TECHNICAL PATTERNS AND STOCHASTIC PROPERTIES OF ASSET RETURNS

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This study investigates the empirical evidence for the profitability of the chart patterns used widely by practitioners to identify market trend movements. The results show that for a certain group of traders, trading strategies based on the patterns identified in the stock market can generate abnormal returns after correcting for the three Fama-French factors. Further, it shows that the standard econometric and mathematical finance models used to simulate stock returns cannot capture the full complexity of the true market data generating process. The analysis also demonstrates that the stochastic volatility model proposed by Heston does provide improved performance and does explain a substantial part of the abnormal returns. This is accomplished by simulating more complex volatility innovation structures and describing the market dynamics more accurately.

BIOGRAPHICAL SKETCH

Shawn (Xianzheng) Kong was born in Nanjing, China and lived in that beautiful garden city for eighteen years. He is his parents' only child. After high school in Nanjing, he went to Beijing, the capital of China, to pursue his college studies in business at Renmin University of China, which is consistently ranked at the top in social sciences in China. At Renmin University, Shawn pursued studies in statistics, business and economics.

During his college studies, Shawn was enchanted by the ability of economic science to explain various puzzles in the business world and society. After completing his bachelor's degree, he was awarded a scholarship to attend Boston College to pursue a master's degree in economics. After completion of the master's degree, Shawn decided to enhance his research background by pursuing doctoral study in the Ph.D. program at the Dyson School of Applied Economics and Management at Cornell University. Cornell is located in Ithaca, New York, which is a city as beautiful as his hometown. At Cornell, Shawn pursued in-depth studies in economics and finance and gradually developed his research interests to combine academic research with financial industry practice.

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CHAPTER 1

INTRODUCTION

The Market Technicians Association defines technical analysis as a method of evaluating securities by analyzing statistics generated by market activity. Since the development of modern technical analysis by Charles Dow in the late nineteenth century, it has been widely used by various market participants to forecast the market. However, in academia, technical analysis often receives unflattering criticism. As Samuelson (1965) commented:

There is no way of making an expected profit by extrapolating past changes in the futures price, by chart or any other esoteric devices of magic or mathematics. The market quotation already contains in itself all that can be known about the future and in that sense has discounted future contingencies as much as is humanly possible.

However, later research indicated that this comment might be premature. Hundreds of empirical studies have been published to investigate the profitability of technical analysis, but the results have been mixed. Several papers have analyzed and discovered the profitability of various technical analysis methods including filter rules (Alexander (1961); Stevenson and Bear (1970) and Sweeney (1986)), moving average (Brock, Lakonishok & LeBaron (1992); Sapp (2004)), price channel (Lukac, Brorsen, &

Irwin (1988)), relative value strength (Goodacre, Bosher & Dove (1999)) and genetic programming (Allen & Karjalainen(1999)) etc.

This study makes two contributions to the existing research on technical analysis.

First, it provides the most comprehensive profitability analysis of chart patterns, one of the most important, but also difficult to program technical analysis methods. We show that most of the patterns generate abnormal profits for several days after they close. These profits cannot be fully explained by the transaction cost level. We also design a portfolio trading strategy to show that some alpha remains even after we control the Fama-French risk factors.

Although many technical analysis methods have been programmed and tested systematically in the literature and have been studied carefully for many years, empirical studies of chart patterns were not studied systematically until recently due to the difficulty in implementing computer-automated graphic recognition.

However, these chart patterns are important pillars of technical analysis theory, as they are traditionally considered to represent the turning point of the price trend. As Edwards and Magee (1991) stated,

In most cases, when a price trend is in the process of Reversal, either from up to down or from down to up, a characteristic area or 'pattern' takes shape on the chart, becomes recognizable as a Reversal Formation."

One advantage of chart patterns is that they help mitigate data-snooping biases, which is a well-known weakness of many technical analysis methods, such as moving average crossover, momentum and Alexander's filter. Chart patterns have much less flexibility in terms of parameter selection. Only one smoothing parameter is required to make the smoothed price graph similar to that of chartists. Only a very narrow range of the smoothing parameter values can satisfy this requirement. In contrast, thousands of possible parameter combinations exist in the moving average crossover method, making it vulnerable to data-snooping concerns.

In addition, the survivorship bias of the chart patterns is mitigated by using the definition of these patterns used in the early version of the most influential technical analysis textbooks published before our data sample (Edwards and Magee, 1991).

Chart patterns can also be compatible with buy-and-hold strategies. When using moving average crossover strategies, traders take a long position whenever a short-horizon moving average is higher than a long-horizon moving average. Conversely, they take a short position whenever the short-horizon moving average is lower than the long-horizon moving average. These strategies provide long/short guidance for each day, so it is impossible to combine them with a buy-and-hold strategy. In contrast, chart pattern rules advocate zero positions when the patterns are absent, which presents the possibility of combining them with a buy-and-hold strategy. Thus, chart patterns can be used by both speculative short-term traders and long-term investors, who can reduce their positions when the chart patterns indicate a downward signal.

A few previous studies have investigated some specific chart patterns. Chang and Osler (1999) analyzed the profitability of head-and-shoulders patterns on six foreign exchange markets and found significant profit in the yen and mark. Lo, Mamaysky, and Wang (2000) applied kernel smoothing techniques to better identify recognition skills and further prove the information content of the chart patterns. However, three important issues limit the utility of their methods. First, as Jegadeesh (2000) pointed out, the profitability of the chart patterns is not calculated. Second, the kernel-smoothing methods need right-side information, so the one-day return abnormalities found were not valid. Third, the only bootstrap test Lo et al. (2000) provided was a random walk model. Therefore, the possibility that the abnormal return could have been generated by more complex, but known, market data-generating patterns, is omitted. Our study addresses the above issues and makes a comprehensive profitability analysis for chart patterns.

