			Subsample4 (06.06 - 05.10, N = 48)		
	Estimate	R^2	Break Date	Estimate	R^2	Break Date	Estimate	R^2	Break Date	Estimate	R^2	Break Date
$\beta_0^{SZ}{}_{CI}$	0.0062 (0.0092)	0.0980	04.97 (05.96 – 11.98)	0.0032 (0.0051)	0.0761	03.01 (02.98 – 11.05)	-0.0022 (0.0038)	0.0022	06.06 (07.04 – 05.10)	0.0068 (0.0076)	0.0981	
$\beta_1^{SZ}{}_{CI}$	3.7906 (2.2159)*			2.9286 (2.3287)			-0.7193 (3.1903)			6.4369 (3.1000)**		
$\beta_2^{SZ}{}_{CI}$	1.3157 (0.7621)			0.8889 (0.7826)			-0.0669 (0.5564)			-1.2427 (1.4834)		

Note: The sample for the *SZCI* is from January 1993 to May 2010.[1] The procedure to get critical values of the break date has reached the upper bound on the number of iterations and consequently the resulting confidence intervals for these break dates are incorrect. The confidence levels for the break occurrence are computed with heteroskedasticity and serial correlation consistent covariance matrix being constructed following Andrew (1991) and Andrews and Monahan (1992) using a quadratic kernel with automatic bandwidth selection based on an AR (1) approximation. The residuals are pre-whitened using a VAR (1).Standard errors are provided in the bracket. * and ** indicate significance at the 10% and 5% levels, respectively.