Identification of a Two-way Reflexivity Model in an Integrated Investment Decision-support 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 integration of multi-dimensional event factors can improve performance, in which we emphasize on one key thing that previous studies have neglected: a two-way reflexivity model of investors' decisions and market reactions. This model is thoroughly studied using VAR method in the paper. Our studies show that it plays an important role in investment decision making, particularly it is useful for portfolio building and risk control, and thereby it is an integral part of a three-layer integrated investment decision-support framework. The framework incorporating this key aspect is promising, because our experimental results show that it outperforms single-dimensional traditional methods and benchmark indices.*

Keywords: two-way reflexivity model, integrated investment framework

1 Introduction

While there are a crowd of finance methods (such as fundamental analysis, technical analysis, contrarians' theory, etc) in stock markets to help identify investment opportunities, they have different characteristics and accordingly, strengths and weakness [1, 2, 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]. Meanwhile, a number of expert systems, knowledge engineering and other technologies are used to help the finance methods identify investment opportunities [5, 6, 7, 8, 9]. However, some research problems were observed in these technology-based methods. Here are major problems that we shall consider throughout the paper:

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) and a few others consider other dimensions of stock market structures (such as fundamental factors). However, it is observed that these different methods and/or different dimensions of stock markets are not integrated in a systematic way and so their performance for sound investment decision making is limited [10].

Lack of Investigation into Two-way Reflexivity Relationship: while traditional methods focus on single dimensions of stock market structure, they often ignore an important aspect - inter-dimensional (or two-way reflexivity) relationship between these dimensions. Due to these problems, these methods can not be used to assist investors in identifying investment opportunities, and their performance is limited.

Therefore, in this paper, we concentrate on these problems and propose a novel three-layer integrated framework composed of *Analysis*, *Synthesis*, and *Investment Decision Support*, in which we emphasize a key thing: identification of a two-way reflexivity model of investors' decisions and market reaction.

The remaining of the paper is organized as follows. In section 2, we provide a summarized description of the three-layer framework and its related concepts. In section 3, we describe analysis of multi-dimensional pattern components and focus on one key thing – a two-way reflexivity model of investors' decisions and market reactions. In section 4, we describe the synthesis of the pattern components, and a prototype of optimizing investment decision making and its evaluation in brief.

2 A Three-Layer Investment Framework of Analysis, Synthesis and Decision Support

In our previous studies [10], based on the studies of multi-dimensional stock market structure, we propose a novel three-layer integrated framework to help investors analyze and synthesize multi-dimensional stock market structures, and support investment decisions. This three-layer integrated investment decision support framework is illustrated in Figure 2.

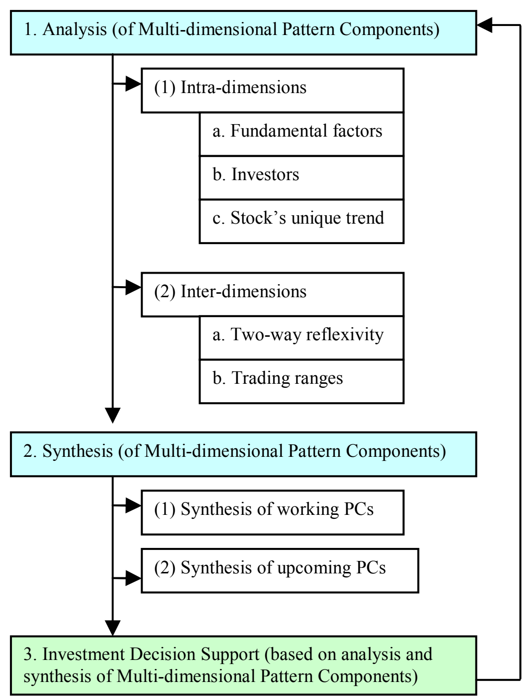


Figure 1: Three-layer Investment Decision-support Framework

First layer: Analysis of Stock Market Structures (or Multi-dimensional Pattern Components)

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:

$$M= f\,(m_1,\, m_2\, ...mi...\, m_n)'$$

where m_i is the i^{th} dimensional market pattern component. Multi-dimensional pattern components include fundamental factors, investors' behaviors, unique trends of stocks, investor's reasonable trading ranges in line with stock's fundamental values, and most importantly, a two-way reflexivity model of investors' behaviors and market reactions.

