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ESTIMATION OF MEAN AND VARIANCE EPISODES IN THE PRICE RETURN OF THE STOCK EXCHANGE OF THAILAND

Theodore Bos and Pongsak Hoontrakul

ABSTRACT

This paper extends the novel and useful recent work of Inclán and Tiao (1994). Their invention was a procedure, based on CUSUM statistics, that would estimate the location of change points in the variance of a time series. This paper will show, with a Monte Carlo analysis, that the basic Inclán and Tiao procedure will also estimate changes in the average of a time series. This will invalidate prior work using earlier forms of the procedure. This paper will also introduce a procedure that will statistically identify whether an estimated change point is a change in average, variance, or both. To show the practical value of these new procedures, they will be applied to the daily return on the index of the Stock Exchange of Thailand (SET). This will be augmented with a description of the more important of these turning points in the life of the SET.

1. INTRODUCTION

Recent work of Inclán and Tiao (1994) presented a new procedure that would estimate change points in variance. They called this procedure the iterated

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cumulative sum of squares (ICSS) algorithm. It was immediately obvious to finance researchers that this procedure could help in estimating when risk (variance of return) of an asset changes. The ICSS algorithm has been applied to estimating change points in the volatility of stock returns by Aggarwal, Inclán and Leal (1996). More recently Bos, Ding and Fetherston (BDF, 1998) attempted an improvement in the ICSS procedure and also applied that improved procedure to the volatility of stock returns. That attempt used the critical boundaries of Tanazaki (1995) in the hope that those nonlinear boundaries would improve the estimates of the original ICCS which uses linear boundaries. Bos and Fetherston (1992) showed that the linear boundaries, first used by Brown, Durbin and Evans (1975), lead to higher incidences of breaks in the middle of the data set.

In their empirical work, BDF hypothesized that their estimated change points in the variance of Thai stock returns might be related to changes in the mean of those stock returns. This paper will revisit that concern. Using Monte Carlo analysis, Section 3 of this paper shows that changes in the mean of a process will indeed be picked up by the ICCS as changes in the variance. Thus the original ICCS procedure will pick up both changes in mean and variance. Section 4 introduces a procedure that will estimate whether an estimated change point is either a change in mean, or variance, or both. This new procedure can be grafted to the original ICCS procedure. Section 5 applies this new set of procedures to daily price returns of the Stock Exchange of Thailand (SET).

2. BACKGROUND

In econometrics all the work on cumulative sum (CUSUM) of squares originates with Brown, Durbin and Evans (BDE, 1975). That paper created the CUSUM and CUSUM of squares statistics, and showed how those measures could be used to help determine whether or not the estimated parameters of a regression changes over time. The implicit assumption underlying every regression is that its parameters (the coefficient of the constant, the slopes, and the error variance) are constant over time. The CUSUM statistics are based on what are called *recursive residuals*. These are the standardized one-period ahead prediction errors from estimates of regressions based on data sets which grow one observation at a time.

It is known, but not widely understood, that a regression estimate without any independent variables is simply the mean and variance of the dependent variable. It is in this way that the CUSUM statistics can be used first of all to look for changes in the mean and variance of a series using the methods of

BDE, and now secondly to estimate change points in the variance using Inclán and Tiao's ICSS.

We will now develop the basic CUSUM concepts for a single series. Let

$$y_t = \mu + \varepsilon_t$$

where μ is the constant unknown mean of y_t, and σ^2 is the constant unknown variance of ε_t and y_t. The process of calculating first the recursive residuals, and then the CUSUM statistics starts with the first observation, y_1. With only this one observation, the predicted value of the next observation is equal to the first, as we have no other information. We can standardize the resulting prediction error, add an observation to our information set and estimate of the next observation, and continue to the end of the data set. In this way, the recursive residuals are

$$w_r = \frac{y_r - \left(\sum_{i=1}^{r-1} y_i \Big/ r-1 \right)}{\sqrt{\left(\frac{r}{r-1}\right) s_y^2}} \quad r = 2, 3, \ldots, n$$

where s_y^2 is the estimated variance of all the y_t. Hence by the definition of the recursive residual, the numerator of w_r is the prediction error, (actual − predicted), while the denominator of w_r is the standard deviation of the one period ahead prediction error.

From these recursive residuals, one can calculate the CUSUM statistics.

The CUSUM statistic is defined as

$$W_r = \sum_{t=1}^{r} w_t \quad r = 2, 3, \ldots, n$$

and the CUSUM of squares statistic is defined by

$$s_r = \frac{\sum_{t=1}^{r} w_t^2}{\sum_{t=1}^{n} w_t^2}, \quad r = 2, 3, \ldots, n$$

Inclán and Tiao (1994) center the CUSUM of squares so that its mean is zero

$$s^*_r = \frac{\sum_{t=1}^{r} w_t^2}{\sum_{t=1}^{n} w_t^2} - \frac{r}{n}, \quad r=2, 3, \ldots, n$$

Once the CUSUM of squares is centered, the original BDE critical boundaries are then horizontal, instead of diagonal, and hence easier to visualize and work with. In prior work, the time series plot of the CUSUM statistic was popular among users because of the intuition to be gained from it. The simple act of centering the CUSUM of squares statistic did the same thing for the CUSUM of squares.

