Asian Journal of Information Technology 5(7): 732-741, 2006

Identification of Two-Way Reflexivity Dynamics 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 study shows how the integration of multi-dimensional stock market dynamics can improve performance and proposes a three-layer integrated investment decision-support framework. In the framework, we emphasize on one key dynamics that previous studies have neglected: two-way reflexivity dynamics between investors' decisions and market reactions. This dynamics is thoroughly studied using VAR method in the study. Our studies show that the dynamics 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 dynamics is promising and our experimental results showed that it outperformed single-dimensional traditional methods and benchmark indices.

Key words: Two-way reflexivity, 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 are two problems 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.

Lack of investigation into two-way reflexivity dynamics: 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.

Because of these problems, existing methods can not assist investors to identify investment opportunities very well and their performance is regarded as limited. In this study, 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 a key dynamics at first layer of the framework: identification of a two-way reflexivity model of investors' decisions and market reaction.

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.

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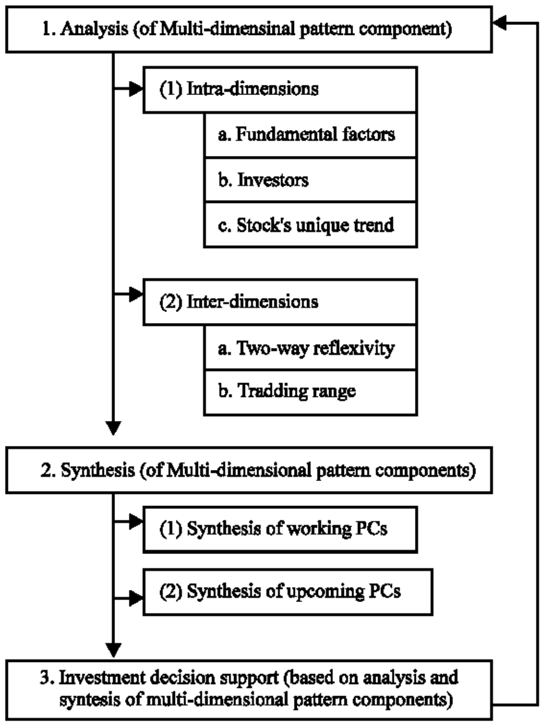


Fig. 1: A Three-layer Integrated Decision-support Framework

This integrated framework consists of three layers: (1) *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. 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: A TWO-WAY REFLEXIVITY MODEL OF INVESTORS' DECISIONS AND MARKET REACTIONS

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

Introduction of the model: Investors' decisions and market reactions have not a casual or sequential relationship as traditional methods usually assumed, but a two-way reflexivity relationship. 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 Fig. 2.

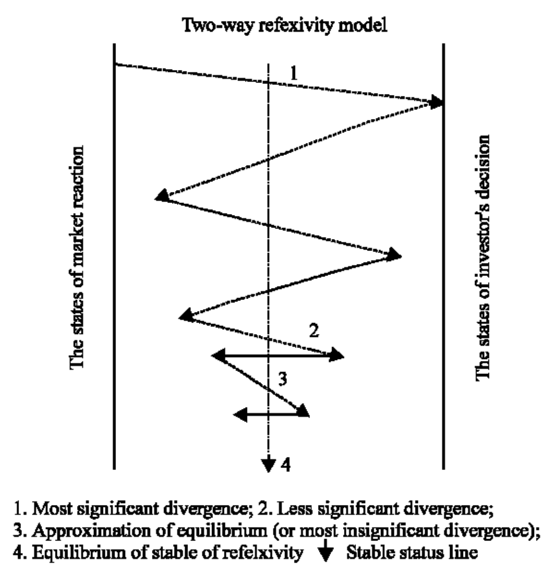


Fig. 2: A Two-way reflexivity model

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 (which can be represented by 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 (which can be 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, thus market is becoming bullish.
  - Bearish Open-end, where divergence increases the strength of sell-side investors, thus market is becoming bearish.
- Dead-end mode: where divergence is static (which can be DM = ó, where ó 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.