To model the pattern components, we used the concepts of pattern components, which are the basic unit components that derive from each dimension of stock market structures, with features of being understandable, interpretable, usable and reusable for both finance practitioners and academics.

Second layer: Synthesis of Working and Upcoming Multi-dimensional Pattern Components, in order to disclose whole market situations and so to identify investment opportunities.

Third layer: Investment Decision Support Based on the Functions of Analysis and Synthesis.

This framework incorporates the concepts and advantages of multi-dimensional stock market structures and traditional investment methods, and thereby can help investors make optimal decisions.

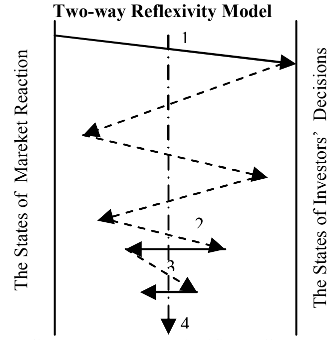
3 First Layer: Analysis of Two-way Reflexivity Model of Investors' Decisions and Market Reactions

In the first layer, we focus on identification of a two-way reflexivity model of investors' decisions and market reactions.

3.1 Introduction of the Model

Investors' decisions and market reactions have a two-way reflexivity relationship, rather than casual or sequential relationships as traditional methods usually 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's reactions. Such two-way reflexivity process continues until it reaches a stable balance status. In other words, during this interactive process, the divergence between states of investors' decisions and market's situations fluctuates (usually diminishes) with different levels of significance. The process is illustrated in Figure 2.

Two-way Reflexivity Model



1. Most significant divergence; 2. Less significant divergence; 3. Approximation of Equilibrium (or most insignificant divergence); 4. Equilibrium or stable status of reflexivity; ↓ Stable Status line

Figure 2: a Two-way Reflexivity Model of Investors' Thinking and Market Reaction

Following list related concepts and measurements:

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: Close-end mode, Open-end mode and Dead-end mode.

Close-end mode: in a reasonable period, divergence keeps decreasing (or DM <0) and finally it reaches stable status balance. This is the most of the 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:

1) Bullish Open-end, where divergence increases the strength of buy-side investors, thus market is becoming bullish.
2) Bearish Open-end, where divergence increases the strength of sell-side investors, thus market is becoming bearish.

Dead-end mode: where divergence is static (or DM = σ, σ is a constant) in a reasonable period and on average, it is neither close-end nor open-end. Only a few of such cases exist 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 the market will finally fall back to the balance status.

3. 2 Using Vector Auto-Regression (VAR) Method to Identify Modes of the Model

VAR methods have a significant difference from traditional methods in that in VAR system all variables are assumed to be inherent so it overcomes their shortcomings. A number of studies [11, 12, 13] revealed that VAR methods can be used to identify interactive relationship among multiple financial factors. For example, not only monetary policy has an effect on stock return, but stock return will affect making of monetary policy.

In our experiments, we used following tools of VAR:

- Granger-causality tests: Granger-causality requires that lagged values of variables of variable A (i.e. change of brokers' recommendations or an industry indices) are related to subsequent values in variable B (i.e. market reactions or another industry index), keeping constant the lagged values of variable B and any other explanatory variables.
- Forecasting: VAR forecasts extrapolate expected values of current and future values of each of the variables using observed lagged values of all variables, assuming no further shocks;
- Impulse Response Functions (IRFs): IRFs trace out the expected responses of current and future values of each of the variables to a shock in on eof the VAR equations (note: shocks can be defined/measured in different ways).