Inclán and Tiao's ICSS procedure goes as follows:

Starting with the whole time series as the data segment being analyzed:

(1) Calculate the centered CUSUM of squares statistic for the data segment;
(2) Find the largest excursion beyond their version of the centered BDE critical boundaries;
(3) If one is found, mark this as an estimated change point in the variance of the time series segment under study;
(4) Split the particular data segment into two parts at this point.

Then follow the same sequence of steps with each new data segment until no more change points are found.

3. ICCS IN THE PRESENCE OF MEAN CHANGES

In the conclusion of their paper BDF hypothesize that the Inclán and Tiao ICCS procedure is also a predictor of mean changes – as well as a predictor of variance changes. In this section we will test this hypothesis with a Monte Carlo study. This analysis will be somewhat consistent with the simulations of Inclán and Tiao and those of the next section. Thus we analyze the reaction of the ICCS procedure to data segments each of the following characteristics:

(a) 100, 200, and 500 observations;
(b) mean and variance changes of 1 (no change), 2, and 3 standard deviations;
(c) mean or variance changes at 25%, 50%, or 75% of the series length.

This selection will give us information as to the sensitivity of the ICCS algorithm to mean and variance changes of various sizes in data segments of varying lengths.

One hundred thousand replications were carried out for each case. The results are summarized in Table 1 and Figs 1 and 2. From these displays the following can be inferred:

(i) mean changes will be picked up by the ICCS algorithm;
(ii) the longer the data set, the closer the point estimates for both mean and variance changes;
(iii) if the break is near the beginning of the data set, the more unreliable the estimate.

The goal of this section is satisfied by point (i). Although as Inclán and Tiao had intended, the ICCS is able to estimate step changes in variance, it is also able to estimate step changes in the mean. This was not intended by Inclán and Tiao, but yet is to be expected as the formula for the estimated variance contains the estimated mean. Thus when a user of the ICCS algorithm estimates a change point, the user is left with two possibilities – either the change point is a mean change or a variance change. This leaves the ICCS algorithm somewhat weak. The next section will introduce a method to estimate whether an estimated change point is a mean change or a variance change.

4. EXTENSION OF ICCS TO ESTIMATE MEAN CHANGES

The results in the above section clearly show that the ICCS algorithm will signal a change if a series experiences either a mean change or a variance change. Also properties of the point estimate of a break point seem somewhat similar for both mean and variance changes. While at first glance the identification problem between mean and variance changes causes a dilemma in the use of the ICCS, that property is actually beneficial. Research into estimating mean changes can now utilize the ICCS – except for the fact that the identification question exists. In this section we propose a simple solution to this question, and will study the effects of the ensuing extended ICCS using a Monte Carlo analysis. We will call the extended ICCS method ICCS:MV, where MV stands for mean and variance.

We suggest the following addition to the ICCS procedure. After all change points have been estimated using the original ICCS procedure, go through the data again two segments at a time. Let there be k estimated change points – not counting the two end points of the series being investigated. Thus there will be $(k+1)$ statistically stationary segements. Going through the data two segements at a time will help us determine what type of change has occurred at each

Table 1.

Number of Observations	Change Type	Where	Size	Estimated Change Points Probability	Average	Standard Deviation
100	NONE			0.034	50.7	18.7
100	Mean	25	2	0.124	42.2	14.6
100	Mean	50	2	1.000	50.4	6.7
100	Mean	75	2	1.066	73.3	8.0
100	Mean	25	3	0.344	37.7	15.2
100	Mean	50	3	1.168	50.8	6.3
100	Mean	75	3	1.164	74.4	7.1
100	Variance	25	2	0.160	51.7	14.9
100	Variance	50	2	0.523	56.4	10.5
100	Variance	75	2	0.420	71.9	11.5
100	Variance	25	3	0.404	44.7	14.9
100	Variance	50	3	0.947	54.7	8.8
100	Variance	75	3	0.848	73.7	9.7
200	NONE			0.039	99.6	33.6
200	Mean	50	2	0.553	72.6	31.3
200	Mean	100	2	1.133	101.0	14.3
200	Mean	150	2	1.133	147.7	16.1
200	Mean	50	3	1.353	64.7	27.8
200	Mean	100	3	1.159	101.3	13.6
200	Mean	150	3	1.202	149.0	15.0
200	Variance	50	2	0.475	81.8	28.9
200	Variance	100	2	0.898	107.3	18.6
200	Variance	150	2	0.750	143.2	22.0
200	Variance	50	3	1.094	68.6	24.2
200	Variance	100	3	1.065	105.4	15.3
200	Variance	150	3	1.038	147.2	18.1
500	NONE			0.045	250.8	84.5
500	Mean	125	2	1.424	165.2	74.5
500	Mean	250	2	1.138	252.1	37.5
500	Mean	375	2	1.179	371.4	40.5
500	Mean	125	3	1.253	144.9	57.3
500	Mean	250	3	1.145	252.4	36.5
500	Mean	375	3	1.190	371.9	40.0
500	Variance	125	2	1.130	163.0	57.1
500	Variance	250	2	1.071	258.3	39.6
500	Variance	375	2	1.054	361.8	48.7
500	Variance	125	3	1.356	147.7	45.6
500	Variance	250	3	1.091	255.5	36.6
500	Variance	375	3	1.077	368.9	42.9