Our second contribution is that we incorporated stochastic volatility models in bootstrap analysis of technical analysis profitability. To the author's knowledge, this research is the first attempt to use the stochastic volatility method with the bootstrap method to assess the profitability of technical analysis. In this study, we investigate whether bootstrapping the stochastic volatility models, compared with other widely used market models can generate similar technical patterns and provide good explanations for the abnormal returns found. The stochastic volatility model explicitly incorporates the effect of volatility on the change in the variance process as well as the correlation between the price innovation and the volatility innovation. In other words, it models the volatility of volatility. In addition, it uses implied volatility, which is considered by Poon and Granger (2003) as a better proxy for volatility forecast than historical volatility. We find this structure successfully captures more of the market dynamics than widely used financial econometrics models.

The inspiration for this topic draws from the development of the stochastic volatility models in financial mathematics. These models have become popular for derivative pricing and hedging in the last twenty years as the existence of a non-flat implied volatility surface has been noticed and become more pronounced. The stochastic volatility models provide rich volatility structures that may explain the abnormal returns generated by technical patterns.

Neither the use of the bootstrap methodology to evaluate technical analysis in the finance literature nor the stochastic volatility models in the mathematical finance literature is particularly new. The contribution of this paper lies in the combination of these two techniques. In the stochastic volatility models, two new structures are incorporated in the data-generating process: the effect of the volatility on the change in the variance process (volatility of volatility) and the correlation between price innovation and volatility innovation. It would be interesting to determine whether the simulations based on this richer structure increase the chance of beating the patterns in the original market data.

Before introducing our methodology in Chapter II, we first review the origins and the key developments in general technical analysis profitability analysis.

At the very beginning, instead of testing the profitability of technical analysis directly, researchers tackled this issue by examining the auto-correlation of returns, the classic work was performed by Kendall and Hill (1953). They found that with few exceptions each period's price change was not significantly correlated with the preceding period's price change or with the price change of any earlier period. They concluded that the knowledge of past price changes yields no substantial information about future price changes. However, as Fama and Blume (1966) argued, the simple linear relationships that underlie the serial correlation model were not able to detect the complicated patterns that chartists perceived in market prices. Fama (1970) further suggested that "there are types of nonlinear dependence that imply the existence of profitable trading systems, and yet do not imply nonzero serial covariances. Thus, it is desirable to directly test the profitability of various trading rules. In addition, transaction cost and risk are difficult to incorporate into statistical analysis." All of these factors moved researchers' focus to testing technical analysis profitability directly.

Alexander (1961) offered the earliest influential empirical paper on the profitability of technical trading rules. He argued that financial market trends are masked by small random shocks and, if movements smaller than a specified size are filtered, the trend will be observable and profitable. He designed a simple trend-following strategy to buy after the price moves up x% and sell after the subsequent high minus x%. He found that these filter rules generated larger gross profits than the buy-and-hold strategy. For example, the best performing trades, using a 15% and 20% filter, generated 8.9% and 11.3% profit per trade. These profits are not likely to be explained by commissions.

However, Mandelbrot (1963) found that Alexander's filter rules failed to account for price jumps and exaggerated profit. Fama and Blume (1966) further tested Alexander's filter rules on the daily closing prices of 30 individual securities in the Dow Jones Industrial Average for 1956-1962. They found that after taking into account commissions, only 4 of the 30 securities had positive average returns per filter.

In contrast to the stock market, Stevenson and Bear (1970) and Sweeney (1986) showed that strategies similar to those Alexander used generate excess return in the commodities futures market and foreign exchange rates market after cost. The strategies not only significantly outperformed the buy-and-hold strategy but were also robust after the capital asset pricing model was taken into account.

During the same time, many theories were proposed to explain the abnormal returns generated by technical analysis. Working (1949) argued that market information is ambiguous or comes in pieces, so prices change gradually and form a trend. Treynor and Ferguson (1985) established a model under which an informed trader can use past price information to estimate whether current information is already incorporated in the price. De Long (1990a, 1990b, 1991) proposed that if the noise is very strong, the best choice for a rational arbitrager would be to follow what the irrational traders do instead of going against them.

On the empirical side, with the development of new mathematical tools and the use of computers, Brock, Lakonishok, and LeBaron (1992) introduced the bootstrap method within the technical profitability analysis. They implemented model-based bootstrap methods (moving average-oscillator and a trading range breakout) for making statistical inferences about technical trading profits. They analyzed 26 technical trading rules using 90 years of daily stock prices data from the Dow Jones Industrial Average and found that they all outperformed the market.

The remaining four chapters of this thesis are organized as follows: Chapter 2 describes the methodology of pattern recognition. Chapter 3 studies the profitability of the trading strategies and analyzes the cost. Chapter 4 presents the bootstrap simulation results of the financial econometrics models, describes the stochastic volatility model and its bootstrap simulation results. Chapter 5 summarizes the essay.

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CHAPTER 2

METHODOLOGY

2.1 Introduction

The patterns tested here include the most popular charts in standard technical analysis textbooks for the Chartered Market Technician (CMT) qualification (Edwards and Magee, 1991, chs. 6-9; Murphy, 1999, chs. 5-6). These include head and shoulders, inverse head and shoulders, triangle tops and bottoms, rectangle tops and bottoms, as well as broadening tops and bottoms. According to Edwards and Magee (1991), these patterns have been widely used since at least the 1920s. Aronson (2007) also describes these chart patterns as the pillar of technical analysis.

To obtain an intuitive understanding of a technical pattern, the graph created by Edwards and Magee (1991) is presented in Figure 1. This figure illustrates a chart with a head-and-shoulder pattern.

