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An Integrated Investment Decision-Support Framework Analyzing and Synthesizing Multi-Dimensional Market Dynamics

[1]Wanli Chen, [1]Longbing Cao and [2]Zhe Qin
[1]Faculty of Information Technology, University of Technology, 235-253 Jones Street, Ultimo, Sydney, Australia, 2000
[2]Nanning Prefecture Education College, Nanning, Peoples Republic of China

Abstract: In stock markets, the performance of traditional technology-based investment methods is limited because such methods only take into account single-dimensional event factors. The study shows how the integration of multi-dimensional event factors can improve performance. We propose a novel three-layer integrated framework composed of Analysis, Synthesis and Investment Decision Support. At the first layer, multi-dimensional stock market structures are identified, in which we emphasize two key aspects that previous studies have neglected: unique trends of stocks-the patterns which relate only to individual stocks themselves and a two-way reflexivity relationship of investors' decisions and market reactions. At the second layer, multi-dimensional pattern components are synthesized to reflect real (and potential) market situations. At the third layer, a prototype integrates the functions of first two layers for investment decision support. The framework covers multi-dimensions of market structures and incorporates the concepts and advantages of traditional investment methods. The framework is promising, because experimental results indicated that it outperformed market baselines and single-dimensional conventional methods.

Key words: Synthesis, two-way reflexivity model, unique trends

INTRODUCTION

While there are a number of finance methods (such as fundamental analysis, technical analysis, contrarians' theory) in stock markets which help identify investment opportunities, they have different characteristics and accordingly, different strengths and weaknesses[1]. There is an increasing need to integrate the different methods and it is becoming more and more common for finance practitioners to adopt different methods simultaneously in order to achieve an optimized investment result[2]. At the same time, a number of expert systems, knowledge engineering and other technologies are used in conjunction with the finance methods in identifying investment opportunities[3-7]. However, some research problems have been observed in these technology-based methods. Here are three problems that we shall consider throughout the study:

Single-dimension vs integration of multi-dimensions: These technology-based methods mainly focus on technical analysis (such as patterns of stock price and volume movements), with a few which consider other dimensions of stock market structures (such as fundamental factors). However, most integration-related methods have two limitations: they either integrate a particular technology-based method or an algorithm into a system or a framework (i.e., multi-agent framework)[8-10] or integrate some conventional investment methods (in limited dimensions or levels) with technology-based methods[11-13]. No integration related methods cover different dimensions of stock market structures as a whole to reflect the whole market situation, nor are different conventional methods integrated in a systematic way to incorporate their advantages. As a result, integration-based methods are unable to help investors to thoroughly and comprehensively understand the market and to identify all potential investment opportunities. Because of these limitations, their performance for sound investment decision making is limited. Difficulty of the integration arises from their different and incompatible features. For instance, methods focusing on the dimension of stock price and volumes are often quantifiable but not qualitative and interpretable; on the other hand, methods focusing on the dimension of fundamental factors are qualitative and interpretable, but not quite quantifiable or linkable to other technologies.

Corresponding Author: Wanli Chen, Faculty of Information Technology, University of Technology, 235-253, Jones Street, Ultimo, Sydney, Australia, 2000

Lack of investigation into unique trends and two-way reflexivity relationships: Additionally, their results (or identified patterns) can not be distinguished or recognized on separate levels-general level, group level or individual level. Particularly they often ignore unique trends of stocks, that is, patterns which only relate to individual stocks themselves. Furthermore, while traditional methods focus on single dimensions of stock market structure, they often ignore inter-dimensional (or two-way reflexivity) relationship between these dimensions. Because of these problems, these methods can not assist investors to identify investment opportunities and their performance is regarded as limited.

Lack of domain knowledge-dependent feature: These technology-based methods often neglect or misunderstand the importance of domain knowledge, thus it is difficult for their results to be interpreted, understood, used and reused by practitioners and academics.

Therefore, in this study, we address these problems and propose a novel three-layer integrated framework composed of Analysis, Synthesis and Investment Decision Support. In the framework, the multi-dimensional pattern components in line with different investment methods are identified at the first layer, in which we emphasize two key things: Identification of unique trends of stocks using the domain knowledge-dependent Autosplit method and building a two-way reflexivity model of investors' decisions and market reaction. These pattern components are then integrated at the second layer and followed by optimal investment decision support at the third layer. Since the framework integrates multi-dimensional stock market structures and incorporates the concepts and advantages of traditional investment methods, (such as fundamental analysis, technical analysis and finance psychology) and related data mining methods, it can offer improved performance.

A THREE-LAYER FRAMEWORK OF STOCK MARKET STRUCTURE ANALYSIS, SYNTHESIS AND INVESTMENT DECISION SUPPORT

A GOLDEN TRIANGLE MODEL AND MULTIPLE-DIMENSIONAL STOCK MARKET STRUCTURE

A considerable number of studies have been conducted in regard to stock market structure.