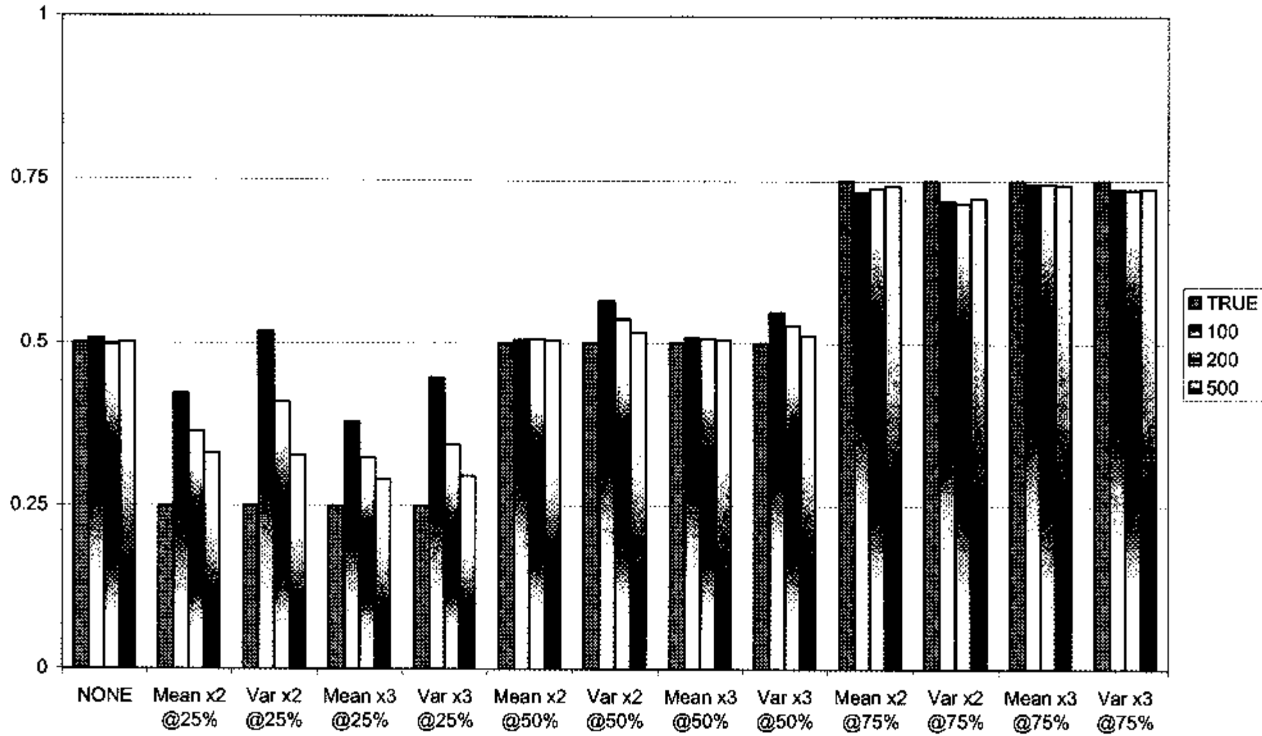

Fig. 1. Average of Estimated Break Points.