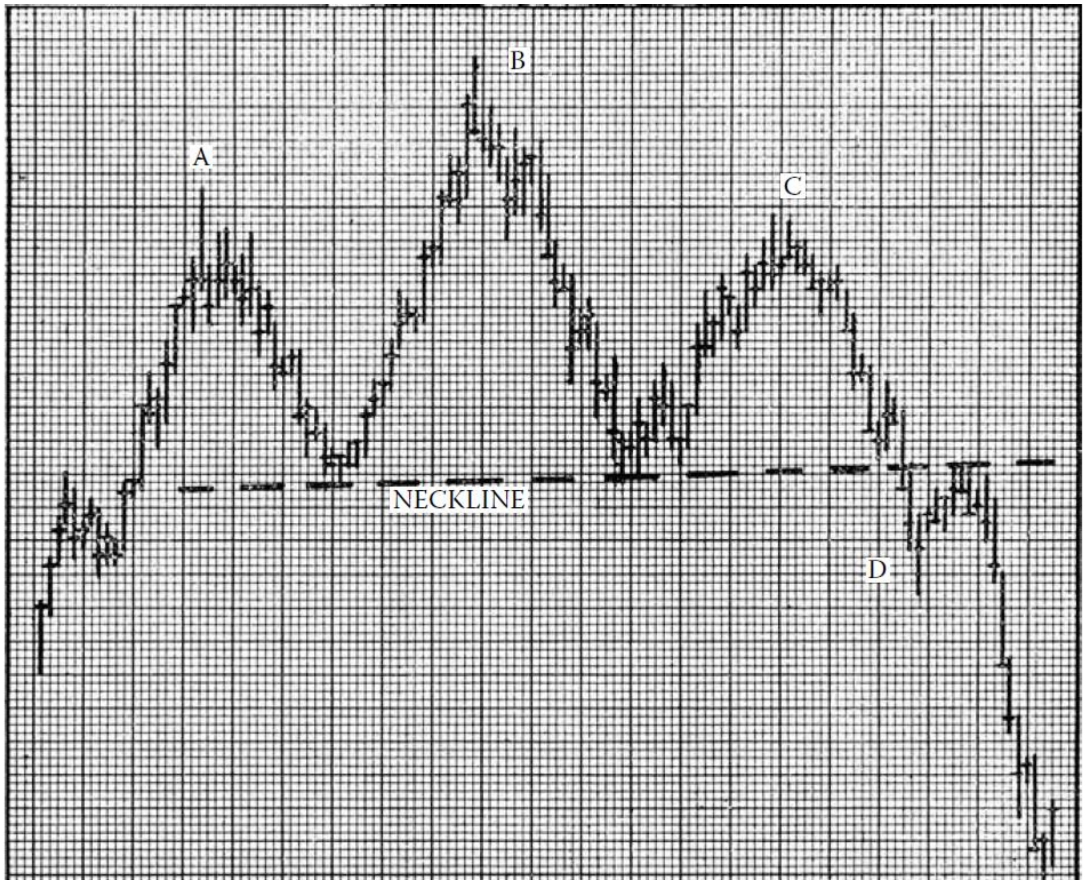

Figure 1: Head-and-Shoulders Pattern

Visually this pattern is formed by three maximums A, B, C, the two local minimums between them that form the neckline, and the breakout D. To use a computer to identify this pattern in a time series, we need to identify all of these five extremes and a smoothed method is required to eliminate the small zigzags in the price graph.

Three steps are needed to construct an algorithm to automate pattern detection and to make the trading decision:

1. Smooth the original price-time series to eliminate noise for pattern recognition. A new time series $\hat{P}_t$ will be constructed from the original time series P_t so that the noise can be eliminated before searching for the extremes that construct the pattern.
2. Define patterns by their geometric properties illustrated by the technical analysis classics. A series of local extremes E_i from the smoothed time series $\hat{P}_t$ must be identified and used to construct the pattern.
3. Specify the trading strategy, including entry, filtering and exit methods.

2.2 Smoothing

As we have seen in Figure 1, the patterns can be recognized as a combination of large local maximums and minimums. However, the original data contain so many local maximums and minimums that, in practice, most people need to use their eyes to filter "whiplash" signals. Taking this into consideration, Lo, Mamaysky, and Wang (2000) used the kernel-smoothing method to smooth the tiny zigzags. However, this method implicitly uses information that cannot be observed at decision time. Not only is it not a feasible method for decision makers at the time of pattern breaks, but it may also be a contributor to the abnormal empirical distribution of return as discovered in their paper. To overcome these drawbacks, this paper uses exponential moving average methods on daily close price, which only use information before the decision time, to smooth the price time series and, thus, provide a feasible estimate at the entry/exit time. The formula for constructing the exponential moving average is as follows:

$$\hat{P}_t = \begin{cases} P_t & t = 1 \\ \alpha P_{t-1} + (1-\alpha)\hat{P}_{t-1} & t > 1 \end{cases} \tag{1}$$

Several methods can be used to choose the smoothing parameter α. Among them, according to Hardle (1990), the most popular one is the cross-validation method in which α is chosen to minimize the cross-validation function:

$$\min_{\alpha} \frac{1}{T} \sum_{t=1}^{T} (P_t - \hat{P}_{t,\alpha})^2 \tag{2}$$

This function provides a measure of the ability of the estimator to fit each observation P_t. By selecting the smoothing parameter that minimizes this function, we obtain an estimator that minimizes the asymptotic mean-square error. We also made a comparison with the kernel smoothing method and the results are similar so it is not included here. The results are available upon request.

2.3 Pattern Recognition

The automated pattern recognition program used to recognize the technical patterns includes the relative position of five critical points in the price graph of $\hat{P}_t$. For the head-and-shoulders pattern in the graph, we need three local maximums, with the middle maximum (point B) higher than the left (point A) and right (point C) maximums, while the left and right maximums are at similar levels (within 1.5% of their average). We also need two local minimums, again at similar levels, that form the neckline shown in the graph. To make the notation consistent, I use E_1, E_3, and E_5 to represent the local maximums A, B, and C in Figure 1 and E_2 and E_4 to refer to the local minimums. Thus, the body of the pattern is formed by five consecutive local extremes.

The neckline E_2E_4 is also important since after the pattern body is formed we wait for the downside penetration of the neckline to complete the pattern and take position. This is the typical method, as specified in Edwards and Magee (1991). In some cases, the price does not move in the direction indicated by the technical analysis; in such a case, it does not form a valid chart pattern and no indication of direction can be inferred from the incomplete pattern. These incomplete patterns are not included in my samples.