Using vector auto-regression (VAR) methods 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[9-11] 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 affects making of monetary policy. In our experiments, we used following tools of VAR to model the two-way dynamics:

- Granger-causality tests: Granger-causality requires that lagged values of variables of variable A (e.g. change of brokers' recommendations or an industry indices) are related to subsequent values in variable B (e.g. 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), e.g. 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, e.g. 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 $100(\log p_t - \log p_{t-1})$ of following indices, which derive from a web site Http://finance.yahoo.com.au:

- 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:

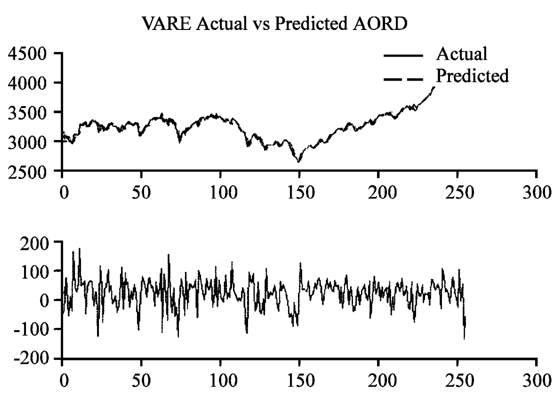
GRANGER CAUSALITY PROBABILITIES

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.

RESULTS OF VAR ESTIMATE



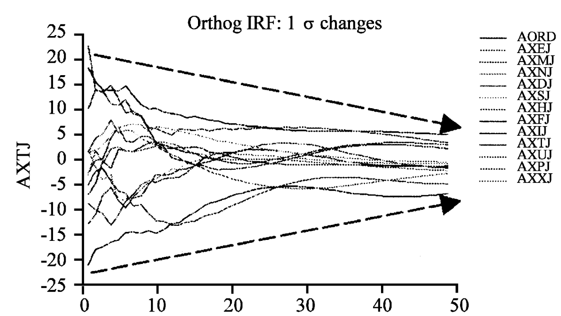
As above graph indicates, predicted results basically match actual results and difference is controlled in a small and reasonable range.

RESULTS OF IMPULSE RESPONSE FUNCTIONS (IRFs)

IRFs have following roles in the two-way model:

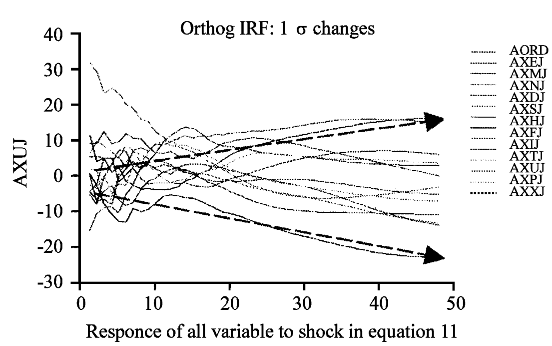
- IRFS represent a method used to examine the interactions between variables in a VAR model. A shock (e.g. dramatic change of an industry) to the system is imposed and the dynamic interactions of the variables based on the estimated coefficients are simulated for all variables (e.g. all other industries) in the system.
- IRFs trace out expected responses of current and future values of each of the variables (e.g. each industry indices) to a shock (e.g. dramatic change of an industry) in on eof the VAR equations.

Therefore, IRFs can be used to trace different modes of divergence movement. For example, in following figure, a closed-end mode is derived from impulse response functions and we observe the divergence is becoming smaller and smaller.