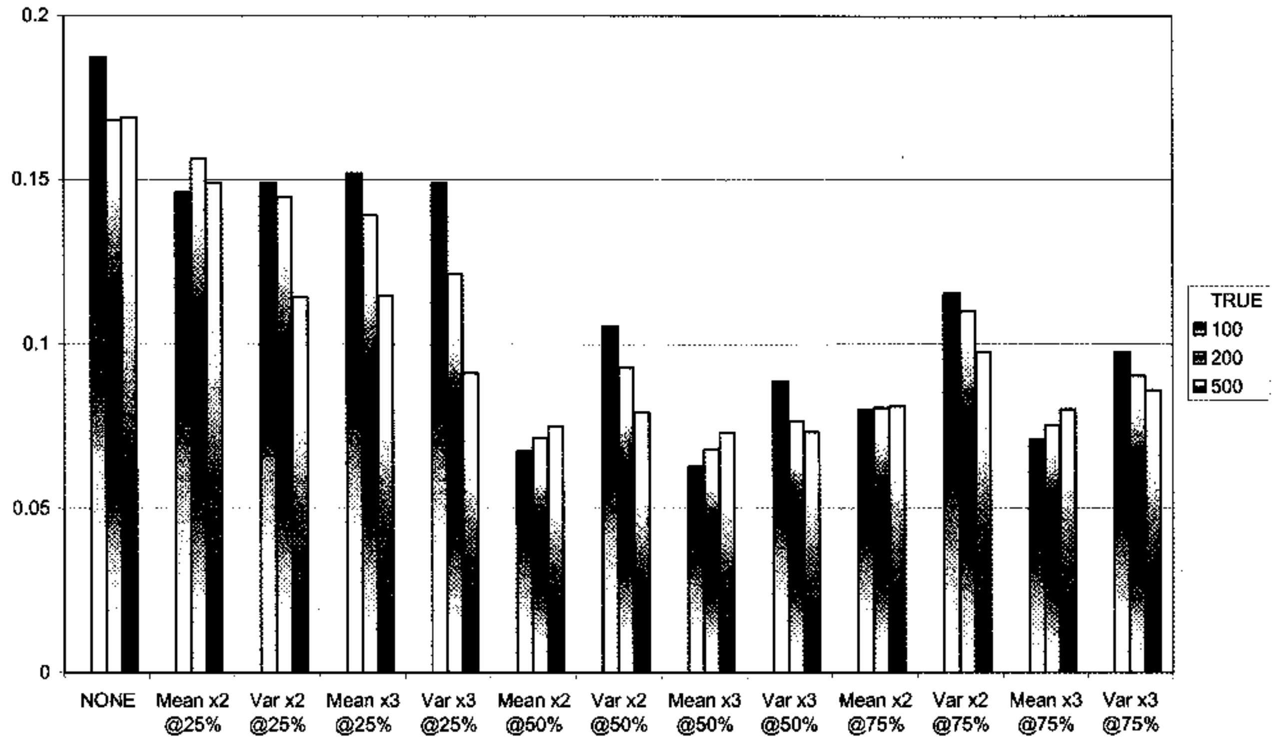

Fig. 2. Standard Deviation of Estimated Break Points.

estimated break point. Let *BPj* denote the *j*th estimated break point. Thus to determine the nature of the break at *BPj* we need the segments on each side of that point. Call these segments 1 and 2 where the elements of segment 1 are x_{1i}, $i = 1, 2, \ldots, n_1$; and the elements of segment 2 are x_{2i}, $i = 1, 2, \ldots, n_2$. We first hypothesize that the break point is a change in the mean. If this is true, then if we mean-standardize both segments then if the combination of the two line segements is passed through the ICCS then the two joined segements are expected to be stationary. By mean-standardize, we mean that each segment is transformed to the deviation from its mean. Thus the two joined segments would become:

$$(x_{11} - \bar{x}_1), (x_{12} - \bar{x}_1), \ldots, (x_{1n_1} - \bar{x}_1); (x_{21} - \bar{x}_2), (x_{22} - \bar{x}_2), \ldots, (x_{2n_2} - \bar{x}_2)$$

Secondly, we hypothesize that the break point is a change in the variance. If this is true, then if we variance-standardize both segments then if the combination of the two line segements is passed through the ICCS then the two joined segements are expected to be stationary. By variance-standardize, we mean that each element is divided by the standard deviation of its segment. Thus the two joined segments would become:

$$\frac{(x_{11} - \bar{x}_{1,2})}{s_1}, \frac{(x_{12} - \bar{x}_{1,2})}{s_1}, \ldots, \frac{(x_{1n_1} - \bar{x}_{1,2})}{s_1}; \frac{(x_{21} - \bar{x}_{1,2})}{s_2}, \frac{(x_{22} - \bar{x}_{1,2})}{s_2}, \ldots, \frac{(x_{2n_2} - \bar{x}_{1,2})}{s_2}$$

We pass the data from the two segments through this process and record the results.

(i) If the mean-standardized segments are *stationary* and the variance-standardized segments are *stationary*, then the break is estimated to be in both mean and variance.
(ii) If the mean-standardized segments are *stationary* and the variance-standardized segments are *nonstationary*, then the break is estimated to be in the mean only.
(iii) If the mean-standardized segments are *nonstationary* and the variance-standardized segments are *stationary*, then the break is estimated to be in the variance only.
(iv) If the mean-standardized segments are *nonstationary* and the variance-standardized segments are *nonstationary*, then the cause of the break is undetermined. The cause for the break could be a change in mean or variance, but most likely it is something else.

The above can be summarized in a table as follows:

Table 2.

		Mean-standardized	
		If stationary	If nonstationary
Variance-standardized	If stationary	Mean and variance change	Variance change
	If nonstationary	Mean change	Undetermined

This additional procedure was put into the Monte Carlo analysis of the previous section. These results are shown in Table 3. This table contains a large amount of interesting information. We direct the reader to the panel with 500 observations per series. From Table 1, we see that if there are no breaks of any kind, then there will be slightly less than the expected frequency of false positives – 4.5% instead of the expected 5%. This is better than the opposite – too many false positves. Referring back to Table 3, if there are no breaks and if the ICCS:MV procedure estimates a break (a false positive), then 92.9% of these will register as variance breaks. One would hope that false positives get evenly distributed among the four choices, but that is not the case.

Now we direct the reader to mean changes in series of 500 observations. Regardless of where the change was, most of the time the change was correctly identified as a mean change (eg. 62.7% for a 2.0 standard deviation change in the mean after observation 125). It is extremely interesting to note that when the ICCS:MV estimates a mean change, then the average point estimate of the location of that change is very close to the true change. Also, and perhaps more important, the standard error of this location is extremely small – meaning that the estimate of the location of the mean change is extremely precise. Although the point and interval estimates of the location of a mean change are very good, it must be noted that if a mean change occurs, the ICCS:MV procedure can still label this as a variance change – an 18.1% chance of being labeled as a variance change for a 2.0 standard deviation change in mean after observation 375.

Now moving to the part of Table 3 with 500 observations and variance changes, we see that the probability of correctly identifying a variance change is very high – much higher than correctly identifying a mean change. Yet, the properties of the point and interval estimates are quite disappointing in comparison to those of the mean changes – the point estimates are clearly biased, and the standard errors are very large.

Table 3.