Basically, a typical stock market structure (including microstructures and macrostructures) in relation to stock returns and investment has following components: investors, fundamental factors and stock itself[14-17].

On surveying the research literature related to stock market structure, we found that stock markets have multi-dimensional constituents and so have proposed a novel analysis method, what we call a Golden Triangle model. The model is illustrated in Fig. 1.

As shown in Fig. 1, stock price formation is the result of integral co-enforcement of multi-dimensional event factors, including fundamental factors (or company values)-dimension 1, investors-dimension 2 and stock-dimension 3. In the Golden Triangle model, company value represents the real value of the stock and most fundamental factors are related to it. It is relatively stable and may be compared to the supporting point of a lever. But stock movement (of price and volume) is volatile because it is triggered by investors' ever-changing behaviours. Technical analysis is used to identify patterns of the investors' behaviours behind the change of stock prices and volumes. Investors constitute the demand and supply of stock markets and their behaviours (particularly over-pessimism or over-optimism) trigger the change of supply and demand relationship (i.e., over-demand or over-supply), represented by volatile stock prices and volumes. On the other hand, fluctuating market situations affect investors' behaviours and decision making. The inter-dimensions of the Golden Triangle model (i.e., a two-way reflexivity relationship of investors' decisions and market reaction-dimension 4, reasonable trading ranges in line with company values-dimension 5 are areas worthy of further

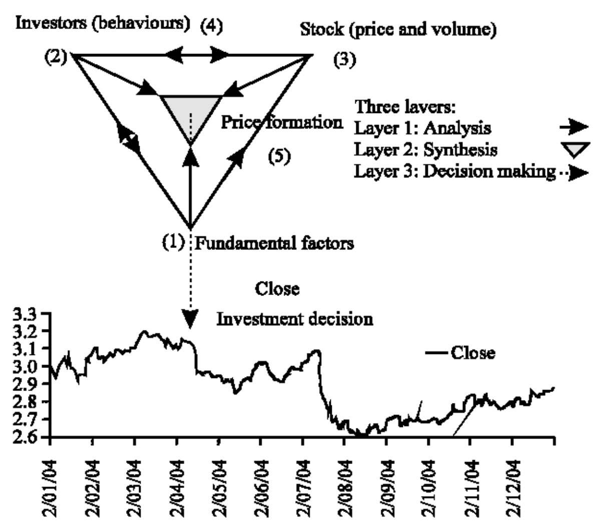


Fig. 1: The golden triangle model of stock markets

investigation. These dimensions affect different size of markets and so they have different levels of strength.

CONCLUSION

In conclusion, as shown in Fig. 1, stock markets have following horizontal multi-dimensions (including both intra-dimension and inter-dimensions) and vertical multi-levels of event factors:

Intra-dimensions: The angles (or dimensions) of the Golden Triangle model, including fundamental factors investors', potential supply and demands and unique trends of stocks.

Inter-dimensions: The interactions between the angles of the Golden Triangle model, including two-way reflexivity of investors' decision and market reaction and reasonable trading ranges in line with company values.

Multi-levels: When considering their effect strength (i.e., how many stocks they affect), these dimensions can be classified at different levels, including general-levels (as they affect all stocks in the market), group-levels (as they affect an industry or a group of stocks in the market) and individual-levels (as they only affect an individual stock).

Three-layer integrated framework of analysis, synthesis and investment decision support: Based on the discussions of multi-dimensional stock market structures in preceding section, we propose a novel three-layer integrated framework to describe the characteristics and relationships of the analysis and synthesis of multi-dimensional stock market structures and to provide investment decision supports accordingly. The three-layer framework is illustrated in Fig. 2.

First layer: Analysis of stock market structures: Since stock price formation is an integral enforcement of multiple event factors within market structures, it can be decomposed into multi-dimensional pattern components and this can be mathematically described as follows:

$$M = f(m_1, m_2 \ldots m_i \ldots m_n)'$$

where m_i is the ith dimensional pattern component, as discussed in section 2.1.

Second layer: Synthesis of stock market structures: Once individual pattern components are identified and modelled from the historic data set at the first layer,

