

Synthesis of Multi-Dimensional Market Dynamics in an Integrated Investment Framework

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Abstract: In stock markets, the performance of traditional technology-based investment methods is limited because they only take into account single-dimensional event factors. The paper shows how the synthesis of multi-dimensional stock market dynamics can improve performance and proposes a three-layer integrated investment decision-support framework. In this study, we discussed different synthesis methods for different dimensional market dynamics. The integrated investment framework with incorporating this key dynamics is promising and our experimental results showed that it outperformed single-dimensional traditional methods and benchmark indices.

Key words: Synthesis, multi-dimensional, market dynamics, integrated investment framework

INTRODUCTION

While there are a crowd of finance methods (such as fundamental analysis, technical analysis, contrarians theory) in stock markets to help identify investment opportunities, they have different strengths and weakness^[1-3]. There is an increasing need to integrate the different methods in stock markets and it is becoming more and more common for finance practitioners to adopt different methods simultaneously to get an optimized investment result^[4]. However, some research problems have been observed in existing technology-based methods. Here is a problem that we shall consider throughout the study:

Single-dimension vs integration of multi-dimensions: Existing technology-based methods mainly focus on technical analysis, with a few which consider other dimensions. However, none of integration-related methods covers 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 can not help investors to thoroughly and comprehensively understand the market and to identify all potential investment opportunities

Because of this problem, existing methods can not assist investors to identify investment opportunities very well and their performance is regarded as limited. In this paper, we address these problems and propose a novel three-layer integrated decision-support framework composed of Analysis, Synthesis and Investment Decision Support, in which we emphasize synthesis methods for multi-dimensional dynamics.

Description of a three-layer integrated investment decision-support framework: In our previous studies^[5], based on surveys on multi-dimensional stock market structure^[6-8], we propose a novel three-layer integrated framework analyzing and synthesizing multi-dimensional stock market dynamics and supporting investment decisions. This three-layer integrated investment decision support framework is illustrated in Fig. 1.

This integrated framework consists of three layers:

Analysis of stock market structures: Since stock price formation is the result of integrated enforcement of multiple event factors within market structures, it can be decomposed into multi-dimensional dynamics, in which we focus on a two-way reflexivity dynamics between investors behaviors and market reactions. To model these multi-dimensional stock market dynamics, we proposed concepts of pattern components, which represent basic unit components that derive from each dimension of stock market structures, with features of being understandable, interpretable, usable and reusable for finance practitioners and academics;

Synthesis of stock market structures: After individual pattern components being identified and modelled from historic data set at the first layer, working and upcoming pattern components can synthesize to reflect current and potential market situations;

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.

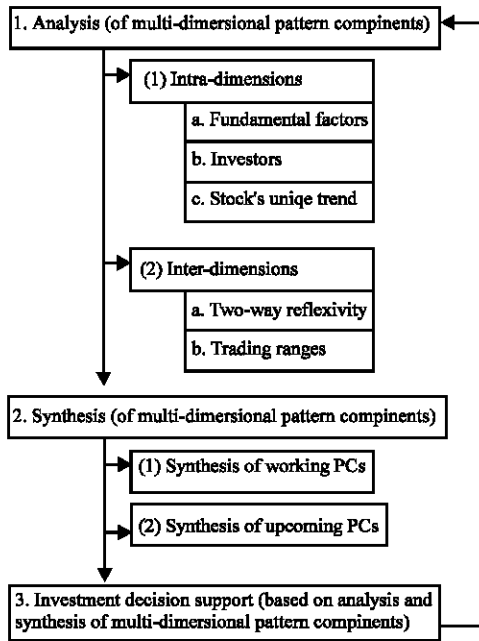


Fig. 1: A Three-layer integrated decision-support framework

This three-layer integrated framework has a cyclic process: after the third layer, the results of investment decision-support can be used to adjust or optimize both the models of pattern components identified 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 so optimal investment decisions can be achieved.

First layer: Identification of multi-dimensional dynamics:

In the first layer, we focus on identification of multi-dimensional dynamics. Please see our previous studies^[5,9,10].

Second layer and third layer: Synthesis and decision support:

The 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). Based on these attributes, integration can be achieved either by simple summing up strength of working and upcoming pattern components, or by using Hermites interpolation of both strength and directions of working and upcoming pattern components, which include two-way reflexivity model of investors decisions and market reactions we discussed in previous sections. Different synthesis methods will be discussed in this study.