Number of Observations	Change Type	Where	Size		All Change Points	Estimated Change Type			
						Both	Mean	Variance	Undetermined
100	NONE			Proportion		17.8%	0.0%	82.1%	0.1%
				Average	50.7	52.3	34.0	50.3	23.5
				Stdev.	18.7	21.5	0.0	18.0	0.5
100	Mean	25	2	Proportion		41.5%	22.6%	33.8%	2.0%
				Average	42.2	43.4	25.4	52.9	25.4
				Stdev.	14.6	12.9	1.7	10.1	3.0
100	Mean	50	2	Proportion		8.3%	78.7%	10.1%	2.9%
				Average	50.4	51.3	50.2	51.9	48.6
				Stdev.	6.7	12.1	2.0	17.0	3.6
100	Mean	75	2	Proportion		75.5%	10.9%	11.8%	1.9%
				Average	73.3	74.5	74.5	65.2	69.8
				Stdev.	8.0	4.8	2.2	17.6	5.9
100	Mean	25	3	Proportion		46.5%	42.4%	7.8%	3.3%
				Average	37.7	48.3	25.2	49.0	25.0
				Stdev.	15.2	12.4	1.0	18.0	1.9
100	Mean	50	3	Proportion		15.9%	72.9%	8.0%	3.2%
				Average	50.8	54.2	50.1	50.9	49.7
				Stdev.	6.3	9.6	0.7	16.6	1.9
100	Mean	75	3	Proportion		20.8%	68.1%	7.2%	3.9%
				Average	74.4	76.0	75.0	65.6	72.9
				Stdev.	7.1	7.4	0.7	20.8	3.1
100	Variance	25	2	Proportion		10.6%	0.0%	89.4%	0.0%
				Average	51.7	57.8	NA	51.0	34.0
				Stdev.	14.9	16.1	NA	14.6	0.0

Table 3. Continued.

Number of Observations	Change Type	Where	Size		All Change Points	Estimated Change Type			
						Both	Mean	Variance	Undetermined
100	Variance	50	2	Proportion		8.0%	0.0%	92.0%	0.0%
				Average	56.4	58.3	NA	56.2	28.0
				Stdev.	10.5	14.6	NA	10.1	23.0
100	Variance	75	2	Proportion		12.1%	0.0%	87.9%	0.0%
				Average	71.9	73.4	81.0	71.7	90.0
				Stdev.	11.5	13.3	0.0	11.2	0.0
100	Variance	25	3	Proportion		14.0%	0.0%	85.9%	0.0%
				Average	44.7	50.1	53.5	43.8	39.2
				Stdev.	14.9	15.6	7.4	14.6	12.6
100	Variance	50	3	Proportion		6.2%	0.0%	93.8%	0.0%
				Average	54.7	55.2	NA	54.7	47.6
				Stdev.	8.8	13.9	NA	8.4	18.2
100	Variance	75	3	Proportion		8.1%	0.0%	91.9%	0.0%
				Average	73.7	73.0	77.0	73.7	NA
				Stdev.	9.7	14.2	0.0	9.2	NA
200	NONE			Proportion		11.4%	0.0%	88.6%	0.0%
				Average	99.6	99.5	NA	99.6	66.0
				Stdev.	33.6	40.7	NA	32.6	0.0
200	Mean	50	2	Proportion		33.0%	51.0%	11.9%	4.1%
				Average	72.6	102.1	50.3	94.9	49.4
				Stdev.	31.3	23.0	2.0	38.6	2.6
200	Mean	100	2	Proportion		5.4%	77.5%	13.1%	4.0%
				Average	101.0	103.6	100.2	105.7	98.4
				Stdev.	14.3	26.3	2.2	34.7	4.8

Table 3. Continued.

Number of Observations	Change Type	Where	Size		All Change Points	Estimated Change Type: Both	Mean	Variance	Undetermined
200	Mean	150	2	Proportion		29.5%	52.1%	13.9%	4.5%
				Average	147.7	149.3	149.6	138.8	142.5
				Stdev.	16.1	12.1	2.4	37.4	8.4
200	Mean	50	3	Proportion		26.0%	62.4%	8.0%	3.7%
				Average	64.7	98.5	50.0	76.3	49.2
				Stdev.	27.8	26.9	0.8	40.9	3.4
200	Mean	100	3	Proportion		10.3%	76.4%	9.3%	4.0%
				Average	101.3	111.3	100.1	100.9	99.7
				Stdev.	13.6	21.9	0.8	36.5	2.2
200	Mean	150	3	Proportion		17.9%	67.2%	11.9%	2.9%
				Average	149.0	152.7	150.0	138.1	149.0
				Stdev.	15.0	14.8	0.7	37.6	2.3
200	Variance	50	2	Proportion		8.5%	0.0%	91.5%	0.0%
				Average	81.8	94.6	70.0	80.6	36.5
				Stdev.	28.9	31.0	0.0	28.4	19.5
200	Variance	100	2	Proportion		5.0%	0.0%	95.0%	0.0%
				Average	107.3	106.9	11.0	107.4	76.0
				Stdev.	18.6	27.3	0.0	18.0	47.0
200	Variance	150	2	Proportion		6.6%	0.0%	93.4%	0.0%
				Average	143.2	142.6	NA	143.3	116.0
				Stdev.	22.0	28.8	NA	21.4	60.8
200	Variance	50	3	Proportion		16.4%	0.0%	83.5%	0.0%
				Average	68.6	86.4	56.7	65.0	76.0
				Stdev.	24.2	26.2	21.4	22.2	39.5

Table 3. Continued.