Representation of Investors' Decisions

An important constituent of two-way reflexivity model is to figure out (or model) investors' behavior and thinking. While Investors' thinking and behaviors can not be quantified directly, they can be represented by following ways:

- Horizontal representation - Changes of different constitutions (or group investors) of stock market (or investors as a whole) and their relationship, which indicates flows of funds and investors' intention (or focus), i.e. relationship of change of industry indices indicate relationship of group (industry) investor's behaviors.
- Vertical representation - Changes of influential investors' behaviors affect other investors' actions, i.e. brokers not only have a number of clients, but their recommendations affect individual investor's decisions.

Experiment 1: Using VAR to Identify Group (or Industry) Investors' Two-way Reflexivity Model

While the change of market constitutions (industry groups) are based on the change of investor's thinking or behaviors, two-way relationship of group (or industry) investors' thinking and market reactions can be represented by the relationship of change of different industry indices.

In our study, the Data source is based on weekly data from 31 March 2000 to 31 March 2005 with a total of 260 observations (not including 17/09/01). The data include weekly return 100(log p_t- log p_{t-1}) (and volumes) from Http://finance.yahoo.com.au, of following indices:

- All Ordinaries, ^AORD
- S&P ASX 200 Energy, ^AXEJ
- S&P ASX 200 Materials, ^AXMJ
- S&P ASX 200 Industrials, ^AXNJ
- S&P ASX 200 Consumer Discretionary, ^AXDJ
- S&P ASX 200 Consumer Staples, ^AXSJ
- S&P ASX 200 Health Care, ^AXHJ
- S&P ASX 200 Financials, ^AXFJ
- S&P ASX 200 Information Technology, ^AXIJ
- S&P ASX 200 Telecommunication Services, ^AXTJ
- S&P ASX 200 Utilities, ^AXUJ
- S&P ASX 200 Property Trusts, ^AXPJ
- S&P ASX 200 Financial-x-Property Trusts, ^AXXJ

Following are examples of experimental results:

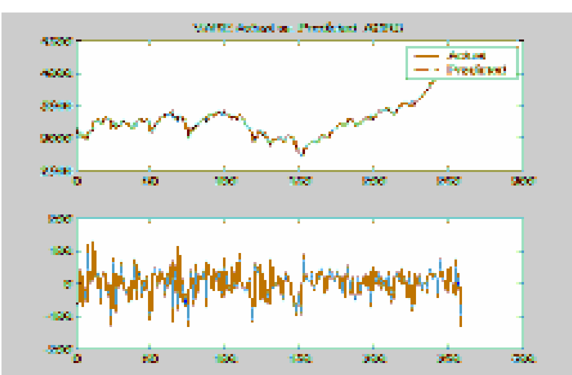
1. Granger Causality Probabilities

Variable	AORD	AXEJ	AXMJ	AXNJ	AXDJ	AXSJ	AXHJ	AXFJ
AORD	0.00	**0.04**	NaN	NaN	NaN	NaN	NaN	**0.03**
AXEJ	**0.07**	0.00	NaN	NaN	NaN	NaN	NaN	0.04
AXMJ	**0.03**	NaN	0.00	NaN	0.02	NaN	NaN	0.02
AXNJ	NaN	NaN	**0.08**	**0.00**	**NaN**	**0.09**	**0.02**	**0.04**
AXDJ	NaN	**0.02**	NaN	NaN	0.00	**0.08**	NaN	NaN
AXSJ	NaN	**0.08**	NaN	**0.05**	NaN	0.00	NaN	NaN
AXHJ	NaN	0.00	NaN	NaN	NaN	NaN	0.00	NaN
AXFJ	NaN	NaN	NaN	NaN	NaN	NaN	NaN	0.00

Analysis of Granger Causality Test: the format of above output is such that the columns reflect the Granger causal impact of the column-variable on the row-variables. That is:

- AXEJ and AXFJ exert a significant Granger-causal impact on AORD.
- AORD and AXFJ exert a significant Granger-causal impact on AXEJ.
- AORD, AXDJ and AXFJ exert a significant Granger-causal impact on AXMJ.
- SXMJ, AXSJ, AXHJ and AXFJ exert a significant Granger-causal impact on AXFJ.
- AXEJ and AXSJ exert a significant Granger-causal impact on AXDJ.
- AXEJ and AXNJ exert a significant Granger-causal impact on AXSJ.