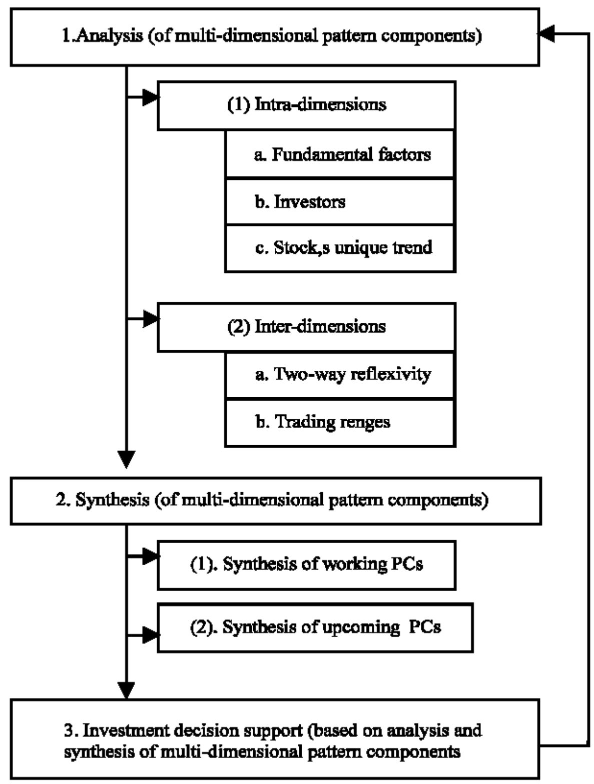


Fig. 2: Three-layer framework of analysis, synthesis and decision making

working and upcoming pattern components can be integrated to reflect current (or potential) stock market situations and this can be mathematically described as follows:

$$S_t = f_t(p_1, p_2 \ldots p_i \ldots p_n)'$$

where S_t indicates the synthesis result at time t; p_i indicates the ith pattern components that either are identified previously but still working at time t, or are upcoming as new pattern components at time t.

Third layer: Investment decision support based on analysis and synthesis: Once potential investment opportunities are identified and trading strategies are created based on the result of the second layer, they can be inputted to investors' knowledge base and then be used to help investors optimize their decision making. This can be mathematically described as follows:

$$Ds = f(s_1, s_2 \ldots s_i \ldots s_n)'$$

where s_i indicates the i^{th} appropriate trading strategies derived from the results of synthesis, which supports investors' decision making.

The three-layer framework has a cyclic process. After the third layer, the results of investment decision support can be used to adjust (or to optimize) both the models of pattern components identified previously at the first layer and the models of integration at the second layer. In the cyclic process, parameters of pattern components and their synthesis can be optimized and optimal investment decisions can be achieved accordingly.

Pattern components in the three-layer framework: As we discussed in previous sections, difficulties of integration of different investment methods and different dimensions of stock market structure derive from their incompatible and different features and this makes them non-linkable in the same way as legacy systems in IT have been incompatible. To solve the integration problems of such systems, we use the concept of components in Information Technology[18,19]. Thus, in the three-layer framework, concepts of *pattern components* are used for modelling different dimensional market structures.

We define *pattern components* as predictable event factors with following features:

Firstly, they are basic unit components which derive from each dimension of stock market structures and they are understandable, interpretable, usable and reusable for finance practitioners and academics.

Secondly, they have interfaces (or common features) so that they are linkable and integratable to each other (or different methods). For instance:

- They all have numerical modelling and categorical descriptions.
- The models are based on their effects on stock returns (or the change of stock prices and/or volumes).
- They have an effect period (with a beginning and ending time point).
- They have different effect strength on the market at different time points (or stages) during their effect period.
- Different pattern components affect stocks at different levels, for instance, at individual stock level, or at group stock level, or at a general level.

Thirdly, stock market situations (including price and/or volume) are the result of integral co-enforcement (or aggregation) of multi-dimensional pattern components.

Finally, at a past time point T, market situations can be decomposed into separate working pattern components and this is compatible with the first layer of the framework. At a new time point T+1, new market situations can be derived by integrating multi-dimensional patterns that are either working or upcoming and this is compatible with the second layer of the framework.

In details, each pattern component has common attributes as follows:

Effect Beginning Time: In a fair and efficient market, effect beginning time of an event is the same as its first formal announcement (or disclosure) time. But in trading practice, the effect beginning time can be earlier than its formal announcement time, as related news has been disclosed earlier.

Ending time: Usually this indicates the moment when the effect strength diminishes to zero level and no longer has any effect.

Period length: This indicates how long the effect of pattern components last. Basically, period length = ending time-beginning time.

Effect stages and effect strength: Within an effect period of pattern components, we observe that their effect strength (ES) on stock returns fluctuates (usually decreases) at different times, in a range of [0, 1], which indicates from none effect to the strongest effect. Based on the changing effect strength (ES), the effect period of pattern components can be decomposed by different stages from *deepest* to *shallow* to *vanish*. Following shows an example of the stages:

$$\textbf{Stage} = \begin{cases} \textbf{1 (deepest), where } 0.9 < ES <= 1; \\ \textbf{2 (deep), where } 0.5 < ES <= 0.9; \\ \textbf{3 (shallow), where } 0.1 < ES <= 0.5; \\ \textbf{4 (vanish), where } 0 < = 0.1; \end{cases}$$

Price formation formula to represent the framework: A significant number of studies reveal that stock price formation is the result of an integral enforcement of multiple event factors (or pattern components)[20-22] , which can be mathematically described as follows:

$$P = W \bullet E + N \tag{1}$$

where P denotes the price formation (or returns) of a stock; $W = (w_1, w_2, \ldots, w_n)$ and w_i is the effecting weight of ith recognized pattern component in a multi-dimensional pattern component series E, where w_i is in (0, 1), which indicates from none effect to the strongest effect; $E = (e_1, e_2, \ldots, e_n)$ and e_i is the price formation (or returns) models determined by the ith recognized pattern component; N denotes trivial price formation by unrecognized factors.