Number of Observations	Change Type	Where	Size		All Change Points	Estimated Change Type			
						Both	Mean	Variance	Undetermined
200	Variance	100	3	Proportion		4.8%	0.0%	95.2%	0.0%
				Average	105.4	106.1	NA	105.3	96.0
				Stdev.	15.3	25.8	NA	14.5	46.7
200	Variance	150	3	Proportion		4.5%	0.0%	95.5%	0.0%
				Average	147.2	144.1	NA	147.3	164.5
				Stdev.	18.1	30.5	NA	17.2	2.5
500	NONE			Proportion		7.1%	0.0%	92.9%	0.0%
				Average	250.8	247.9	NA	251.1	NA
				Stdev.	84.5	99.6	NA	83.2	NA
500	Mean	125	2	Proportion		22.5%	62.7%	11.1%	3.7%
				Average	165.2	267.0	124.8	202.0	120.9
				Stdev.	74.5	55.4	2.5	107.4	8.3
500	Mean	250	2	Proportion		3.3%	79.3%	12.5%	4.9%
				Average	252.1	271.4	250.1	260.9	248.3
				Stdev.	37.5	72.4	2.0	98.0	6.3
500	Mean	375	2	Proportion		7.8%	70.4%	18.1%	3.7%
				Average	371.4	373.7	374.7	357.5	370.7
				Stdev.	40.5	44.8	2.2	89.0	9.1
500	Mean	125	3	Proportion		12.8%	73.2%	10.0%	4.0%
				Average	144.9	239.6	125.0	177.6	124.0
				Stdev.	57.3	68.3	0.9	106.1	4.2
500	Mean	250	3	Proportion		6.0%	80.0%	9.5%	4.5%
				Average	252.4	291.3	250.1	248.2	249.8
				Stdev.	36.5	59.9	1.0	103.5	1.5

Table 3. Continued.

Number of Observations	Change Type	Where	Size		All Change Points	Estimated Change Type: Both	Mean	Variance	Undetermined
500	Mean	375	3	Proportion		12.7%	71.3%	13.0%	3.0%
				Average	371.9	384.1	375.0	342.8	374.7
				Stdev.	40.0	37.5	0.7	99.1	1.9
500	Variance	125	2	Proportion		11.3%	0.0%	88.7%	0.0%
				Average	163.0	207.1	NA	157.4	43.0
				Stdev.	57.1	61.3	NA	54.1	8.0
500	Variance	250	2	Proportion		3.1%	0.0%	96.9%	0.0%
				Average	258.3	255.6	27.0	258.4	313.0
				Stdev.	39.6	61.9	0.0	38.6	15.0
500	Variance	375	2	Proportion		3.2%	0.0%	96.8%	0.0%
				Average	361.8	351.4	NA	362.2	233.0
				Stdev.	48.7	75.5	NA	47.5	164.0
500	Variance	125	3	Proportion		21.2%	0.0%	78.8%	0.0%
				Average	147.7	180.3	154.5	138.9	112.7
				Stdev.	45.6	42.4	5.5	42.3	39.8
500	Variance	250	3	Proportion		3.2%	0.0%	96.8%	0.0%
				Average	255.5	255.6	344.0	255.5	127.4
				Stdev.	36.6	61.7	0.0	35.4	110.2
500	Variance	375	3	Proportion		2.8%	0.0%	97.2%	0.0%
				Average	368.9	360.6	100.0	369.1	241.5
				Stdev.	42.9	74.9	0.0	41.5	170.8

The above properties of the estimates of the ICCS:MV, as expected, get somewhat worse as the series length decreases. We can summarize the properties of the ICCS:MV as follows:

(i) Although not absolutely precise, the ICCS:MV generally does what it is expected to do.
(ii) If the true change is a mean change:
  (a) the probability that the ICCS:MV mis-identifies it is often between 15% and 20%.
  (b) The point estimate is unbiased; and
  (c) The standard error is very small.
(iii) If the true change is a variance change:
  (a) the probability that the ICCS:MV mis-identifies it is very small;
  (b) The point estimate is biased; and
  (c) The standard error is quite large.

Though these properties are not clean as one would like, they are better than the alternative, which prior to this paper was a misunderstanding of the nature of change signals generated by the ICCS.

5. APPLICATION OF ICCS:MV

To gain some practical insight into the ICCS:MV it was applied to 5,514 daily observations of the return in the market index of the Stock Exchange of Thailand (SET). The data used begins on May 2, 1975 and ends on September 22, 1997. Out of those 5,514 observations, 69 changes points were estimated. This level of aggregation corresponds to the application of the ICCS. Of those 69 estimated change points, for only one (November 27, 1978) could the type of change point not be determined – corresponds to the bottom right corner of Table 2. Also of the 69 estimated change points, not one was estimated to be caused by a variance change only. All five estimated variance changes were in conjuction with mean changes. The other 63 estimated change points were mean only changes. The dates of the estimated change points are displayed in Table 4 along with the estimated mean and standard deviations of the intervening episodes. This information is also shown graphically in Fig. 3.

The interesting aspect of this empirical analysis is that the vast majority of the estimated change points were identified as mean changes, and most of the rest were estimated to be both changes in mean and variance. From the Monte Carlo analysis of the previous section of this paper we note that if the true change is a variance change, then it is very likely that the ICCS:MV will identify it as such. Also if the true change if a mean change, then most often

Table 4. Results of ICCS:MV on SET Daily Returns.