2. Results of VAR Estimate

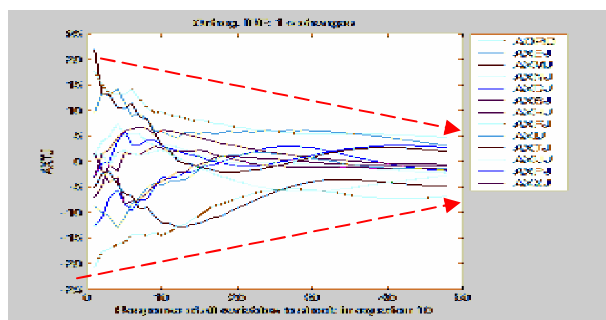


As above graph indicates, predicted results basically match actual results, and difference is controlled in a small and reasonable range. It indicates that performance of VAR estimate is basically good.

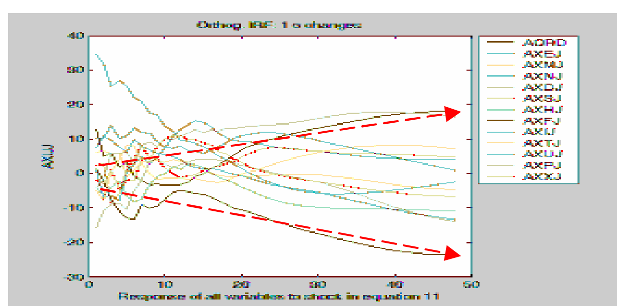
3. Results of Impulse Response Functions (IRFs)

IRFs have following roles in two-way reflexivity model:

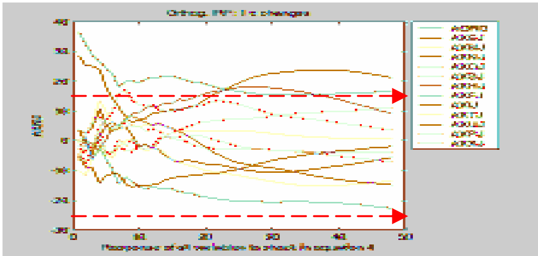
- IRFS represent a method used to examine the interactions between variables in a VAR model. A shock to the system is imposed and the dynamic interactions of the variables of the variables based on the estimated coefficients are simulated for all variables in the system.
- IRFs trace out the expected responses of current and future values of each of the variables (i.e. each industry indices) to a shock (of one industry change) in on eof the VAR equations.
- IRFs can be used to trace different modes of divergence movement of the model. For example, a closed-end mode is derived from impulse response functions as follows, and we observe the divergence is becoming smaller and smaller.



In following figure, an open-end mode is derived from impulse response functions, and we observe the divergence is becoming bigger and bigger.



In following figure, a dead-end mode is derived from impulse response functions, and we observe the divergence does not change much.



Usage of the Modes and the Models

Above experimental results (modes and models) of two-way reflexivity model identified have following usage:

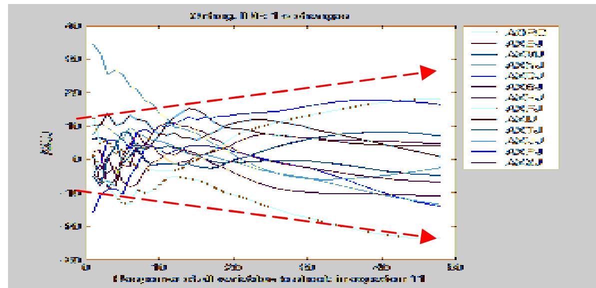
Firstly, they can be used for portfolio building and trading strategy setup. Once the modes and models (including related correlations and interactions) are identified, their characteristics can be use integrated in the process of related portfolio and trading strategy building. For example, if lead/lag relationships exist among variables, investors' portfolios need to have these constituents and adjust their holdings or weights during the period accordingly.