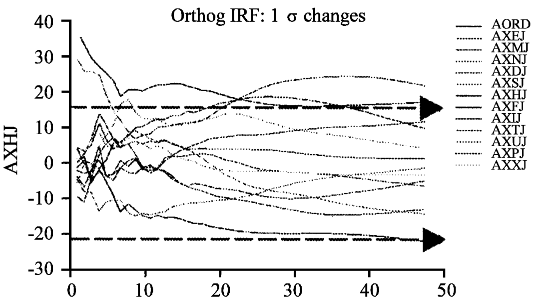
Responce of all variable to shock in equation 10

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



Responce of all variable to shock in equation 11

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



Responce of all variable to shock in equation 4

Usage of the Modes and the Models

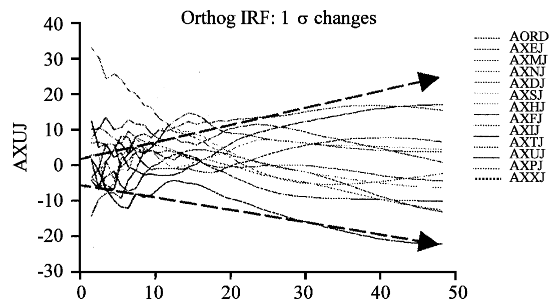
The above experimental results of the two-way reflexivity model identified have following usage.

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. In details:

- If they have positive relationship (e.g. 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 (e.g. 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.

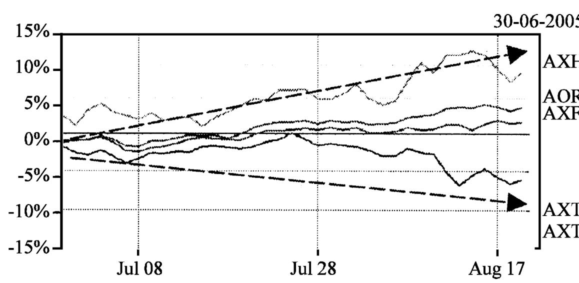
Secondly, they can be used for risk control or decision support of hedging risks. That is, the risks of one stock (or indices) can be hedged or controlled by other correlated stocks with opposite features in the portfolio. For example, a stock's risk of depreciation can be hedged by a correlated stock's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

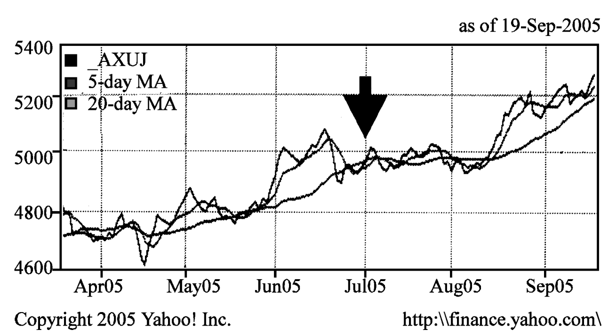


Responce of all variable to shock in equation 11

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 (e.g. 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 obtained the following results:

- Cases that technical analysis ignores investment opportunities but the two-way reflexivity model successfully identifies them: 42%;
- Cases that technical analysis signals wrong investment opportunities but the model successfully corrects them: 35%;
- Cases that both technical analysis and the model successfully identify investment opportunities: 32%;
- Success rate of using both technical analysis signals and the model 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 sources 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:

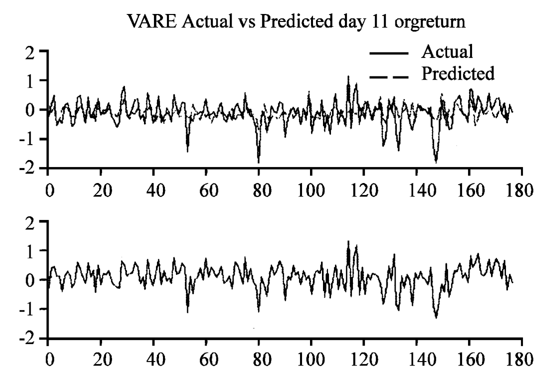
- Returns on price or volumes on following days- day 1, day2, day3, day4, day 5;
- Absolute change of brokers' recommendation broker-rec-25 (which derives from b-2.5);
- Comparative change of brokers' recommendation broker-rect-t2t1 (which derives from b_{t2}- b_{t1}).

