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Economic Foundations of Technical Analysis

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ABSTRACT

Though technical analysis has gained huge popularity among the practitioners for over two centuries, it is still known as "voodoo finance" to academicians due to lack of solid theoretical supports. Among all the technical indicators, price patterns and volume signals attract the most disputes due to their subjective identification processes. While, many pieces of empirical evidence have been found to support the profitability of technical analysis , showing that those indicators indeed help the speculators to "beat" the market, no one theoretical or statistical model has been developed to replicate all price movements and stylized facts that are documented in financial market. Besides, no existing literature can further justify how the price trends following the chart patterns are pre-determined.

Therefore, the aim of this thesis is to go a step further to develop a solid theoretical model to replicate those charting indicators, specifically the price patterns and the visual price–volume relations. I approach this goal from the standpoint of technicians that "Price are determined by the demand and supply" and "History repeats itself", by extending the classic work of Day and Huang (1990). Such extension leads to a new theoretical framework where both price and volume series are simultaneously determined by the endogenous buying and selling orders from two types of market players, fundamentalists and chartists. In the thesis, I show that (1) the seemingly chaotic fluctuations in price and price–volume relations in the real market can be simulated with high compatibility; (2) most of the commonly-seen chart patterns and their following predictive powers can be easily replicated, (3) most of the price–volume relations found in researches, not limited to the volume signals in chart patterns, can be simulated, (4) popular stylized facts documented by extensive literature can be captured, and (5) the nonlinear causality relations between the simulated price–volume series is confirmed using the nonlinear Granger causality test as well.

This thesis also goes further to provide economic arguments to the rationale of technical analysis. It is demonstrated that supporting zones and resisting zones can be developed and

once price falls into these zones, the previous trend will be reversed and a reversal point occurs. As a result, chart patterns can be used to predict the trends and help speculators to detect these supporting zones and resisting zones. Plausible economic justifications can also be offered to the relations between the asset returns and volume.

Besides the theoretical supports to the visual technical indicators, I also empirically examine the volume signals in chart patterns. Perceptually Important Point (PIP) Identification Process is used to detect different patterns in three Asian financial markets, namely the Hong Kong Hang Seng Index, the Singapore Straits Time Index and the Japan Nekkei 225. By comparing the conditional returns on the chart patterns to the original unconditional returns using goodness-of-fit test, I confirm that most of the chart patterns are informative in the three Asian financial markets except the double tops and double bottoms. Furthermore, our study distinguishes from previous empirical literature by introducing the corresponding volume signals to the evaluations, and it is shown that the previous unsatisfactory results of double tops and double bottoms in chi-square test and most of the results in Kolmogorov-Smirnov test can be greatly improved.

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Chapter 1

Introduction

What are the determinants of the asset price fluctuations? And why are financial markets full of fluctuations? These questions are among the most long-lasting topics in finance. Since the early 1960s, random walk hypothesis has been dominating and attempting to provide explanations to these intriguing questions. Samuelson (1965) shows that stock prices follows random walks. Fama (1970) confirms that the return series is close to random walks if the prices on traded assets such as stocks, bonds and property already reflect all publicly available information, leaving asset returns unpredictable. This class of hypothesis is commonly known as the Efficient Market Hypothesis (EMH) which asserts that financial markets are informationally efficient. By introducing the concept of arbitrage, the EMH argues that though some of the traders in the market are not rational, the market should still be efficient. But later a lot of empirical studies in behavioral finance have found evidence that goes against this hypothesis, especially against the availability of close substitutes and whether arbitrageurs can bear the "noise trader risk" noted in De Long et al. (1990). Putting all these together suggests that arbitrage in reality is risky and may therefore be limited. Meanwhile, though the EMH is widely accepted in academia, practitioners in the real world are still able to use some strategies to outperform the market. Among those strategies, technical analysis, which involves visual inspection of past asset prices without regard to any underlying economic fundamentals, attracts the most disputes. Charting, firstly introduced by Dow Jones, is a widely-used technical skill among speculators since the last century. Nowadays, not only ordinary investors are fans of charting, many professional fund managers and speculators are also adopting similar strategies to help them in decision making.

Until recent years, an increasing number of studies has shown that technical analysis does have some predictive power and is proved to be profitable in different markets and geographical areas. For instance, Brock et al. (1992) find that two commonly used trading rules do have forecasting abilities for Dow Jones Industrial Average index from 1897 to 1987. Allen and Karjalainen (1999) find that the technical rules can in fact help investors earn excess returns compared to the random walk model and the GARCH model. In the literature review of Park and Irwin (2007), most of the empirical studies on the technical trading strategies find positive results. Though past literature mainly focuses on the identification of various chart patterns and their profitability of these patterns in financial markets (Curcio et al. (1997), Lucke (2003), Fu et al. (2007)), no study is found to explain the underlying internal working mechanisms that determine these chart patterns and explain how the corresponding price-volume relations occur. In this thesis, I aim to fill the gap in the literature by exploring such internal mechanisms through a proper framework that captures some distinguished characteristics of multi-agents in the financial markets.

The most distinguished features of the model lies in the common saying in technical analysis, that is “History repeats itself.” The predictability of chart patterns implies the deterministic property of the underlying price dynamics. Therefore, in order to support and justify the predictability of chart patterns, in contrary to previous studies that include stochastic components, I use a purely deterministic nonlinear dynamics so that price dynamics are seen to follow some chaotic movements, but the trend of the patterns is predetermined. In fact, some studies have already demonstrated that a deterministic process could be the underlying reason that is responsible for the seemingly irregular stock movements. Day and

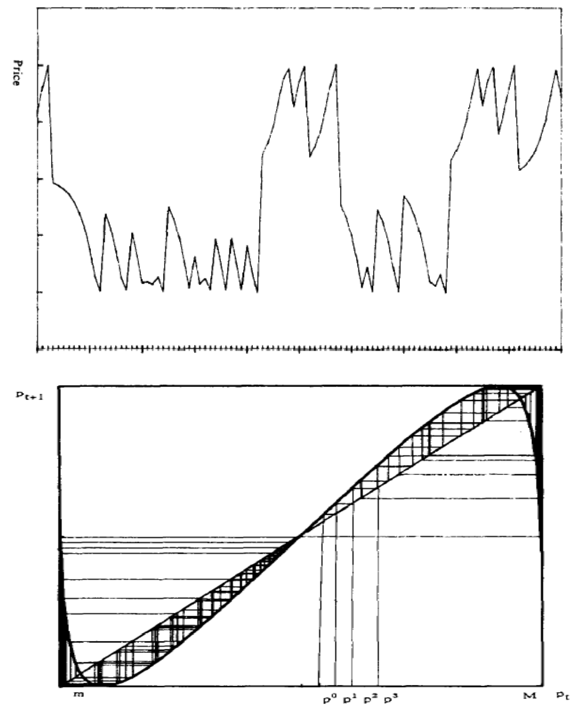

Figure 1.1: Illustration of the simulation of Day and Huang(1990).

Huang (1990) are among the pioneers that make use of deterministic heterogeneous agent model (HAM) to explain the chaotic asset price fluctuations and the switch between bull and bear markets (as shown in Fig. 1.1). Huang et al. (2010) also document the possibility of replicating three different types of crisis, namely the sudden crisis, the smooth crisis and the disturbing crisis, using similar deterministic model. Based on this backdrop, I am motivated to explore further on the potential of HAM in simulating various chart patterns and therefore provide a solid justification that explains the underlying internal working mechanisms of such chart patterns.

In Chapter 2 of the thesis, I first investigate these internal mechanisms that trigger the occurrences of various chart patterns using a deterministic heterogeneous agent model. It is shown that, with a reasonable set-up of parameter values, the model can be used to replicate well-known chart patterns and their predictive powers. More importantly, the profitability of the chart patterns can be justified by the resistance and support zones discovered in our framework. Once the price falls into these zones, the existing trend is halted and reversed. Through this deterministic nonlinear dynamics, it is inferred that supporting and resistance lines used in technical analysis can be extrapolated by the chart patterns and the asset price movements can be systematically explained using the theoretical framework developed.

Moving away from the theoretical modeling of chart patterns in Chapter 2, I switch my focus to an empirical work of chart patterns. I draw my attention closer to volume signals. It is noted that to facilitate the confirmation of the visual identification of financial patterns, some auxiliary tools such as volume signals are also important in practice. However, in spite of the importance of volume signals in technical analysis, it has been somewhat ignored in the past literature of investigating the profitability of chart patterns. Therefore, by using the PIP(Perpetually Identified Process) introduced by Fu et al. (2007), I detect five popular patterns in time series of three different markets in Hong Kong, Singapore and Japan. I firstly define the volume signals and examine the informational role of volume signals by looking into the conditional returns on the chart patterns without volume signals and the conditional returns on the chart patterns with volume signals. I find that (1) the chart patterns are indeed informative as shown in Chi-square goodness-of-fit test and (2) volume signals is vital as they significantly improve the results in terms of both Chi-square goodness-of-fit test and Kolmogorov-Smirnov test.

After supporting the importance of volume signals in technical analysis empirically, in Chapter 4, I extend the model in Chapter 2 to include trading volume in the heterogeneous agents model. It is showed that asset price series and volume series are simultaneously determined by selling and buying pressures from fundamentalists and chartists within a market maker framework. The simulations of the model covers all well-known price volume relations including the price-volume co-movements, the volume signals in the chart patterns, and the correlation between the price change per se and the volume. Furthermore, it is demonstrated that even with such a simple framework, the price-volume co-movements can still be well-explained.

Finally, Chapter 5 summarizes the key findings of the thesis and offers some potential extensions in future research.

Chapter 2

Modelling Chart Patterns

2.1 Introduction

According to Menkhoff and Taylor (2007), technical analysis is as important as fundamental analysis for short term predictions and trading decisions. However, in spite of the facts that nowadays major brokerage companies publish technical commentary routinely either on the whole market or individual security, many traditional academicians still hold negative attitudes on technical analysis unanimously that such rules do not exist and technical analysis, especially pattern analysis, which depends mostly by visual judgement without any theoretical support, is not useful.

Most of the existing studies supporting technical indicators, such as Brock et al. (1992), Neely and Weller (2003), Sapp (2004), concentrate on the areas of technical trading rules that can be quantitatively measured. Up to now, only few attentions have shed lights on another essential component of technical analysis, an almost entirely visual signal detection process: the chart pattern analysis. And those existing ones mostly discuss the intellectual detection process for the patterns[1], which leaves us only little literature focusing on the establishment of models that can explain the presence of pattern-based trading rules. The

[1] See Perng et al. (2000), Chung et al. (2004), Fu et al. (2007), etc..

closest model is recently set up by Friesen et al. (2009). They extend a jump-diffusion model by introducing confirmation bias, a concept from psychology and succeed in replicating the head and shoulders and double tops patterns triggered by stochastic signals. However, the results are still premature and not very similar to those observed in the real market.

To fill this gap, in this chapter, I present a theoretical model that can replicate all well-known chart patterns and explain the existence of chart patterns and its forecasting power.

The framework I adopt is a heterogeneous agent model with the market maker. In the past twenty years, HAM is a very popular financial market modelling methodology that explicitly incorporates demand and supply between traders with heterogeneous beliefs. According to Black (1986), in the same market at the same time, it is not only possible that different groups of traders form exactly opposite beliefs about future price, but it is also necessary to have these heterogeneous beliefs in order to complete a transaction. Based on this simple realization, HAM reflects how the interactions between different agents within the market affect the price[2]. Especially, among them, studies by Day and Huang (1990), Farmer and Joshi (2002) and Chen et al. (2001) introduce a special agent, named the market maker so that the market can tolerate and absorb the excess demand or supply from the other agents in each period. Studies such as Chiarella and He (2003), He and Li (2007), He and Li (2008) show that HAM has great potentials on market modelling since not only all the stylized facts can be well simulated but key financial market behaviors can also be well-explained. In this case, if a model is capable of capturing all the stylized facts of price movements, it should also be capable of replicating other patterns of price movements, including chart patterns.

The capability of a model to replicate chart patterns is desirable but not satisfactory. With the set up of adaptive beliefs of chartists, I introduce the resisting zones and supporting zones, which are the regimes corresponding to the terms "resistance line" and "supporting line" in the technical analysis and explain the predictive power of the chart patterns. The

[2]See Beja and Goldman (1980), Day and Huang (1990), Brock and Hommes (1998), Lux (1995), Lux (1998), Tramontana et al. (2010).

core of chart analysis is to discover the signals that help chartists to form the expectations of the resistance line and supporting line by specific price patterns. Once the speculators determine the resistance and support levels, the following trends are pre-determined and the price will never recross the resistance/supporting lines.

I deliberately eliminate any external shocks in this framework, which is particularly meaningful to investigate when studying the chart patterns. One of the premise of technical approach is that technicians believe, "history repeats itself.", which indicates patterns in the same category are supposed to have the same predictive implication. For instance, in the head and shoulders pattern, after the breakout, the price will drop sharply and it will not recross the neckline in a short period. As a result, it is not difficult for us to get another conclusion that those patterns and the corresponding resisting/ supporting lines cannot be determined by external stochastic signals. Admittedly, the price series are full of noises and each pattern has its failure rate. However, in this study, in order to investigate the potential and the predictability of chart patterns, I just simplify my model in a purely deterministic process.

The rest of chapter is organized as followed. Section 2 describes our framework of model by analyzing the demand or supply from the agents. Section 3 presents our results, including almost every well-known pattern. In Section 4, I check the fitness of our results with the stylized facts of financial data. The last section gives us the conclusion of this chapter.

2.2 The Buying and Selling Pressures

Price dynamics are investigated under the classic framework of Day and Huang (1990). In this framework, six assumptions are made for simplicity.

(i) There are only three types of traders in the market: the fundamentalists, the chartists, and the market maker. Fundamentalists and chartists firstly trade with each other, and then the market maker takes up the aggregate excess demand (or supply) from them and adjust the price in the next period accordingly.

(ii) The intrinsic properties of each group determine that investors cannot switch to the other group by their own willingness. Different from Lux (1995), Lux (1998), Gao and Li (2011), I believe that fundamentalists are referred to those mutual fund managers or other professional investors who are supposed to have more exclusive information than the chartists (However, in this set up of models, the strategy of fundamentalists is not necessarily more profitable than the one of chartists and neither the fundamentalists nor the chartists are determined to beat the other type of participants.). On the contrary, chartists can only trade on public information such as historical prices. In our framework, the chartists are simplified as trend-followers[3].

(iii) The population for each group is the same, and no trader is allowed to enter or exit the market, so the group size remains unchanged for both the fundamentalists and the chartists for all the periods.

(iv) All the investors in each group are alike, which means that they share exactly the same strategy.

(v) Only one risky asset is available.

(vi) There is no budget constraint. Both types of traders can buy (or sell) as much as they are willing to based on their strategies.

2.2.1 Fundamentalists

The first type of player is the fundamentalist. Fundamentalists believe in the fundamental approach of asset pricing and expect that the asset price p_t will fluctuate in a reasonable zone (m, M) owing to some external disturbances but will eventually converge to its intrinsic value u_t^f. By acknowledging information such as cash flows and dividends, fundamentalists

[3] Beside of the trend-followers, two other types of chartists, contrarians and momentums are also widely documented in the past literature. See Bondt and Thaler (1985), Bondt and Thaler (1987), Lakonishok et al. (1994), Chan et al. (1996). However, in our framework, only the trend-followers, who take almost the opposite strategy from fundamentalists, are introduced.

could derive an accurate estimation of the fundamental value of the asset. In practice, they are assumed to be fund managers or professionals in banks or other financial institutions. They are confident and make their independent decisions without being influenced by trends or temporary fluctuations. From their point of view, any fluctuation is caused only by short-term external disturbances. Thus, they will decisively buy in when the fundamental value of the asset u_t^f is above the current price p_t. When the price lowers even further, the expected capital gains will be higher, so they will continue buying with even more orders. Similarly, when $u_t^f < p_t$, they will sell orders, and the higher p_t is, the greater potential capital loss the fundamentalist will expect. Therefore, the demand function of fundamentalists is defined as:

$$\alpha(p_t) = \begin{cases} (u_t^f - p_t) \cdot A(u_t^f, p_t), & \text{if } m_t \leq p_t \leq M_t. \\ 0, & \text{if } p_t < m_t \text{ or } p_t > M_t. \end{cases} \tag{2.1}$$

Here, u_t^f is the fundamental value of the risky assets. In my model, what most distinguishes fundamentalists from chartists is that fundamentalists have sophisticated investment strategies and access to all internal information. Therefore, by updating the information for each period Ω_t, they are able to obtain the fundamental value of the asset for each period u_t^f. Particularly in practice, it should be noticed that stock prices have a tendency to rise anyway in the long run. Therefore, to capture the general upward trend in the price series, the present chapter assumes the fundamental value u_t^f increases with a simplified setup of business cycles. It is assumed that the length of each business cycle is rs periods ($r \geq 2$). The business cycle consists of an expansion for $(r-1)s$ periods with an economic growth rate of g and a following recession for s periods with a growth rate of $(-g/2)$[4].

[4] Admittedly, the setup of the business cycle is rather strong. However, in order to reflect the stock price behavior that results from the long-term economic growth rate, I just introduce a very simple assumption on the business cycle. On one hand, it is enough to capture the upward trend in the stock price. On the other hand, it is very concise that it does not complicate the basic nonlinear dynamics framework.

The economic growth rate $g(t)$ is

$$g(t) = \begin{cases} g, & t \in [(r(i-1)s, (ri-1)s) \\ -g/2, & t \in [(ri-1)s, ris] \end{cases}, \ i = 1, 2, 3, ..., n,$$

where s is a constant that determines the length of business cycle and r is the ratio between the length of the expansion and recession in each business cycle. Therefore, the fundamental value u_t^f increases steadily with the dynamics as

$$u_{t+1}^f = (1 + g(t)) \cdot u_t^f.$$

To examine the sole effect of the introduction of growth rate, I compare two simulated time series where business cycles are (not) taken into consideration in Fig. 2.1. We could easily notice that the time series exhibit an upward trend when the parameter of economic growth is incorporated in the upper panel, which is more compatible with the real market. However, even if the parameter of economic growth rate $g(t)$ is not introduced, i.e. in the lower panel in Fig. 2.1, patterns can still be found in the simulated series. Thus, the existence of chart patterns should still attribute to the basic framework with adaptive beliefs.