- If they have positive relationship (i.e. the rise of one's price granger cause the rise of another's price, verse visa), investor's holding weight need to move from lead ones to lag ones as time goes by. For example, in above experiments, we found that AXEJ exert a significant positive Granger-causal impact on AORD (this was also confirmed by impulse response function). Therefore, we can put them in a portfolio, as one event of AXEJ can granger cause change of AORD.
- If they have negative relationship (i.e. the rise of one's price granger cause decrease of another's, verse visa), investors can increase the weight (or buy) of lead ones followed by the decrease of the weight (or sell) of lag ones as time goes by. For example, in above experiments, we found that AXFJ exert a significant negative Granger-causal impact on AORD. Therefore, we can put them in a portfolio, as one event of AXFJ can granger cause change of AORD.

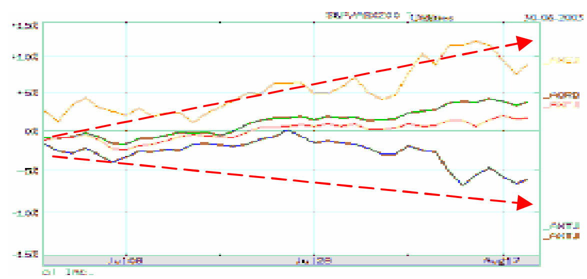
Secondly, they can be used for risk control or decision support of hedging risks. That is, the risks of one stock (or indices) can be hedged or controlled by other correlated stocks with opposite features in the portfolio. For example, a stock's risk of depreciation can be hedged by a correlated stock's appreciations.

A Case Study of Using above Pattern Components to Improve Technical Analysis

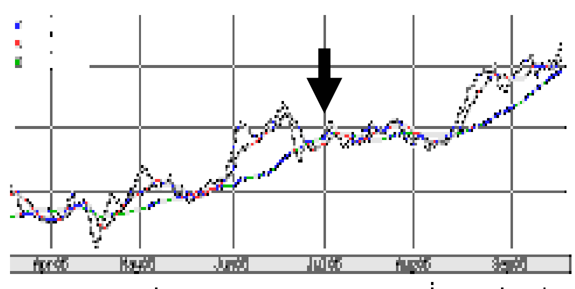
Experimental results of models (such as impulse response functions) can be used for improvement of traditional technical analysis. For example, on 30/06/05, we obtained following impulse response functions (or predicted response) in response of a shock of indices AXUJ.



Following indicates real market movement of related indices. As it shows, the results of impulse response functions are basically compatible with real movement of related (indices) variables.



According to following graph of indices AXUJ.ax, on 31/06/05, 5-day MA cross above 20-day MA, which indicates a bullish market and triggers a buy signal, based on technical analysis. But this is a wrong decision, as there was a smooth price movement during following period.



From VAR analysis (i.e. related impulse response functions), we derived that the price would move smoothly, and this is compatible with real market trends. Therefore, the results of VAR analysis can help investors improve decisions derived from technical analysis.

Justification by More Experiments

Similar to above case studies, we identify and investigate the investment points in all the in-samples (in Year 2004) and out-samples (in first half year of 2005) and their relationship to technical analysis, and got following results:

- Cases that technical analysis ignores investment opportunities but Pattern components of two-way reflexivity model successfully identify them: 42%;
- Cases that technical analysis signals wrong investment opportunities but Pattern components successfully corrected them: 35%;
- Cases that both technical analysis and Pattern components successfully identify investment opportunities: 32%;
- Success rate of using both technical analysis signals and Pattern components to successfully identify investment opportunities: 72%.

