行政院國家科學委員會專題研究計畫成果報告

自我組織圖與金融時間序列中的幾何圖像辨識

Self-Organizing Maps as a Foundation for Charting or Geometric Pattern Recognition in Financial Time Series

計畫編號: NSC 90-2415-H-004-018
執行期限: 90年8月1日至91年7月31日
主持人: 陳樹衡 Email: chchen@nccu.edu.tw
執行機構及單位名稱: 國立政治大學經濟學系

中文摘要:

圖像辨識(charting) 是技術分析 (technical analysis) 中相當重要的一種方法。儘管在實務上, charting 己有相當悠久的歷史。然而, 與其對應的學術研究卻幾乎不存在。僅有的研究只有 Chang and Osler(1994), Osler and Chang (1995), Lo, Mamaysky and Wang (2000) 三篇。而直到目前爲止, 圖像的建立仍是靠著分析師 (technical analysts) 的經驗與判斷。本研究嘗試利用自我組織圖 (self-organizing maps) 來建立圖像辨識的基礎, 並沿此來發展金融時間序列中幾何形態 (geometric pattern) 分析的基礎。利用美股三大指數, 本研究發現經由自我組織圖所發現的圖像, 的確夾帶重要的市場資訊, 且這樣的資訊是無法經由傳統時間序列模型來刻畫。

Abstract:
For a long time technical analysts have detected trading signals with charts. Nonetheless, from a scientific viewpoint, charts are somewhat subjective objects. Using Kohonen's self-organizing maps (**SOMs**), this research proposes a systematic and automatic approach to charting, or more generally, stated, geometric pattern recognition. It is found that the charts discovered using SOM in empirical time series do transmit useful information, and that it is hard for such information to be captured by ordinary econometric methods.

Keywords: Chartists, self-organized maps, competitive learning, monotone hypothesis, one-sided studentized range test

1 Introduction

For a long time technical analysts have detected trading signals with *charts*. Some of them even consider that what they are doing is a science ([3]), and for this, they are frequently called *chartists*. Since chartists engage in a well-established profession in the financial industry, there is little doubt that charts, to some extent, do transmit signals. Nonetheless, from a scientific viewpoint, charts are somewhat *subjective objects*. In general, well-articulated definitions of charts do not exist, while *partial* algorithmic information based on *local extrema* is available for some charts ([1]; [12]; [11]). In practice, analysts still rely on their *experience* when identifying charts. Some charts identified by technical analysts are given in Figures 1 and 2.

In this study, we would like to facilitate a breakthrough by bringing *charting* into a formal analysis. Our motivation is quite obvious: *if charts do transmit information, then the time series of asset prices should exhibit some unique patterns.* However, these patterns may be too complicated and hence too controversial to be described *algorithmically.* Therefore, there is no way we can attempt to "define" these charts by means of formal equations. Nonetheless, technical analysts usually can recognize charts simply by visual inspection, which suggests a process of automatic classification and segmentation without supervising. So, what we need is a kind of machine intelligence which is able to simulate this cognitive process, and it is from this viewpoint that self-organizing maps (**SOMs**), as an *unsupervised learning scheme*, seem to be an ideal tool to serve this purpose.

The application of SOMs to economics and finance only began very recently. The current state of the SOM applications in economics and finance can be best described in the edited volume "*Visual Explorations in Finance*" by [2]. In this book, SOMs have proven to be an effective methodology for analyzing problems in finance, economics and marketing. The volume contains various applications of SOM, including the analysis of financial statements, the prediction of bankruptcies, forecasting and long-term interest rates, the selection of mutual fund managers, the evaluation of investment opportunities, trading stock indices, market analysis and customer segmentation.

Despite their usefulness as revealed in the book by [2], the potential relevance of SOMs to charting has never been examined. On the other hand, the foundation of charting has not been well established in the literature. This study assumes that SOMs can be a reasonable approximation process for human cognitive activities in relation to charting, and for attempts to incorporate charts into a systematic analysis.

In this study, we propose using **SOMs** to search for and identify charts, and to test whether these charts are informative in the following respects:

- Firstly, we would like to examine the information contents of the charts discovered by the SOMs. The statistical tests based on *profitability* will be conducted.

- Secondly, it would be interesting to know whether the SOM is able to discover some information that ordinary econometrics can not. The Monte Carlo simulation methods will be applied.

The remainder of this paper is organized as follows. Section 2 gives a brief introduction to SOMs. Section 3 explains why we choose SOMs to discover financial patterns. Section 4 describes the experiment design and the parameter settings for SOMs. Section 5 examines the information contents of charts discovered by the SOMs and proposes two kinds of tests to test profitability. Section 6 summarizes the results and presents concluding remarks.