In above price formation equation, reading from left to right, we see the analysis of stock price formation into multi-dimensional pattern components-layer 1 of the framework; reading from right to left we see the synthesis of multi-dimensional pattern components into stock price formation-layer 2 of the framework.

Basic justification methods of the framework: Concepts of return are used to justify the analysis and synthesis of pattern components, since return can be used to evaluate their performance and directly represents the process of price formation. In this study, three types of returns are adopted: Absolute-differenced Return (described by $R_t = (P_1\text{-}P_0)/P_0$), Differenced-logarithmic Return (described by $R_t = \Delta \log (y_t) = \log (y_t/y_{t-1})$) and Comparative Return (described by $AR_{it} = R_{it}\text{-}R_{mt}$, where R_{it} is the actual return of the stock at time t and $R_{mt} = \acute{o}_i+\beta_i R_{mt}$, the returns predicted by a market regression model using the parameters from the estimation period of market and industry indices).

FIRST LAYER: ANALYSIS OF MULTI-DIMENSIONAL PATTERN COMPONENTS

Identification of pattern components of fundamental factors: Fundamental factors constitute a large number of components which affect different levels of stock markets and this can be described as follows:

$$Fp = f\,(p_g, p_i, p_c)$$

where p_g indicates general-level fundamental factors; p_i indicates industry-level (or group-level) fundamental factors; p_c indicates individual-level fundamental factors.

In detail, general-level fundamental factors are mathematically described as follows:

$$F_g = f\,(g_1, g_2 \ldots g \ldots\ldots g_n)'$$

where g_i indicates the i^{th} general-level fundamental factors. According to the reviews of market structures, g_i can be one of the following: News of macro-economic activities (such as unemployment, GDP growth and business climate); Inflation (CPI, PPI and wage developments); Balance of payments (trade and current account) and changes in official interest rates.

Similarly, industry-level fundamental factors are mathematically described as:

$$F_i = f\,(i_1, i_2 \ldots i_i \ldots i_n)'$$

where i_i indicates the ith industry-level fundamental factors. According to the reviews of market structures, i_i can be one of the following: news concerning industry economic activity (industrial production, industry growth, industry sales and industry business climate); policy and regulation changes in relation to the industry; and news concerning competing industries and chain industries (suppliers or demanders).

Similarly, individual-level fundamental factors are mathematically described as:

$$F_c = f\,(c_1, c_2 \ldots c_i \ldots c_n)'$$

where c_i indicates the i^{th} company-level fundamental factors. According to the reviews of market structure, c_i can be one of the following: Financial Factors (such as cash flow, return on assets, conservative gearing, history of profit retention for funding future growth and soundness of capital management); Management Factors (such as appointment or resignation of important directors and management; change of company mission and goals and increase or decrease of branches); Company's environment factors (such as takeover bid, emerging competitors, co-operation).

Modelling: Each fundamental pattern component is modelled using Least Square Regression (LSR) and/or Auto-Regression methods. We depart from a number of earlier related studies by excluding the event factors that coincide with other major events (such as corporate news related to other event factors). The reason for excluding these events, is to ensure that we are capturing the impact (if any) of pattern components per se on market (prices) and not simply the effect of other events. During the modelling process, both attributes of pattern components and some statistical and economic findings are obtained. Accordingly trading rules are established. In the study, we investigated some examples, which included upgrade/downgrade of profit forecast, change of interest rate and change of important directors/managements. Related back-testing results show that models are solid.

Identification of investors' potential supply and demand pattern components: In stock markets, investors' potential supply and demand include a number of components, which can be mathematically described as follows:

$$F_{sd} = f\,(s_1, s_2 \ldots s_i \ldots s_n)'$$

where s_i indicates the i^{th} investors that have effect on market current (or potential) supply and demand. According to the reviews of market structure, s_i can be change of shareholdings of following investors: large influential investors, institutional investors, brokers, directors' interest and group investors.

The effect of each type of investors on market (or potential demand and supply) depends on its attributes, including its long-term or short-term focus, risk taking ability, influential ability to others or even whole market, trading strategies, its cash flow.

Modelling: Each investors' potential demand and supply pattern component is modelled using Least Square Regression (LSR) and/or Auto-Regression methods. During modelling process, both attributes of pattern components and some statistical and economic findings are obtained. Accordingly trading rules can be established. In the study, we investigate some examples, including important change of directors' interest, significant change of influential investors' holdings and change of brokers' recommendations. Related back-testing results showed that models are solid.