Definition 1: Head and Shoulders

Formally, the head-and-shoulders pattern is characterized by a sequence of five consecutive local extremes E_1 to E_5 such that

$$\text{Head and Shoulders} \equiv \begin{cases} E_1, E_3, \text{ and } E_5 \text{ are local maximums} \\ E_2 \text{ and } E_4 \text{ are local minimums} \\ E_1 < E_3, \quad E_3 > E_5 \\ E_1 \text{ and } E_5 \text{ are within } 1.5\% \text{ of their average} \\ E_2 \text{ and } E_4 \text{ are within } 1.5\% \text{ of their average} \end{cases}$$

The inverse head-and-shoulders pattern is the mirror image of the head-and-shoulders pattern and it can be similarly defined as follows:

$$\text{Inverse Head and Shoulders} \equiv \begin{cases} E_1, E_3, \textit{and } E_5 \textit{are local minimums} \\ E_2 \textit{ and } E_4 \textit{are local maximums} \\ E_1 > E_3, \;\; E_3 < E_5 \\ E_1 \textit{ and } E_5 \textit{ are within } 1.5\% \textit{ of their average} \\ E_2 \textit{ and } E_4 \textit{ are within } 1.5\% \textit{ of their average} \end{cases}$$

Similarly, the bodies of other chart patterns in Edwards and Magee (1991) can be characterized by the five consecutive local extremes.

Definition 2: Triangle

The geometric characteristic of triangle patterns can be specified as the shrinking trading range, which requires lower and lower maximums and larger and larger minimums. Thus, it can be represented by a sequence of five consecutive local extremes such that

$$\text{Triangle Top} \equiv \begin{cases} E_1, E_3, \textit{and } E_5 \textit{are local maximums} \\ E_2 \textit{ and } E_4 \textit{are local minimums} \\ E_1 > E_3 > E_5 \\ E_2 < E_4 \end{cases}$$

The triangle bottom pattern is the reverse:

$$\text{Triangle Bottom} \equiv \begin{cases} E_1, E_3, \text{and } E_5 \text{ are local minimums} \\ E_2 \text{ and } E_4 \text{ are local maximums} \\ E_1 < E_3 < E_5 \\ E_2 > E_4 \end{cases}$$

Definition 3: Rectangle

In a rectangle pattern, the security is traded in a narrow range until it breaks out. It is formed by three tops and two bottoms. Tops are at approximately the same level (within 0.75% of their average), and bottoms are also at approximately the same level (within 0.75% of their average).

$$\text{Rectangle Top} \equiv \begin{cases} E_1, E_3, \text{and } E_5 \text{ are local maximums} \\ E_2 \text{ and } E_4 \text{ are local minimums} \\ E_1, E_3, \text{and } E_5 \text{ are within } 0.75\% \text{ of their average} \\ E_2 \text{ and } E_4 \text{ are within } 0.75\ \% \text{ of their average} \end{cases}$$

$$\text{Rectangle Bottom} \equiv \begin{cases} E_1, E_3, \text{and } E_5 \text{ are local minimums} \\ E_2 \text{ and } E_4 \text{ are local maximums} \\ E_1, E_3, \text{and } E_5 \text{ are within } 0.75\% \text{ of their average} \\ E_2 \text{ and } E_4 \text{ are within } 0.75\% \text{ of their average} \end{cases}$$

Definition 4: Broadening

A broadening pattern shows that the amplitude of market movements gradually increases. To fulfill the geographic characteristic, for the broadening top pattern the consecutive five extremes must satisfy the conditions $E_5 > E_3 > E_1$ and $E_2 > E_4$ while the bottom pattern indicates the reverse.

$$\text{Broadening Top} \equiv \begin{cases} E_1, E_3, \text{ and } E_5 \text{ are local maximums} \\ E_2 \text{ and } E_4 \text{ are local minimums} \\ E_1 < E_3 < E_5 \\ E_2 > E_4 \end{cases}$$

$$\text{Broadening Bottom} \equiv \begin{cases} E_1, E_3, \text{ and } E_5 \text{ are local minimums} \\ E_2 \text{ and } E_4 \text{ are local maximums} \\ E_1 > E_3 > E_5 \\ E_2 < E_4 \end{cases}$$