Experiment 2: Two-way Reflexivity Model of Brokers' recommendations and Market Reactions

Modeling a two-way reflexivity relationship of the change of brokers' recommendations and stock's returns is important. Brokers not only are important investors, but have huge influences on other investors. The change of their recommendations reflects and indicates investors' thinking and decisions. Therefore, change of brokers' recommendations and their effect can be used to investigate two-way reflexivity models of investors' thinking and market reactions. Data source include daily price and volume series of top 33 stocks of ASX during the period of Year 1995-2005 and their weekly change of brokers' recommendations, including:

- Returns (on price or volumes) on following days- day 1, day2, day3, day4, day 5;
- Absolute change of brokers' recommendation broker-rec-25 (which derives from b-2.5);
- Comparative change of brokers' recommendation broker-rect-t2t1 (which derives from b_{t2}- b_{t1}).

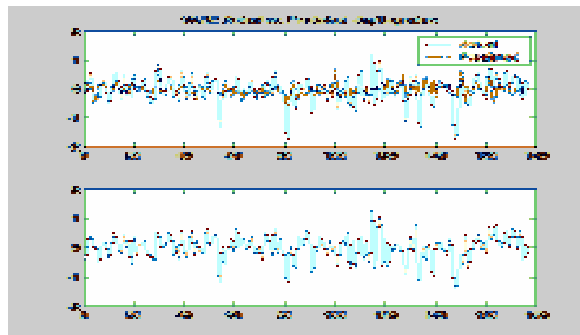
1. Granger Causality Probabilities

Variable	day1logprice	day2logprice	averagelogre	brokerrect25	brokerret1t2	day1logvolum	day2logvolum	averlogvolum
day1logprice	0.00	0.00	0.00	NaN	0.00	NaN	NaN	NaN
day2logprice	0.00	NaN	NaN	0.00	0.00	**0.02**	NaN	0.00
averagelogre	0.00	0.01	0.00	**0.09**	0.00	NaN	**0.01**	**0.02**
brokerrect25	NaN	NaN	NaN	0.00	0.00	0.01	NaN	NaN
brokerret1t2	NaN	NaN	NaN	0.00	**0.03**	NaN	**0.01**	0.00
day1logvolum	**NaN**	**0.10**	**0.03**	**0.07**	NaN	**0.08**	**0.08**	NaN
day2logvolum	NaN	NaN	NaN	0.**04**	NaN	NaN	0.00	0.00
averlogvolum	NaN	NaN	0.01	NaN	NaN	0.00	**0.01**	0.00

The format of the output is such that the columns reflect the Granger-causal impact of the column-variable on the row-variable. That is, broker-rec-25 (and day2-log-return and aver-log-return) exert a significant Granger-causal impact on average-log-return while other variables do not. On the other hand, broker-rect-25 exerts a significant impact on average-log-return, day1-log-return and day2-log-return.

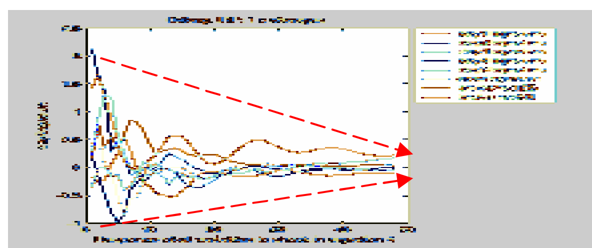
2. VAR Estimates

Following graph represents VAR estimate for a stock ANZ. It shows that predicted ones basically match the actual results and actually it represents smoothing of actual ones.



3. Impulse Response Functions (IRFs)

In following graph, a closed-end mode is derived from impulse response functions, and we observe the divergence is becoming smaller and smaller.



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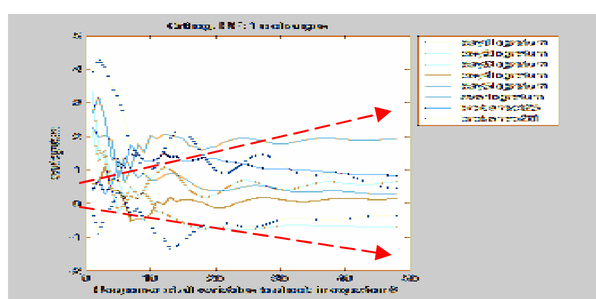
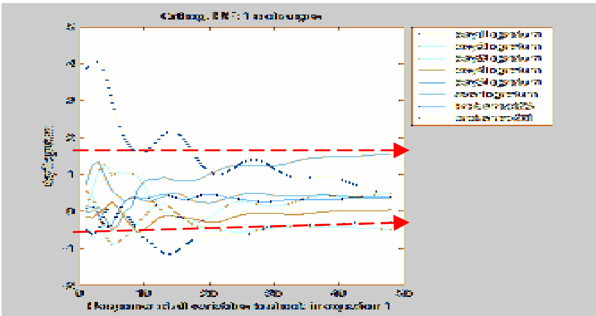