Identification of unique trends using a domain knowledge-dependent quasi autosplit method: In stock markets, unique trends of a stock belong only to the stock itself and dramatically affect the market situations of the stock. Unique trends derive from the unique characteristics of multi-dimensions of stock structure, including its unique stock price and volume movement, its unique shareholder constitutions and its unique company-level fundamental factors. Although few relevant studies have been done, the identification of unique trends is significant in research and trading practice. Unique trends of a stock can be defined and identified in following ways:

Firstly, unique trends of a stock can be a clean data set after excluding general-level trend, group-level trend and noise from original data sets of the stock. That is, unique trend = whole dataset-general-level trend-group-level trends-noise

Therefore, we can use the comparative returns concepts to identify unique trends, which is the difference between real market price and the predicted price using regression of market and/or industry movement (as we discussed in section 2.5). In this study, the modelling excludes the 'contaminated' effects of market and/or industry and focuses on the unique trends of the stock.

Secondly, unique trends of a stock can be trends (or features) discovered which have most significant correlation with the stock itself. That is,

unique trend = {u|u in Trends and correlation (u, stock) is maximum}

Thirdly, unique trends of a stock can be the result of integral effects of individual-level pattern components of the stock. That is,

unique trend = Σ individual-level pattern components

Based on the above definitions, we adopt a Domain Knowledge-dependent Quasi Auto-split method to identify unique trends of a stock.

Domain knowledge-dependent quasi auto-split method: Traditionally, data mining methods such as AutoSplit[23] and other technologies are used to identify independent hidden variables in stock markets. When we use them in studies of unique trends, we found the following problems: These methods generate a large number of patterns, many of which are uninteresting to domain experts (i.e., investors) or irrelevant to problems in trading practices. Moreover, discovered models are difficult for finance domain users to understand and they may be totally incompatible with known domain knowledge. Although domain knowledge-dependent features are important in solving the problems, few existing technology-based methods can incorporate domain knowledge into their mining process.

To solve these problems, we propose a Domain Knowledge-dependent Quasi Auto-Split method, which integrates finance domain knowledge (i.e., pattern components discovered) with AutoSplit method in the following ways:

Firstly, we integrate known pattern components in pre-processing: For instance, we can determine the dimension size (or number of variables) based on the number of identified pattern components plus reasonable extra unknown variables and this also can reduce the unpredictable span of a data series by excluding the effects of known pattern components.

Secondly, we integrate known pattern components during processing: For instance, in the formula of Autosplit X = H*B, after discovering and modelling P known pattern components, we can obtain first P columns of H (hidden variable matrix) which represent each pattern component's effect models and their attributes B (base matrix) which represent each stock's contribution or strength to the effect of the pattern component. Then we need to figure out attributes of each stock's hidden variables, which are the remaining columns of H after first P columns. To obtain these columns in H, since only individual stock contributes non-zero strength to the unique trend, we can set their related rows of B as

(0, 0…1…0), where 1 indicates the individual stock's strength. Based on these known base vector B and stock series X, we can easily work out the unique trends in H, that is , H=XB-1.

Finally, we integrate known pattern components after processing: That is, after processing, we need to integrate domain knowledge to understand and interpret hidden variables identified. For example, we can identify which stocks (or other dimensional variables) contribute most or have highest correlation with the hidden variables; or which known pattern components have the same or similar representation patterns as the hidden variables have.

We executed experiments for data sets of top 33 stocks and 11 industry indices of ASX (Australian Stock Exchange) for the period of year 1995-2005 and results (unique trends of stocks discovered) are interesting, interpretable and useful for both trading practitioners and academics.

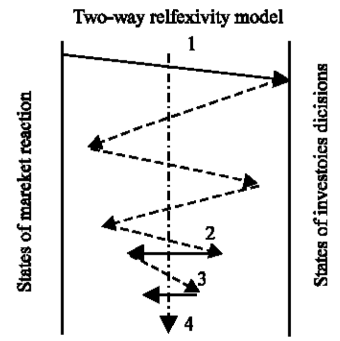
Two-way reflexivity model of investors' decisions and market reactions: Investors' decisions and market reactions have a two-way reflexivity relationship, rather than casual or sequential relationships as traditional method have often assumed. Basically, investors make decision based on market situations. On the other hand, investors' investment decisions (especially influential investors' decisions) not only constitute a new part of market situations, but also can be able to affect market conditions and then trigger market reactions. Such two-way reflexivity process continues until it reaches a stable balance status. In other words, during this interactive process, the divergence between investors' decisions and market situations fluctuates (usually diminishing) with different levels of significance. The process is illustrated in Fig. 3.