Besides, in Eq. (2.1), m_t and M_t are the minimum and maximum boundaries, respectively, of the price fluctuations set up by fundamentalists. Black (1986) has defined that an efficient market should be fluctuated within a reasonable bound $(\frac{1}{k}u_t^f, ku_t^f)$, where k is a pre-selected factor ($k > 1$) and u_t^f is the fundamental value of the risky asset. For fundamentalists, if the price exceeds the boundaries, the market is considered to be unreasonable, so the fundamentalists will exit the market until the price returns to an efficient state. Therefore, the minimum and maximum boundaries are defined as below,

$$M_t = ku_t^f \qquad and \qquad m_t = \frac{1}{k}u_t^f.$$

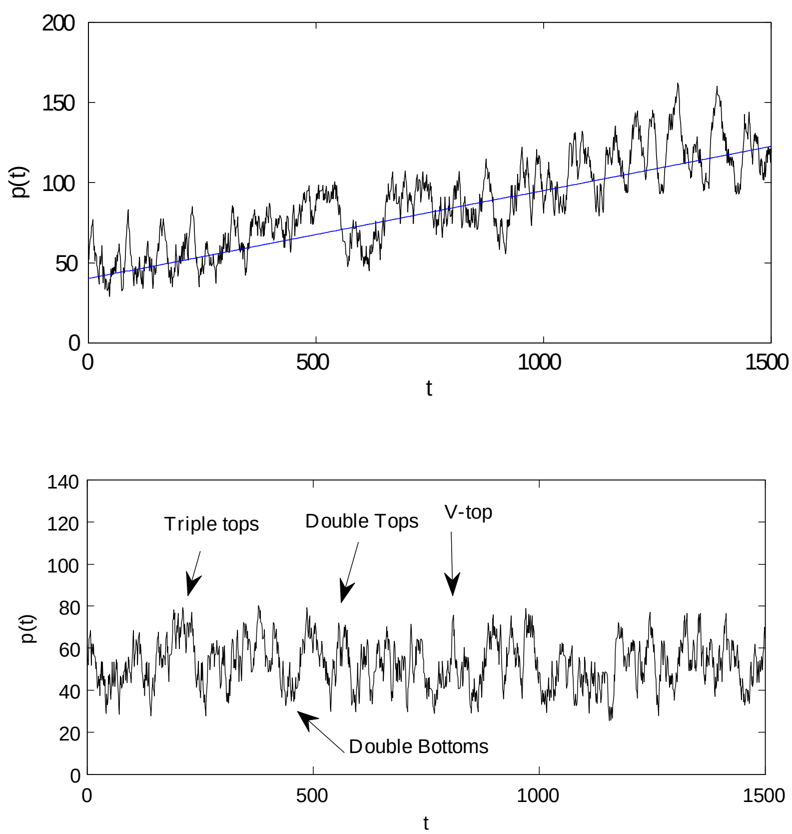

Figure 2.1: The comparison of simulations when business cycle is not considered (upper panel) and when business cycle is considered (lower panel). In the simulations, the default parameter set is adopted, and the initial price is set as 61.5

Furthermore, in Eq. (2.1), $A(\cdot)$, firstly introduced in Day and Huang (1990), is a chance function with respect to the fundamental value u_t^f and the current price p_t. It depicts the psychological behaviors of investors so that, when the price moves close to the upper boundary M_t, the probability of losing the existing gains increases. When the price moves closer to the lower boundary m_t, the probability of missing the opportunity to buy the stock is also higher. Therefore, the chance function can be depicted as

$$A(u_t^f, p_t) = a(p_t - m(u_t^f))^d (M(u_t^f) - p_t)^d, \tag{2.2}$$

where a, d_1, d_2 are the parameters that describe how sensitive fundamentalists can be when the price nears their psychological boundaries and $a > 0$, $d < 0$. A simple illustration of chance function when u^f is simplified to a constant can be found in Fig. 2.2.

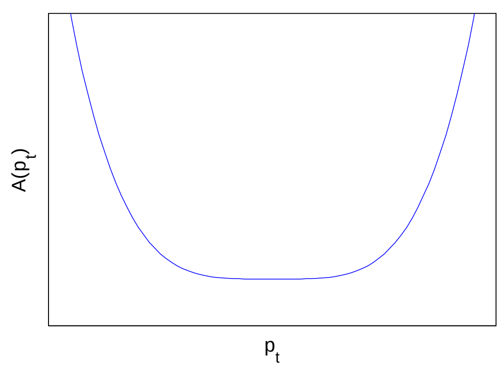

Figure 2.2: The chance function $A(\bullet)$

Similarly, if u^f is a constant, a simple illustration of the demand function of fundamentalists is depicted in Fig. 2.3. Several properties can be derived from the diagrams. (1)When $p_t > u^f$, fundamentalists are net sellers of shares. And when $p_t < u^f$, fundamentalists are net buyers of shares. (2)When $m < p_t < M$, $\alpha(p)$ is a monotonically decreasing function.

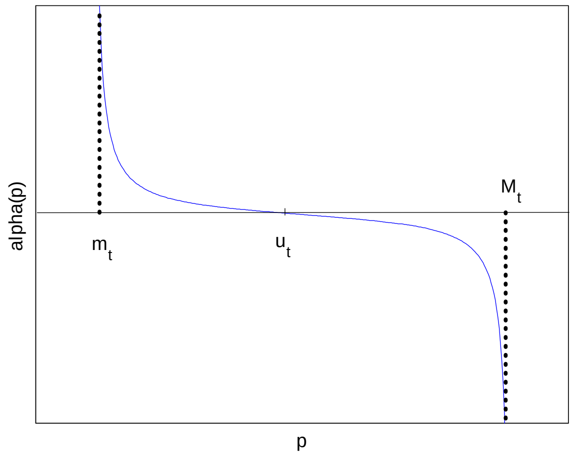

Figure 2.3: Illustration of the function of $\alpha(p)$.

2.2.2 Chartists with Adaptive Beliefs

The other type of player is the chartist. Chartists are traditionally considered to have weaker positions in the market. They do not bother themselves with the reasons behind price fluctuations but simply observe the asset price from the market itself. In my model, the chartist is simplified to extract two signals from the market; the first one is the trend. One of the chartists' most important beliefs is that prices move in trends in a certain psychologically comfortable zone $[\mathbf{P}_{k-1}, \mathbf{P}_k)$. Most of the techniques used by chartists is simply to chase the price up and down. It implies that when the price p_t is above their expected short-run investment value u_t^c, the existing trend is upward. So the higher the asset pricing, the more enthusiasm chartists have to buy the stock. Moreover, when p_t is below u_t^c, based on the existing downward trend, chartists will sell. And the more the price diverge from the investment value, the more they sell. So in this chapter, I adopt several psychological thresholds $\mathbf{P}_k$, which divide the whole trading regime $[\mathbf{P}o, \mathbf{P}n]$ into n mutually exclusive sub-regimes according to their previous trading experiences with the same length λ, that is

$$\mathbb{P} = [\mathbf{P}o, \mathbf{P}_1) \cup [\mathbf{P}_1, \mathbf{P}_2) \cup ... \cup [\mathbf{P}_{n-1}, \mathbf{P}_n],$$
$$\text{and } \lambda = \mathbf{P}_{k-1} - \mathbf{P}_k.$$

In each subregime $[\mathbf{P}_{k-1}, \mathbf{P}_k)$, the chartists' demand function $\beta(p_t)$ can be defined as a linear function of the spread between p_t and u_t^c, which is

$$\beta(p_t) = b \cdot (p_t - u_t^c), \text{ if } p_t \in [\mathbf{P}_{k-1}, \mathbf{P}_k), \tag{2.3}$$

where $b > 0$ is constant which measures the strength of chartists' responses to the price deviation.

The second essential information that chartists want to observe from the market is the short-run investment value u_t^c. Unlike the fundamentalist, the chartist neither has the access to the internal information, nor cares about such exclusive news. Chartists will update their expectations of the investment value based on the public information such as the prices in previous periods[5]. For example, it is well known that most technicians will use technical indicators calculated by past prices to assist them to estimate future prices, such as oscillators or moving averages. However, in the present model, the chartist takes an adaptive belief of u_t^c based on historic price following Huang et al. (2010) and Huang and Zheng (2012). The mechanism is as below.

At period t, if the initial price p_t locates at the kth regime $[\mathbf{P}_{k-1}, \mathbf{P}_k)$, the short-run investment value can be simply equal to the average of the top and the bottom threshold prices

$$u_t^c = (\mathbf{P}_{k-1} + \mathbf{P}_k)/2, \text{ if } p_t \in [\mathbf{P}_{k-1}, \mathbf{P}_k), k = 1, 2, ..., n.$$

After one-step price dynamics in period $t+1$, there are two possibilities.

[5] Detailed discussions can be found in Day (1997) and Westerhoff (2003).

Case I If the current price p_t decreases to p_{t+1} insignificantly, remaining at the same regime, there are sufficient reasons for the chartist to believe that the short-run investment value remains the same, that is,

$$u_{t+1}^c = u_t^c = (\mathbf{P}_{k-1} + \mathbf{P}_k)/2, \text{ if } p_{t+1} \in [\mathbf{P}_{k-1}, \mathbf{P}_k), k = 1, 2, ..., n.$$

Case II When the price in the current period p_t escapes from the original regime $[\mathbf{P}_{k-1}, \mathbf{P}_k)$ to a lower regime $[\mathbf{P}_{k-2}, \mathbf{P}_{k-1})$ or some even lower regimes, the "regime switching" appears[6]. In this condition, the chartist believes that it is not simply the regular fluctuation but the change in the short-run fundamental value of stock that leads to the jump in price.

$$u_{t+1}^c < u_t^c \text{ and } u_{t+1}^c = (\mathbf{P}_{k-2} + \mathbf{P}_{k-1})/2, \text{if } p_{t+1} \in [\mathbf{P}_{k-2}, \mathbf{P}_{k-1}), k = 1, 2, ..., n.$$

Following Huang et al. (2010), if we assume $\mathbf{P}o = 0$, the trading regime is therefore, $\mathbb{P} = [0, \lambda) \cup [\lambda, 2\lambda) \cup ... \cup [(n-1)\lambda, n\lambda]$. As a result, $p_t \in [\mathbf{P}_{k-1}, \mathbf{P}_k)$ is identical to $p_t \in [(k-1)\lambda, k\lambda)$ and $k - 1 = \lfloor p_t/\lambda \rfloor$ and $k = \lceil p_t/\lambda \rceil$. For each period t, the short-run investment value can be calculated as

$$\begin{aligned} u_t^c &= (\mathbf{P}_{k-1} + \mathbf{P}_k)/2 = ((k-1)\lambda + k\lambda)/2 = (2k-1) \cdot \lambda/2 \\ &= (\lfloor p_t/\lambda \rfloor + \lceil p_t/\lambda \rceil) \cdot \lambda/2, \text{if } p_t \in [\mathbf{P}_{k-1}, \mathbf{P}_k), k = 1, 2, ..., n. \end{aligned}$$

Thus, the chartist can substitute their expectations on the short-run investment value into Eq. (2.3) and form their demands (or supplies) for the risky asset.

[6] Similar regime switching processes in nonlinear investment strategies have been widely applied in previous literatures, such as Huang and Day (1993), Ang and Bekaert (2002), Guidolin and Timmermann (2007), Guidolin and Timmermann (2008).

2.2.3 The Market Maker

In order to complete our framework of HAM to absorb the excess demand from the two agents mentioned above, I introduce a third agent, the market maker. It is not uncommon to see the existence of market makers in many stock exchanges such as New York Stock Exchange (NYSE) and NASDAQ Stock Exchange. Market makers can accelerate the liquidity of market and enable the market participants who concern about the transaction costs get into or out of a desired position in a short period of time. And clearly market makers are exposed to sudden exogenous inventory shocks. To compensate this exposure, they are given more advantages on information, such as the limited authority for regulating the trading process, full knowledge of the limit order book, and first knowledge of the orders arriving on the systems. A lot of researchers dig the incentive behind the behaviors of market makers and they attribute two possible reasons for the market maker trading behavior. One is the asymmetric information models proposing that the market maker will form an upward expectations if they receive net buy orders. In this case, they will adapt the price to a higher level in the next period so that they can sell their inventories at a better price. The other concern is about active inventory control. In practice, a dealer may confront both problems. No matter what reasons are behind, the results are always the same; the price would be adjusted to increase following net buy orders and the price will decline when having net sell orders from investors.

The price dynamics is therefore completed as a nonlinear process

$$p_{t+1} = p_t + \eta \cdot (\alpha(p_t) + \beta(p_t)). \tag{2.4}$$

In Eq. (2.4), η is the speed of adjustment, measuring the adjustment speed of market maker according to the excess demand. To simplify the model, I just assume η is a constant[7].

[7] The speed of adjustment is assumed to depend on the penalty of being away from the optimum inventory and on the cost of adjustment. And it also varies if there is an exogenous shock, see Hasbrouck and Sofianos

Eq. (2.4) depicts the dynamic relations between trades and prices. When the total excess demand from the fundamentalist and the chartist is positive, the market marker will adjust the price to a higher level in the next period. When the total excess demand is negative, the market maker will adjust the price to a lower level. [8]

2.3 Model Simulations

In this section, it is demonstrated that the time series generated by our HAM is highly compatible with reality with high robustness. In each time series with reasonable initial price, almost all well-known patterns are found. Due to space restriction, I will only discuss head and shoulders, V-shaped and measured moved up in details. The other patterns are only illustrated in various simple diagrams. For each pattern, I demonstrate that the following trend after the price pattern is consistent with the text book predictions[9]. All the results not only visually look like those chart patterns in technical analysis, but support the predictability of chart patterns.

Considering the continuity in both Chapters 2 and 4, I adopt the same default parameter set as follows,

$$u_1^f = 50, d_1 = d_2 = -0.3, k = 2, \lambda = 7.5, s = 25, a = 1, b = 2.25, \eta = 1, g = 0.0008, r = 4$$ [10]

(1993).

[8] For this nonlinear dynamics, the steady state is when $p_t = p_{t+1}$. That leads to $\alpha(p) + \beta(p) = 0 \Longrightarrow$ The equilibrium exists when $(u_t^f - p_t) \bullet A(\cdot) + b(p_t - u_t^c) = 0$. If fundamentalists are ignorable, the market can be assumed as only consisting of chartists, therefore the equilibrium exists when $p_t = u_t^c$.

[9] In order to illustrate more clearly and explicitly, some classical examples in either the Murphy(1999) or Bulkowski(2000) are compared with our results later.

[10] For the selection of parameter set, in our simulations, it shows that the appearance of various patterns is not very sensitive to the initial value and the parameter values. In each time series with randomly-selected initial value, most of the popular chart patterns can be discovered. Therefore, since similar price series have been simulated in Huang and Zheng (2012), we just follow the default parameter set in Huang and Zheng (2012) for convenience.

2.3.1 Head and Shoulders Patterns

The reverse pattern is the most interesting pattern, since it indicates that the existing trend is halted and a reverse point occurs. The most popular and reliable reverse pattern is the head and shoulders (later referred as the HS) since the failure rate of the HS tops can be as low as 7% and the failure rate for the HS bottoms can reach to the level of 5%. A standard HS top pattern, given by Murphy (1999), has following characteristics in common (See the right panel of Fig. 2.4.):

1) It has a prior uptrend.

2) Three peaks exist, which are the left shoulder, head and right shoulder, respectively.

3) The pattern is considered as completed when the price breaks a flatter trend line named as "neckline", which connects the reaction lows, the two bottoms between three peaks. The neckline at a top pattern usually slopes slightly upward, but sometimes, horizontal pattern happens. This important trend line has great implication in that once the price breaks the neckline the return move after the pattern will not re-cross this line normally.

We look back to our results when the initial price $p_0 = 61.6$ in the left panel of Fig. 2.4, the pattern I generate satisfies all the features of the HS pattern. The pattern appears from $t = 2300$ to $t = 2600$. There are the left shoulder, the head and the right shoulder, from left to right. And we notice that it matches the description in chart analysis. There are two pullbacks after the completion of the patterns, however, these two pullbacks never move above the resistance line.

2.3.2 V-shaped (Spike)

Unlike the head and shoulders, V-shaped is rarely seen in reality. However, it attracts a lot of attention because once happens, the magnitude of V-shaped is normally huge without any transition period. A usual V-shaped pattern includes a sudden drop which causes a loss of almost half the value during a very short period and a subsequential sudden climb that

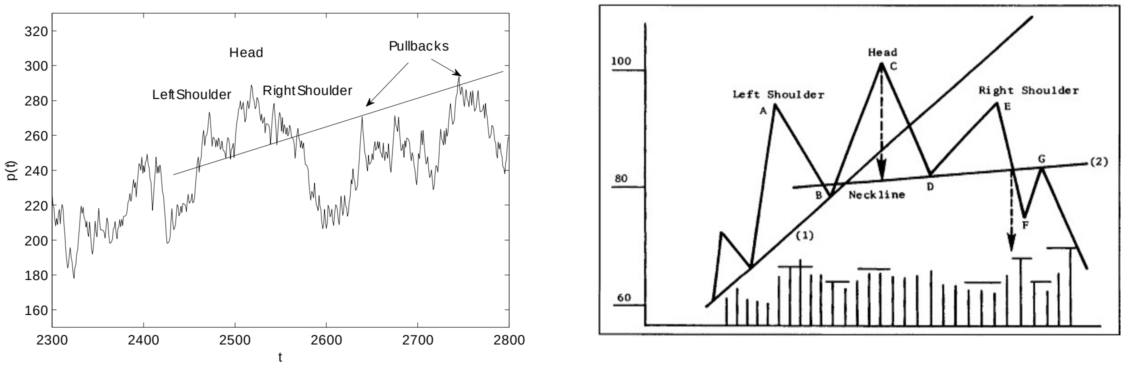

Figure 2.4: Head and shoulders. The left panel is the simulations and right panel is the example.

brings the price back to the previous level. Due to its own properties, both academics and practitioners conclude that it is a result from some unpredictable external disturbances.

While in my study, I successfully generate many V-shaped patterns with this purely deterministic nonlinear dynamics, for example, when $p_0 = 61.13$ from $t = 1600$ to $t = 1700$ (as in Fig. 2.5). It is strong evidence to support our hypothesis that a nonlinear price dynamics can also be the underlying factors of the V-shaped pattern.

The phase diagrams for the V-shaped are interesting. All the points can be divided into two groups by the 45° line. In the phase diagram of a V-shaped pattern, it is found that while the declines in the first half of the pattern are dominated by the sudden declines since the magnitude of the drop is really huge, the second half of the pattern is dominated by sudden rises.

2.3.3 Measured Move Up

The measured move up is a continuation pattern. It refers to a general market advance which is broken into two equal and parallel moves by a reverse move. This pattern distinguishes itself since it shows strong implications of trend lines and channels.

Continuation patterns demonstrate some common characters. For example, the measured

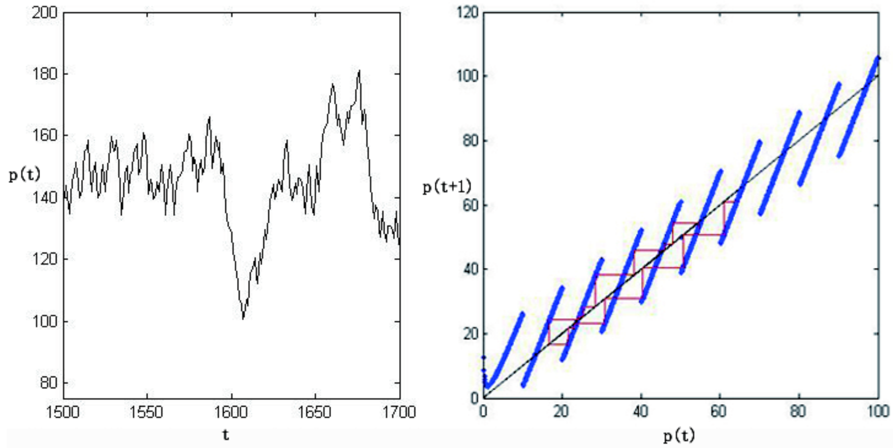

Figure 2.5: V-shaped. Left panel is the simulations and right panel is the phase diagram for V-shaped pattern.

move up shares a lot of features with flags and pennants. The difference between them is that in the pattern of measured move up, the sharp prior trend is changed to the continuous waves bounded by two parallels (first leg labeled as "AB" in Fig. 2.6) and after a short corrective phase ("BC"), the trend would be resumed as the second leg ("CD"). The simulation provided in Fig. 2.6 is selected from $t = 2000$ to $t = 2600$ when $p_0 = 61.52$.

2.3.4 Other Popular Patterns

Besides the patterns discussed above, this model is also able to reproduce other popular patterns with the same parameter set. Figs. 2.7-2.10 give a brief review of our results.

2.3.5 Whole Time Series

Besides the individual chart patterns, this part intends to demonstrate the power of our simulated time series in the long term. The series with the initial value $p_0 = 61.52$ from $t = 0$ to $t = 4000$ is selected and illustrated in Fig. 2.11. The head and shoulders, rectangle, flag, triangles, V-shaped, double tops, and the measured move up can be easily discovered.