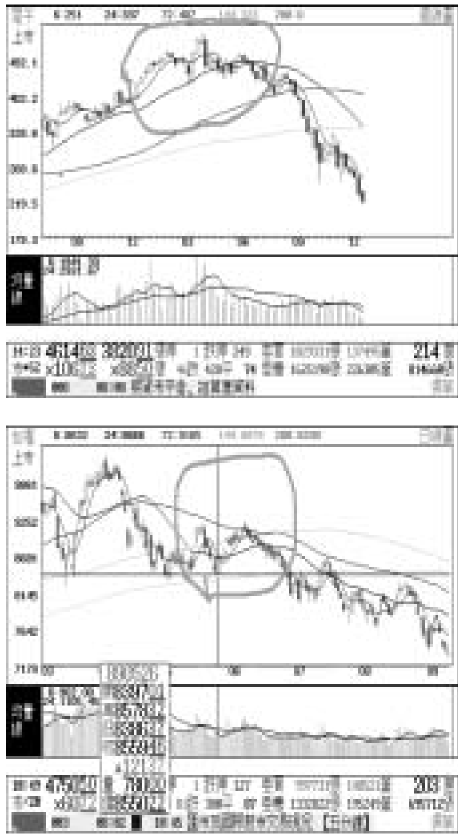

Figure 1: Figures identified by technical analysts: head-and-shoulders (top) and double tops (bottom).

Data Source: Cheng-Wen Lin at cnYES.com

2 Self-Organizing Maps

In contrast to the artificial neural networks (**ANNs**) which are used for *supervised learning*, SOMs are another special class of artificial neural networks. The SOMs are used for *unsupervised learning* to achieve *auto classification*, *data segmentation* or *vector quantification*. Unlike the supervised ANNs, SOMs do not require the user to know in advance the exact objects that they are looking for. This convenience is particularly important when one can only effectively recognize some patterns by *visual inspection* rather than by mathematical descriptions.

The SOMs adopt so-called *competitive learning* among all neurons. The output neurons that win the competition are called *winner-takes-all* neurons. In SOMs, the neurons are placed on the sites of an n-dimensional lattice. The value of n is usually 1 or 2. Through competitive learning, the neurons are tuned to represent a group of input vectors in an organized manner. The mapping from a continuous space to a discrete one or a two-dimensional space achieved by the SOMs reserves the spatial order.

Among a number of training algorithms for SOMs, Kohonen's learning algorithm is the most popular one ([9]; [5]). Kohonen's learning algorithm adopts a heuristic approach. Each neuron on the lattice has a weight vector of m components attached. The m is the number of input variables of the input data sets. The winning neuron and its close neighbors in the lattice have their weight vectors adjusted towards the input pattern presented on each iteration. Unlike other clustering methods such as k-means clustering ([8]), Kohonen's SOMs have the advantage that the final training outcome is insensitive to the initial settings of weights. Therefore, Kohonen's SOMs have found a wide variety of applications in image processing, target detection, 3D dynamic modeling, the classification of pulse signals of the autonomic nervous system, speech processing, etc.

In the training process, the weights of the winning neuron and its close neighbors are updated according to (1),

$$w_j(n+1) = w_j(n) + \eta(n)\pi_{j,i(z)}(n)[z - w_j(n)], \quad (1)$$

where $w_j(n)$ is the weight vector of the jth neuron at the nth iteration, $\pi_{j,i(z)}(n)$ is the *neighborhood function* (to be defined below) of node indices j and

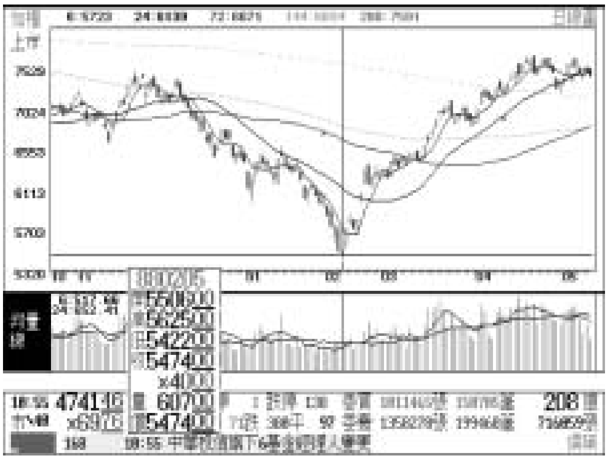

Figure 2: Figures identified by technical analysts: v-reversal.

Data Source: Cheng-Wen Lin at cnYES.com

$i(z)$,

$$i(z) = arg \min_{j} \mid\mid z - w_j \mid\mid, j = 1, 2, ..., d^2, \quad (2)$$

and $\eta(n)$ is the *learning rate* at iteration n.

We take for the neighborhood function the *Gaussian* form,

$$\pi_{j,i(z)} = \exp\left(-\frac{d^2_{j,i(z)}}{2\sigma^2(n)}\right), \quad (3)$$

where $\sigma(n)$ is some suitably chosen, monotonically decreasing function of iteration times n. Here, the effective width σ decays with n according to (4).

$$\sigma(n) = \sigma_0 \exp\left(-\frac{n}{\tau_1}\right), \quad (4)$$

where σ_0 and τ_1 are constants. The learning rate decays in a similar manner:

$$\eta(n) = \eta_0 \exp\left(-\frac{n}{\tau_2}\right), \quad (5)$$

where η_0 and τ_2 are constants.