In following figure, a dead-end mode is derived from impulse response functions, and we observe the divergence does not change much.

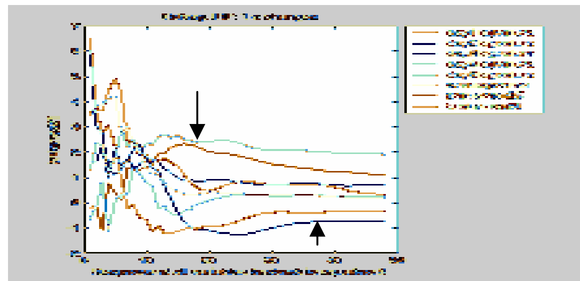


Usage of the Modes and the Models

In above experiments, by using VAR, we analyze the two-way interactions between brokers' recommendation and market reactions (i.e. returns of prices and volumes at different following days). Once their correlations and interactions are identified, they can be used for trading strategy building. For instance, if lead/lag relationships exist among variables of change of brokers' recommendations and following returns, they can be used for adjustment of trading strategies.

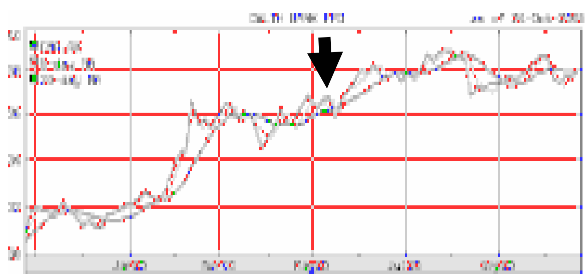
- If a change of brokers' recommendation granger cause change of returns of price or volumes in following days, related trading (buy or sell) can be triggered on change of broker's recommendations, as following positive returns can be achieved. For example, in above experiments, we found that broker-rec-25 exert a significant Granger-causal impact on average-log-returns. Therefore, on the event of significant change of brokers' recommendations (b_t-2.5), investors can trade to take the opportunities of high returns.
- On the contrary, if a change of returns of price or volumes granger cause s a change of brokers' recommendation in following days, brokers' recommendation related investors' action can be derived and taken as investment opportunities. For example, if an institution is also a broker and his investment decisions depend on brokers' recommendations, its following decision can be derived and taken. in above experiments, we found that day2-volume-return exert a significant impact on broker-rect-t2t1, thus day2-volum-return can be used to predict next absolute change of brokers' recommendations.

In addition, the relationships can also be used to control risks or decision support of hedging risks. In other words, one stock (or indices)'s risk can be hedged or controlled by including other correlated stocks with opposite features. For example, a stock's risk of depreciation can be hedged by a correlated stock's appreciations. In above experiments, we found that two variables (day5-log-volum and day3-log-volum) reflect quite differently to a shock of one variable (broker-rec-2t1), therefore, we can adjust holding size of the stock in these two different days, and this will help large investors adjust their VWAP strategies and control risks accordingly.