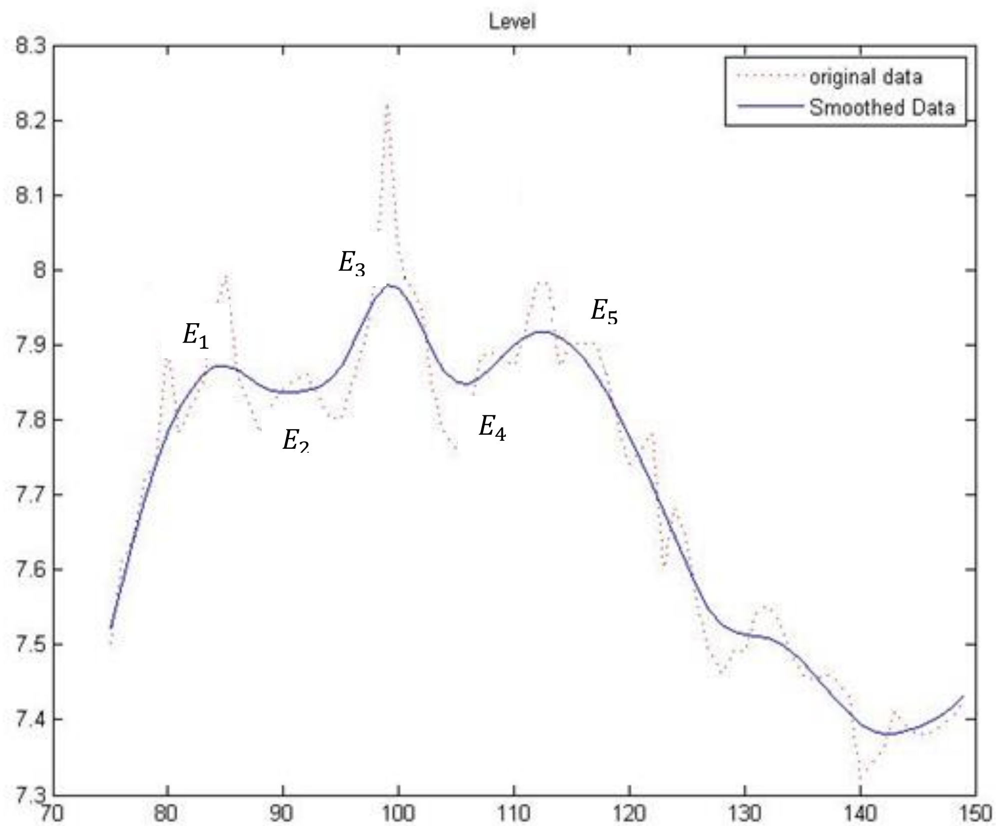

Figure 2: Head-and-Shoulders

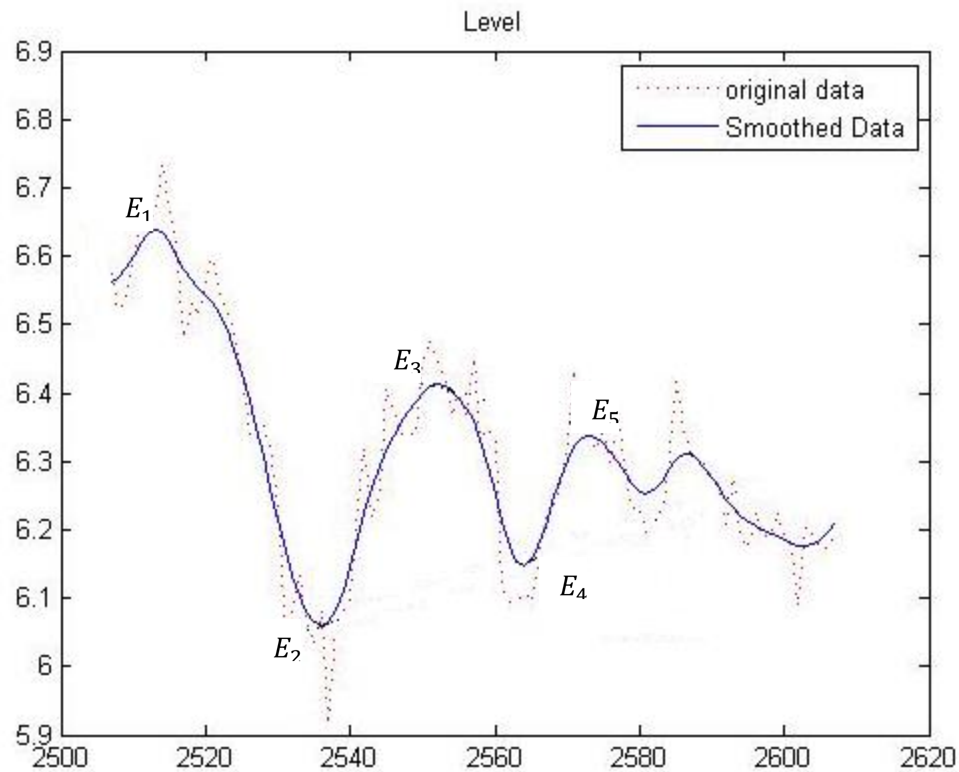

Figure 3: Triangles

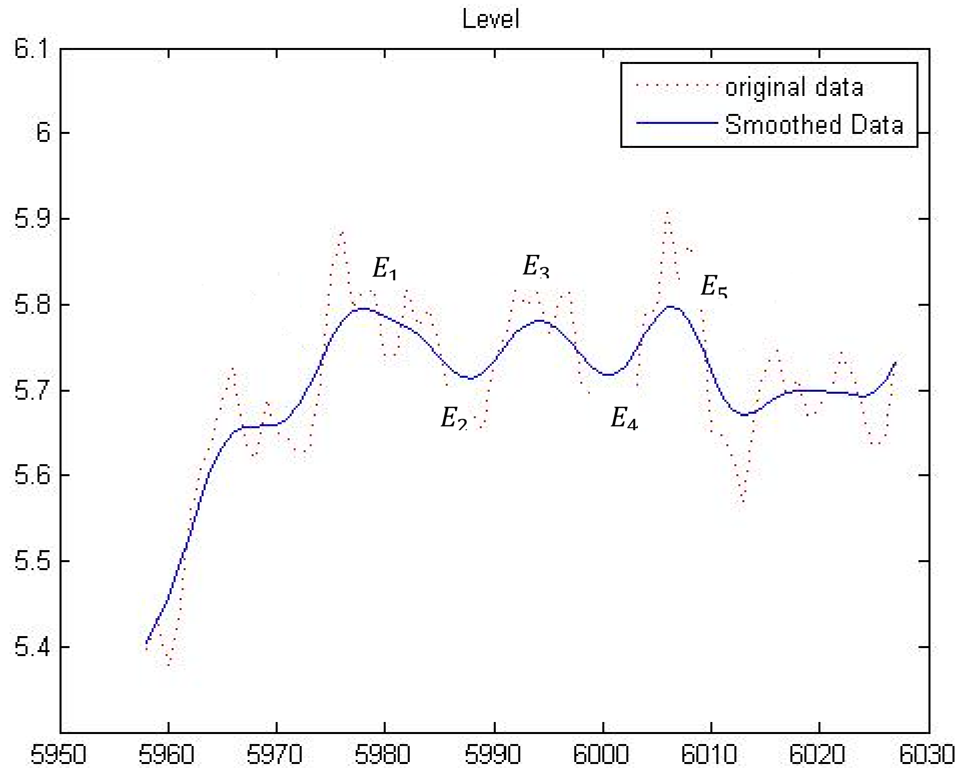

Figure 4: Rectangles

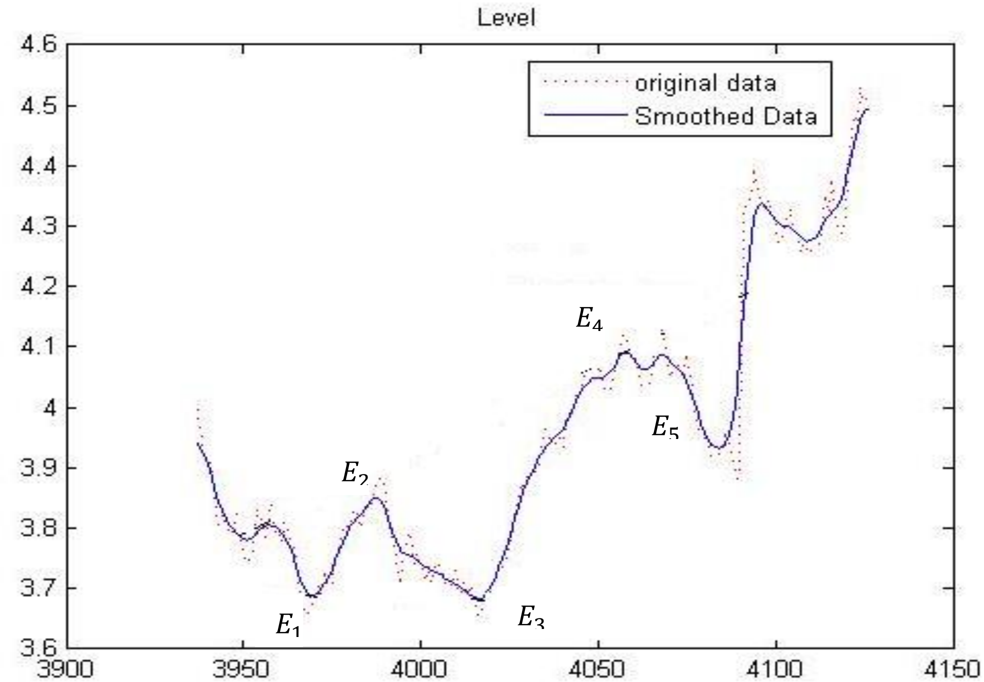

Figure 5: Broadenings

To illustrate the effect of the smoothing and recognition algorithm, I show the first identified patterns in our sample in Figures 2 through 5. In each of these graphs, the solid lines are the raw prices P_t and the dashed lines are the smoothed prices $\widehat{P}_t$. One can see that this method filtered small zigzags and keeps the basic structure of the patterns.

2.4 Trading Strategy

Most technical analysis manuals (e.g. Edwards and Magee (1991), Murphy (1999), Kirkpatrick and Dahlquist (2010)) suggest entering the market after the price has penetrated the neckline. Following Chang and Osler (1999), we take as our entry price the closing price on the day of the neckline's penetration. However, other filtering methods have also been proposed in studies in some other technical analysis methods. The use of a filter means that, when a pattern breaks out, we wait until it surpasses a certain range to take action. Following Brock, Lakonishok, and LeBaron (1992), we also implemented 0.5% and 1% filters for the analysis. In contrast to the moving average method implemented Brock et.al (1992), the chart patterns with these filters generate slightly worse performance than entering the position immediately when the price penetrates. Thus, the best entry time for establishing positions in the technical patterns is immediately after the prices penetrate the resistance level.

The final choice is how to exit our positions. According to Brock, Lakonishok, and LeBaron (1992), the two most popular methods are fixed length or fixed price level (or a combination of these two). Fixed length indicates that we should clear the position after a certain amount of time regardless of what the return is at that time, while fixed price means clearing the position when it arrives at a pre-specified price level, regardless of how long it takes to arrive at the level. Within the fixed price method, both profit-taking and stop-loss levels must be specified to avoid the possibility that the time series ends without the position being cleared. In some research, the fixed price method must be combined with a maximum tolerated time to avoid the difficulty that some equities never touch the profit-taking or stop-loss levels. For the purposes of this paper, the fixed length method works better since the abnormal return, if any, is triggered by the specific geometric movements of prices and is assumed to disappear after a limited time. Also, it provides an observable return series as time elapsed after the position entry.