The training takes a long time with almost all neurons initially having their weights updated. This training phase is called the *ordering phase*. During this phase, as the learning rate and effective width gradually decrease, the topological ordering of the weight vectors takes place. During this phase, the initial effective width assumes a large value and the weights of virtually all of the neurons are updated. Through competitive learning, the weight vectors gradually settle down to form a topological order. The weights then settle down gradually during the second phase of learning named the *convergence phase* where only the weights of the winning neuron and perhaps its nearest neighbors are updated according to the case presented.

3 Why SOMs?

Very little research has been devoted to charting. The only research papers known to us are [1], [12], and [11]. The first two papers dealt with only one specific chart, namely, the *head-and-shoulders*. [11] was more general. They focused on five pairs of technical patterns that were among the most popular patterns of traditional technical analysis: head-and-shoulders and inverse head-and-shoulders, broadening tops and bottoms, triangle tops and bottoms, rectangle tops and bottoms, and double tops and bottoms. In the following, we shall briefly review how the analysis of charting was conducted in these papers, and point out the *departure* in our proposed approach.

The main contribution of [1] and [12] was to propose an algorithm for detecting head-and-shoulders patterns by looking at properly defined local extrema. The idea based on *a sequence of local extrema* was then adopted by [11] and was further extended to include the detection of other charts. However, what is really interesting in [11] is their incorporation of the idea of a *smoothing estimator*. They used kernel regression as a preprocessor to *smooth* the price series first, then built their charts from these smoothed series rather than by using the original series.

Our approach to SOMs differs from the above-mentioned alternative in the way that charts are built. Basically, we do not assume any knowledge of charts, and try to "define" them from the beginning. The philosophy of SOMs is to let the data speak for themselves. Here is how it works. If there is a pattern known as *double tops*, which is a pattern repeatedly observed in the price series, then the SOM *should*, in principle, have the capability to *group* or *segregate* this pattern from others. This is because our visual inspection can "see" the difference and that visual difference in terms of an appropriate distance measure should make our SOM machine able to "see" the difference, too. Similarly, this mechanism works for other charts. Therefore, by using the SOM, charts are *automatically defined* and built.

Of course, at this moment, it is too early to judge which idea is more suitable for charting without any empirical content. However, there are some reasons to expect that our approach based on SOMs has some advantages over the alternative. First, charting, like fingerprint identification, handwriting analysis and face recognition, are tasks that are hard to supervise in a precise way. Therefore, attempts to give a rigid definition may end up with a poor approximation. It is in this sense that unsupervised learning, like SOMs, may sound more profound as opposed to any other human-written programs, particularly given the evidence that it has already been successfully applied to many other similar tasks ([10]).

Secondly, since the SOM is a kind of unsupervised learning, not only does it have the potential to discover the charts known to us, but it also has the capability to discover those that are unknown to us. This possibility deserves further exploration. Considering that financial markets are highly complex adaptive systems, it would be a surprise if charts used 10 years ago would be exactly the same as those used now. What may be hypothesized instead is that charts may undergo a series of adaptations as feedback to traders' reactions to charts. Nevertheless, charting based on the above-mentioned alternative is static and hence is unable to test this hypothesis. Therefore, the SOM can be even more promising than the alternative when what concerns us is *dynamic charting*.

Based on the above discussion, to consider *charting using SOMs* can be an interesting research methodology to be taken either as a parallel or an extension of the existing methodology based on the *kernel regression* proposed by [11].

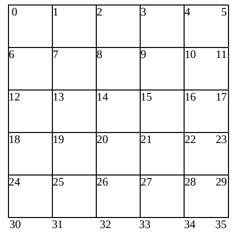

Figure 3: Pattern indices and their corresponding positions in a 6×6 lattice of SOMs.

Table 1: Parameter setup for the implementation of the 2-dimenisonal d × d SOM.

Window width	60, 90, 120
Dimensionality of SOM	2
Number of neurons	6×6
Ordering phase initial learning rate	0.900
Ordering phase learning rate decay rate	455.120
Ordering epoch	1000
Ordering phase initial radius	8.485
Ordering phase radius decay rate	467.654
Convergence phase initial learning rate	0.100
Convergence learning rate decay rate	333.808
Convergence phase initial radius	1.000
Convergence phase radius decay rate	434.294
Convergence phase epoch	1000

4 Experiment Design

4.1 Empirical Analysis

In this paper we present the results of the application of the SOM to financial time series data. The data sets to be segmented are three empirical stock indices, which are the Dow Jones, Nasdaq, and S&P 500. The original data sets cover the daily closing prices from 1/1/80 to 3/31/00 and have 5118, 5110, and 5101 observations, respectively.

What we intend to do is to take a sliding window with different window width w moving from the first period to the last period of the whole data set indexed by t ($t = 1, ..., T$), so that all T observations will further subdivide into $T - w + 1$ subsamples, each with w observations of a time series. Each subsample represents a time series pattern. The SOM is then used to automatically divide all patterns into groups or clusters in such a way that members of the same group are *similar* (*close*) in the Euclidean metric space. The w observations of each subsample are normalized between 0 and 1. A two-dimensional 6×6 SOM is used to map the $T-w+1$ records into 36 clusters.[1] The 6×6 lattice of SOMs is presented in Fig. 3.