Stable Status balance (SSB) indicates the status where investors decisions and their market reactions reach a stable balance. Based on SSB, we can measure the divergence of states and its movement as follows:

Divergence = current state of two-way reflexivity-SSB

Divergence Movement (DM) = Divergence_{t1}-Divergence_{t0}

where Divergence_{t1} indicates diverge of current state to SSB and Divergence_{t0} indicates diverge of previous state to SSB. Divergence Movement (DM) can be classified into three modes: Closed-end mode, Open-end mode and Dead-end mode.



1. Most significant divergence; 2. Less significant divergence;
3.Approximatin of Equilibrium(or significant divergence);
4.Equilibrium or stable status of reflexivity;
: Stable status line

Fig. 3: Two-way reflexivity model of investors' thinking and market reaction

Closed-end mode: In a reasonable period, divergence keeps decreasing (or DM<0) and finally it reaches stable status balance. This applies to most cases in stock markets.

Open-end mode: In a reasonable or limited period, divergence keeps increasing (or DM>0) so that the gap can only become bigger and bigger. Such open-end modes have two directions:

- Bullish Open-end, where divergence increases the strength of buy-side investors and the market becomes bullish.
- Bearish Open-end, where divergence increases the strength of sell-side investors and the market becomes bearish.

Dead-end mode: In a reasonable or limited period, divergence (or gap) keeps a same extent (or DM = a constant) and on average, it is neither close-end nor open-end. There is only a few of such cases in stock markets.

The modes discovered can be used to help identify investment opportunities, as they disclose the divergence of current market state to stable balance status. For instance, in a bullish open-end mode, investors can expect that the market will finally fall back to a balanced status.

Using Vector Auto-Regression (VAR) method to identify the modes and model: VAR methods have a significant difference from traditional methods in that in a VAR system all variables are assumed to be inherent. A significant number of studies[24-26] revealed that VAR methods were effective for identification of interactive relationship among multiple financial factors.

In this study, we used tools of VAR, including Granger-causality tests, forecasting and Impulse Response Functions (IRFs), to investigate a horizontal two-way relationship between group (or industry) investors' decisions (represented by industry indices) and to investigate a vertical two-way relationship of effects of influential investors' decision on other investors (represented by the effects of changes in brokers' recommendations on the market). In the experiments, we modelled these two-way reflexivity models and their modes of divergence among variables, such as log return of the stock and change of brokers' recommendations. Models of such two-way reflexivity were back tested and their applications were investigated. The results were found to be solid and the models were found to be particularly useful for portfolio building and risk controls.

SECOND LAYER: SYNTHESIS OF MULTI-DIMENSIONAL PATTERN COMPONENTS

As price formation is the result of integral co-enforcement of multiple forces (or pattern components), we can treat each pattern component as an individual force with attributes of strength (its quantity side, or how much it is), direction (its quality side, or where it goes) and length (how long it lasts). The modes of synthesis are based on these attributes.

Force strength (FS): This indicates the strength of pattern components based on their models. '+' indicates it forces stock price to move Up and '–' indicates it forces prices to movie Down. Based on attributes of FS, in the first mode of integration, we can sum up FS of all working and upcoming pattern components for their synthesis and this can be described as follows:

IR (Synthesis) = Σ (+FS of pattern components)/Σ (-FS of pattern components)-1

$$\text{Then investment decisions can be} = \begin{cases} \text{Buy, if IR>bechmark (default value 0)} \\ \text{Hold, if IR = bechmark (default value 0)} \\ \text{Sell, if IR<bechmark (default value 0)} \end{cases}$$

Force directions (FD): This indicates the direction of movement of pattern component. FD can be the change slope (or angle) of predicted price movement minus previous price movement compared to the moving average of price movement in a reasonable previous period.

$$FD = \text{arc sine } ((IR_{t1}-IR_{t0})/MA)$$

where IR_{t0} indicates previous IR (of price movement), IR_{t1} indicates predicted IR (of price movement); MA indicates moving average of IR (of price movement) in a reasonable period.

Based on the attributes of both Force Strength and Force Directions (similar to the concepts of Forces in Physics), in the second mode of integration, we can use Hermite's Interpolation to calculate the integration result of pattern components.

Based on the integration results of multi-dimensional pattern components and their attributes, we can adopt the following trading rules:

- If its FD indicates Up, its FS is High and its effect period is Long, then the trading signal is Buy.
- If its FD indicates Down, its FS is High and its effect period is Long enough to meet trading goals, then the trading signal is Sell.
- If its FD is Neutral (neither up nor down), its FS is Weak or Medium, or its effect period is too Short to meet trading goals, then the trading signal is Hold.

Experiments and evaluation: We triggered trading signals (buy, sell or hold) at 80 important time points based on the integration results of pattern components, in ASX (Australia Stock Exchange) for the period of 01/01/2005-30/6/2005. It was observed that trading performance (with 48% aggregate returns) was much better than the performance of benchmark market indices 4.16%, top performing funds 20% (Morningstar) and conventional methods (i.e., 14% for MACD method in our experiments).