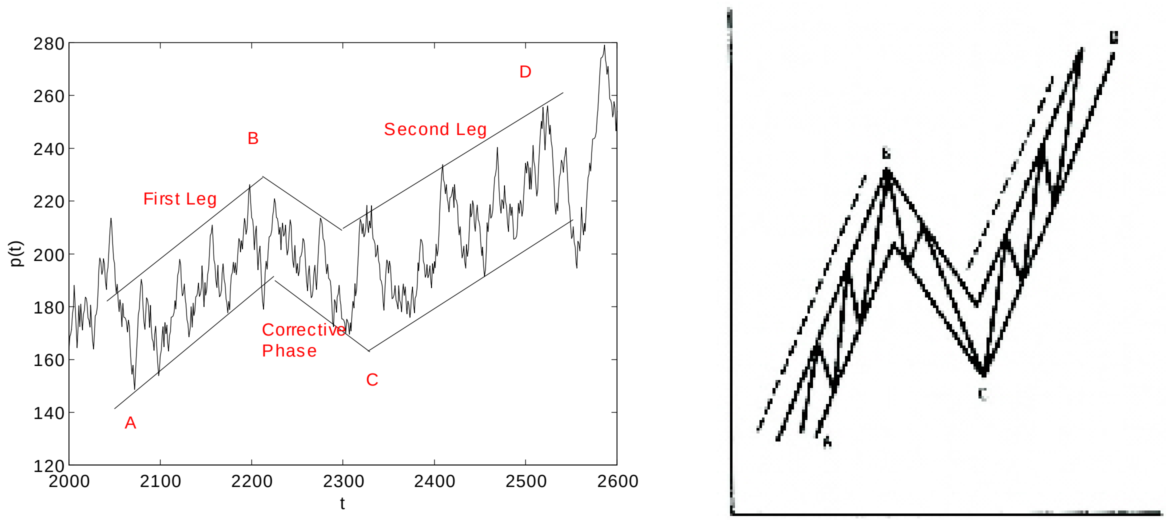

Figure 2.6: Measured move up. Left panel is the simulations and right panel is the example.

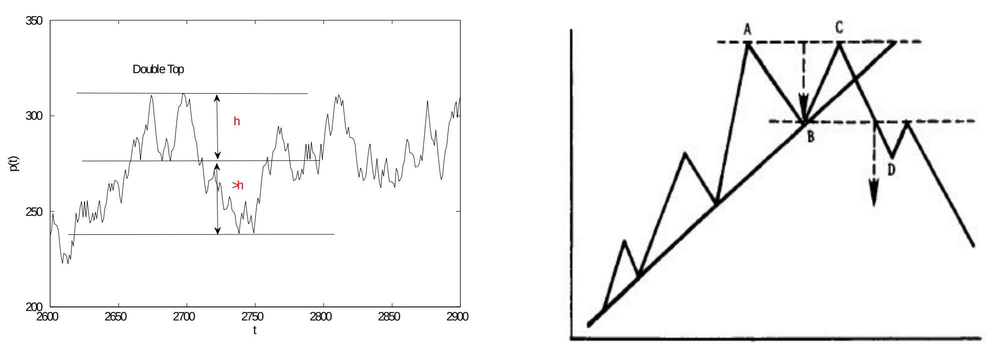

Figure 2.7: Double tops in the simulations (left panel) and its example (right panel).

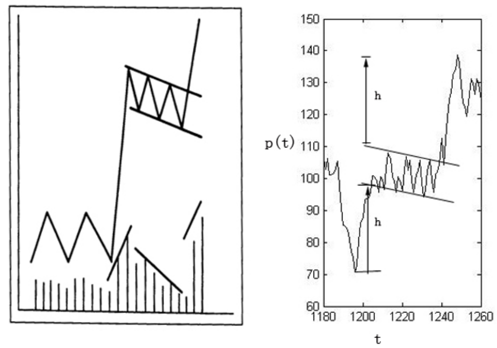

Figure 2.8: The flag in the simulations (right panel) and its example (left panel).

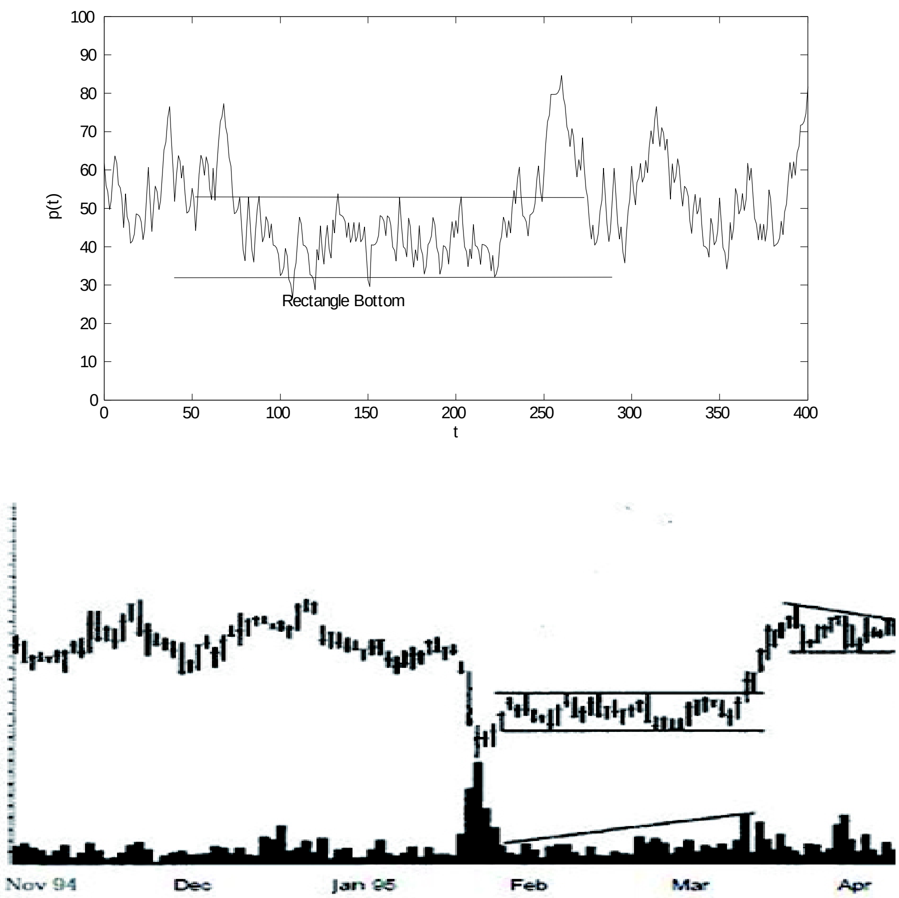

Figure 2.9: Rectangle bottoms in the simulations (upper panel) and its example (lower panel).

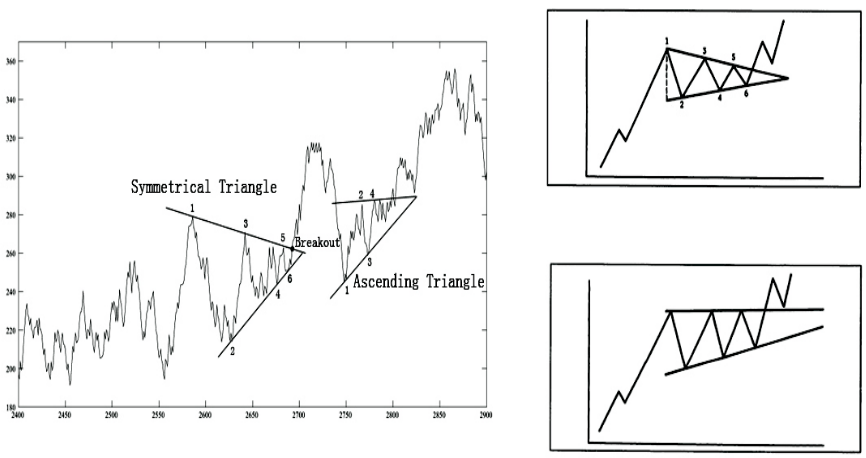

Figure 2.10: Triangles in our simulations (left panel) and its example (right panel).

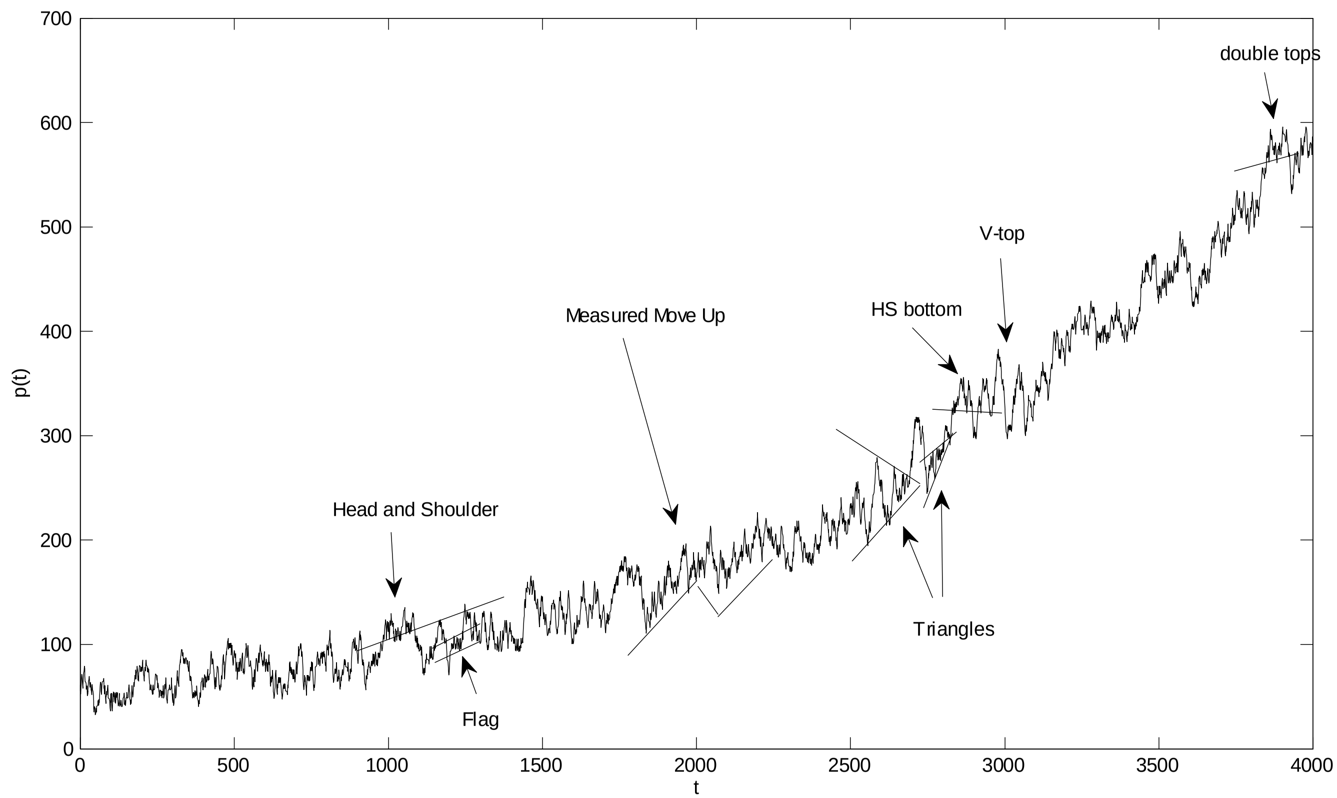

Figure 2.11: Simulations of the price dynamics when $p_0 = 61.52$ from $t = 0$ to $t = 4000$

2.4 Support Line and Resistance Line

In financial market, prices move along a series of peaks and troughs. It is believed that the direction of these peaks and troughs determine the trend of the market. The troughs, so-called support, happen at a level where buying interest is sufficiently strong to dominate selling pressures. Consequently, the previous downwards trend is halted and reversed. Similarly, the peaks, so-called the resistance happen at a level when the selling pressures overcome the buying interest. In technical analysis, the underlying essence of chart patterns or even other technical indicators such as moving average is the support line and resistance line. All chart patterns are visual signals which help us to discover hidden resistance and support level. A straightforward example is the neckline in the head and shoulders pattern. By justifying the characteristics of support and resistance in the technical analysis, the underlying mechanism in this nonlinear dynamics can explain the reason why our model can replicate the occurrences of chart patterns and their implications on their following trends.

Proposition 1 *In each regime, if p_t falls into $[p_k^{r_a}, p_k^{r_b})$, where $p_k^{r_a} = f^{-1}(\mathbf{P}_k)$ $(p_k^{r_a} < \mathbf{P}_k)$ and $p_k^{r_b} = f^{-1}(u_{k+1}^c)$ $(p_k^{r_b} < \mathbf{P}_k)$, $p_{t+1} > p_t$ and $p_{t+2} < p_{t+1}$. A reversal point is evolved at $t+1$, so p_{t+1} is the resistance point, and $[p_k^{r_a}, p_k^{r_b})$ is the so-called resisting zone. On the other hand, if p_t falls into $[p_k^{s_a}, p_k^{s_b})$, where $p_k^{s_a} = f^{-1}(u_{k-1}^c)$ $(p_k^{s_a} > \mathbf{P}_{k-1})$ and $p_k^{s_b} = f^{-1}(\mathbf{P}_{k-1})$ $(p_k^{s_b} > \mathbf{P}_{k-1})$, $p_{t+1} < p_t$ and $p_{t+2} > p_{t+1}$. A reversal point is evolved at $t+1$, so p_{t+1} is the supporting point, and $[p_k^{s_a}, p_k^{s_b})$ is the so-called supporting zone.*

If we extend the proposition to the whole trading regime, $[p_1^{r_a}, p_1^{r_b}) \cup [p_2^{r_a}, p_2^{r_b}) \cup \cdots \cup [p_k^{r_a}, p_k^{r_b}) \cup \cdots \cup [p_n^{r_a}, p_n^{r_b})$ is the resisting zone. Any price falls into this regime, the existing upward trends will be stopped at next period. Similarly, $[p_1^{s_a}, p_1^{s_b}) \cup [p_2^{s_a}, p_2^{s_b}) \cup \cdots \cup [p_k^{s_a}, p_k^{s_b}) \cup \cdots \cup [p_n^{s_a}, p_n^{s_b})$ is the supporting zones of the whole regime. Fig. 2.12 is the phase diagram that displays the resisting zones and supporting zones in our multi-regimes set-ups.

Proposition 2 *Assuming any $\Delta p/\mathbf{P}\max = (p_{t+1} - p_t)/\mathbf{P}\max \to 0$. When the price moves*

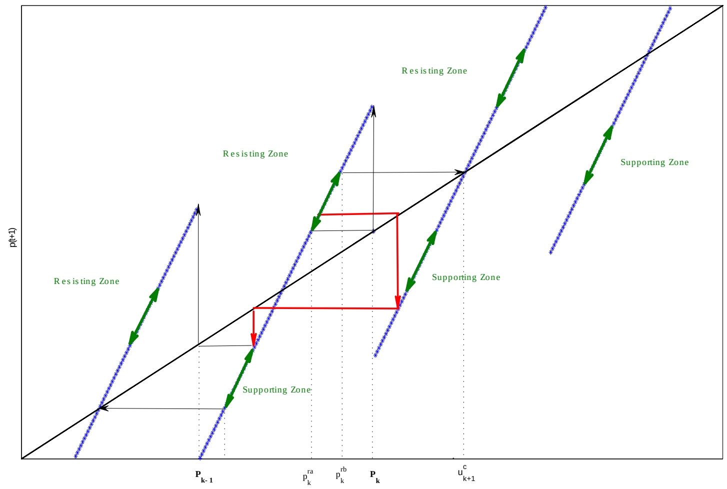

Figure 2.12: Resisting zones and supporting zones across different regimes

from lower regime to the higher regime, unavoidably, the price will drop to the resisting zones somehow and the trend will be reverted. In the real world, speculators can infer the resisting zone by analyzing the visual "resistance line", which consists of reversal points $p_{t+1,j}$, $j = 1, 2, ..., n$ *which represents the jth time that the price drop into the resisting zones. To find out the resistance line based on the history prices,*

$$E(\mathbf{P}_k^r \mid p_{t+1,1}, p_{t+1,2}, ..., p_{t+1,n}) = \frac{1}{2}(p_k^{r_a} + p_k^{r_b}).$$

And similar cases also occur to the supporting zones. If we connect all the expected value of resistance/support points across different regimes, it will form an upper resistance line and a lower support line(see Fig. 2.13). And for the price series, it will exhibit a certain pattern that the price bounces between these two lines across different regimes.

Proposition 3 *A price channel (measured move up/down pattern) is a continuation pattern that slopes up or down and is bound by the upper and lower trend lines. Take measured move up as example. The upper trend line marks resistance which is so-called channel line and the*

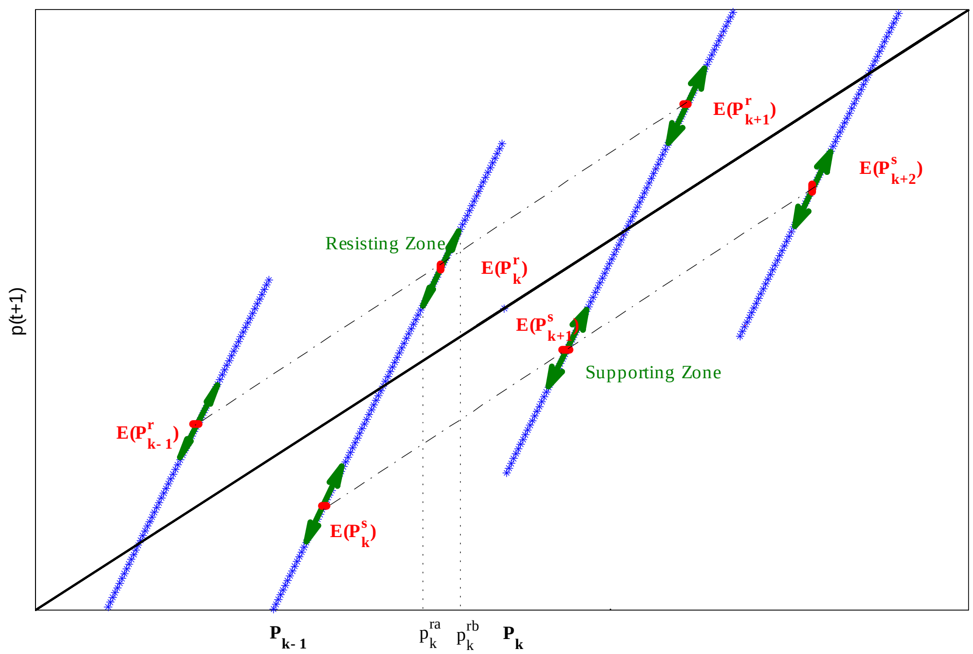

Figure 2.13: Resistance line and support line observed in the price series

lower trend line marks support, so-called the basic up trendline.

2.5 Measurement of Fitness of Our Model—Stylized Facts

The previous discussion demonstrates that the simulations are capable of visually matching the price dynamics in the real market and it shows why this model can explain the predictability of chart patterns. Another question arises: how about the performances of our simulations statistically?

It has been found that some characteristics of financial time series distinguish them from others, such as excess volatility, volatility clustering, and unit roots. Thus, this section is devoted to evaluate our results with these stylized facts and see whether this model can fit the real data.

2.5.1 Fat Tails

Fat tail is one of the most famous stylized facts in financial time series. It depicts that, compared to a normal distribution, the distributions of returns for stocks or index have heavier tails and the possibility of achieving an excess return or loss is higher. So I calculate the kurtosis of our simulations and compare it with the log return series of S&P 500 and Dow Jones Industrial Average (DJIA). Table 2.1 displays the summary statistics of my results and the real data of 2557 daily observations in S&P 500 and Dow Jones Industrial Average from 03/07/2003 to 03/07/2010[11]. The parameter set I adopt is the default parameter set stated previously. It is clear that the existence of excess volatility and the kurtosis in the simulated time series is quite compatible with the well-known indices.