In the next chapter we examine the results from two different perspectives. The first method reports the expected return given the observation of a specific kind of pattern. The second method reports the cumulative return if we trade a portfolio composed of all stocks that are in the holding period after a pattern is completed.

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CHAPTER 3

PROFITABILITY ANALYSIS

3.1 Data

The analysis in this study is conducted using US common stocks daily data from the Center for Research in Security Prices (CRSP) for ten years (from 1999 to 2008). The stocks are further required that all observations are required to be positive. There are 9,800 qualified stocks in our sample with 13,402,346 daily observations in total. On average each stock contains 1,368 observations. The longest time span was 2,515 days.

Table 1: Occurrence Frequencies of Each Pattern

Stock Day	1999-2008
BOTop	28373
BOBtm	28602
TRTop	40191
TRBtm	49135
RETop	42614
REBtm	30136
HSTop	34381
HSBtm	41930
Total	295362

Table 1 lists the occurrence frequencies of each pattern in the sample. The two triangles are the most frequently occurring pattern, composed of 30% of the total patterns observed while the two broadening patterns take only 18%. On average each stock contains about 5.5 observations per year. These frequencies are similar to those reported by Chang and Osler (1999).

3.2 Returns

To the best of our knowledge, none of the previous literature has delivered a comprehensive profitability analysis of chart patterns. Chang and Osler (1999) only analyzed head and shoulders, and Lo, Mamaysky and Wang (2000) only reported a different return distribution after the pattern ends. This study tries to give a comprehensive analysis of the profitability across different chart patterns by investigating whether the aggregate returns after the patterns break out are statistically and economically significant.

For each stock, the procedure outlined in Section 2.3 is applied to identify all occurrences of the patterns defined.

For each pattern detected, the return d days after the pattern has completed was computed. Specifically, consider a window of prices P_t from time t to time $t+d$ (d from 1 to 30) and suppose that the identified pattern p is completed at t. Then we take the conditional return R as $(P_{t+d} - P_t)/P_t$. Therefore, for each stock, we have eight sets of such conditional returns, each conditioned on one of the eight patterns of Section II.B. Then for each stock the return is standardized by subtracting its mean and dividing by its standard deviation. After that we take the average returns per day by dividing the aggregate standardized return by the holding period.

After that we take the average of the standardized returns across all of the stocks and the outcomes are reported in Table 2. Following Chang and Osler (1999), this study reports the average returns for 1 day, 3 days, 5 days, 10 days, 15 days, 20 days, 25 days and 30 days after the pattern ends, so that we can have an intuitive observation of the average return changes across time.