In this paper, we consider three different w, their being 60, 90, and 120. Then the results can be compared with different window sizes. The control parameters used to conduct this experiment are given in Table 1.

4.2 Monte Carlo Analysis

Are charts unique characteristics of financial time series that are neglected in ordinary financial time series modeling? Is the SOM a relevant tool in financial charting? If yes, can charting be addressed as well in the context of financial time series modeling? Or, is it difficult for it to be captured in the ordinary model of financial time series?

To answer these questions, Monte Carlo simulations based on the ordinal financial time series models are required. In this study, we consider one famous price model, namely, the Fama-French model ([4]).

In [4], the natural log of stock price $p_t (\equiv \log P_t)$

[1] Regarding the question why the two-dimensional lattice model is used for the SOM, we do not have a theoretical answer here. However, the following observations may lend support for the usage of a two-dimensional map. First, in practice, only a low-dimension lattice (no more than three dimensions) has been used. Second, in commercial packages, only low-dimension maps are implemented, and almost all use the two-dimensional lattice as a default setting. Third, in his book ([10]), Kohonen mentioned that the original idea of the SOM is enlightened by the structure of the human brain. The brain has a surface area of 2400 cm^2. The cerebral cortex is like a two-dimensional map. It is divided into a few areas like the motor cortex, somatosensory cortex, visual cortex, auditory cortex, etc. Each area is responsible for one kind of memory or control. Therefore, the two-dimensional lattice model most resambles the structure of the human brain.

is considered as the sum of a random walk q_t and a stationary component, z_t,

$$p_t = q_t + z_t, \tag{6}$$

$$q_t = q_{t-1} + \mu + \eta_t, \tag{7}$$

$$z_t = \phi z_{t-1} + \epsilon_t, \tag{8}$$

where μ is expected drift and η_t and ϵ_t are white noise, and $\mid \phi \mid< 1$.

Using this model ((6)-(8)) with different parameter settings, one can simulate artificial time series of prices. In this experiment, we consider three different parameter settings: $\phi = 0.9$, 0.975, and 1.0, and $\mu = 0$ in all cases. A quasi-random generator is applied to generate 6000 observations for each model setting. The control parameters used to conduct this experiment are the same as those in Table 1.

5 Information Contents Of Chart

So far, we have only demonstrated how SOMs are used to built charts. However, how do we know that these charts can indeed reveal trading signals rather than *just clusters*? In the following, we first briefly review the answer given by [11], and then present ours.

The tests proposed by [11] involve comparing the unconditional distribution of returns with the corresponding conditional empirical distribution, that is conditional upon the occurrence of a technical pattern. The idea behind these tests is straightforward: "*if technical patterns are informative, conditioning on them should alter the empirical distribution of returns; if the information contained in such patterns has already been incorporated into returns, the conditional and unconditional distribution of returns should be close.* (Ibid, p. 1726. Italics Added.)" [11] mentioned that this is a *weaker test* of the effectiveness of technical analysis because informativeness does not guarantee a profitable trading strategy. Nonetheless, they argue that it is a natural first step in a quantitative assessment of technical analysis.

The tests proposed in this study are basically in line with the assertions of [11], and hence they are also *information-based* tests. However, unlike [11], what interests us is not just the conditional returns defined as the *one-day return* starting d days following the conclusion of an occurrence of a pattern (in their case $d = 3$), but the conditional *trajectory of returns*. When the time structure of informativeness among different patterns is different, it may make us wait longer for some patterns than for others to see their significance. In this case, tests based on conditional trajectories are more appropriate than tests based on a specific one-day observation.

Furthermore, conditional trajectories enable us to do a follow-up investigation of the aftermath of each pattern. As we shall see later, this can help us test some even more interesting behavior, such as the *monotone hypothesis*, which is unavailable in the context of [11]. The monotone hypothesis can be particularly relevant when trades are not synchronous in terms of occurrence with charts.

5.1 Normalized Equity Curves

Based on the discussion above, we now propose the following test based on a *normalized equity curve*. First, we ask a simple question: *once a specific chart is observed, what are the stock returns in the following H days?* In other words, we are investigating the time series plot

$$R_{h,j} = \ln P_{t+h} - \ln P_t, \quad h = 1, 2, ..., H, \tag{9}$$

where t is the day on which pattern (chart) j is observed ($j = 1, 2, ..., d^2$). $\{R_{h,j}\}_{h=1}^{H}$ is referred to as the *normalized equity curve* of chart j.

Now, we make the following observation. Suppose that the patterns constructed by the SOMs are able to transmit trading signals, then what we expect from these equity curves is that there are *abnormal returns* in the curves or there are *systematic* movements, such as *monotone increasing* or *decreasing movements*, as in the most ideal cases. They can be of other types, but the bottom line is that they cannot be *erratic* or *random*. Finally, since each pattern appears many times in the whole series, instead of drawing a single equity curve, we are presenting an average of them, i.e. what we actually draw is the time series plot of $\bar{R}_{h,j}$:

$$\bar{R}_{h,j} = \frac{\sum_{k=1}^{n_j} R_{h,j:k}}{n_j}, \tag{10}$$

where k refers to the kth occurrence of chart j, and n_k is the total number of occurrences of chart j. If we consider the trading strategy of buying an asset and holding it for 40 days when chart 3 appears, then $\bar{R}_{40,3}$ is the expected return associated with this strategy.