[11] Considering the frequency of the price adjustment by the market maker and the corresponding switching of strategies of two agents, following Huang and Zheng (2012), I compare the simulated time series with the daily data in the real market.

Table 2.1: Summary of statistics

Statistics	Skewness	Kurtosis
the log returns for our results	-0.173	13.4
the log returns for S&P500	0.274	14.9
the log returns for the DJIA	0.025	14.8

2.5.2 Unit Root

Another stylized fact is the nonstationarity of financial time series, which can be eliminated after the first difference of the original time series. To examine whether our model is compatible with the real financial data in this stylized fact, I investigate both the original price series $\{p_t\}$ and the return series $\{r_t\}$, which is the first difference of the price series. With the Augment Dickey-Fuller test (see Table 2.2), it is found that the statistics is insignificant for the $\{p_t\}$ but significant for $\{r_t\}$. Unit root for the return series $\{r_t\}$ is rejected. It implies that the original price series is a unit root process, but after the first difference, the return series is stationary.

Table 2.2: The ADF test for the existence of unit root process

Dickey-Fuller test for unit root (No. of obs: 4000)	price p_t	return r_t
Test statistics	0.024	-62.5
P-value	0.961	0.000*

2.5.3 Volatility Clustering

Volatility is another important topic in financial markets and lots of financial econometrics models are designed to fit the dependence relations in financial empirical data. This part discusses whether the simulated time series actually reflect the behaviors of volatility clustering. It has been documented that the raw return series neither have straightforward autocorrelation problem nor low order correlations, but volatility clustering indicates that it is not simply independent. If we take the absolute value of our return series $\{\mid r_t \mid\}$ or get the square returns $\{r_t^2\}$, we find that the autocorrelation functions decay very slowly.

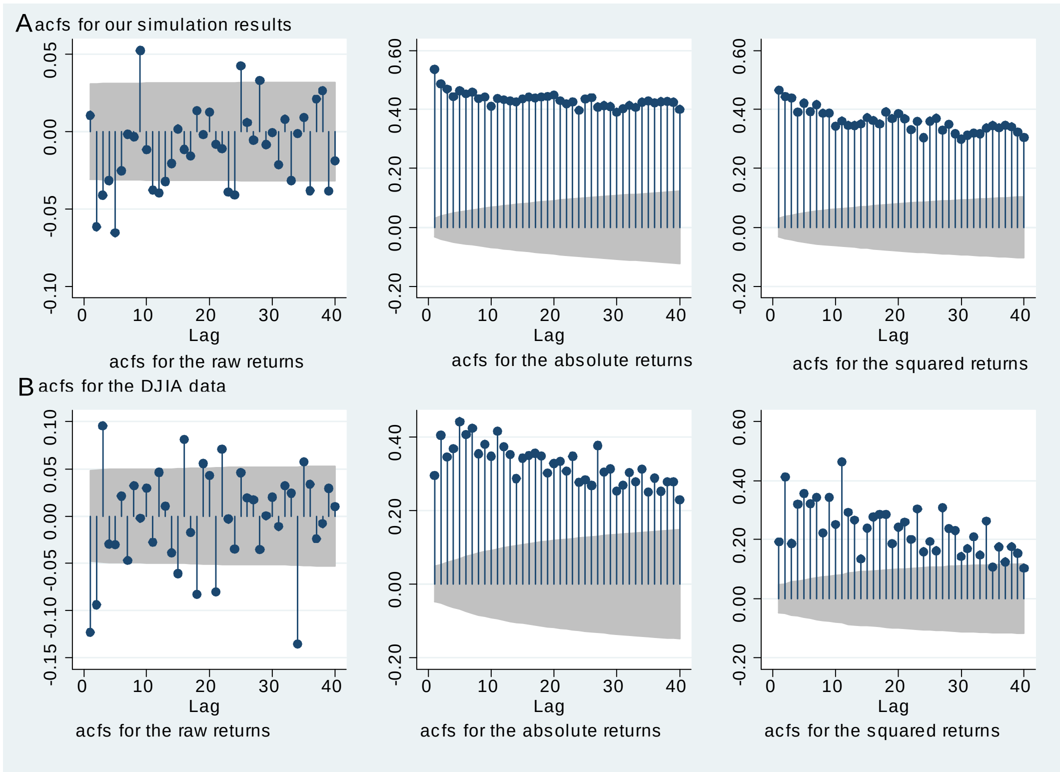

Figure 2.14: Comparison of the ACFs between our generated series and DJIA

In our test for autocorrelation in Fig. 2.14, Group A shows the test results of ACF graphs for the raw returns, the absolute returns and the squared returns for the artificially generated series by this model. Group B covers the test results of the same ACF graphs for the DJIA data. It is found that the ACFs of $\{r_t\}$ from both the simulated data and the DJIA data are trivial, which showed no autocorrelations in these two series. However, for the $\{| r_t |\}$ and $\{r_t^2\}$ series, the ACFs for both results (the shadow area is the critical level) decay tremendously slowly, which suggest the presence of volatility clustering.

2.6 Conclusions

Many possible factors, such as data snooping and survivorship bias, have been used to challenge the feasibility of technical analysis and charting. However, if a method of analysis and trading does not work, it would not be so popular. Even the technical analysts themselves assert that the chart pattern is probably a self-fulfilling process. The essential difference between socioeconomic systems and physical systems is the involvement of human behaviors. So if we want to figure out the mechanism behind the price fluctuation, we should take the human behaviors into our consideration.

This study develops a very simple deterministic heterogeneous agent model under the market maker framework of Day and Huang (1990). With the introduction of adaptive belief and business cycle, the performance of the model is greatly improved in the following aspects:

1. It is shown that the model is able to simulate almost all the sophisticated chart patterns in technical analysis using the same parameter set and the same initial value, including both reverse and continuation patterns.

2. Since it is a purely deterministic model, with the introduction of the resistance and support zones in this nonlinear dynamics, it can be safely inferred that once the price falls into those resistance and support zones, a reversal point in the next period are formed. So the following trends after the chart patterns are pre-determined, and the predictive power of the pattern can be explained theoretically.

3. While the model is very simple, it is also quantitatively well-fitted since our simulations could match the stylized facts.

All of the above-mentioned aspects indicate that this framework is highly compatible with the real market mechanism. With this robust and powerful model, we aim to provide another perspective to the same old question, i.e. what factors affect the seemingly irregular price movements. We reach a conclusion that the possible underlying mechanism could be the internal dynamics of the market itself.

Chapter 3

Does the Volume Signal in Chart Patterns Work?

3.1 Introduction

While many empirical studies have proven the informativeness or profitability of technical analysis, numerous papers just focus on those technical trading rules that can be quantitatively measured[1]. Chart patterns were seldom examined until the 1990s as a result of its characteristic of purely visual identification. Among those existing literature on chart patterns, the results vary depending on patterns, markets, and even sample periods. For example, Curcio et al. (1997) and Lucke (2003) provide limited evidence on the profitability of technical patterns in foreign exchange markets, while Caginalp and Laurent (1998) show that chart patterns can create substantial profits to speculators. Chang and Osler (1999) propose an algorithm to identify the head and shoulders pattern and establish a strategy of entering and exiting the market based on such recognition. They prove that head and

[1] such as Alexander (1961), Fama (1970), Sweeny (1988) for filters, Houthakker (1961) for stop-loss orders, Cootner (1962), Van Horne and Parker (1967), James (1968), and Dale and Workman (1980) for moving averages, Irwin (1984) for channels, and Levy (1967a), Levy (1967b), Jensen and Benington (1970) for relative strength.

shoulders can generate statistically significant profits in the Mark and Yen markets but not in others. In view of the mixed evidence, most academics are still holding negative attitudes towards the profitability of chart patterns.

In fact, technicians in the real world do not solely rely on chart patterns themselves. Since the identification process is purely visual, different technicians can discover different patterns in the same time series. Even the technicians themselves also admit that each chart pattern can fail in many cases. For some patterns like double bottoms, the failure rate can be as high as 64% according to Bulkowski (2000). Therefore, to improve the reliability of chart patterns, volume signal is widely applied as an important tool to determine whether certain chart patterns are completed or failed.

Surprisingly, to our knowledge, no previous study has investigated the profitability of chart patterns with the volume signals. Therefore, this chapter uses a newly introduced algorithm, the Perpetually Important Point (PIP) identification process to empirically examine informational role of the chart patterns with the volume signals, in Hong Kong Hang Seng Index, Singapore Straits Time Index and Japan Nikkei 225 Index[2]. This PIP approach is firstly introduced by Fu et al. (2007). Different from the classic methodology of identifying charting signals by Chang and Osler (1999) and Lo et al. (2000), the similarity measurement introduced by Fu et al. (2007) is the very similar to the human identification process. In the human identification process, patterns are depicted as several points along with their corresponding relations. For example, the head and shoulders pattern should at least consist of a head point, two shoulder points, and a pair of neck points. Therefore, with the similarity measurement introduced in Fu et al. (2007), the PIPs can be discovered by calculating the maximum distance (MD) between prices.

This study distinguishes itself by introducing certain rules for the corresponding volume

[2] It is noteworthy that some of the academicians assert that the profitability of technical analysis results from the corresponding risk by taking this strategy. Therefore, to avoid the disputes, we just evaluate the informational role of the chart patterns and volume signals.

series. In order to examine the informational role of both chart patterns and volume signals, the returns solely conditional on chart patterns and those conditional on both chart patterns and volume signals are compared with the unconditional returns of the entire financial time series by χ^2 goodness-of-fit test and the Kolmogorov-Smirnov test. If volume signals work, the conditional returns on both price and volume should significantly improve the results of the conditional returns solely on price patterns.

The structure of the chapter is organized as follows. Section 2 introduces the algorithm of the PIP identification methods for pattern-detection and the corresponding rules for pattern-matching. Section 3 defines volume signals in chart patterns. Section 4 reports our empirical results, which show that with the help of volume signals, the profitability of chart patterns are confirmed in all the five patterns of the three markets. Finally, Section 5 concludes.

3.2 Methodology of Automating Technical Analysis

Constructing an algorithm to detect technical patterns automatically is essential for both empirical studies and practitioners' applications in reality. It not only helps analyze massive financial time series efficiently but also eliminates bias from individual judgements. With the development of artificial intelligence, nowadays, we could find out customized matching scheme to discover flexible time series patterns. The algorithm following Fu et al. (2007) contains two phases, PIP identification process and pattern-matching.

3.2.1 Perpetually Important Point (PIP) Identification Process

In artificial intelligence, researchers have concentrated in finding similar time series and time series database. Abundant algorithms measuring Euclidean distance exist to evaluate similarity between time series. Comparing similarity between time series is difficult in financial time series because these patterns may be similar in the overall shape but with different amplitudes and/or durations. Fortunately, in human identification process, these patterns can be characterized by a few data points, which is the so-called perpetually important point (PIP). Therefore, by measuring the maximum distance (MD) between prices, we can discover some PIPs in a given subsequence.

The procedure of THE PIP identification can be described as below.

(1) A financial time series $\{p_1, p_2, ..., p_m\}$ is divided based on rotation windows with the length l to obtain $(m - l)$ subsequences as $\{p_{1,}...p_l\}, \{p_2, ..., p_{l+1}\}, ...\{p_{m-l+1,}..., p_m\}$.

(2) In each window $\{p_k, ..., p_{k+l-1}\}$, the first two PIPs will be the first and last PIPs, which is p_k, p_{k+l-1}.

(3) The next PIP will be the point in price with maximum distance to the first two PIPs.

(4) The fourth PIP will then be the point on the series with maximum distance to its two adjacent PIPs.

The above PIP location process continues until we discover all required PIPs in each pattern, i.e. in head and shoulders patterns, the number of perpetually important point is 7[3] and the process is illustrated in Fig. 3.1. Then, two questions arise in this procedure. How to determine the MD and the length of each subsequence?

3.2.2 Maximum Distance

Among different definitions of MD, Fu et al. (2007) select three most widely-adopted MDs, the Euclidean distance (ED), the perpendicular distance (PD) and the vertical distance (VD) to evaluate their efficiency and effectiveness. For the efficiency, Fu et al. (2007) show that the VD measurement is the fastest method. In terms of the effectiveness, both the VD and PD have better performances. Besides, in the VD measurement, as illustrated in Fig. 3.2, high fluctuated points would be considered as PIPs, which is specifically suitable for the

[3] In the head and shoulders pattern, 7 PIPs are needed. For an integrated head and shoulder pattern, one head point, two shoulder points, two trough points, one beginning point and one ending point are needed. Considering the continuity, in this chapter, following Fu et al. (2007), the number of PIP for all patterns is assumed to be 7.

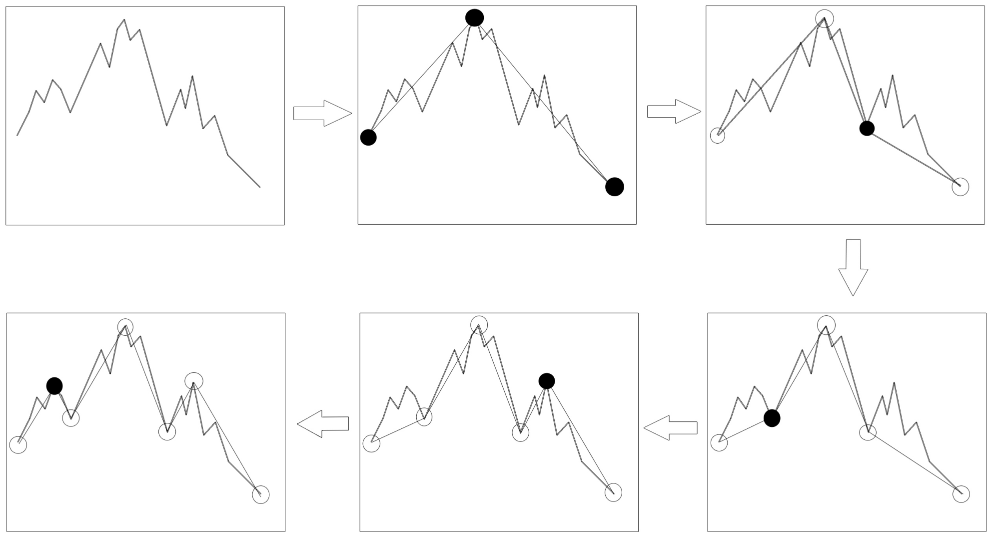

Figure 3.1: Identification of seven perceptually important points.

financial time series. As a result, the VD measurement as defined in Eq.(3.1) is the best choice for the PIP identification process for chart patterns.

$$VD(p_1, p_2, p_3) = |y_c - y_3| = |(y_1 + (y_2 - y_1)\frac{x_3 - x_1}{x_2 - x_1}) - y_3|, \tag{3.1}$$

where $x_3 = x_c$.

In this case, by measuring the VD, PIPs can be detected in each subsequence with a given window.

3.2.3 Determination of the Length of Window

To detect the appearances of financial patterns described by certain rules, subsequence time series matching is needed. Subsequence time series matching is different from the whole matching process since it requires that every possible subsequence $S = (s_1, ..., s_w)$ in the entire original series $p = (p_1, ...p_m)$ should be examined, where $w << m$. However, in technical analysis, there is no rigid requirement on the duration of a certain technical pat-

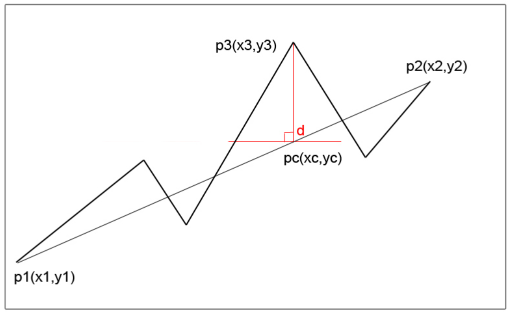

Figure 3.2: Illustration of vertical distance

tern. The pattern may appear in different resolutions rather than in a fixed window with a size l (for example, in Lo et al. (2000), $l = 35$). Therefore, this chapter searches a specified pattern template within a time series using a sliding window with a window size varying from l_1 to l_2. When the length is l_1, the subsequences of the original series are $\{p_{1,} ... p_{l_1}\}, \{p_2, ..., p_{l_1+1}\}, ..., \{p_{m-l_1+1,} ..., p_m\}$ so the number of subsequences needed to be examined is $(m - l_1 + 1)$. When the length is l_2, the original time series are divided into $(m - l_2 + 1)$ subsequences including $\{p_{1,} ... p_{l_2}\}, \{p_2, ..., p_{l_2+1}\}, ..., \{p_{m-l_2+1,} ..., p_m\}$. So the total number of subsequences δ is

$$\delta = \sum_{i=l_1}^{l_2-l_1+1} (m - i + 1) = (m - l_1 + 1 + m - l_2 + 1)(l_1 - l_2 + 1)/2,$$

where m is the length of the entire time series.

In this chapter, I mainly focus on the evaluation of reversal patterns[4] which are the most popular technical indicators. Most of reversal patterns are mid-term patterns which last longer than one month (30 days) but less than 4 months (120 days). Therefore, to find

[4] According to Murphy (1999), the most popular reversal patterns are referred as the (inverted) head and shoulder, double tops (bottoms), the round tops and the spike.

all potential patterns within a given time series, this chapter simply assumes $l_1 = 30$ and $l_2 = 120$. In this way, by measuring the VD between prices, I can detect several PIPs in each window. The next question is whether these PIPs can match the pre-determined rules of chart patterns.

3.2.4 Rule-based Pattern-matching Approach

Fu et al. (2007) introduce two different pattern-matching approaches: template-based approach and rule-based approach. However, since the template-based pattern-matching approach fails in round top, this chapter adopts the rules-based approach to identify different patterns. The key advantage of the rule-based approach is that it can explicitly define the relationship between PIPs. For example, in the head and shoulders patterns, the two shoulders must have the same degree of amplitude and these two shoulders have to be lower than the head. For the double tops/ bottoms pattern, the two tops/bottoms should be of the same level. The differences between the two tops/bottoms, in this case, are defined as within 15% in average.

Following Lo et al. (2000), I describe the reversal technical patterns in rule format. After the identification of seven PIPs (from p_1 to p_7) in each subsequence, the rules describing the relationships between these seven PIPs are provided. This chapter investigates five common patterns in the stock market, including head and shoulders (HS), inverted head and shoulders (IHS), double tops (DTop), double bottoms (DBot) and round top (RTop).

Rule set 1 (head and shoulders pattern)

- $p_4 > p_2$ & p_6 (The head is higher than the shoulders.)
- $p_2 > p_1$ & p_3 (The left shoulder p_2 is the local maximum.)
- $p_6 > p_5$ & p_7 (The right shoulder p_6 is the local maximum.)
- $p_3 > p_1$ (The left trough is higher than the beginning point.)

- $p_5 > p_7$ (The right trough is higher than the ending point.)
- $p_2 - p_6 < 0.15(p_2 + p_6)/2$ (Two shoulders should be in the same price level which is defined within 15% in average.)
- $p_3 - p_5 < 0.15(p_3 + p_5)/2$ (Two troughs should be in the same price level which is defined within 15% in average.)

Rule set 2 (inverted head and shoulders pattern, similar case as the head and shoulders)

- $p_4 < p_2$ & p_6
- $p_2 < p_1$ & p_3
- $p_6 < p_5$ & p_7
- $p_3 < p_1$
- $p_5 < p_7$
- $p_2 - p_6 < 0.15(p_2 + p_6)/2$
- $p_3 - p_5 < 0.15(p_3 + p_5)/2$

Rule set 3 (double tops)

- $p_3 - p_5 < 0.15(p_3 + p_5)/2$ (Two tops should be in the same price level which is defined within 15% in average.)
- $p_3 > p_2$ & p_4 (The left top should be the local maximum.)
- $p_2 > p_1$ (The beginning trend is upward in the pattern.)
- $p_5 > p_4$ & p_6 (The right top should be the local maximum.)
- $p_6 > p_7$ (The trend after the right top is downward.)