In the first mode of synthesis, based on attributes of FS, we can simply sum up FS of all working and upcoming pattern components and this can be outlined as follows:

$$IF \text{ (Integrated force)} = \Sigma(FS_i)$$

where i indicates ith individual pattern component.

This mode does not take into account attribute of force directions, except assuming that individual forces directions or angles are all same (say, 90° or -90°). In other words, integrated forces direction depends on whether their final value is positive (+, which indicates Up) or negative (-, which indicates Down). Accordingly, this mode can be outlined as follows:

$$IF = \Sigma (+FS_i) / \Sigma (-FS_j) - 1$$

where + FS_i indicates ith positive strength, and -FS_j indicates jth negative strength.

Then investment decisions can be made according to the results of IF. For instance, a positive value of IF which exceeds benchmark indicates an opportunity of Buy, whereas a negative value of IF which is below benchmark indicates an opportunity of Sell. In other cases, investors need to hold. These decisions are outlined as follows:

$$\text{Then decision} = \begin{cases} \text{Buy, if } IF > \text{benchmark (default 0)} \\ \text{Hold, if } IF = \text{benchmark (default 0)} \\ \text{Sell, if } IF < \text{benchmark (default 0)} \end{cases}$$

The following Fig. 2 provides another example of synthesizing pattern components of investors potential demand and supplies within a short time (in one hour):

Advantages of using synthesis mode 1:

- It is simple and easy to use;
- It is appropriate for one-time (or short-term) synthesis and analysis;
- It is compatible with finance practitioners decision-making routines.

Disadvantage of Using Synthesis Mode 1: It is not suitable for long-term synthesis, as it do not take into account the change (or trend) of moving directions.

In the second mode of synthesis, based on the attributes of both Force Strength and Force Directions (similar to the concepts of Forces in Physics), we can use Hermites Interpolation to calculate the integration result of pattern components.

Each pattern component can be treated as an individual force and so their synthesis indicates their

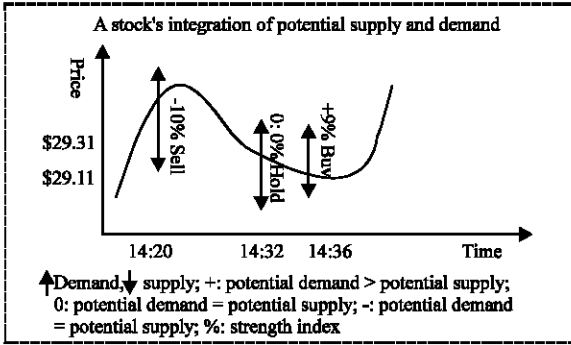


Fig. 2: An example of synthesis mode 1

integrated force. Fig. 3 illustrates an example of integrated forces using Hermite's Interpolation to compute integrated forces, where the final integrated force indicates the result of synthesis.

Advantage of synthesis mode 2: It is suitable for long-term synthesis, as it takes into account changes (or trend) of both effect strength and moving directions.

Disadvantage of synthesis mode 2:

- It is not as simple and easy to use as the synthesis mode 1;
- It is not quite compatible with practitioners traditional decision-making routine.

In synthesis mode 3, synthesis can be achieved following the concepts of vector (or Autosplit), as vectors (or matrices) can represent integration of pattern components and thereby indicate their contributions to each stock into stocks returns. Similar to the AutoSplit concepts^[9], two vectors H and B can be integrated into a data series of stock returns X, as follows:

$$H[n \times 1] * B[l \times m] = X[n \times m]$$

where each column of H[nx1] indicates a data series of the effect of a pattern component at different time points of the period; each row of B[lxm] indicate a data series of each stock (or constituents) contributions or strength to a pattern component. Each column of X[nxm] indicates a data series of a stock return (which is an integration result) at different time points in a period.

In other words, at a time point t, a stock ns synthesis result X(n, t) of multiple pattern components = Σ (each pattern component effect at t * stock ns strength or contribution to the pattern component)

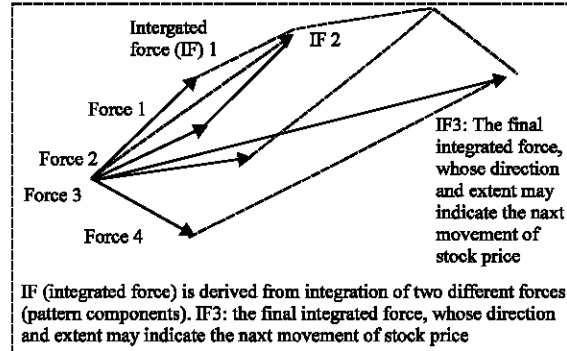


Fig. 3: An example of synthesis mode 2

Advantage of synthesis mode 3:

- It integrates users domain knowledge and pattern components and so the synthesis results are more interpretable and usable for users.
- It is suitable for both short-term synthesis and long-term synthesis, as it does take into account the change (or trend) of both effect strength and moving directions in time series and so it is useful to identify investment opportunities at particular trading points.