#	Episode	Average	Standard deviation	Number of Trading Days
1	May 2, 1975 to May 21, 1975	–0.0117	0.0090	13
2	May 22, 1975 to May 28, 1975	0.0092	0.0090	5
3	May 29, 1975 to July 2, 1975	0.0011	0.0090	24
4	July 3, 1975 to July 28, 1975	0.0048	0.0090	17
5	July 29, 1975 to August 6, 1975	–0.0021	0.0090	7
6	August 7, 1975 to October 6, 1975	–0.0016	0.0090	42
7	October 7, 1975 to October 8, 1975	–0.0017	0.0090	2
8	October 9, 1975 to October 27, 1975	–0.0002	0.0090	12
9	October 28, 1975 to March 8, 1976	–0.0012	0.0081	89
10	March 9, 1976 to June 3, 1976	–0.0008	0.0081	58
11	June 4, 1976 to March 30, 1977	0.0009	0.0081	204
12	March 31, 1977 to April 28, 1977	0.0036	0.0081	19
13	April 29, 1977 to May 3, 1977	0.0128	0.0081	2
14	May 4, 1977 to July 28, 1977	0.0034	0.0081	59
15	July 29, 1977 to August 15, 1977	0.0136	0.0081	10
16	August 16, 1977 to August 23, 1977	0.0072	0.0081	6
17	August 24, 1977 to October 11, 1977	0.0013	0.0081	35
18	October 12, 1977 to December 14, 1977	0.0028	0.0081	43
19	December 15, 1977 to October 13, 1978	0.0010	0.0081	207
20	October 16, 1978 to December 14, 1978	0.0040	0.0081	41
21	December 15, 1978 to March 19, 1979	–0.0017	0.0081	64
22	March 20, 1979 to May 23, 1979	–0.0078	0.0081	42
23	May 24, 1979 to May 30, 1979	0.0314	0.0081	5
24	May 31, 1979 to October 5, 1979	–0.0010	0.0081	90
25	October 8, 1979 to January 18, 1980	–0.0027	0.0081	70
26	January 21, 1980 to November 12, 1980	–0.0007	0.0081	203
27	November 13, 1980 to December 9, 1980	0.0026	0.0081	18
28	December 11, 1980 to August 17, 1982	–0.0004	0.0081	413
29	August 18, 1982 to September 13, 1982	0.0129	0.0081	19
30	September 14, 1982 to September 20, 1982	–0.0212	0.0081	5
31	September 21, 1982 to October 8, 1982	0.0007	0.0081	14
32	October 11, 1982 to December 16, 1982	–0.0003	0.0081	46
33	December 17, 1982 to December 14, 1983	0.0003	0.0081	245
34	December 15, 1983 to October 29, 1984	0.0000	0.0081	218
35	October 30, 1984 to November 6, 1984	0.0000	0.0081	6
36	November 7, 1984 to April 2, 1985	0.0008	0.0081	99
37	April 3, 1985 to July 15, 1985	0.0012	0.0081	67
38	July 16, 1985 to July 3, 1986	–0.0007	0.0081	239
39	July 4, 1986 to June 19, 1987	0.0032	0.0090	238
40	June 22, 1987 to July 22, 1987	0.0106	0.0090	21
41	July 23, 1987 to August 3, 1987	–0.0091	0.0090	8

Table 4a. Continued.

#	Episode	Average	Standard deviation	Number of Trading Days
42	August 4, 1987 to October 16, 1987	0.0071	0.0090	53
43	October 19, 1987 to January 19, 1988	−0.0055	0.0155	62
44	January 20, 1988 to March 25, 1988	0.0047	0.0155	47
45	March 28, 1988 to April 28, 1988	0.0013	0.0155	22
46	April 29, 1988 to September 13, 1989	0.0017	0.0155	339
47	September 14, 1989 to February 5, 1990	0.0014	0.0155	99
48	February 6, 1990 to February 8, 1990	−0.0059	0.0155	3
49	February 12, 1990 to August 2, 1990	0.0030	0.0123	117
50	August 3, 1990 to September 3, 1990	−0.0093	0.0177	21
51	September 4, 1990 to February 26, 1991	−0.0008	0.0177	120
52	February 27, 1991 to July 16, 1991	−0.0014	0.0177	93
53	July 17, 1991 to August 16, 1991	0.0016	0.0177	21
54	August 19, 1991 to August 22, 1991	−0.0032	0.0177	4
55	August 23, 1991 to November 25, 1991	−0.0003	0.0177	64
56	November 26, 1991 to May 4, 1992	0.0013	0.0177	106
57	May 6, 1992 to June 11, 1992	−0.0005	0.0177	26
58	June 12, 1992 to June 23, 1992	0.0025	0.0177	8
59	June 24, 1992 to September 8, 1992	0.0005	0.0177	52
60	September 9, 1992 to November 6, 1992	0.0053	0.0177	42
61	November 9, 1992 to November 25, 1992	−0.0093	0.0177	13
62	November 26, 1992 to October 4, 1993	0.0008	0.0177	208
63	October 5, 1993 to April 19, 1994	0.0021	0.0177	131
64	April 20, 1994 to November 17, 1994	0.0011	0.0177	145
65	November 18, 1994 to May 31, 1995	−0.0003	0.0177	128
66	June 1, 1995 to July 23, 1996	−0.0006	0.0177	278
67	July 24, 1996 to September 27, 1996	−0.0022	0.0177	46
68	September 30, 1996 to June 16, 1997	−0.0040	0.0177	174
69	June 17, 1997 to September 22, 1997	0.0008	0.0177	67

the ICCS:MV will identify it correctly – but also that the ICCS:MV might often identify it as a both in both mean and variance. Thus it is quite certain that the mean changes estimated by the ICCS:MV in this data set are truly changes in the mean, and that the location estimates of these change points are likely to be very accurate. It is also possible that, in this analysis, the points identified as being changes in both mean and variance are truly changes in the mean only.