Table 2: Daily Stock Market Return

The average standardized return if we buy (for bottom pattern) or sell (for top pattern) the stock after the pattern ends and liquidate our position after the following specific days in the stock market. BO means the Broadening pattern, TR means the Triangle pattern, RE means the Rectangle pattern and HS means the Head and Shoulder pattern. The numbers in parenthesis are t-ratios.

Patterns	Day1	Day3	Day5	Day10	Day15	Day20	Day25	Day30
BOTop	0.0103	0.0099	0.0076	0.0036	0.0022	0.0017	0.0012	0.0011
	(15.59)	(19.15)	(23.30)	(13.78)	(12.89)	(9.88)	(7.93)	(6.97)
BOBtm	0.0071	0.0109	0.0090	0.0046	0.0035	0.0028	0.0024	0.0018
	(3.75)	(11.38)	(10.36)	(7.63)	(6.31)	(6.21)	(5.95)	(6.50)
TRTop	0.0087	0.0102	0.0100	0.0055	0.0031	0.0020	0.0015	0.0012
	(12.38)	(19.64)	(30.70)	(21.03)	(18.48)	(12.15)	(9.71)	(7.76)
TRBtm	-0.0013	0.0053	0.0063	0.0043	0.0032	0.0025	0.0022	0.0018
	(-2.03)	(1.89)	(7.20)	(7.16)	(5.76)	(5.43)	(5.38)	(4.81)
RETop	0.0044	0.0041	0.0034	0.0019	0.0014	0.0008	0.0006	0.0004
	(5.56)	(7.98)	(10.50)	(7.26)	(8.60)	(5.00)	(3.93)	(2.78)
REBtm	0.0050	0.0056	0.0048	0.0025	0.0018	0.0014	0.0013	0.0011
	(3.28)	(5.96)	(5.67)	(4.22)	(3.32)	(3.23)	(3.31)	(2.99)
HSTop	0.0034	0.0040	0.0038	0.0021	0.0013	0.0009	0.0006	0.0003
	(4.53)	(7.87)	(11.80)	(8.16)	(7.80)	(5.25)	(4.16)	(2.74)
HSBtm	0.0001	0.0021	0.0021	0.0012	0.0010	0.0011	0.0010	0.0008
	(0.84)	(3.01)	(3.24)	(2.73)	(2.70)	(3.17)	(3.22)	(2.94)

The results are striking. With the exception of the one-day holding return of the triangle bottom and inverse head and shoulder pattern, the magnitudes of the mean returns during buy periods are significant. Average returns during sell periods are of similar magnitude but negative, resulting in large differences between buy and sell mean returns. Please note that to make it easier to compare, all the “top” patterns’ returns are reversed to demonstrate the return if we short the equity.

The table further demonstrates that for most patterns the average returns achieve their maximums in around 3-5 days. The cumulative return achieved their maximums in a wider range, from 5 days to 25 days but on average the cumulative returns achieved their maximums in around 15 days.

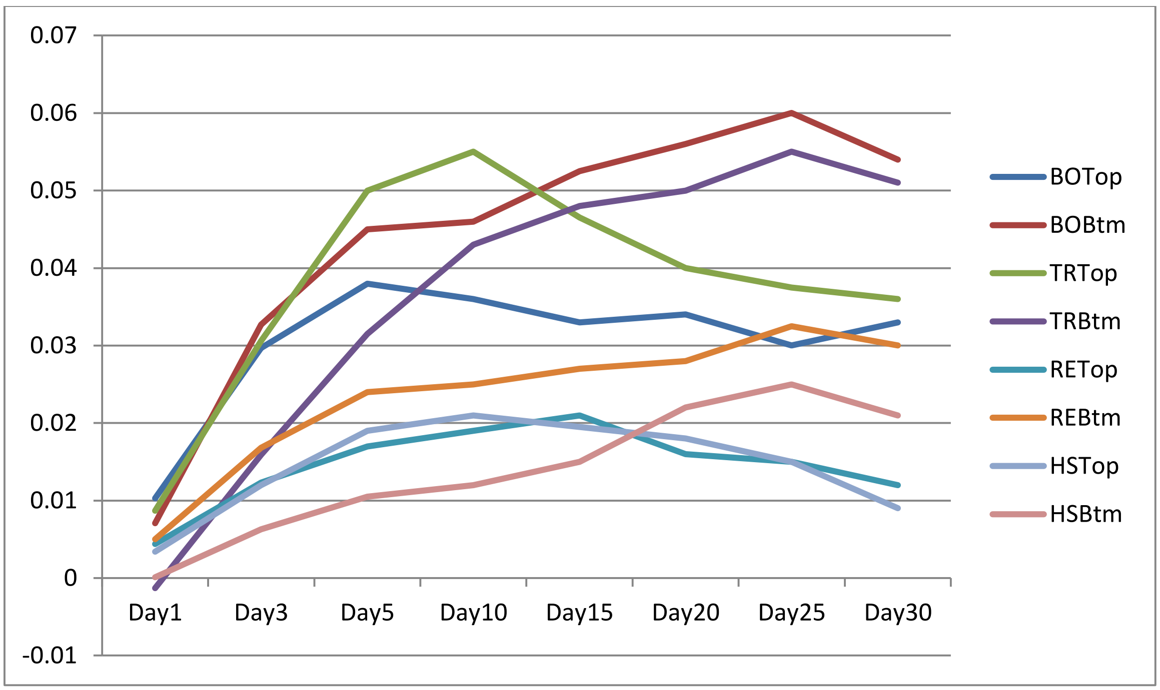

Figure 6: Cumulative Return across Days

This result is similar to those of other chart pattern studies; for example, the reports by Chang and Osler (1999) for the yen (1.52%) and mark (0.78%) with the head and shoulder pattern. Compared with studies using other kinds of technical analysis methods, like Brock, Lakonishok, and LeBaron (1992), one can see that this profit is relatively higher.

One possible explanation is that these patterns usually occur around the turning points of the trend (Edwards and Magee, 1991), therefore their impact on future market movement is relatively stronger during a short period of time.