5.2 Tests for Abnormal Returns

Given the normalized equity curve, one can examine the profitability of charts by testing whether excess returns in the aftermath are significantly positive or negative. Formally speaking, let

$$\left((\bar{R}_{h,j} - \mu_h) \pm t^{0.95}_{n_j-1} s_{h,j} \right) \tag{11}$$

be the 90% confidence interval of excess returns for chart j, where μ_h is the respective unconditional mean return of holding this risky asset for h days (consider the simple buy-and-hold strategy), and $s_{h,j}$ is the corresponding standard deviation of $R_{h,j:k}$. By this construction, if the line $(\bar{R}_{h,j} - \mu_h)_{h=1}^{H}$ moves beyond the boundary $0 \pm t_{n_j-1}^{0.95} s_{h,j}$, then the *null hypothesis*

$$H_0 : \mu_{h,j} - \mu_h = 0, \quad h = 1, 2, ..., H$$

is rejected, where $\mu_{h,j}$ is the respective mean of the equity curve of the chart j, i.e. there are abnormal positive or negative returns in the equity curves. (However, as we shall see later, this test is very causal.)

While the test outlined above is straightforward, its validity crucially depends on the assumption that the original return series is *independent*. Given the recent developments in financial econometrics, particularly with regard to the independence tests, this assumption is highly skeptical. When returns are correlated, even though $\bar{R}_{h,j}$ is still an unbiased estimator, the s_j can be inefficient and make the null hypothesis hard or easy to reject. As a result, a modified test is proposed as follows. This modified test is based on the *persistence* of a chart. For example, if at period t, chart j is observed, it may continue to appear for the next $m-1$ days. In this case, we count the appearance of chart j only once but attach to it a *duration* of m days. By means of this segmentation, the series $R_{h,j:k}$ $(k = 1, ..., n_j)$ can be divided into F_j times of appearance and within each a duration of m_f periods, where $f = 1, ..., F_j$. In other words,

$$\begin{aligned} \{R_{h,j:k}\} &= \bigcup_{f=1}^{F_j} A_{n,j:f} \\ &= \bigcup_{f=1}^{F_j} \left\{ R_{h,j:q}, q = \sum_{l=0}^{f-1} m_l, ..., \sum_{l=0}^{f} m_l - 1 \right\} \end{aligned}$$

with $m_0 \equiv 0$.

Then, to avoid *serial dependence*, each $A_{n,j:f}$ will be counted as only one observation, and, as a total, we only have F_j observations. The return on each observation $A_{n,j:f}$ can be chosen as the *mean* or *medium* of $A_{n,j:f} \equiv \{R_{h,j:q}, q = \sum_{l=0}^{f-1} m_l, ..., \sum_{l=0}^{f} m_l - 1\}$. We denote it by $R_{h,j}^{f}$ $(f = 1, ..., F_j)$. The mean and the standard deviation are computed based on these F_j observations. Then the 90% confidence interval can be constructed accordingly. In this experiment, we trace the equity curves for 40 periods $(H = 40)$. Figures 4 and 5 are two examples of abnormal tests for S&P 500 and FF(1) with sliding window (w) equal to 90. There are 18 and 9 cases the equity curves move beyond the 90% boundary in Figure 4 and 5, respectively.

Table 2 reports the summary results of the abnormal tests. For the empirical data, there are a total of 116 equity curves exhibiting abnormal returns after the previous associated charts have been recognized. Nasdaq appears to have the least number (29) of curves that have excess returns and the S&P 500 appears to have the most (48). This seems to indicate that the SOM might not be a good tool to find informative geometric patterns in the Nasdaq series, as compared to the other two series, or that the Nasdaq itself inherently has less informative patterns. However, another view is that the tests we used here are not suitable methods for detecting the information contained in the equity curves for the Nasdaq series. In the next subsection, we apply another test to the equity curves and see if the Nasdaq still has the worst performance.

For the artificial data, there are 108 cases, a little less than the case of the empirical data, the equity curves move beyond the 90% boundary. This result seems to be a little strange because in Fama-French models, the log price ((6)-(8)) can be rewritten as:

$$p_t = \mu + p_{t-1} - (1 - \phi) z_{t-1} + \varepsilon_t \tag{12}$$

where $\varepsilon_t = \epsilon_t + \eta_t$. In our experiment $\mu = 0$ and ϕ is close to 1. Since z_{t-1} is unobservable, the best way to predict the next few periods' prices is to use the current price. This indicates that the information contained in the equity curves only depends on the last observations, i.e. the last observations in the charts. Then any geometric patterns would not be expected to be efficient in terms of detecting information.

One reason for explaining this finding is that the above tests for abnormal returns imply that we perform a lot of tests (40 times in our cases) all at once at the same time. Such testing procedures will cause the test size to increase, resulting in the null hypothesis being rejected more frequently.