THIRDLAYER: OPTIMAL INVESTMENT DECISION MAKING SUPPORT

Trading strategies based on the results of analysis and synthesis: In previous study, individual pattern components and their synthesis were identified with their unique attributes. Their identifiable attributes include direction, strength, effect period and effect stages. Based on the attributes of their synthesis results, trading strategies can be created and they can be used as an aid to investors' decision making. This procedure is illustrated below using four key attributes:

Direction: This is classified as Up, Down, or Neutral. Accordingly, investors can make the following decisions: Buy at the beginning (or ending) of Up (or Down), sell at the ending (or beginning) of Up (or Down), Hold in the period of Neutral.

Strength: This is classified as Strong, Weak, or Neutral. Accordingly, investors can make the following decisions: Trade (buy or sell) with high volume at Strong, trade (buy or sell) with low volume at Weak, Trade (buy or sell) at medium volume at Neutral.

Effect period: This is classified as Long, Short, or Medium. Accordingly, investors can make the following decisions: Adopt or adjust trading long-term strategies within a period of Long, but in a period of Short or Medium, they need to react punctually to markets or trade quickly to catch opportunities and to make use of reasonable trading range concepts.

Stages: This is classified by Strongest, Strong, Shallow, Vanishing. Accordingly, investors' decisions can be: Start trade (sell or buy) at the Strongest or Strong stage; hold or close trade at the stage of Shallow or Vanishing.

A prototype of investment DSS system to implement the three-layer framework: A prototype of Integrated Three-layer Framework Investment DSS system (ITFIDSS) is designed to implement the entire modelling, trading strategy making and decision support processes of the three-layer framework which we discussed in previous sections, in order to optimize investors' decision makings. The simplified architecture of the prototype is illustrated in Fig. 4. Inputs of ITFIDSS include stock list, historic stock prices, news, announcements of ASX and other information related to different dimensions of stock market structures and conventional investment methods. ITFIDSS include three modules-analysis, synthesis and investment decision making. The inputs were processed through these modules and created outputs, including more investment opportunities being identified and more efficient and profitable investment decision being made accordingly. There is an interactive process between the DSS system and users, through user profiles and expert domain knowledge Fig. 4.

We adopt an RDP (Requestor-Dispatcher-Provider) model to depict the structure of the prototype Fig. 5. In this study, once Requestor sends users' request to Dispatcher, Dispatcher will choose an appropriate Provider and then the Provider will look into model base, knowledge base, data base and expert domain base to find an appropriate solution. When this process is reversed, the solution will be passed to users. Details of components of the RDP models will be discussed in our other publications.

System implementation and evaluation: The proposed prototype is a KB-DSS in essence, thus building it involves the capabilities, functionality and structures of both DSS and ES with emphasis on the support of DSS. We adopted a KB-DSS methodology proposed[27]. Additionally, Evolutionary Prototyping proposed[28] was used as an aid. The initial prototype was implemented by mainly using C++. An industry partner, Tricom Australia Ltd, contributed expert domain knowledge and was involved in the prototype implementation.

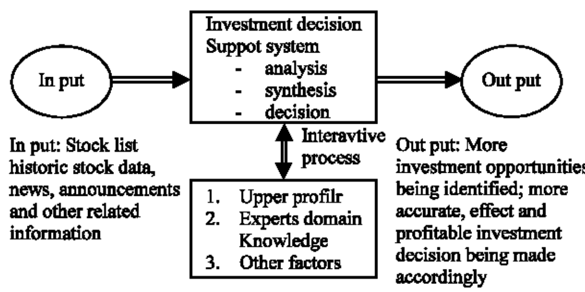


Fig. 4: A simplified architecture of an ITFIDSS system

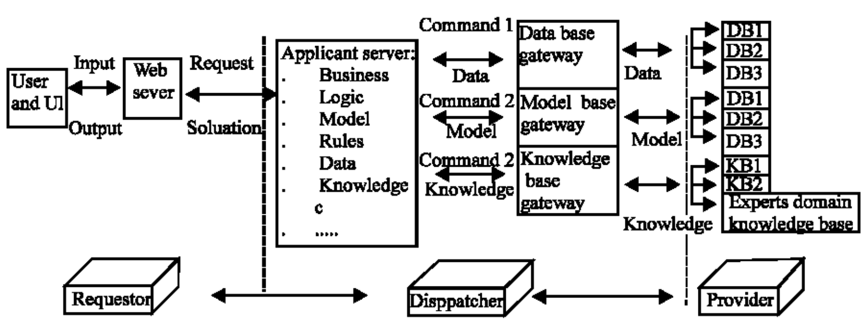


Fig. 5: a System structure of ITFIDSS using an RDP model

Table 1: The performance of a prototype of itfidss and its comparison with baselines