Rule set 4 (double bottoms, similar case as the double tops)

- $p_3 < p_2$ & p_4
- $p_2 < p_1$
- $p_5 < p_4$ & p_6
- $p_6 < p_7$
- $p_3 - p_5 < 0.15(p_3 + p_5)/2$

Rule set 5 (round top)

- p_3 & $p_4 > p_2$ (The trend is upward in the first part of the pattern.)
- p_4 & $p_5 > p_6$ (The trend is downward in the second part of the pattern.)
- $p_2 - p_1 > 0.15(p_2 + p_1)/2$ (The price increases significantly at the beginning.)
- $p_6 - p_7 > 0.15(p_6 + p_7)/2$ (The price drops significantly at the end.)

3.3 The Informational Role of Volume

3.3.1 Definition of Volume Signals

Volume signals in technical analysis are widely used in reality (see Murphy (1999) and Bulkowski (2000)). However, only a few studies investigate the role of volume in the visual judgement of technical analysis. This section intends to fill the gap by constructing conditional returns on not only the occurrence of price patterns but the occurrence of both price patterns and the corresponding volume signals. Admittedly, different chart patterns have different specific volume patterns. For instance, in Double Bottom, the volume of the left bottom is usually higher than the one of the right bottom. But two rules are universally applicable in the chart analysis.

(1) In reversal tops/bottoms patterns, the overall volume trend during the patterns should be downward sloping. It is a clear signal that the dominant power in the market is switching from buying/selling to selling/buying. Therefore, a downward sloping volume should be more informative than an upward sloping volume.

(2) When the price penetrates the support/resistance line, the pattern is assumed to be almost completed. Volume plays an essential role to determine whether it is just a short-term turbulence or a real breakout. If it is a substantial breakout, the volume should be significantly high (for example, higher than the volume before the breakout by 20%, or any acceptable level). Once the reversal pattern is completed, the previous trend will stop and start to drop in a top pattern or climb in a bottom pattern. Take the inverted head and shoulder as an example, in the 330 patterns discovered by Bulkowski (2000), successful breakout on high volume is 74% and only 26% of successful breakout happened when the volume is very low. And the volume in the breakout days is significantly higher than the volume in the days before the breakout by 63% and this number becomes even higher to the level of 91% for the double tops.

To quantitatively express these two visual criteria, I introduce two corresponding rules to facilitate the examination.

(1) To discover the general trend during the pattern, I compute its average turnover during the first and second halves, τ_1 and τ_2, in each qualified pattern filtered by the previous rules of charts. Following the definition by Lo et al. (2000) , if $\tau_1 > 1.2\tau_2$, I categorize this as a "decreasing volume" event which satisfies the first rule.

(2) The last perpetually identifiable point, p_7 is regarded as the breakout. If the breakout volume is significant higher than the average volume during the patterns by 20%, it would be considered as the volume signal in the breakout.

3.3.2 Goodness-of-fit Tests

A simple diagnostic to test the informativeness of the 5 technical patterns is to compare the quantiles of the conditional returns with their unconditional counterparts. If conditioning on these patterns or patterns plus the volume signals provides no incremental information, the quantiles of the conditional returns should be similar to those of unconditional returns. In particular, I compute the deciles of unconditional returns and tabulate the relative frequency $\overset{\curlywedge}{\delta}_j$ of the conditional returns falling into decile j, $j = 1, ..., 10$:

$$\overset{\curlywedge}{\delta}_j \equiv \frac{\text{number of conditional returns in decile } j}{\text{total number of conditional returns}}$$

Under the null hypothesis that the returns are independently and identically distributed(IID) and the conditional and unconditional distributions are identical, the corresponding goodness-of-fit test statistic Q is given by

$$\sqrt{n}(\overset{\curlywedge}{\delta}_j - 0.10) \overset{a}{\sim} N(0, 0.10(1 - 0.10)), \tag{3.2}$$

$$Q = \sum_{j=1}^{10} \frac{(n_j - 0.1n)^2}{0.1n} \overset{a}{\sim} \chi^2_9, \tag{3.3}$$

where n_j is the number of observations falling into decile j and n is the total number of the conditional returns.

Another comparison of the conditional and unconditional distributions of returns is provided by the Kolmogorov-Smirnov test. Two samples, denoted by $\{Z_{1t}\}_{t=1}^{n_1}$ and $\{Z_{2t}\}_{t=1}^{n_2}$ are tested. Each of them are i.i.d. with cumulative distribution functions (CDFs) $F_1(z)$ and $F_2(z)$, respectively. The Kolmogorov-Smirnov statistic is used to test the null hypothesis of $F_1 = F_2$ and is based on the CDFs $\overset{\curlywedge}{F}_i$ of both samples:

$$\overset{\curlywedge}{F}_i(z) = \frac{1}{n_i}\sum_{k=1}^{n_i} \mathbf{1}(Z_{ik} \leq z), i = 1, 2,$$

where $\mathbf{1}(\cdot)$ is an indicator function. The corresponding statistic is given by the expression

$$\gamma_{n_1,n_2} = (\frac{n_1 n_2}{n_1 + n_2})^{1/2} \sup_{-\infty<z<\infty} |\overset{\curlywedge}{F}_1(z) - \overset{\curlywedge}{F}_2(z)|. \tag{3.4}$$

Under the null hypothesis $F_1 = F_2$, the statistic γ_{n_1,n_2} should be small. Furthermore, the limiting distribution of the statistic is also provided as

$$\lim_{\min(n_1,n_2)\to\infty} \Pr(\gamma_{n_1,n_2} \leq x) = \sum_{k=-\infty}^{\infty} (-1)^k \exp(-2k^2x^2), x > 0 \tag{3.5}$$

An approximate α-level test of the null hypothesis can be performed by computing the statistic and rejecting the null if it exceeds the upper 100αth percentile for the null distribution given by Eq. (3.5).

3.4 Empirical Results

3.4.1 The Data and Sampling Procedure

To check the robustness of our inferences, I apply the goodness-of-fit test and the Kolmogorov-Smirnov test to the data based on the log returns of the indices as well as the trading volumes obtained from different Asian markets, including Hong Kong Hang Seng Index(HSI), Singapore Straits Time Index(STI), and Japan Nikkei 225[5]. We select the same number of observations, 2600 daily returns for each index, so that the samples are comparable among different markets[6].

[5] We choose the indices other than some specific stocks for two reasons. One is that we do not have to consider any subjective bias in the stock selecting process in this case. The other reason is that there is no missing price observation in this case.

[6] The available volume data of Hong Kong Index is the shortest which consists of 2600 observations. Considering the compatibility, we select the same observations for the other two markets.

3.4.2 Computing the Conditional Returns

To avoid the disputes over the profitability of chart patterns, instead of testing for the profitability, followingLo et al. (2000), I evaluate the informational role of chart patterns by examining the returns conditional on the patterns and the unconditional daily returns.

Firstly, I introduce a lag parameter d because in practice, it takes chartists a few days to detect the completion of a certain pattern as they can only confirm their visual judgement after verifying with other auxiliary tools such as volume signals. Thus, if a pattern is discovered by the PIP process documented above in the window of prices $\{p_t\}$ from t to $t+l$, then the identified pattern is completed at $t+l$. Instead of computing the log return $\log(1+r_{t+l+1})$, I compute the one-day compounded return d days after the pattern has completed[7]. So the expression of conditional return is $\log(1+r_{t+l+d+1})$.

In all, for each index, 10 sets of conditional returns are obtained for the test. 5 sets are conditional returns $\left\{r^c_{i,t}\right\}$, $i = 1, ..., 5$, each of which conditions on one of the 5 patterns stated in Section 3.2. The other 5 sets are returns conditioning on both these chart patterns and volume signals as $\left\{r^v_{i,t}\right\}, i = 1, ..., 5$.

I calculate the *unconditional* continuously compounded returns $\left\{r^u_{t,i}\right\}, i = 1, ..., 5$ and compare the empirical distribution functions of these returns with those of the conditional returns. To facilitate such comparisons, I standardize the unconditional returns by subtracting means and dividing them by standard deviations. Therefore, each normalized return series has zero mean and unit variance.

3.4.3 Summary of Statistics

Table 3.1 summarizes the statistics for the price, volume and daily returns in all three markets, the Hang Seng Index from 08/29/2002 to 13/01/2013, the Straits Time Index

[7] I simple assume $d = 3$ in all empirical procedures to keep consistency.

from 13/10/1997 to 13/01/2013 and the Nikki 225 from 10/06/2002 to 13/01/2013[8]. It includes statistics—means, standard deviations, skewness, excess kurtosis and the number of observations.

Table 3.2 counts the frequency of each technical indicator detected in three indices. Table 3.2 shows that the most common patterns among three markets are double tops and double bottoms (see the row labeled "Entire"), with about 2000 occurrences of each. However, in the study of technical analysis, double tops and double bottoms are the most unreliable patterns. The occurrences of other chart patterns are considerably fewer, between 300 and 1000. Furthermore, with volume signals stated in Section 3.3, more than 90% of the pattern candidates are ruled out. Especially for the double tops/bottoms, only about 5%-10% detected patterns are left[9].

Table 3.3 summarizes the statistics (means, standard deviations, skewness and excess kurtosis) of two cases, the one-day normalized conditional returns without volume signals and the ones with volume signals. Conditional returns are defined as the daily returns of three days following the completion of technical indicators with/without volume signals. The unconditional returns have been standardized. For the purpose of comparison, the statistics of unconditional returns are also provided. According to our results, the moments of conditional results are significantly different from those of raw series.

Besides, the statistics provide intuitive implication on the profitability of chart patterns. For the top patterns, such as the head and shoulders, double tops and round tops, the following trend after these patterns is assumed to drop significantly (It is said that the magnitude of the decline is directly related to the patterns as well.) Therefore, the expected

[8] Data is collected from Internet (finance.yahoo.com). I choose the most updated data till 13/01/2013 and collect 2600 observations for all three markets. However, since the data of volume is unavailable in Straits Time Index from 10/01/2008 to 03/12/2012, the most updated 2600 observations for STI is from 13/10/1997 to 13/01/2013.

[9] In this study, HS, IHS, RT, DT, DB are selected since the occurrences of the rest patterns are too small, which means after the filter of volume signals, the sample sizes of other indicators are too small for the goodness-of-fit test.

Table 3.1: Summary statistics of prices, returns and volumes in Hang Seng Index, Straits Time Index and Nikkei 225 markets

Markets	**Sample**	**Mean**	**S.D.**	**Skew**	**Kurt**	**N**
	p_t	17765.560	4839.979	-0.046	2.194	2600
Hang Seng Index	r_t	-0.000	0.016	-0.042	12.240	2599
	V_t	1.25×10^9	1.040×10^9	1.416	7.580	2600
	p_t	2014.031	626.318	0.954	3.604	2600
Straits Time Index	r_t	-0.000	0.014	-0.025	10.811	2599
	V_t	1.33×10^8	9.98×10^7	2.105	13.094	2600
	p_t	11490.450	2887.863	0.869	2.513	2600
Nikkei 225	r_t	0.000	0.0155	0.522	11.071	2599
	V_t	3.71×10^7	1.37×10^8	3.733	16.736	2600

Table 3.2: Frequency counts for 5 technical indicators detected among Hang Seng Index, Straits Time Index, and Nikkei 225

Markets	**Sample**	**HS**	**IHS**	**RTop**	**DTop**	**DBot**
Hang Seng Index	Entire	309	314	995	2382	2134
	With Volume Signals	30	38	90	203	124
Straits Time Index	Entire	472	646	644	3024	1865
	With Volume Signals	40	61	48	223	111
Nikkei 225	Entire	504	618	687	3042	1489
	With Volume Signals	29	54	38	78	134

conditional returns are supposed to be negative. Similarly, the expected conditional returns of bottom patterns are supposed to be positive. These beliefs are supported by our results in Table 3.3. For instance in the Hang Seng market, the conditional returns on the chart patterns with volume signals, have negative mean for HS, RTop and DTop and positive mean for IHS and DBot.

Table 3.3: Summary statistics of raw and conditional one-day returns of Hang Seng Index, Straits Time Inex and Nikkei 225

Markets	**Sample**	**Moments**	**Raw**	**HS**	**IHS**	**RTop**	**DTop**	**DBot**
Hang Seng Index	Without volume signals	Mean	0.000	-0.003	-0.009	-0.004	0.000	0.034
		S.D.	1.000	0.000	0.953	0.028	0.006	0.750
		Skew.	0.267	-0.914	-0.815	0.433	-0.352	-0.160
		Kurt.	11.776	1.619	5.359	6.322	30.346	4.666
	With Volume Signals	Mean	N.A.	-0.045	0.152	-0.628	0.106	0.045
		S.D.	N.A.	-0.001	1.179	1.912	0.918	0.723
		Skew.	N.A.	-0.266	-1.303	0.298	0.012	-0.320
		Kurt.	N.A.	2.549	4.964	5.034	6.760	5.792
	Without volume signals	Mean	0.000	-0.000	-0.080	0.034	0.075	0.029
		S.D.	0.0142	0.011	0.854	1.392	0.696	0.860
Straits Time Index		Skew.	0.025	0.444	-0.206	0.159	-0.142	-0.418
		Kurt.	10.815	4.002	2.348	9.108	3.385	4.001
	With Volume Signals	Mean	N.A.	-0.187	0.093	0.140	-0.022	0.040
		S.D.	N.A.	0.784	0.784	1.323	0.794	0.768
		Skew	N.A.	-0.004	0.122	-0.385	-0.156	-0.560
		Kurt.	N.A.	2.853	2.683	2.038	3.383	5.024
Nikkei 225	Without volume signals	Mean	-0.000	-0.072	-0.093	-0.034	-0.022	0.020
		S.D.	0.155	0.785	0.784	1.392	0.794	0.878
		Skew	-0.522	0.356	0.122	0.149	-0.156	-0.481
		Kurt.	11.071	8.250	2.683	9.108	3.383	4.167
	With volume signals	Mean	N.A.	-0.201	0.129	-0.426	-0.859	0.051
		S.D.	N.A.	1.094	0.932	1.155	0.817	0.984
		Skew	N.A.	0.592	0.398	0.432	-0.760	-0.739
		Kurt.	N.A.	4.103	5.928	3.354	4.106	4.481

3.4.4 Empirical Results

Tables 3.4, 3.5, 3.6 report the fitness for the conditional one-days normalized returns for all five patterns for the sample of the Hang Seng Index from 2001 to 2013, the Straits Time Index from 1997 to 2013 and the Nikkei 225 from 2002 to 2013. The five technical indicators are as follows: the Head and Shoulders, the Inverted Head and Shoulders, the Round tops, the Double Tops/Bottoms. For each pattern, the percentage of conditional returns that falls within each of the 10 unconditional-return deciles is tabulated. Asymptotic z-statistics for this null hypothesis are reported, and the χ^2 goodness-of-fitness test statistics Q are reported in the last column with the p-value in parentheses. I compare the two results: with and without volume signals. All the results are consistent with our daily observations on the chart patterns and the corresponding volume signals. Table 3.4 shows that most of the conditional returns in the Hang Seng Index are significantly different from the original unconditional series, which proves the informational role of the technical indicators. The only exception is the most commonly-seen pattern, DT, in which the p-values of the test statistics Q is 0.132. However, with volume signals, the result improves and the null hypothesis is rejected at 1% significance level. Similarly in Table 3.5, the results in the Straits Time Index suggest that only the DT seems to provide little incremental information as the corresponding p-value of test statistics is 0.2412. However, the situation can be improved by adding volume signals. After applying the volume factor, the p-value of test statistics is zero. In Table 3.6, for the Nikkei 225 index, there is overwhelming significance for all 5 indicators, with p-values that are zero to three significant digits. Basically, almost all the patterns provide substantial information for the investors, except some cases for the Double Tops and Double Bottoms. It is consistent with the reality as well since the reliability of Double Tops/Double Bottoms is considered as the lowest among these patterns. But with the help of the volume pattern, the reliability can be significantly improved.

Table 3.7 presents the Kolmogorov-Smirnov test of the equality of conditional and unconditional one-day return distributions for the three different stock indices. We can see that in the Hang Seng Index, without volume signals, only returns conditioning on the RTop and DBot can yield significant difference from the unconditional ones. But after filtering of volume signals, all the five patterns are statistically significant at the 1% significance level. For the Straits Time Index, the p-value ranges from 0.054 for HS to 0.295 for all five patterns, which implies the inability to distinguish between the conditional and unconditional distributions of normalized returns. With the volume signals, conditional returns are statistically different from unconditional returns at 5% significance level level. And for the Nikkei 225, the results of chart patterns are mixed. The IHS and RTop yield statistically significant test statistics at 1% significance level. The HS and DTop yield statistically significant test statistics at 5% significance level, and the DBot fails to reject the null hypothesis. With volume signals, the statistical significance level of HS, DTop and DBot patterns increases to 1%, 5% and 5%, respectively.