5.3 Tests for the Monotone Hypothesis

The confidence interval only provides us with a preliminary examination. It is not equivalent to a test for the monotone increasing or decreasing hypothesis in which we are more interested. On the other hand, as mentioned in the previous subsection, the testing procedure for abnormal returns is not conservative and the test results are not robust. Then we need to apply another test that is able to test the monotone hypothesis and that makes controlling the exact test size easy.

The null hypothesis should be

$$H_0 : \mu_{1,j} = \mu_{2,j} = ... = \mu_{H',j}, \tag{13}$$

and the alternative hypothesis is

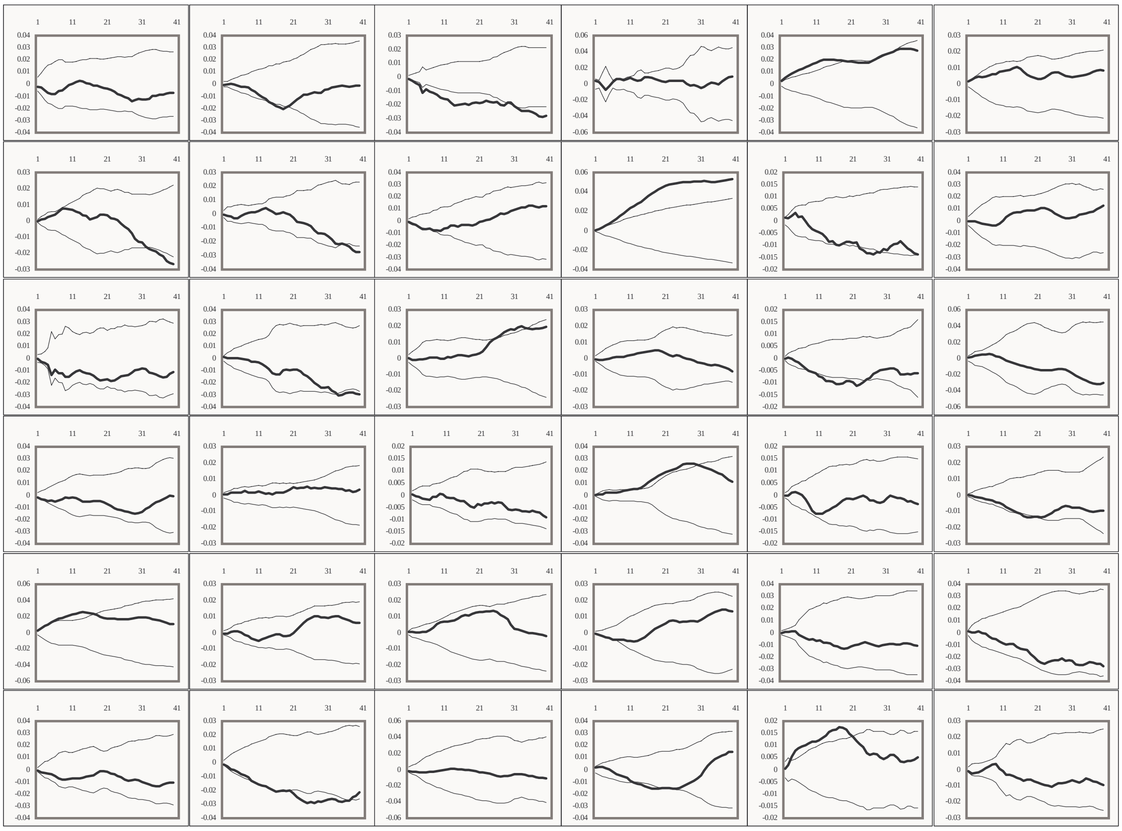

Figure 4: 6×6 equity curves of S&P 500 (w = 90).