Disadvantage of synthesis mode 3:

- It is not as simple and easy to use as mode 1;
- it is not quite compatible with practitioners traditional decision-making routine.

Based on the three modes of synthesis discussed in previous sections, integrated results of upcoming and working pattern components can be obtained and then these integrated results can be used to trigger trading rules as they indicate investment opportunities.

Trading rules based on the integration result of synthesis methods: Based on the synthesis results of multi-dimensional pattern components and their attributes, we can adopt the following examples of 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.

Trading points triggered by above trading rules: In trading practice, trading time points triggered by trading rules are recognized on intra-day, daily, weekly or monthly bases. The following figure illustrates examples of different integrated forces on the daily basis in a short period 19/01/2005 – 07/02/2005.

In real trading practice, it is often difficult (and sometimes unnecessary) to identify the synthesis at minimum-length time point (say, on the basis of seconds or minutes). Rather than massive synthesis identification at each minimum-length time point, only important trading points need to be identified in most trading practice. The most important trading points are those which indicate that new pattern components are upcoming and other important pattern components are working and so they can trigger most important (and most profitable) trading signals. For example, in the above Fig. 4, *four* trivial trading points can be replaced by *one* important trading point A (whose strength and direction are represented by a dashed line). In another example, in the following Fig. 5, *three important* trading points are identified using synthesis methods during the first half year of 2005 and this process is much more efficient than identifying 130 individual daily trading points. Therefore, by adopting important trading points, investors trading processes become more efficient and this is most compatible with investors trading practice.

Third layer: investment decision support: Individual pattern components and their synthesis are identified with their unique attributes. Their identifiable attributes include directions, strength, effect period, effect stages, etc. Based on the attributes of their synthesis results, trading strategies can be created and be used as an aid of investors decision making. For instance, for the attribute Direction, it has value of UP, Down or Neutral. Accordingly, its related trading strategy is Buy at the beginning of UP, sell at the ending of Down, Hold at the period of Neutral.

The three-layer framework is implemented in a DSS prototype - ITFIDSS. Proposed prototype is a KB-DSS in essence and we adopted a KB-DSS methodology proposed by Klein and Methlie^[11]. The initial prototype was implemented by mainly using C++. An industry partner, Tricom Australia Ltd, contributed expert domain knowledge and involved in the prototype implementation. More description of these layers of the framework and the design of the prototype can be found in our previous study^[5].

Based on our experiments of the prototype, we obtained following evaluation results

Real transaction results: 10 real investors were chosen to use the prototype to identify real important

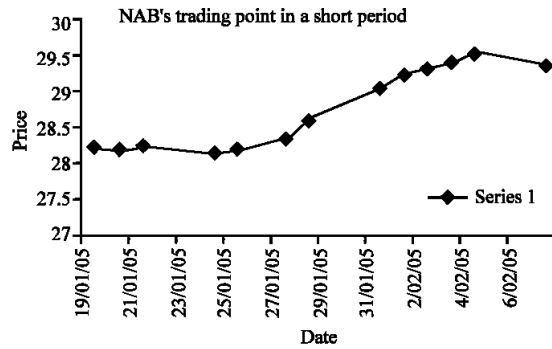


Fig. 4: An example of trading points in a long period

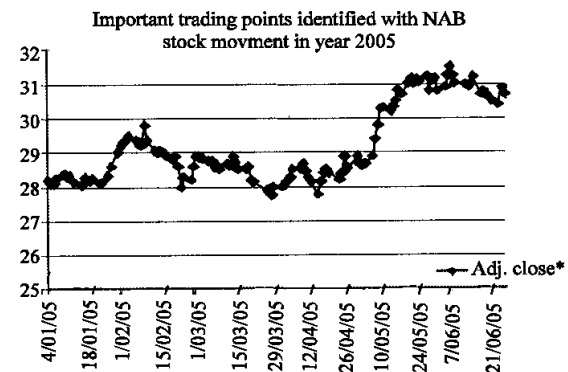


Fig. 5: An example of trading points in a short period

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). Following table illustrates performance of the prototype and its comparison with market baselines.