Granger Causality Probabilities

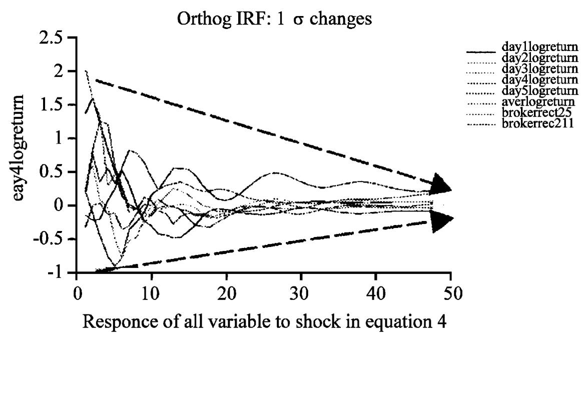
Variable	day1logprice	day2logprice	averagelogre	brokerrect25	brokerret1t2	day1logvolum	day2logvolum	averlogvolum
day1logprice	0.00	0.00	0.00	NaN	0.00	NaN	NaN	NaN
day2logprice	0.00	NaN	NaN	0.00	0.00	0.02	NaN	0.00
averagelogre	0.00	0.01	0.00	0.09	0.00	NaN	0.01	0.02
brokerrect25	NaN	NaN	NaN	0.00	0.00	0.01	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 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.

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.



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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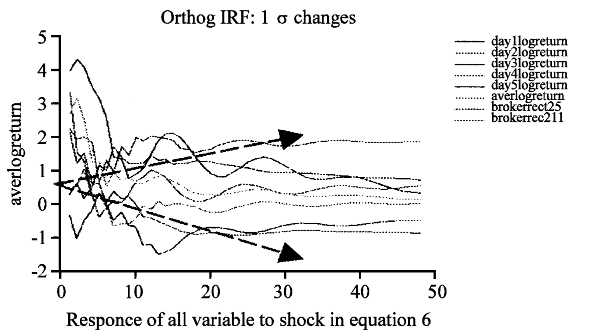
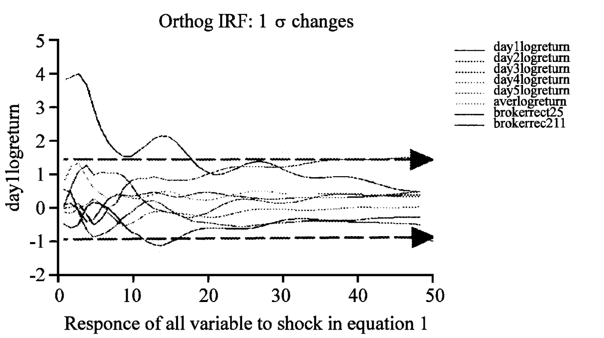


In following figure, a dead-end mode is derived from impulse response functions and we observe the divergence does not change much.

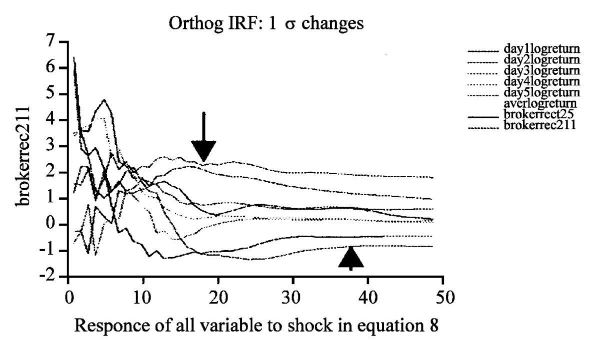


Usage of the Modes and the Models

In above experiments, by using VAR, we analyze the two-way interactions between brokers' recommendation and market reactions (e.g. 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.