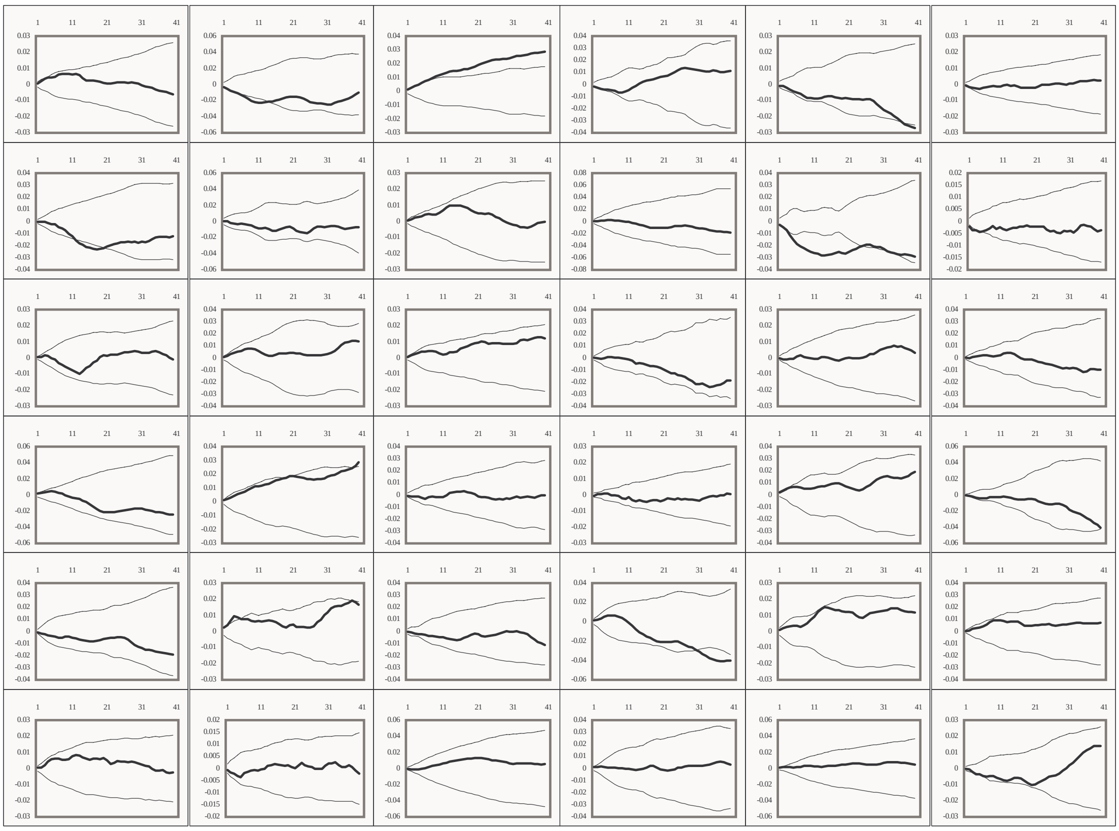

Figure 5: 6×6 equity curves of FF(1) (w = 90).

Table 2: Results of the tests for abnormal returns.

w	Dow-Jones	Nasdaq	S&P500	FF (.9)	FF (.975)	FF (1)
60	18	11	16	18	13	14
90	15	8	18	11	13	9
120	6	10	14	11	9	10
Tol.	39	29	48	40	35	33
	116			108		

A number of the equity curves among the 36 move beyond the 90% boundary for each data set and sliding window. We count one for each equity curve if it moves beyond the 90% boundary once or more than once within 40 periods. "FF(ϕ)" refers to the Fama-French model ((6)-(8)) with parameter ϕ. "w" refers to the width of the sliding window. "Tol." refers to the total number of counts for each data set.

$$H_a : \mu_{1,j} \leq \mu_{2,j} \leq \ldots \leq \mu_{H',j}, \tag{14}$$

or

$$H_a : \mu_{1,j} \geq \mu_{2,j} \geq \ldots \geq \mu_{H',j}, \tag{15}$$

in a one-way layout with at least one strict inequality.

In the context of the balance one-way fixed effects analysis of variance model, [6] proposed a one-sided studentized range test (**OSRT**), which rejects H_0 iff

$$\max_{1 \leq i \leq i' \leq H'} \frac{\sqrt{F_j}(\bar{R}_{i',j} - \bar{R}_{i,j})}{S_j} \geq g_{H',\alpha,\nu}, \tag{16}$$

or

$$\max_{1 \leq i \leq i' \leq H'} \frac{\sqrt{F_j}(\bar{R}_{i,j} - \bar{R}_{i',j})}{S_j} \geq g_{H',\alpha,\nu}. \tag{17}$$

In the equations above,

$$S_j = \frac{\sum_{h=1}^{H'} \sum_{f=1}^{F_j} (R_{h,j}^f - \bar{R}_{h,j})^2}{H'(F_j - 1)},$$

and $g_{H',\alpha,\nu}$ in the test (16) or (17) is the *critical point* chosen in this test that has size exactly equal to α, and $\nu = H'(F_j - 1)$.

However, the size and power of this test are quite difficult to calculate. The method suggested in [6] for critical point computation works only for small H'. In [7], a method is proposed for the exact calculation of the probability

$$Prob\left\{\max_{1 \leq i \leq i' \leq H'} \frac{\sqrt{F_j}(r_{i,j} - r_{i',j})}{S_j} \geq g\right\}. \tag{18}$$

Using this method, the critical point $g_{H',\alpha,\nu}$ and the power function of the **OSRT** can be computed.

Table 3: Results of the one-sided studentized range test (**OSRT**).

w	Dow-Jones	Nasdaq	S&P500	FF (.9)	FF (.975)	FF (1)
60	2 (0)	2 (0)	1 (1)	1 (0)	0 (0)	2 (1)
90	1 (1)	3 (2)	4 (3)	0 (0)	1 (1)	0 (0)
120	3 (1)	3 (3)	2 (1)	1 (0)	1 (0)	1 (1)
Tol.	6 (2)	8 (5)	7 (5)	2 (0)	2 (1)	3 (2)
	21 (12)			7 (3)		

A number of equity curve among the 36 reject the null hypothesis, i.e. they accept the monotone hypothesis, for each data set and sliding window. The number of rejections at the 90% significance level is tabulated, and the number at the 95% significance level appear in parentheses. "FF(ϕ)" refers to the Fama-French model ((6)-(8)) with parameter ϕ. "w" refers to the width of the sliding window. "Tol." refers to the total number of counts for each data set.