This outcome seems to be at odds with current thought in financial research. It is common nowadays to posit that the mean return series on an asset is constant over time, while the variance of that series varies perhaps according to some autoregressive scheme.

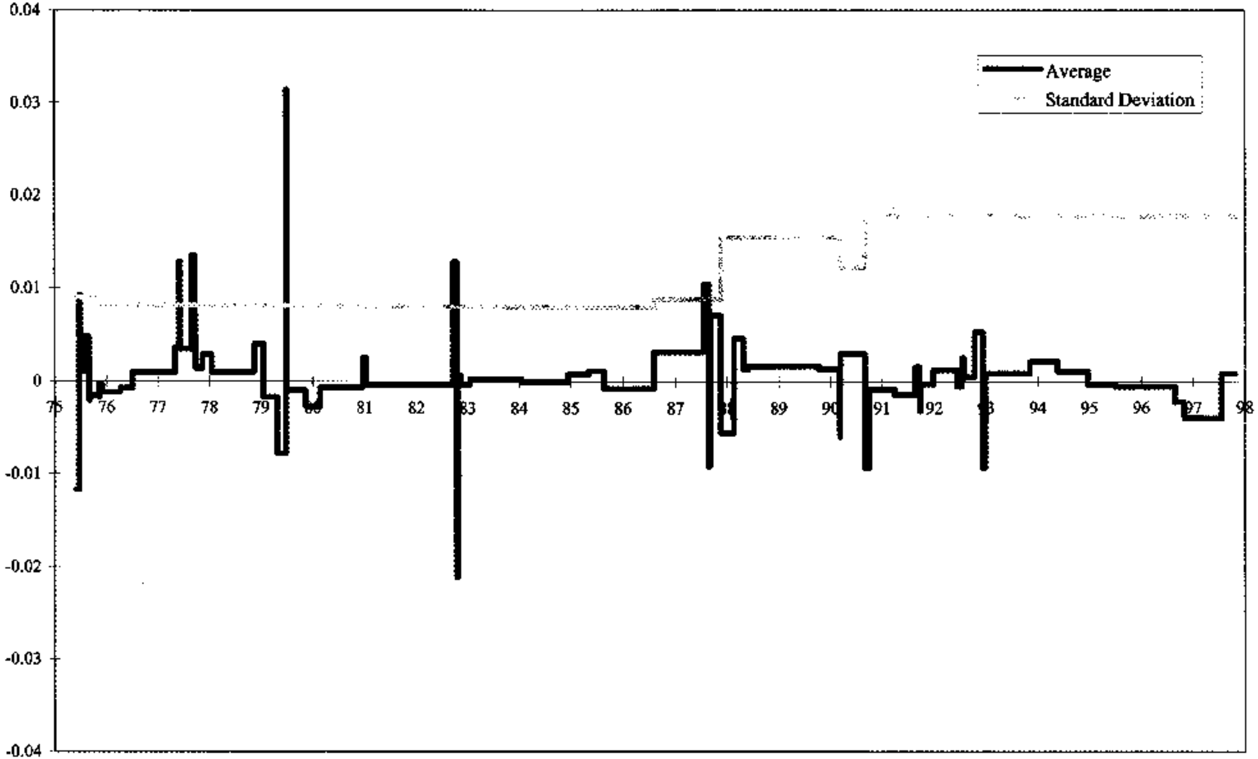

Fig. 3. Results of ICCS:MV on SET Daily Returns.

6. SUMMARY AND CONCLUSION

This paper points out that the IT ICCS procedure erroneously identifies all changes in a series as changes in variance. In particular with a Monte Carlo analysis in Section 3 it is seen that changes in mean will also be picked up as changes in variance by the ICCS. By judicious use of partial mean and variance standardization of segments, this paper introduces ICCS:MV, an extension of ICCS. This extension allows for the statistical identification of the type of change point. While the statistical properties of the new ICCS:MV are not completely desirable, the direction that the new procedure takes has great promise.

As the goal of the ICCS:MV is to estimate when and what mean and variance changes occur in a time series, it is an interesting tool for financial research which, among other things, is interested in the mean and variance – the return and risk – of assets. In the recent annals of financial research, much emphasis has been put on the identification of changes in variance – mostly through ARCH and its derivatives. When the ICCS:MV is applied to daily returns of the index of the Stock Exchange of Thailand, it is discovered that the nearly all, if not all, the estimated changes are attributed to changes in the mean. Some changes are estimated to be changes in both mean and variance, but the ICCS:MV can easily mistake true mean changes as changes in both.

The authors hope that this paper will spark further theoretical and applied work on the ICCS:MV that focuses on its quality control features.

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