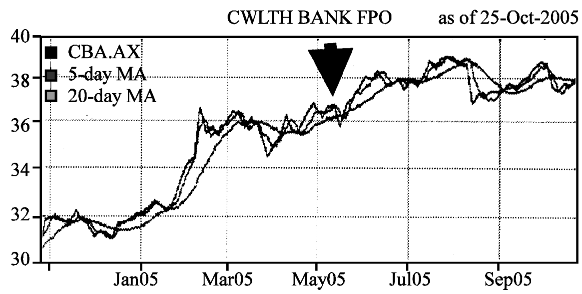
- If a change of brokers' recommendation granger cause change of returns of price or volumes in following days, related trading (buy or sell) can be triggered on change of broker's recommendations, as following positive returns can be achieved. For example, in above experiments, we found that broker-rec-25 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.

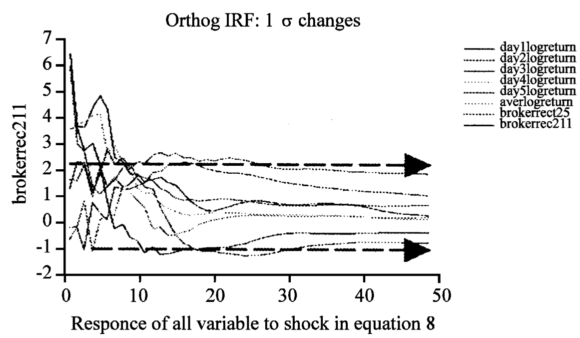


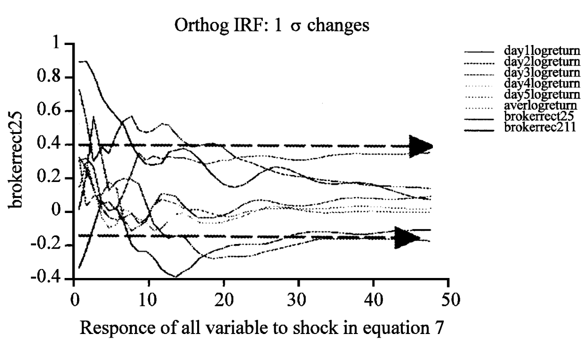
A case study of using the modes to improve technical analysis: Above experimental results (e.g. models derived from impulse response functions) can be used for improvement of traditional technical analysis. For example, according to following figure for CBA stock, on 06/05/05, 5-day MA cross down 20-day 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.

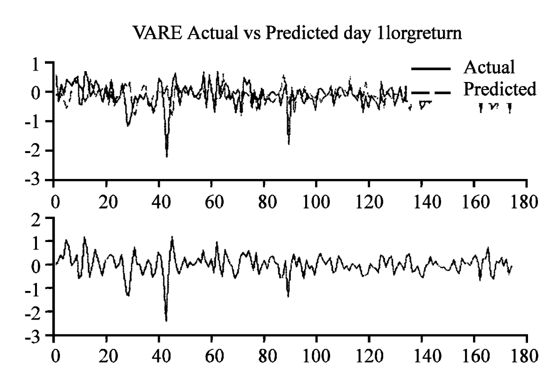
We investigated broker's recommendations for CBA disclosed on 6/05/05 by Yahoo.Finance and found that the value was 2.54 (which indicated that change of recommendation is 0) and recommendation was Hold.



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 and VAR estimates, which indicate that future values of returns basically do not change much.







Therefore, this case study successfully 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 the two-way reflexivity model successfully identifies them: 46%;
- Cases that technical analysis signals wrong investment opportunities but the model successfully corrects them: 33%;
- Cases that both technical analysis and the model successfully identify investment opportunities: 36%;
- Success rate of using both technical analysis signals and the model to successfully identify investment opportunities: 79%.

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 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[12]. 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 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 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%

As above table 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 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, 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(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

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 a new key dynamics – a two-way reflexivity model.

CONCLUSION

In this paper, 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 a key dynamics that previous studies neglected: a two-way reflexivity model of investors’ decisions and market reactions. We studied the modes model and investigated their usage using VAR methods and relegated tools. 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 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. In particular, we will focus on further optimization and usage of the two-way reflexivity model (including parameter optimization) in the integrated framework.

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