Measurement (1): Success rate of prediction of stock movement direction	Success rate of stock movement direction (in the period 01/07/2005-30/08/2005)	Success rate of stock movement direction (in the training period)	Success rate of stock movement direction (in the testing period)
ITFIDSS prototype	92 (%)	87 (%)	90 (%)
Conventional method (MACD)	16 (%)	57 (%)	62 (%)
Excess Success rate	76 (%)	30 (%)	28 (%)
Measurement (2): Mean prediction error variance (of returns)	Mean Prediction error variance (in the period 01/07/2005-30/08/2005)	Prediction error variance (in training period)	Prediction error variance (in testing period)
ITFIDSS prototype	0.11	0.09	0.12
Conventional method (MACD)	2.33	3.21	2.86
Excess mean prediction error variance	-2.22	-3.12	-2.74
Measurement (3): Aggregate returns	Aggregate Returns (in the period of 01/07/2005 -30/08/2005)	Aggregate Returns (in training period)	Aggregate returns (in testing period)
ITFIDSS prototype	55 (%)	62 (%)	48 (%)
Compared with following baselines:			
S and P/ASX 200 Accumulation (ASX, 2005)	4.33 (%)	22.57 (%)	4.16 (%)
Excess returns (1)	50.67 (%)	39.43 (%)	43.84 (%)
Median returns of fund management (Bowerman, 2005)	7.1 (%)	13.1 (%)	4 (%)
Excess Returns (2)	47.9 (%)	48.9 (%)	44 (%)
Australian hedge funds (RBA 2005)	11 (%)	12.2 (%)	5.7 (%)
Excess returns (3)	44 (%)	49.8 (%)	42.3 (%)
Top performing funds (Morningstar)	17.6 (%)	45 (%)	20 (%)
Excess Returns (4)	37.4 (%)	17 (%)	28 (%)
Conventional methods (such as a technical analysis-MACD in my experiments)	12 (%)	29 (%)	14 (%)
Excess returns (5)	43 (%)	33 (%)	34 (%)

Based on experiments of the prototype, we got following evaluation results:

- Real transaction results. 10 real investors were chosen to use the prototype to pick up real important trading points in ASX market in evaluation period (01/07/2005 -30/08/2005) and thus real transaction results were obtained. Similar experiments were executed in training period (01/01/2004-31/12/2004) and testing period (01/01/2005-30/06/2005). In Table 1. illustrates performance of the prototype and its comparison with market baselines.
- The prototype of the integrated framework is promising and outperforms both market baselines (i.e., performance of Australian market index ASX and fund managers) and conventional investment methods (such as MACD) in ASX markets.
- Perception Measures. In the experiments, users of the prototype (ten real investors and fund managers, including a broker from my industry partner Tricom.com) used and interacted with the prototype and evaluated it using perception measures. In the analysis, I tested the response average against the mid-point of the scale-5 which is noted as Sometimes useful (or Sometimes ease of use, or Sometimes convicted that decisions are correct, or Sometimes the decision process is under control). All proportional differences were tested by using the two-tailed Fisher's Exact Test. The users gave positive feedbacks on these aspects in both experiment and real trading practice and this is illustrated in following Table 2, where and the usefulness scores can simply be presented along with their statistical significance as indicated by the two-tailed p-value.

Table 2: Users' perception measures of prototype of ITFIDSS

Users perception measures	Results
Scoring of usefulness:	8.9
-p value	0.003
Scoring of ease of use	7.7
-p value	0.012
Scoring of conviction that decisions are correct	8.4
-p value	0.049
Scoring of control of the decision process	7.7
-p value	0.038

More importantly, the users indicated that the ITFIDSS could help them gain a competitive edge, because it provided a systematic framework to integrate their work with different investment methods and helped them understand stock market comprehensively and thoroughly by disclosing new dimensions-two-way reflexivity model and unique trends of stocks.

CONCLUSION

In this study, we proposed a novel three-layer integrated framework of stock markets, composed of Analysis, Synthesis and Investment Decision Support. The framework incorporated advantages of conventional investment methods and integrated multi-dimensional and multi-level pattern components of stock market structures and this assisted investors to make optimal investment decisions. In the framework, we emphasized two key aspects that previous studies neglected: unique trends of stocks-patterns which relate only to individual stocks themselves and a two-way reflexivity model of investors' decisions and market reactions. These two aspects help investors comprehensively and thoroughly understand market situations and so identify more investment opportunities. Experiments indicated that the framework and its prototype were promising and outperformed market baselines and conventional methods.

Our future study includes adopting more methods to model the analysis and synthesis of multi-dimensions and multi-levels of stock market structures and to further investigate their attributes and optimize related parameters. Additionally, we will investigate the further optimization and usage of unique trends of stocks and two-way reflexivity model of investors' decision and market reactions.

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