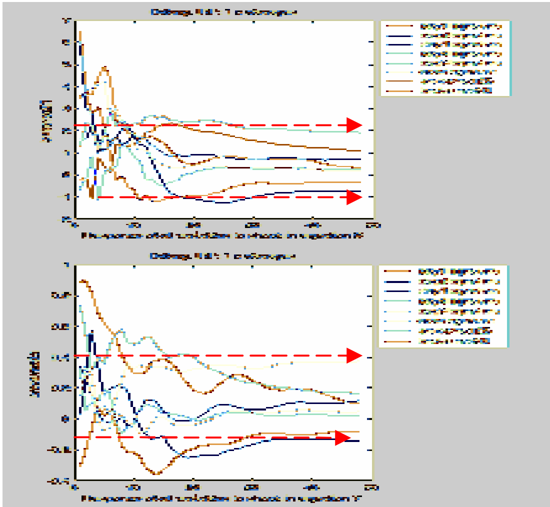


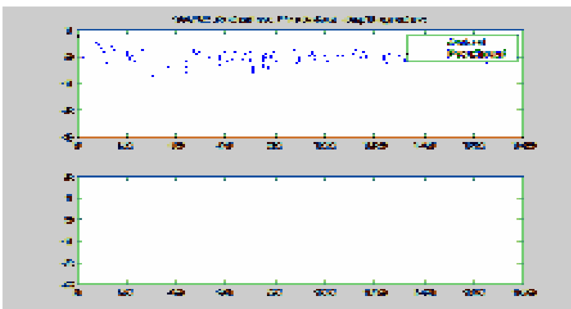
A Case Study of Using above Pattern Components to Improve Technical Analysis

Above experimental results (i.e. models derived from impulse response functions) can be used for improvement of traditional technical analysis. For example, according to following figure for CBA stock, on 06/05/05, 5-day MA cross down 20-day MA, which indicates a bearish market and triggers a sell signal, based on technical analysis. But this is a wrong decision, as there was a relatively smooth (or a bit up) price movement during following period.



We investigated broker's recommendations for CBA disclosed on 6/05/05 by Yahoo.Finance, and found that the value is 2.54 (change of recommendation is 0) and recommendation is hold. According to relevant two way reflexivity results from VAR tools, since no change of recommendations and the absolute value is close to 2.5, there should no significant returns in following periods (or days in the following week) and the trading signal should be hold. This is also compatible with following results of IFRs, which indicates that future values of returns basically do not change much.





Therefore, this case study indicates that two way reflexivity relationships from VAR tools can improve technical analysis.

Justification by More Experiments

Similar to above case studies, we investigated the investment points for top 30 stocks in Australian Stock Market of all the in-samples (in Year 2004) and out-samples (in Year 2005) identified, based on results of VAR tools and their relationship with the results of technical analysis, and found that:

- Cases that technical analysis ignores investment opportunities but Pattern components of two-way reflexivity model successfully identify them: 46%;
- Cases that technical analysis signals wrong investment opportunities but Pattern components successfully corrected them: 33%;
- Cases that both technical analysis and Pattern components successfully identify investment opportunities: 36%;
- Success rate of using both technical analysis signals and Pattern components to successfully identify investment opportunities: 79%.

4 Second Layer and Third Layer: Synthesis and Decision Support

As 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 sum-up of strength of working and upcoming pattern components, or by using Hermite's 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.

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 [14]. The initial prototype was implemented by mainly using Jess and Java. An industry partner, Tricom Australia Ltd, contributed expert domain knowledge and involved in the prototype implementation.

Based on experiments of the prototype, we got following evaluation results: 10 real investors were chosen to use the prototype to identify 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). Following table illustrates performance of the prototype and its comparison with market baselines.

Table 1: The Performance Evaluation of the Prototype ITFIDSS and its Comparison with Baselines

Measurement (1): *Success rate of*	*Success rate (in the*	*Success rate (in the*	*Success rate (in*

prediction of stock movement direction	*evaluation period*	*training period*	*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 (RBA 2005)	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%*

5. Conclusion and Future Work

In this paper, we proposed a novel three-layer integrated framework of stock markets, composed of *Analysis*, *Synthesis*, and *Investment Decision Support*. In the framework, we emphasized on a key thing that previous studies neglected: a two-way reflexivity model of investors' decisions and market reactions. We studied the model using VAR methods. Our studies showed that this key aspect plays an important role in investment decision making, particularly in portfolio building and risk control. 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 further optimization and usage of the two-way reflexivity model (including parameter optimization) in the integrated framework.

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