Table 3.4: Goodness-of-fit diagnostics for the conditional one-day returns, conditional on 5 technical indicators(and volume signals), for the sample of Hang Seng Index

Pattern in HSI	**Decile:**										
	1	2	3	4	5	6	7	8	9	10	Q p-value
HS without volume signals	12.0	14.2	13.3	13.3	10.4	12.3	4.5	3.6	6.8	9.7	202.93
z-statistics	0.52	1.11	0.86	0.86	0.09	0.60	-1.44	-1.69	-0.84	-0.08	(0.000***)
HS with volume signals	10.0	13.3	20.0	13.3	3.3	3.3	3.3	6.7	0	26.7	124.73
z-statistics	0	0.39	1.18	0.39	-0.79	-0.79	-0.79	-0.39	-1.18	1.97	(0.000***)
IHS without volume signals	8.6	12.1	12.7	9.6	3.2	12.4	9.2	13.1	7.0	12.1	40.33
z-statistics	-0.44	0.67	0.87	-0.14	-2.16	0.77	-0.24	0.97	-0.95	0.67	(0.000***)
IHS with volume signals	7.9	10.5	7.9	0	0	23.7	2.6	13.2	15.8	18.4	53.42
z-statistics	-0.27	0.07	-0.27	-1.26	-1.26	1.73	-0.93	0.40	0.73	1.06	(0.000***)
RTop without volume signals	27.6	7.7	6.8	5.0	5.8	3.5	3.9	7.8	7.5	24.2	140.16
z-statistics	2.06	-0.27	-0.37	-0.58	-0.49	-0.76	-0.71	-0.25	-0.29	1.66	(0.000***)
RTop with volume signals	27.8	13.3	2.2	3.3	16.7	2.2	6.7	4.4	2.2	21.1	15.06
z-statistics	1.93	0.36	-0.84	-0.72	0.72	-0.84	-0.36	-0.60	-0.84	1.21	(0.000***)
DTop without volume signals	8.4	12.8	6.9	14.8	10.8	8.4	10.8	10.3	9.4	7.4	31.52
z-statistics	-0.66	1.14	-1.26	1.94	0.34	-0.66	0.34	0.14	-0.26	-1.06	(0.000***)
DTop with volume signals	7.9	7.8	7.8	13.7	8.5	11.3	12.3	10.2	10.8	9.8	206.31
z-statistics	-1.01	-1.08	-1.10	1.81	-0.75	0.63	1.11	0.10	0.37	-0.09	(0.000***)
DBot without volume signals	8.4	9.3	7.1	10.7	11.7	11.2	13.8	11.1	9.0	7.8	5.60
z-statistics	-0.79	-0.35	-1.41	0.34	0.82	0.57	1.87	0.52	-0.49	-1.07	(0.132)
DBot with volume signals	4.8	10.5	5.7	18.6	12.9	9.7	12.1	9.7	8.9	7.3	24.46
z-statistics	-1.31	0.12	-1.10	2.16	0.73	-0.08	0.53	-0.08	-0.29	-0.69	(0.000***)

Table 3.5: Goodness-of fit diagnostics for the conditional one-day returns, conditional on 5 technical indicators(and volume signals), for the sample of Straits Time Index

Pattern in STI	**Decile:**										
	1	2	3	4	5	6	7	8	9	10	Q p-value
HS without volume signals	9.0	10.0	8.5	14.0	14.0	7.2	5.3	11.9	11.0	9.5	8.68
z-statistics	-0.47	-0.02	-0.55	1.42	1.42	-1.00	-1.68	0.67	0.36	-0.17	(0.039**)
HS with volume signals	5.0	7.5	20.0	2.5	25.0	7.5	2.5	25.0	0.0	5.0	40.37
z-statistics	-0.52	-0.26	1.04	-0.78	1.57	-0.26	-0.78	1.57	-1.04	-0.52	(0.000***)
IHS without volume signals	6.8	14.2	20.0	10.2	6.8	7.6	8.2	6.7	9.8	9.8	31.25
z-statistics	-0.76	1.01	2.38	0.05	-0.76	-0.58	-0.43	-0.80	-0.06	-0.06	(0.000***)
IHS with volume signals	3.3	14.8	19.7	8.2	1.6	0.0	8.2	9.8	23.0	11.5	26.03
z-statistics	-0.89	0.63	1.29	-0.24	-1.11	-1.33	-0.24	-0.02	1.73	0.20	(0.000***)
RTop without volume signals	16.5	11.8	5.8	10.1	5.0	11.2	2.6	11.7	8.1	17.4	36.56
z-statistics	1.35	0.38	-0.90	0.02	-1.05	0.25	-1.54	0.34	-0.40	1.55	(0.000***)
RTop with volume signals	25.0	4.2	4.2	4.2	0.0	12.5	0.0	16.7	2.1	31.3	17.83
z-statistics	1.36	-0.53	-0.53	-0.53	-0.91	0.23	-0.91	0.61	-0.72	1.93	(0.000***)
DTop without volume signals	7.2	11.9	7.9	9.9	11.5	12.1	9.4	10.0	10.9	9.3	6.73
z-statistics	-1.73	1.16	-1.29	-0.06	0.90	1.26	-0.36	-0.00	0.56	-0.42	(0.240)
DTop with volume signals	12.1	9.4	7.2	18.9	11.2	8.1	11.7	5.0	8.1	8.5	12.09
z-statistics	0.55	-0.15	-0.74	2.32	0.32	-0.51	0.43	-1.33	-0.51	-0.39	(0.000***)
DBot without volume signals	8.7	8.8	13.8	9.3	9.1	8.4	10.0	11.6	10.4	10.0	30.5329
z-statistics	-0.77	-0.73	2.33	-0.41	-0.57	0.99	-0.05	0.96	0.24	-0.02	(0.000***)
DBot with volume signals	2.7	12.7	17.3	10.0	10.0	8.2	11.8	13.6	6.4	7.3	10.23
z-statistics	-1.76	0.66	1.76	0.00	0.00	-0.44	0.44	0.88	-0.88	-0.66	(0.017**)

Table 3.6: Goodness-of-fit diagnostics for the conditional one-day returns, conditioning on 5 technical indicators(and volume signals) for the sample of Nikkei 225

Pattern in Nikkei 225	**Decile:**										
	1	2	3	4	5	6	7	8	9	10	Q p-value
HS without volume signals	8.2	9.4	8.0	13.2	18.8	6.8	5.0	11.2	10.4	9.0	44.36
z-statistics	-0.47	-0.16	-0.52	0.83	2.29	-0.83	-1.30	0.31	0.10	-0.26	(0.000***)
HS with volume signals	12.4	15.4	9.6	16.0	9.1	4.1	9.2	7.1	9.1	8.0	32.25
z-statistics	1.05	1.81	-0.29	1.90	-0.40	-1.80	-0.22	-0.92	-0.40	-0.73	(0.000***)
IHS without volume signals	6.8	14.2	20.0	10.2	6.8	7.6	8.2	6.7	9.8	9.8	31.25
z-statistics	-0.76	1.01	2.38	0.05	-0.76	-0.58	-0.43	-0.80	-0.06	-0.06	(0.000***)
IHS with volume signals	20.9	12.9	5.8	9.9	6.4	11.9	2.1	11.0	4.1	15.0	42.59
z-statistics	2.52	1.29	-1.62	-0.20	-1.35	0.99	-2.10	0.48	-1.84	1.83	(0.000***)
RTop without volume signals	16.5	11.8	5.8	10.1	5.0	11.2	2.6	11.7	8.1	17.4	36.56
z-statistics	1.35	0.38	-0.89	0.02	-1.05	0.25	-1.54	0.35	-0.40	1.55	(0.000***)
RTop with volume signals	7.89	10.53	0	18.42	2.63	2.63	7.89	21.05	0	28.95	23.72
z-statistics	-0.21	0.05	-1.02	0.86	-0.75	-0.75	-0.21	1.12	-1.02	1.93	(0.000***)
DTop without volume signals	9.3	11.9	7.9	12.1	11.5	9.9	9.4	10.0	10.9	7.2	41.39
z-statistics	-0.42	1.16	-1.29	1.26	0.90	-0.06	-0.36	-0.00	0.56	-1.73	(0.000***)
DTop with volume signals	9.0	18.0	2.6	11.5	7.7	20.5	2.6	10.3	15.4	2.6	22.66
z-statistics	-0.16	1.23	-1.15	0.24	-0.36	1.62	-1.15	0.04	0.83	-1.15	(0.000***)
DBot without volume signals	8.9	9.1	14.3	8.7	8.6	8.2	10.4	12.0	10.5	9.5	31.66
z-statistics	-0.60	-0.50	2.28	-0.71	-0.73	-0.95	0.22	1.03	0.25	-0.28	(0.000***)
DBot with volume signals	7.5	8.3	22.6	1.5	7.5	6.8	9.0	12.0	13.6	11.3	20.78
z-statistics	-0.45	-0.31	2.27	-1.54	-0.45	-0.59	-0.18	0.37	0.64	0.23	(0.000***)

Table 3.7: Kolmogorov-Smirnov test of the equality of conditional and unconditional one-day return distributions

Markets	**Statistic**	**HS**	**IHS**	**RTop**	**DTop**	**DBot**
	γ without volume signal	0.28	0.05	0.18	0.71	0.178
Hang Seng Index	p-value	(0.000***)	(0.390)	(0.000***)	(0.294)	(0.000***)
	γ with volume signal	0.442	0.275	0.220	0.046	0.220
	p-value	(0.000***)	(0.000***)	(0.000***)	(0.000***)	(0.000***)
	γ without volume signal	0.06	0.14	0.51	0.03	0.03
Straits Time Index	p-value	(0.104)	(0.054*)	(0.068*)	(0.089*)	0.295
	γ with volume signal	0.17	0.18	0.26	0.09	0.05
	p-value	(0.042**)	(0.038**)	(0.003***)	(0.084*)	(0.000***)
	γ without volume signal	0.08	0.14	0.11	0.03	0.03
Nikkei 225	p-value	(0.062*)	(0.000***)	(0.000***)	(0.092*)	(0.277)
	γ with volume signal	0.10	0.03	0.13	0.05	0.11
	p-value	(0.000***)	(0.000***)	(0.000***)	(0.032**)	(0.068*)

3.5 Conclusions

In this chapter, I mainly evaluate the informational role of technical indicators and its auxiliary volume signals in the Asian markets, including the Hang Seng Index, the Straits Time Index, and the Nikkei 225 to support the validity of technical analysis, especially the role of volume signals in chart analysis. In order to mimic the visual judgement process, I adopt the PIPs methods to identify five popular technical indicators in 2600 observations in each market. It is found that the most commonly-seen indicators are the double tops/bottoms (but obviously the patterns that appear the most are the most unreliable patterns as well, as shown in our results), about 7 to 8 times the occurrences of the head and shoulders, and even 2-3 times the occurrences of the round top, which is similar to our daily perception of chart patterns. However, even technicians cannot rely solely on chart patterns, therefore, besides the identification of charts in price series, I introduce certain rules for further evaluation. In general, the results indicate that with the additional criteria of volume, 90% of the previous indicators can be ruled out.

After the identification of chart patterns and the introduction of volume signals, I apply χ^2 goodness-of-fit test (Eqs. (3.2) and (3.3)) and Kolmogorov-Smirnov test (Eqs.(3.4) and (3.5)) to compare the returns either conditional solely on chart patterns or on both the chart patterns and volume signals with the original unconditional returns. Our findings are as follows. (1) The statistics confirm the profitability of reversal patterns. In other words, our sample shows that the expected returns for the top patterns are negative, which indicates that the previous trend stops and the price drops sharply, vice versa. (2) In general, it is shown that in the χ^2 goodness-of-fit test, 13 out of 15 chart patterns are informative at the 5% significance level except the Double Bottom in the Hang Seng Index and Double Top in the Straits Time Index, which provide further empirical evidence for the chart analysis. (3) The importance of volume signals is implied in both χ^2 goodness-of-fit test and the Kolmogorov-Smirnov test. In the Kolmogorov-Smirnov test, all the chart patterns filtered by the criteria of volume in the three markets are significantly informative at 10% and more than half of remaining candidates are significantly informative at 1%.

Thus, in summary, our empirical study suggests that the chart analysis is informative in the Hang Seng market, the Straits Time market and the Nikkei 225 market. The usefulness of the chart patterns can also be improved by the introduction of volume signals, which has been somehow overlooked previously.

Chapter 4

Modelling the Price–volume Relations in Financial Markets

4.1 Introduction

Other than its simple interpretation as a liquidity proxy, speculators in real world have discovered the informational roles played by trading volume long time ago. For example, "It takes volume to make prices move," the famous Wall Street adage, reflects the positive correlation between volume and absolute value of price change. Fig. 4.1 shows a typical example of this positive relation, where the trading volume hit an unprecedented level while the price dropped down to a "bottom" in March 2009. Such a price–volume co-movement pattern has appeared frequently and repeatedly in historical series in various financial markets (for example, Black Monday in 1987). Another widely accepted price-volume relation is "volume tends to be heavy in the bull market but light in the bear market", which indicates a positive correlation between the trading volume and the price per se. Moreover, in the theory of technical analysis, volume signals, which is examined in Chapter 3, is one of the most important references for the timing of entry and exit. Only if the chartists observe a sudden increased trading volume can they confirm the breakout of the trend-line.

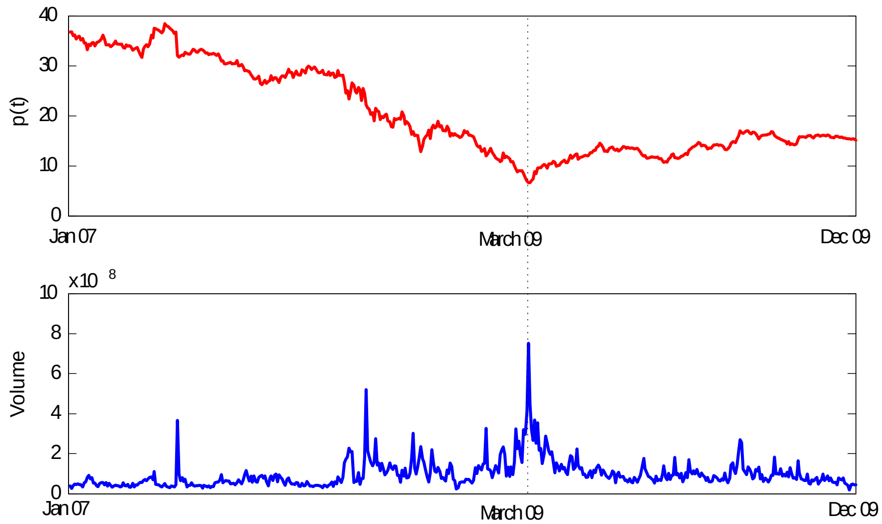

Figure 4.1: Price–volume series of GE (Jan. 1st, 2007- Dec. 31st, 2009)

All of the stated price–volume relations have been supported through a large number of empirical evidence since 1987, the year that Black Monday happened [1]. Researchers have investigated market indexes and individual stocks, chosen different time intervals, selected different combinations of stocks, used data from different time periods in different common stock markets or different future markets, and finally confirmed the existence of a positive correlation between price change per se and volume, and even stronger evidence for one between the trading volume and the absolute value of price change. Most importantly, Hiemstra and Jones (1994) proposes a nonparametric nonlinear Granger causality test and confirmed the nonlinear Granger causality in the price–volume relations in the U.S. market. The nonlinear causality relation between price and volume has subsequently been tested across different markets in numerous empirical studies[2]. Most of these studies are consistent

[1] Literature includes Crouch (1970a), Crouch (1970b), Epps (1975), Epps and Epps (1976), Morgan (1976), Westerfield (1977), Cornell (1981), Tauchen and Pitts (1983), Grammatikos and Saunders (1986), Harris and Gurel (1986), Gallant et al. (1992).

[2] e.g., Pisedtasalasai and Gunasekarage (2007) for South-East Asia emerging markets, Silvapulle and Choi (1999) for the South Korea stock market, GĺÍnduumlz and Hatemi-j (2005) for Central and Eastern European markets, and Saatcioglu and Starks (1998) for Latin America markets.

with the hypothesis that absolute value of the price change and trading volumes have the nonlinear Granger causality relations. Therefore, as Lo et al. (2000) argues, "It is difficult to dispute the potential value of price/volume charts when confronted with the visual evidence".

Theoretically, motivated by Ying (1966), who states that "any model of the stock market which separates prices from volume or vice versa will inevitably yield incomplete if not erroneous results," parallel theoretical studies are developed to explain these relations in the 1980s and 1990s. The first possible explanation is a "sequential arrival of information" model, given by Copeland (1976), and later improved by Jennings and Barry (1983). This pattern of information arrival produces a sequence of momentary equilibria consisting of various stock price–volume combinations before the final complete information equilibrium is achieved. The second explanation for the relations is the "mixture of distributions hypothesis model" derived by Epps (1975) and Epps and Epps (1976). Similar to the sequential information arrival model, Epps and Epps' model also build a particular framework on the way speculators receive and respond to information to justify the positive relation between the volume and the price change *per se.* Some other possible models have also been established, including that of tax and non-tax related motives in Lakonishok and Smidt (1989) and the noise trader model in De Long et al. (1990).

However, on one hand, previous theoretical literature cannot explain the price-volume relations without any external conditions. For instance, the main critique against the sequential information model pointed out its prohibition on short sale. Both the "sequential arrival of information" models and the "mixture of distributions hypothesis" models require external constraints on information. Moreover, Banerjee and Kremer (2010) can only explain the positive price–volume correlations when investors have infrequent but major disagreements.

On the other hand, HAM focusing on the interactions between different types of investors, became highly popular over the next two decades such as Beja and Goldman (1980), Day and Huang (1990), Chiarella et al. (2003), David (2008) and Mendel and Shleifer (2012).

However, most of the existing studies in heterogeneous beliefs focus on the price series, and little attention has been paid so far to the volume. One of the exceptions is Karpoff (1986). Heterogeneous agents with different personal valuations of the asset are introduced in the model and the results are consistent with some established empirical findings including the positive correlation between the absolute value of price change and trading volume. Later on, Chen and Liao (2005) attempt to use an agent-based stock markets model to determine the price–volume series and reproduce the presence of the nonlinear Granger causality relation between the price and volume. They examine the dynamic relations of price–volume on both a macro and a micro level. The results are mixed. Relations can be found in some results but not in others. Therefore, the conclusions of the simulation remain inconclusive. Meanwhile, the authors could not explain the existence of the price–volume relations in their results by the generic property of the financial market itself. Furthermore, Westerhoff (2005), Westerhoff (2006) also propose two HAM models, in which the chartists condition their orders on the price–volume signals.

The present chapter intends to justify the price–volume correlations from the economic perspectives of demand and supply. Following the market maker framework by Day and Huang (1990), two types of investors are examined: fundamentalists and chartists. Fundamentalists will buy/sell orders when the price is below/above the fundamental value. Chartists, instead, are essentially trend followers. Either due to incomplete information or due to a simple belief that the history repeats itself, they make trading decisions based on the investment values estimated from historical data. Interactions between these two types of traders, examined from a dynamic framework, enable us to generate price and volume associated simultaneously and to explore their correlations from an economic perspective.

This model is able to simulate all major features of the price-volume relations documented, which include

(i) a significant volume is accompanied by a large change in absolute value of price change;

(ii) the volume is heavy when the market is bullish and light when the market is bearish;

(iii) volume behaves in a specific pattern as an important signal in chart patterns.

The rest of chapter is organized as follows. In section 2, the model is described. section 3 presents our simulations, and section 4 explains the theoretical implications of the results given by the joint dynamics. section 5 is an extensive study on the positive relation of trading volume and price change *per se.* In section 6, I test the existence of bi-directional nonlinear Granger causality between the absolute value of price change and volume. The final section sets out the conclusion.

4.2 Model

4.2.1 Price Dynamics

In this chapter, the price dynamics is quite the same as Chapter 2. In brief, the demand function of fundamentalists would be as:

$$\alpha(p_t) = \begin{cases} (u_t^f - p_t) \cdot A(u_t^f, p_t), & \text{if } m \leq p_t \leq M. \\ 0, & \text{if } p_t < m \text{ or } p_t > M. \end{cases}, \tag{4.1}$$

where u_t^f is the fundamental value which increases steadily with the economic growth rate. The economic growth rate $g(t)$ is assumed to be

$$g(t) = \begin{cases} g, & t \in [(r(i-1)s, (ri-1)s) \\ -g/2, & t \in [(ri-1)s, ris] \end{cases}, \ i = 1, 2, 3, ..., n,$$

where s is a constant that determines the length of business cycle and r is the ratio between the length of the expansion and recession in each business cycle. Therefore, the fundamental value u_t^f increases steadily with the dynamics as

$$u_{t+1}^f = (1 + g(t)) \cdot u_t^f.$$

Besides, in Eq. (4.1), m_t and M_t are the minimum and maximum boundaries, respectively, of the price fluctuations set up by the fundamentalist and they are defined as below,

$$M = ku_t^f \qquad \mathit{and} \qquad m = \frac{1}{k}u_t^f.$$

Furthermore, in Eq. (4.1), $A(\cdot)$ is the chance function with respect to the fundamental value u_t^f and the current price p_t which can be depicted as

$$A(u_t^f, p_t) = a(p_t - m(u_t^f))^d (M(u_t^f) - p_t)^d,$$

Moreover, for chartists, the demand function is

$$\beta(p_t) = b \cdot (p_t - u_t^c), \text{ if } p_t \in [\mathbf{P}_{k-1}, \mathbf{P}_k), \tag{4.2}$$

in which, u_t^c is the investment value that is updated with adaptive beliefs as below.

At period t, if the initial price p_t locates at the kth regime $[\mathbf{P}_{k-1}, \mathbf{P}_k)$, the short-run investment value can be simply equal to the average of the top and the bottom threshold prices

$$u_t^c = (\mathbf{P}_{k-1} + \mathbf{P}_k)/2, \text{ if } p_t \in [\mathbf{P}_{k-1}, \mathbf{P}_k), k = 1, 2, ..., n.$$

After one-step price dynamics in period $t + 1$, there are two possibilities.