As above Table 1 shows, the prototype of the integrated framework is promising and outperforms both market baselines (e.g. 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 Fishers 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

Table 1: The Performance evaluation of the prototype ITFIDSS and its comparison with baselines

Measurement (1): Success rate of prediction of stock movement direction	Success rate (in the evaluation period)	Success rate (in the training period)	Success rate (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)	In the evaluation period	In the training period	In the 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	In the evaluation period	In the training period	In the testing period
ITFIDSS prototype	55%	62%	48%
Compared with following baselines:			
S&P/ ASX 200 Accumulation	4.33%	22.57%	4.16%
Excess returns (1)	50.67%	39.43%	43.84%
Median returns of fund management	7.1%	13.1%	4%
Excess returns (2)	47.9%	48.9%	44%
Australian hedge funds	11%	12.2%	5.7%
Excess returns (3)	44%	49.8%	42.3%
Top 5 performing funds	17.6%	45%	20%
Excess returns (4)	37.4%	17%	28%
Conventional methods (MACD)	12%	29%	14%
Excess returns (5)	43%	33%	34%

Table 2: Users perception measures of prototype of ITFIDSS

Users perception measures	Results
(1) Scoring of usefulness:	8.9
- P value	0.003
(2) Scoring of ease of use	7.7
- P value	0.012
(3) Scoring of conviction that decisions are correct	8.4
- P value	0.049
(4) Scoring of control of the decision process	7.7
- P value	0.038

presented along with their statistical significance as indicated by the two-tailed p-value.

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.

CONCLUSION

In this study, we proposed a novel three-layer integrated framework of stock markets, composed of *Analysis, Synthesis* and *Investment Decision Support*. This integrated framework incorporates multi-dimensional stock market dynamics. In the framework, we emphasized on different synthesis methods for multi-dimensional market dynamics. Our studies showed that these synthesis methods play an important role in investment decision making. The framework incorporating this key aspect is promising, because our experimental results showed that it outperformed single-dimensional traditional methods and benchmark indices.

Our future work includes adopting more methods to model the analysis and synthesis of multi-dimensions and

multi-levels of stock market dynamics and to further investigate their attributes and optimize related parameters.

REFERENCES

- Joffe, B., 2005. Fundamental analysis, <http://www.sharenet.co.za/free/library/fundamen.htm>, accessed on 11/08/2005
- Pike, T., 2005. Technical Analysis, <http://www.sharenet.co.za/free/library/technica.htm>, accessed on 11/08/2005
- Mendelsohn, L.B., 1995. Artificial intelligence in capital markets, Global trading utilizing neural networks: a synergistic approach, virtual Trading, Probus Publishing Company, Chicago, Illinois.
- Carter, R.B. and H.E. Van Auken, 1990. Security analysis and portfolio management: a survey and analysis. *J. Portfolio Management*, 16: 81-85.
- Chen, W. and Z. Qin, 2006a. Identification of two-way reflexivity dynamics in an integrated investment decision-support framework, *Asian J. Inform. Tech.*, pp: 732-741.
- Remolona, E.M., 2005. Micro and macro structures in fixed income markets: The issues at stake in Europe, <http://www.eu-financial-system.org/April2002%20Papers/Remolona.pdf>, accessed on 11/08/2005
- Stoll, H.R., 2003. Market microstructure, *Handbooks in Economics*, Amsterdam; London and New York: Elsevier, North Holland.

8. Braberman, D., 2005. The Impact of macro news on the term structure, foreign exchange rates and asset pricing, http://www.cass.city.ac.uk/phd/phd_events/pdf/braberman.pdf, accessed on 11/08/2005
9. Chen, W. and Z. Qin, 2006b. Identification of unique trend dynamics in an integrated investment decision-Support framework, *Asian J. Inform. Tech.*, pp: 742-749.
10. Chen, W., L. Cao and Z. Qin, 2006c. An integrated investment decision-support framework analyzing and synthesizing multi-dimensional market dynamics, *J. Intelligent Systems Technologies and Applications*.
11. Klein, M.R. and L.B. Methlie, 1995. *Knowledge-Based Decision Support Systems with Applications in Business*, 2nd (Edn). England: John Wiley and Sons.