Some tables of critical points and minimum sample sizes satisfying certain power requirements are provided. The test and tables will help us conduct a formal test of the monotone hypothesis. A chart j is called *informative* if the monotone hypothesis based on its normalized equity curve is *rejected*. In this experiment, we trace 5 periods ($H' = 5$) of equity curves.

Table 3 presents the results of the **OSRT**. Based on Table 3, there are a total of 21 equity curves in the empirical data set exhibiting a monotone trend at the 90% significance level, in which 12 curves are significant at the 95% level. Notice that the Nasdaq has the most informative charts, while in the last subsection it was judged to be less informative in terms of abnormal tests. The artificial data have much less informative charts than the empirical data. There are only 7 curves that significantly reject the null hypothesis at the 90% level and 3 curves that reject the null at the 95% level. Under the Fama-French models ((6)-(8) or (12)), the monotone hypothesis should not be accepted. Then such results are much more reasonable. We can regard these 7 cases as the "type I error."

Following these results, we can see that the charts in the ordinary financial time series models, such as the Fama-French model, are not useful for the disclosure of information. While they do contain some information in empirical time series, the ordinary time series models would not be expected to be able to capture them. Then the SOM-based geometric pattern recognition seems to be a relevant econometric tool for detecting profitable information in the form of charts (or patterns) involved in empirical data.

6 Conclusions

The ability to recognize patterns is an essential aspect of human intelligence. Herbert Simon, who won a Nobel Prize in economics in 1978, considered pattern recognition critical and emphasized the need to pay much more explicit attention to teaching pattern recognition. Chartists have appeared to be good at engaging in pattern recognition for many decades, yet little academic research has been devoted to a systematic study of this kind of activity. On the contrary, sometimes it has been treated as nothing more than astrology, and hardly considered a science.

Using Kohonen's *self-organizing maps* (**SOMs**), this study has proposed a systematic and automatic approach to *charting*, or more generally, *geometric pattern recognition*. In other words, we have proposed an approach to formulate chartists' behavior in searching for financial patterns (charts).

By applying a series of two-dimensional SOMs to financial time series, financial patterns have been *automatically discovered*. To see whether these patterns transmit profitable signals, "normalized" equity curves have been drawn for each pattern up to a number of days after observing the pattern. Then a 90% confidence interval of excess returns is derived to provide a quick, while not exact, test to see whether these equity curves are statistically monotonically increasing or decreasing. A rigorous analysis of the statistical behavior of equity curves is conducted based on the **OSRT**.

It is found that the charts discovered using SOMs in empirical time series do transmit useful information, and it is hard for such information to be captured by ordinary econometric methods. Then the SOM might be an ideal tool for *simulating* human intelligence in finding or creating patterns that summarize and store useful aspects of our perceptions.

7 計畫成果自評

此研究內容與原計畫相符, 且達成95%的預期目標。此研究極具原創性, 且其結果對財務經濟學與財務計量學將有重要啓示。目前此研究內容已寫成文章投稿至國際學術研討會, 待聽取與會學者意見並適當修改後, 將進一步投稿至國際學術期刊。

References

[1] Kevin Chang and Carol Osler. Evaluating chart-based technical analysis: the head-and-shoulders pattern in foreign exchange markets. *Working Paper*, Federal Reserve Bank of New York, 1994.

[2] Guido Deboeck and Teuvo Kohonen. *Visual Explorations in Finance with Self-Organizing Maps*. Springer, 1998.

[3] Thomas R. Demark . *The New Science of Technical Analysis*. Wiley, 1994.

[4] Eugene F. Fama and Kenneth R. French. Permanent and temporary components of stock prices. *Journal of Political Economy*, 96(2): 246-273, 1988.

[5] Simon S. Haykin. *Neural Networks: A Comprehensive Foundation*. New York: MacMillan, 1994.

[6] Anthony J. Hayter. A one-sided studentized range test for testing against a simple ordered alternative. *Journal of the American Statistical Association*, 85:778-785, 1990.

[7] Anthony J. Hayter and Wei Liu. Exact calculations for the one-sided studentized range test for testing against a simple order alternative. *Computational Statistics and Data Analysis*, 22(1): 17-25, 1996.

[8] Zhexue Huang. A fast clustering algorithm to cluster very large categorical data sets in data mining. *First Asia Pacific Conference on Knowledge Discovery and Data Mining*, Singapore, World Scientific, February, 1997.

[9] Teuvo Kohonen. Self-organized foundation of topologically correct feature maps. *Biological Cybernetics* 43:59-69, 1982.

[10] Teuvo Kohonen. *Self-Organizing Maps*. 2nd Edition, Springer, 1997.

[11] Andrew W. Lo, Harry Mamaysky and Jiang Wang. Foundations of technical analysis: computational algorithms, statistical inference, and empirical implementation. *Journal of Finance*, 55(4):1705-1765, August, 2000.

[12] Carol Osler and Kevin Chang. Head and shoulders: not just a flaky pattern. *Staff Report* No. 4, Federal Reserve Bank of New York, 1995.