Case I If the current price p_t decreases to p_{t+1} insignificantly, remaining at the same regime, there are sufficient reasons for chartists to believe that the short-run investment value remains the same, that is,

$$u^c_{t+1} = u^c_t = (\mathbf{P}_{k-1} + \mathbf{P}_k)/2, \text{ if } p_{t+1} \in [\mathbf{P}_{k-1}, \mathbf{P}_k), k = 1, 2, ..., n.$$

Case II When the price in the current period p_t escapes from the original regime $[\mathbf{P}_{k-1}, \mathbf{P}_k)$ to a lower regime $[\mathbf{P}_{k-2}, \mathbf{P}_{k-1})$ or some even lower regimes, the "regime switching" appears In this condition, the chartist will believe that it is not simply the regular fluctuations but the change in the short-run fundamental value for the stock that leads to the jump in price.

$$u^c_{t+1} < u^c_t \text{ and } u^c_{t+1} = (\mathbf{P}_{k-2} + \mathbf{P}_{k-1})/2, \text{if } p_{t+1} \in [\mathbf{P}_{k-2}, \mathbf{P}_{k-1}), k = 1, 2, ..., n.$$

And again the market maker is introduced in the framework, which is specifically essential to this joint dynamics in that it makes nontrivial trading volume possible even when fundamentalists and chartists share the same prediction of future price movement[3]. Meanwhile, with the introduction of market maker, the phenomenon that liquidity and volume seem unrelated over time can also be easily-understood.

The price dynamics are therefore completed as a nonlinear process

$$p_{t+1} = p_t + \eta \cdot (\alpha(p_t) + \beta(p_t)), \tag{4.3}$$

where η is the speed of adjustment, measuring the adjustment speed of market maker according to the excess demand.

4.2.2 Volume Dynamics

Trading volume is defined as the number of shares or contracts traded in a security or in an entire market during a given period of time. More specifically the volume is commonly re-

[3] Consequently, we can avoid discussing the problems in Berrada et al. (2007).

ported as the number of shares changing hands during one day. To give a plausible definition of volume under the framework of market maker, two situations in the market are investigated. In the first case, fundamentalists and chartists share the same forecasting opinions about the future trend of the asset prices ($\alpha(p_t) \cdot \beta(p_t) > 0$). Both will trade with the market maker so the trading volume for the stock is the absolute value of the aggregate demand from fundamentalists and chartists. In this case, $V_t(p_t) = |\alpha(p_t) + \beta(p_t)|$.

However, according to Black (1986), fundamentalists are most likely to trade with the chartists, which indicates that they hold opposing opinions concerning the future price of the asset ($\alpha(p_t) \cdot \beta(p_t) < 0$). So in the second case, fundamentalists and chartists trade with each other first and the market maker will take up the excess demand (or supply) to obtain a liquid market. The volume in this case is equal to the maximum of the absolute value of the demand for each group[4], which implies $V_t(p_t) = \max(|\alpha(p_t)|, |\beta(p_t)|)$.

In summary, volume can be defined as

$$V_t(p_t) = \begin{cases} |\alpha(p_t) + \beta(p_t)|, & \text{if } \alpha(p_t) \cdot \beta(p_t) > 0, \\ \max(|\alpha(p_t)|, |\beta(p_t)|), & \text{if } \alpha(p_t) \cdot \beta(p_t) < 0. \end{cases} \tag{4.4}$$

4.3 Model Simulations

The price–volume signal is one of the tools widely adopted by technicians. By identifying specific signals to confirm the future trend, the technicians are able to determine the selling and buying signals. In this section, it is shown that the numerical simulations (the price series in the top panel and the volume series in the bottom panel) of our model can capture various price-volume relations. To demonstrate both the capability and the robustness of this heterogeneous agent model, more importantly, to preserve continuity and unity, I adopt

[4]Here, since trading volume records the number of shares transacted every day and there is always a seller for every buyer, one can think of the trading volume as half of the number of shares transacted. That is, if A sells 100 shares to B, the volume is still 100 shares. In this case, when the investors trade with each others, the transaction will be just recorded once.

the same default parameter set as in Chapter 2 ($u_1^f = 50, d_1 = d_2 = -0.3, k = 2, \lambda = 7.5, s = 25, a = 1, b = 2.25, \eta = 1, g = 0.0008, r = 4.$).

4.3.1 Visual Price–volume Comovements

The most well-known example of the positive relation between the absolute change of price and the magnitude of trading volume is the Black Monday of 1987 in the U.S. market. Fig. 4.2 provides a typical price–volume series generated from the default parameter set with $p_0 = 61.69$. In the figure, the dashed lines link the peaks or the bottoms in the price series to their corresponding volumes. The dotted line in the bottom panel indicates a certain warning level for the volume. It is inferred that when the volume hits a certain warning line of volume, the corresponding asset price is either in the peak or in the bottom.

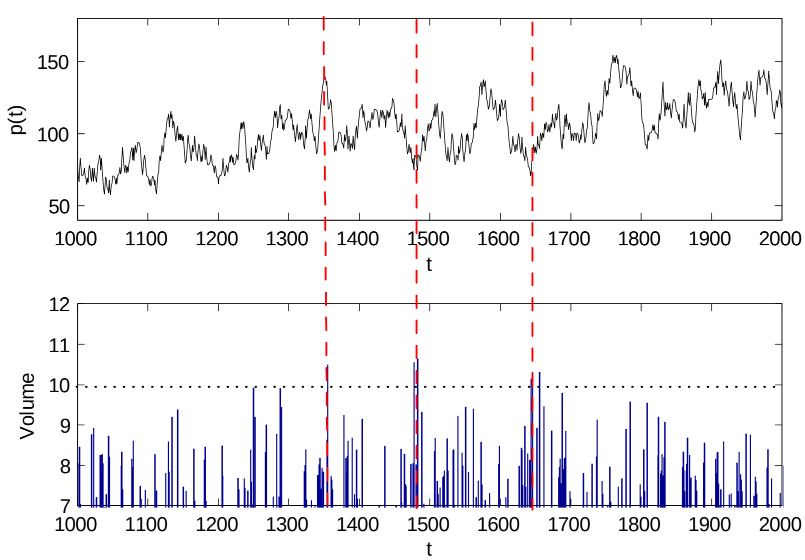

Figure 4.2: Positive correlation between price and volume.

4.3.2 Informational Role of Trading Volume on Asset Returns

Another illustration of the price–volume comovements is given in Fig. 4.3. In the figure, the dotted line links the breakout in the price series in the top panel to the corresponding volume in the bottom panel and the dashed line in the top panel indicates a resistance line based on long-term observation. In all the other periods, the volumes are around the level $V_t = 5$. However, when $t = 139, V_{139} = 19.22$, which is almost four times the daily average volume. Meanwhile, the corresponding price $p_{139} = 27.17$ also drops below the resistance line $p = 40$. This again confirms the price–volume comovements observed by practitioners in daily stock markets and confirms in particular the importance of volume as a tool to determine the break of the resistance line in technical analysis. Furthermore, Fig. 4.4 shows the relation between the asset returns ($r_t = (p_t - p_{t-1})/p_{t-1}$) and the trading volume. The series of asset returns apparently fluctuates around $r = 0$ randomly. In the period $t = 140$, r_{140} is equal to 0.71, an unprecedented high level as well, which means that the trading volume V_{139} does have the predicting power on the asset return r_{140}. Therefore, it shows that our model is able to capture the visual comovements between the absolute value of price change and the volume in our simulations.

4.3.3 Price–volume Signals in Chart Patterns

Chart patterns such as the head and shoulders and the double tops have been widely used by practitioners in the last century. However, because the identification of chart patterns is a purely visual-aid decision-making process, it has attracted criticisms from academics. Even the technicians themselves admit that not all the patterns work in the real market. As a result, technicians rely heavily on volume signal as the most essential criterion to help them to decide whether the patterns fail or complete successfully.

Although different technicians have different perceptions, the major signals of volume include:

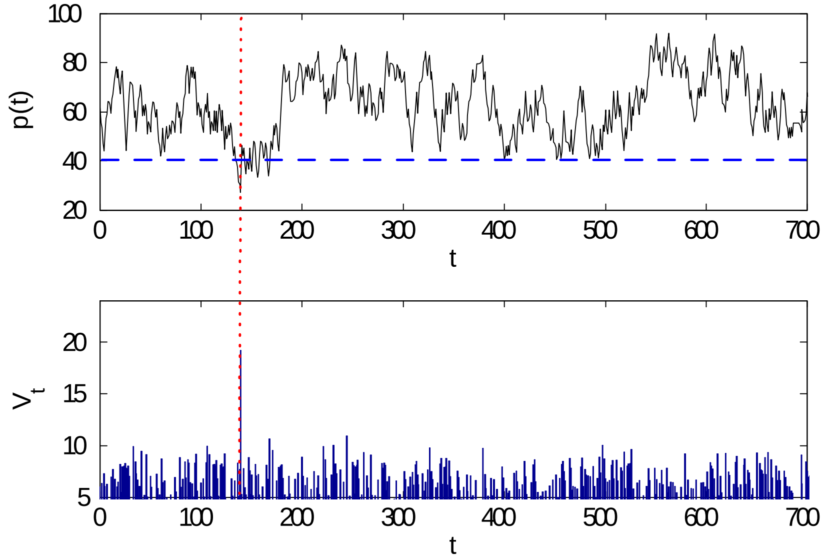

Figure 4.3: The volume signal on the breakout of resistance line.

- The corresponding volume of each peak during the patterns should be significant. This property is compatible with the price–volume comovements I showed above.

- The general trend of volume during the chart pattern should be downward, which indicates that the selling power (or the buying power) is weakening during the pattern.

- The volume is substantially increased when the price breaks the trend-line (such as the neckline in the head and shoulders bottom pattern). This property is the most meaningful signal required by technicians from the observation of trading volume. The most frequently asked questions of technicians include: When the head and shoulders bottom pattern appears to be complete? Will the price drop back below the trend-line again? Sometimes, the buying pressure is not sufficiently large to support a price increase above the trend-line. Therefore, only when the corresponding volume is substantially increased can the technicians confirm that the demand for the stock is very significant this time, which implies the validity of this breakout.

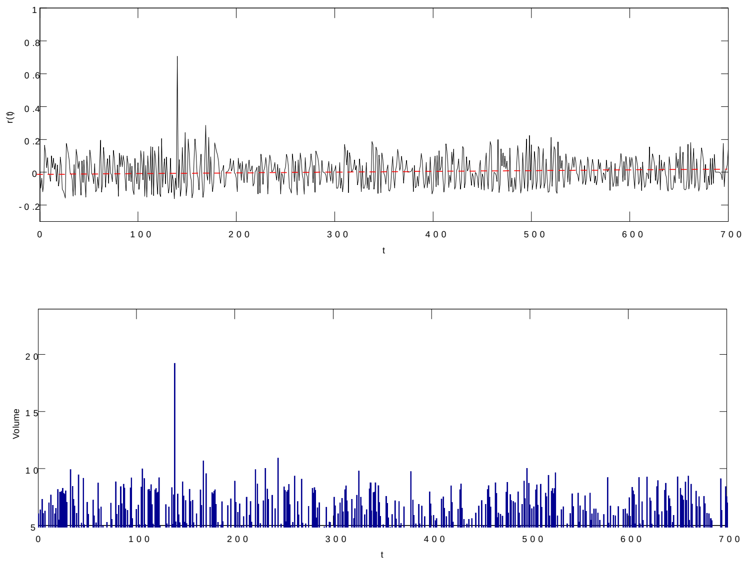

Figure 4.4: Corresponding relations between the asset price return and trading volume.

The following section demonstrates that this model is able to capture these behaviors of volume signals.

Volume Signals in the Head and Shoulders Pattern

In the time series shown in Fig. 4.5, a head and shoulders bottom pattern appears in the simulations when $p_0 = 61.69$ from $t = 700$ to $t = 800$. Bottoms appear including the left shoulder, the head and the right shoulder, from left to right. The volume series indicates the validity of the bottom as usual. The corresponding volume is significantly high in each bottom, and the volume trend is generally downward until the breakout. At the end of the bottom, the suddenly increased volume confirms the breakout of the neckline, that is, the imaginary line connecting the two rises between the shoulders and the head.

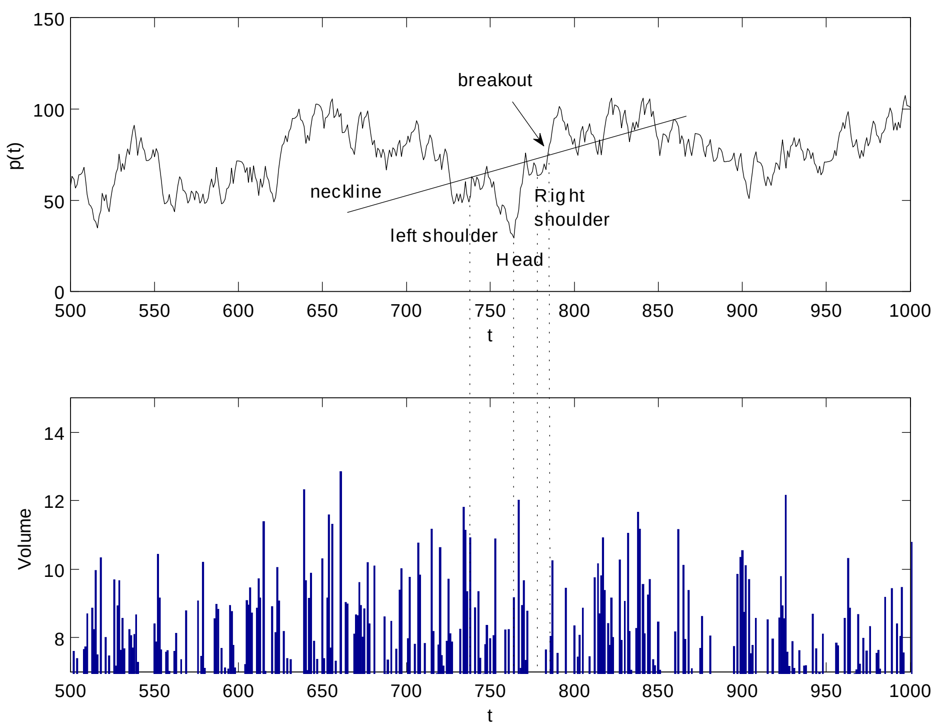

Figure 4.5: Price–volume signals in the head and shoulder pattern.

Volume Signals in the Double Bottoms and the Double Tops

Fig. 4.6 shows our simulations of the double bottoms pattern closely followed by a double tops when $p_0 = 61.62$. In both patterns, the trading volume of each peak is comparatively heavy. Among them, the highest volume occurs on the left bottom (top) and diminished volume appears on the right bottom (top). The volume trend is generally downward. Finally but most importantly, the breakout volumes in both patterns are very heavy.

4.4 Theoretical Implications

One of the advantages of using the HAM to simulate price and trading volume series is that I can determine both series simultaneously with the same simple market mechanism,

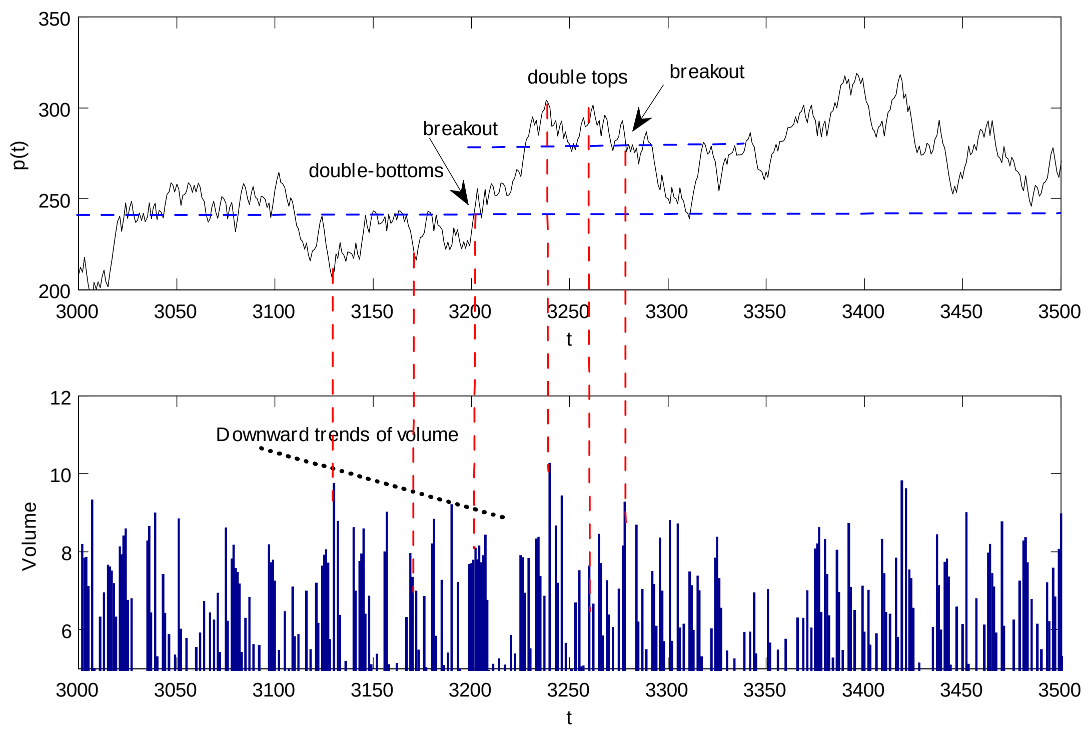

Figure 4.6: Price–volume signals in the double tops and double bottoms patterns.

the buying and selling pressures. Indeed, from the perspective of technicians, the price is not determined by its own value but by demand and supply from the market. Meanwhile, the trading volume is also closely determined by the demand and supply. Therefore, under the framework of this nonlinear dynamics, the price and volume is undoubtedly somehow correlated. This section explains the internal linkages between trading volume and the asset returns, such as the phenomenon in the financial market mentioned in Fig. 3.4 in Section 3.4.2.

For a plausible explanation for the informational role of volume, two conditions in Eq. (4.4) are examined separately.

Case I $V_t(p_t) = |\alpha(p_t) + \beta(p_t)|$ $(\alpha(p_t) \cdot \beta(p_t) > 0)$

It is the case that both the fundamentalist and the chartist agree on the future trend and either buy or sell the orders together Following from Eq. (4.3), the absolute price change thus can be simplified to $|r_{t+1}| = |p_{t+1} - p_t| = |c \cdot (\alpha(p_t) + \beta(p_t))| = c \cdot V_t(p_t)$. In other words, the absolute value of price change $|r_{t+1}|$ is proportional to the volume $V_t(p_t)$.

Case II $V_t(p_t) = \max(|\alpha(p_t)|, |\beta(p_t)|)$ $(\alpha(p) \cdot \beta(p) < 0)$

It is the case that the fundamentalist and the chartist disagree on the future trend of the price movement. In this case, a significant rise in volume would signal a large magnitude of either $|\alpha(p_t)|$ or $|\beta(p_t)|$. Based on Eq. (**??**) and Eq. (4.2), the divergence $|p_t - u_t^c|$ or $\left|p_t - u_t^f\right|$ is very large.[5]

To further explain this case, a phase diagram of our nonlinear price dynamics is provided in Fig. 4.7. In our deterministic model, the future price movement p_{t+1}, p_{t+2} is determined only by the current price p_t. For example, if one step-wise dynamics is considered, when p_t

[5] To explain this causality, we should understand that, in the second condition, when $|\beta(p_t)|$ is very large, according to Eq. (4.2), $|p_t - u_t^c| = |\beta(p_t)|/b$ is also very large. However, the first condition, when $|\alpha(p_t)|$ is very large, implies that either the chance function $A(\cdot)$ (see Appendix) or the divergence of current price p_t from the fundamental value u_t^f, or even both, are very large. In the other word, $A(\cdot)$ is also positively correlated to the divergence $\left|p_t - u_t^f\right|$. Therefore, we can conclude that, in both conditions, a large magnitude of the excess demand of each group implies a large divergence of $\left|p_t - u_t^f\right|$ or $|p_t - u_t^c|$.

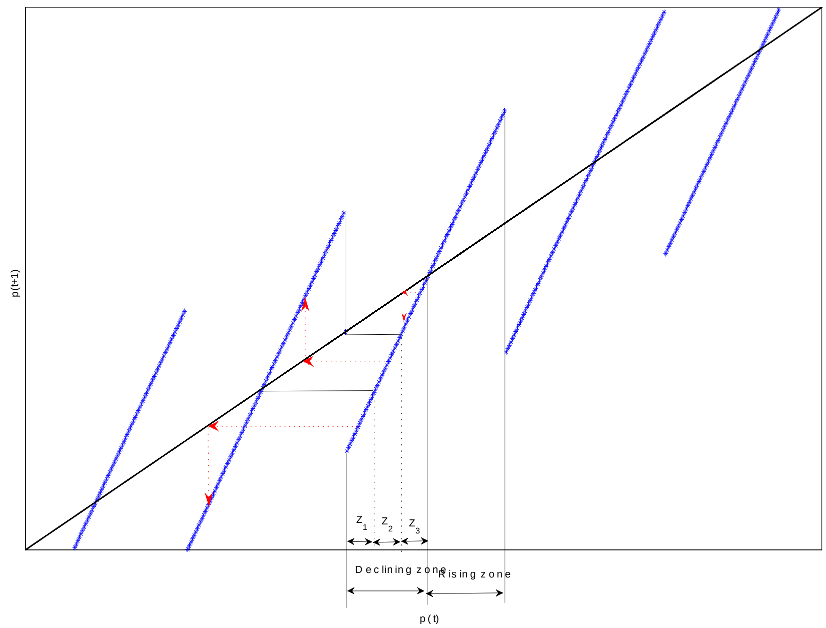

Figure 4.7: Illustration of sudden declining zone, disturbing declining zone and the smooth declining zone when the market cosists only of chartists.

falls above the 45° line, p_{t+1} will rise, and when p_t is below the 45° line, the price will decline accordingly. In this way, each exclusive sub-regime $[\mathbf{P}_{k-1}, \mathbf{P}_k)$ in the figure can be divided into two different zones: the rising zone and the declining zone. If I take the simplest scenario, that the market consists only of the chartists, as an example, the equilibrium $p_{t-1} = p_t$ (which is the intercept of the price dynamics and the 45° line) exists when $p_t = u_t^c$. The interval $(u_t^c, \mathbf{P}_{k+1})$ is the rising zone, and the interval $(\mathbf{P}_k, u_t^c)$ is the declining zone. Similarly, if two step-wise dynamics are considered in the declining zone, with different distances to the equilibrium, three different declines can be further classified as "the smooth decline," "the disturbing decline," and "the sudden decline."

The smooth declining zone, depicted as Z_3 in the figure, is very close to the equilibrium (which implies $|p_t - u_t^c|$ is very small). When p_t falls into Z_3, the one step-wise price p_{t+1} will decline and remains in the declining zones in the same regime, which implies that p_{t+2} will also decline.

The sudden declining zone, depicted as Z_1, is located around the bottom of the price regime (which implies $|p_t - u_t^c|$ is very large). When p_t falls into Z_1, the one step-wise will shift to the declining zone in lower regimes, which implies that p_{t+2} will also decline. In this scenario, the price will drop significantly across different regimes.

The disturbing declining zone, denoted Z_2, is the period between the smooth declining zone and the sudden declining zone. When p_t falls into Z_2, the one step-wise price p_{t+1} will decline to the rising zone of the lower regime, which implies that p_{t+2} will instead rise.

By assuming that the difference between u_t^c and u_t^f is not dramatic, it is reasonable to believe that the current price falls into the suddenly declining zone, by the implication of the large divergence between p_t and u_t^c (or u_t^f). Therefore, in both cases, our deterministic nonlinear dynamics with heterogeneous beliefs is able to provide sufficient evidence of the commonly seen price–volume comovements.

4.5 Higher (Lower) Volume in the Bull (Bear) Market

Another well-known saying regarding volume is, "the volume tends to be higher in the bull market and lower in the bear market." This relation between the trading volume and the price change *per se* is also widely accepted. Karpoff (1987) makes the point that it is not inconsistent that volume may correlate positively with both the absolute change of price or the price change *per se.* "It is likely that the V, Δp relation is not monotonic and the V, $|\Delta p|$ relation is not a one-one function."

In Section 4.2, to support the hypothesis that the interactions between heterogeneous agents may be the mechanism that jointly determines the price and volume series, we aim to establish a model that is as simple as possible and assumes that the population of each group of investors remains unchanged for all the periods. If the group size of investors is allowed to change from period to period, it can be verified that the volume is heavier (lighter) in bull (bear) market without any further assumptions.

The population of investors in a certain market is never unchanging. For private financing purposes, most ordinary households are also willing to speculate in the market, but they are not well trained and have no sophisticated strategies. As a result, they can only observe the market, entering the market when it is bullish to chase the trend, and exiting when it is bearish. On the other hand, fundamentalists, as professional fund managers, will not be influenced by the market fluctuations, so their population remains the same. Therefore, the population ratio of chartists to fundamentalists, denoted by D_t, is higher in a bull market and lower in a bear market. D_t is assumed to be a function of p_t only. In the decision-making process of chartists, when the price enters a new higher regime, not only is the short-run investment value u_t^c updated to a higher value, but the population also increases by a factor d, that is

$$D(p_t) = 1 + d \cdot \lfloor p_t/\lambda \rfloor, \tag{4.5}$$

where $d(d > 0)$ is a constant that measures the sensitivity of noise traders' willingness to enter the market based on the market price and λ measures the length of each regime[6] The demand function of chartists is modified as $\beta(p_t) = b \cdot D \cdot (p_t - u_t^c)$. In this way, I can replicate the behaviors that when the market is bullish, more chartists will be attracted into the market and more transactions will occur. Consequently the volume will be heavier.

To test whether the improvement in the model can help us to represent the relation between the trading volume and the bull (bear) market, I firstly divide the market conditions following Epps (1975), the upstick $\Delta p_t > 0$ implies the bull market and the downstick $\Delta p_t < 0$ implies the bear market. Secondly, I apply Monte Carlo tests to generate 100 initial values $p_1 \sim N(61.65, 0.05)$. The average volume for upticks and the average volume for downticks in each series are then calculated, and the mean of the average volumes in

[6] This implies that, if we assume the populations of the chartists and the fundamentalists are the same in the initial regime $(0, \lambda]$, in the following regime $(\lambda, 2\lambda]$, the population ratio of chartists to fundamentalists D is then $(1 + d)$. In this way, in the kth regime $((k-1)\lambda, k\lambda]$, the ratio D is $(1 + (k-1)d)$.

Table 4.1: Behaviors of trading volume when chartists can exit the market in bear market and enter the market when it is bull

d	$E(V_t)$ when $\Delta p_t > 0$	$E(V_t)$ when $\Delta p_t < 0$	p-value for rank-sum test
d=0	2.5638	2.4998	0.0000***
d=0.01	3.6608	3.5760	0.0000***
d=0.05	9.7150	9.6082	0.0108***

these 100 series is also obtained. The results show that, even under the original assumption that $d = 0$, our model is able to capture the generic property of the financial market, that the average trading volume for upticks significantly exceeds that for downticks, which is in accordance with the phenomenon we observe in the market. If the parameter D is introduced, the differences between the two indicators become even larger. In the second step, I apply the Wilcoxon rank-sum test to examine whether the difference between these two means is significant. The result clearly rejects the null hypothesis that the difference between the medians is equal to zero (the median difference is more significant when $d = 0$).

4.6 Nonlinear Granger Causality Test of the Price–volume Relation

Empirical studies failed to discover price–volume relations until Hiemstra and Jones (1994), which provide a nonlinear Granger causality test to investigate nonlinear relations between prices and trading volume. Since then, the nonlinear relation between price and volume has been proven in a variety of markets. Therefore, to further examine the validity of our model, this chapter uses the nonlinear Granger causality test to check whether there is significant evidence in our simulations for the existence of nonlinear price–volume relations.

4.6.1 Nonlinear Granger Causality Test

The nonlinear Granger causality test given by Hiemstra and Jones (1994) uses a nonparametric statistical method to uncover price–volume relations.

Consider two strictly stationary and weakly dependent time series $\{X_t\}$, $\{Y_t\}, t = 1, 2, 3, ...,$ where X_t^m is the m-length lead vector of X_t , and $X_{t-L_x}^{L_x}$ and $Y_{t-L_y}^{L_y}$ are the Lx-length and Ly-length lag vectors of X_t and Y_t respectively.

For given values of m, L_x, and $L_y \geq 1$, $e > 0$, Y does not strictly Granger-cause X if

$$\begin{aligned}\Pr(\|X_t^m - X_s^m\| < e \mid \left\|X_{t-L_x}^{L_x} - X_{s-L_x}^{L_x}\right\| < e, \left\|X_{t-L_y}^{L_y} - X_{s-L_y}^{L_y}\right\| < e) \\ = \Pr(\|X_t^m - X_s^m\| < e \mid \left\|X_{t-L_x}^{L_x} - X_{s-L_x}^{L_x}\right\| < e)\end{aligned} \tag{4.6}$$

where $\Pr(\cdot)$ denotes probability and $\|\cdot\|$ denotes the maximum norm.

The strict Granger noncausality condition in Eq. (4.6) can be expressed as

$$\frac{C1(m + L_x, L_y, e)}{C2(L_x, L_y, e)} = \frac{C3(m + L_x, e)}{C4(L_x, e)}, \tag{4.7}$$

where joint probabilities can be represented as

$$\begin{aligned}C1(m + L_x, L_y, e) &\equiv \Pr(\| X_{t-L_x}^{m+L_x} - X_{s-L_x}^{m+L_x} \|< e, \| Y_{t-L_y}^{L_y} - Y_{s-L_y}^{L_y} \|< e), \\ C2(L_x, L_y, e) &\equiv \Pr(\| X_{t-L_x}^{L_x} - X_{s-L_x}^{L_x} \|< e, \| Y_{t-L_y}^{L_y} - Y_{s-L_y}^{L_y} \|< e), \\ C3(m + L_x, e) &\equiv \Pr(\| X_{t-L_x}^{m+L_x} - X_{s-L_x}^{m+L_x} \|< e), C4(L_x, e) \equiv \Pr(\| X_{t-L_x}^{L_x} - X_{s-L_x}^{L_x} \|< e).\end{aligned}$$

By using the correlation-integral estimators to estimate the joint probabilities mentioned above, the null hypothesis for $\{Y_t\}$ strictly Granger-causing $\{X_t\}$ in Eq. (4.7) is

$$\sqrt{n}(\frac{C1(m + L_x, L_y, e, n)}{C2(L_x, L_y, e, n)} - \frac{C3(m + L_x, e, n)}{C4(L_x, e, n)}) \overset{a}{\sim} N(0, \sigma^2(m, L_x, L_y, e)). \tag{4.8}$$

Table 4.2: Nonlinear Granger causality test

$L_x = L_y$	H_0: ΔV Do Not Cause Δp			H_0: Δp Do Not Cause ΔV		
	CS	TVAL	p-value	CS	TVAL	p-value
1	0.2212	19.4902	0.0000	0.0387	3.3011	0.0004
2	0.2373	13.2561	0.0000	0.0784	3.8632	0.0000
3	0.2304	8.0993	0.0000	0.0537	1.4892	0.0682
4	0.2441	4.4353	0.0000	0.0970	1.3924	0.0817
5	0.3561	3.6677	0.0001	0.1168	0.9407	0.0734
6	0.4578	2.8371	0.0023	0.0833	1.4286	0.0334
7	0.6250	2.9589	0.0015	0.0875	2.8310	0.0023
8	0.6667	2.4520	0.0071	0.2857	1.5664	0.0944

4.6.2 Test Results

To test the nonlinear Granger causality between the price and the trading volume, linear VAR models are firstly applied on both the simulated price series and the corresponding volume series to remove any linear predictive power and obtain two estimated residual series $\{U_{p,t}\}$ and $\{U_{V,t}\}$. Secondly, the results from an Augmented Dickey–Fuller test indicate the existence of autocorrelation in both series, which suggests that I should take the differences until generating two stationary series. Following Hiemstra and Jones (1994), the lead length is set at $m = 1$ and $e = 1.5\sigma$, $\sigma = 1$. I use the time series from $t = 0$ to $t = 500$, $p_0 = 61.66$. The test results with different sets of L_x and L_y are presented in Table 4.2. The test statistics CS and TVAL here respectively denote the difference between the two conditional probabilities in Eq. (4.7) and the standardized test statistic in Eq. (4.8).

The results in Table 4.2 indicates the unidirectional nonlinear Granger causality from trading volume to stock returns under 1% level of significance. and the existence of nonlinear Granger causality in all circumstances under the level of significance of 10%. In this way, The results show that our numerical simulation can capture the nonlinear Granger causality between the price and volume.

4.7 Conclusions

In this chapter, a simple model with agents holding heterogeneous beliefs is constructed to replicate most of the characteristics of price–volume movements widely known by speculators. Under the framework of market makers, the model regards both price and volume as functions of demand (or supply) from fundamentalists and chartists. It shows, without imposing any external assumptions such as price distributions or risk preferences, that the interaction between heterogeneous agents is sufficient on its own to reflect most of the observed price–volume relations.

Our simulations are comprehensive on three different levels. Firstly, the generalized heterogeneous agent model is able to replicate satisfactorily the price–volume relations, both the trading volume with the absolute change of price and the trading volume with the price change itself. Secondly, since volume is highly valued by technicians, to provide the rationale behind the charting, price–volume signals in chart patterns are also successfully simulated. Thirdly, this model provides a persuasive explanation for volume signals on price changes by introducing the sudden decline zones, disturbing decline zones, and smooth decline zones.

Chapter 5

Conclusions

5.1 Contributions and Findings

Technical analysis is the most commonly used technical skills in the daily markets all over the world. But many academicians have criticized the technical analysis as "voodoo finance" due to the lack of theoretical support. However, many empirical studies have been found to prove the validity of technical analysis and they mostly attribute the sources of observed excess profits to either data snooping bias or self-fulfilling process.

However, the reason that it is very easy to catch on especially to those amateurish speculators cannot well explain its popularity for over two hundred years. It does not make sense to us so far may be just because we do not know about the internal mechanisms yet. Therefore, in this thesis, I replicate most of the visual patterns for price series and volume series and provide possible theoretical explanation by a heterogeneous agent model.

In summary, this thesis contributes to existing literature as below.

First, Chapter 2 and 4 propose the theoretical framework from the perspective of technicians, who believed that "Price actions are indeed determined by the shifts of supply and demand" and "History repeats itself". To better reflect these spirits, our theory is modelled based on interactions between heterogeneous agents and it is purely deterministic. It is shown

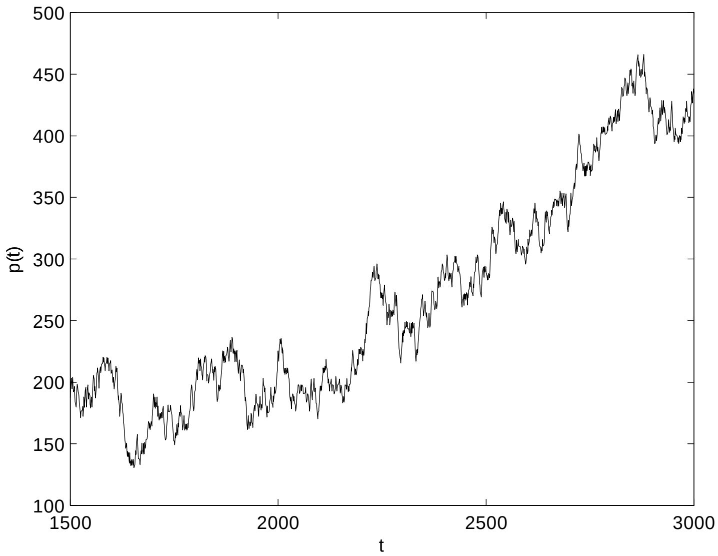

Figure 5.1: Simulations with white noise.

that this deterministic HAM are capable of replicating all the price chartings and most of the price–volume relations and justifying the hidden factors that dominates the price trends and the corresponding volume signals by our deterministic framework. But admittedly, by adding the stochastic process into the dynamics can help us to replicate the unpredictable fluctuations in the financial time series as illustrated in Fig. 5.1[1].

Second, I establish a model as simple as possible. To discover what is the most dominant power that determines the chart patterns, I avoid using many parameters like risk tolerance or discount rate for different asset holding time. It is inferred from past literature that, the seemingly complex price and volume patterns can be duplicated and main stylized facts in financial markets can be captured by such a simple set-up, other parameters that may fit the model into more sensitive and flexible conditions in the reality may not have significant influences on the price patterns themselves.

Third, our thesis targets the most controversial technical indicators—-chart patterns in price and volume series as objectives. It is a purely human visual identification process,

[1] We gratefully thank Prof. He Xuezhong for pointing this out.

which makes it very difficult to be quantitatively measured as a trading strategy. As a result, compared to other technical skills, very few literature has shed lights on this topic. Analyses in Chapter 2 demonstrate that these seemingly unreasonable strategies based on subjective observations can be interpreted properly. And empirical results in Chapter 3 suggests the possible reason why previous empirical studies achieve inconsistent conclusions on the profitability of chart patterns is that the examined price series is separated from the volume series.

Fourth, inspired by Chapter 3, Chapter 4 adopts the same mechanism in Chapter 2, to determine the price and volume series simultaneously by the selling and buying pressures. It self-explanatorily illustrates the nonlinear Granger causality relations discovered between the price and volume series. It demonstrates, that I am capable of replicating not only the behaviors of volume signals corresponding to the chart patterns, but also the positive correlations between the absolute value of price change and the volume and the positive correlations between the price change *per se* and the volume.

Overall, I investigate the chart patterns and volume series by a heterogeneous agent model, which are neglected in so many years. All the evidence in this thesis is conveying two messages, (1) it provides solid supports to the hypothesis that the seemingly chaotic fluctuations can be dominated by a deterministic nonlinear dynamics (2) further justifications are offered to the technical analysis, especially the visual price patterns and volume signals.

5.2 Extensions and Future Research

Further exploration could also be made in following aspects.

First, to develop a very simple model to simulate all the targeting behaviors of price series and volume series, models in Chapter 2 and Chapter 4 impose strict assumptions in our set-ups. For example, the size of each group is assumed to be a constant and each part takes half of the market. It implies that any new investor is not allowed to participate the financial market and the players are assumed to take a specific strategy due to its nature. They cannot switch their strategies according to their own willingness. Therefore, to further explore the possible simulation power, we could release these assumptions subject to specific cases.

Second, in this model, the technician is simplified as the trend follower and follow a simple adaptive belief. However, it would be interesting if we could allow the chartists to apply the chart patterns' strategies stated in this studies or even the volume signals to determine their demands and supplies and test the self-fulfilling power of the volume signals (see Westerhoff (2005) and Westerhoff (2006)).

Third, regarding to the decision-making process, whether the fundamentalists are able to beat the chartists at making a profit is always an interesting topic. According to the EMH, the chartists should be the ultimate losers and exit the market. However, is it necessarily so? Our simple heterogeneous agent model may be useful in answering this question.

Last but not the least, since it has been proved that HAMs can be powerful to duplicate multiple financial crises, various chart patterns and volume signals, still plenty of untouched areas in technical analysis can be further investigated, especially those visual aids tools. Take Elliot Wave theory as example. Elliot Wave theory, a complicated derivation of support/resistance line, is also wide-applied in the reality. Different from chart patterns, mainly focus on the short-run to mid-term price fluctuations, Elliot Wave theory is considered to be capable of analyzing price trends of all time scope. Therefore, it is believed that this HAMs can also be applied to study the behaviors of Elliot Waves.

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