3.3 Transaction Cost

Transactions costs should be considered carefully before such strategies can be implemented. Hurst, Ooi, and Pedersen (2012) performed a detailed transaction cost analysis for the past 100 years. They showed that with the vast change in the US equities microstructure (commission deregulation in 1975, emergence of electronic market makers and dark pools in the 1990s), transaction costs have been reduced dramatically in recent years. According to their estimate, from 1903 to 1992, the one-way transaction cost (including commission and market impact) was 0.36%, consistent with Fama and Blume's (1966) estimate (0.1% for clearing house and 0.2% for commission). However from 1993 to 2002, it was reduced to 0.12% and after 2002, to 0.06%.

Beyond commissions, bid-ask spread is also an important factor in the transaction cost. Jones (2002) included the bid-ask spread in addition to the commission analysis. According to his data, the bid-ask spread around 1960 was about 1% and fell to 0.2% around 2000. Byrne (2010) arrived at similar conclusions. Researchers such as Skouras (2001), Day and Wang (2002), and Korczak and Roger (2002) all assumed transaction costs around this level.

Table 3: Daily Stock Market Return after Transaction Cost

The average standardized return after we subtract the transaction cost from the profit. BO means the Broadening pattern, TR means the Triangle pattern, RE means the Rectangle pattern and HS means the Head and Shoulder pattern.

Panel A	0.4% two way cost							
Patterns	Day1	Day3	Day5	Day10	Day15	Day20	Day25	Day30
BOTop	0.0063	0.0086	0.0068	0.0032	0.0019	0.0015	0.0011	0.0010
BOBtm	0.0031	0.0096	0.0082	0.0042	0.0032	0.0026	0.0022	0.0017
TRTop	0.0047	0.0089	0.0092	0.0051	0.0028	0.0018	0.0013	0.0011
TRBtm	-0.0053	0.0040	0.0055	0.0039	0.0029	0.0023	0.0020	0.0016
RETop	0.0004	0.0028	0.0026	0.0015	0.0012	0.0006	0.0004	0.0003
REBtm	0.0010	0.0043	0.0040	0.0021	0.0015	0.0012	0.0011	0.0009
HSTop	-0.0006	0.0026	0.0030	0.0017	0.0010	0.0007	0.0004	0.0002
HSBtm	-0.0039	0.0008	0.0013	0.0008	0.0008	0.0009	0.0008	0.0007
Panel B:	2% two-way cost							
Patterns	Day1	Day3	Day5	Day10	Day15	Day20	Day25	Day30
BOTop	-0.0097	0.0033	0.0036	0.0016	0.0008	0.0007	0.0004	0.0004
BOBtm	-0.0129	0.0043	0.0050	0.0026	0.0021	0.0018	0.0016	0.0011
TRTop	-0.0113	0.0035	0.0060	0.0035	0.0018	0.0010	0.0007	0.0006
TRBtm	-0.0213	-0.0014	0.0023	0.0023	0.0018	0.0015	0.0014	0.0011
RETop	-0.0156	-0.0025	-0.0006	-0.0001	0.0001	-0.0002	-0.0002	-0.0002
REBtm	-0.0150	-0.0010	0.0008	0.0005	0.0004	0.0004	0.0005	0.0004
HSTop	-0.0166	-0.0027	-0.0002	0.0001	-0.0001	-0.0001	-0.0002	-0.0003
HSBtm	-0.0199	-0.0045	-0.0019	-0.0008	-0.0003	0.0001	0.0002	0.0001

If we reduce the two-way transaction cost of 0.4% according to Jones (2002), triangle bottom, head and shoulder, and inverse head and shoulder one-day holdings return would become negative, as Table III presents. Furthermore, if we use the old cost structure of the 2% two-way transaction cost, most of the one-day and three-day holding return would be negative. The patterns mostly affected are the head and shoulder and the inverse head and shoulder. For head and shoulder, only ten-day holding can generate positive returns, and for reverse head and shoulder, all holding periods of less than 20 days generate negative returns. Thus, the results depend heavily on the cost structures in different history periods.

3.4 Portfolio Trading Method

One of the weaknesses of the described method is that it does not have enough control of the risk factors. Beyond the analysis of average performance of each individual strategy, it is also useful to see if it is possible to explain the above return with the widely used Fama-French factor models by constructing a portfolio strategy purely based on chart patterns.

We thus hold a dynamic portfolio throughout our sample period. On any given day, if a pattern for any stock breaks out, we hold it for 15 days. (It is the optimized holding period that generates the highest cumulative return days in Chapter 3.2. For any given day in the data sample, there are (almost) always some stocks in their holding period.[1] If none of the stocks are held on that day, assume we invest in a T-bill. Figure 7 shows our portfolio holdings across the data sample.

After the portfolio is constructed, its aggregate return is calculated and adjusted with the commonly used Fama-French (1993) risk factors (market risk, small stock risk, and value risk) and obtain the alpha. With this method, we can determine if the Fama-French three-factor model can explain the abnormal returns. The daily market (MKT), size (SMB), and book-to-market (HML) factors, and 1-month T-bill rate data from January 1999 to December 2008 are downloaded from Kenneth French's website.

By this construction, each stock on a specific day is in one of three possible states:

1) State 1: This stock is forming a pattern.
2) State 2: This stock is in one of the 15 days after a pattern ends; i.e., the stock is in a holding period.
3) State 3: The stock is in neither State 1 nor State 2.

If the stock is in State 2, then we count it in the portfolio. Stocks in State 1 or State 3 are not counted in the portfolio.

[1] Except the first few days when none of these patterns has been formed.

Through this we can construct a dynamic portfolio that includes various numbers of stocks, and the number of holdings for a specific day depends on the number of stocks in State 2.

At the end of each trading day, we add to the portfolio the stocks that have just completed a pattern and delete the stocks that have been held for 15 days. We count the number of stocks that will be in the holding period (i.e., State 2) in the next day and set it as N_t.

We allocate $\$1/N_t$ to each stock in the portfolio and hold it over to the next trading day. Then we exclude the stocks that were in their last holding day, add the stocks which enter State 2, and assign this number to N_{t+1}. This is the number of stocks that will be in the portfolio for the next day. We again allocate them evenly, and $\$1/N_{t+1}$ is allocated to each stock.

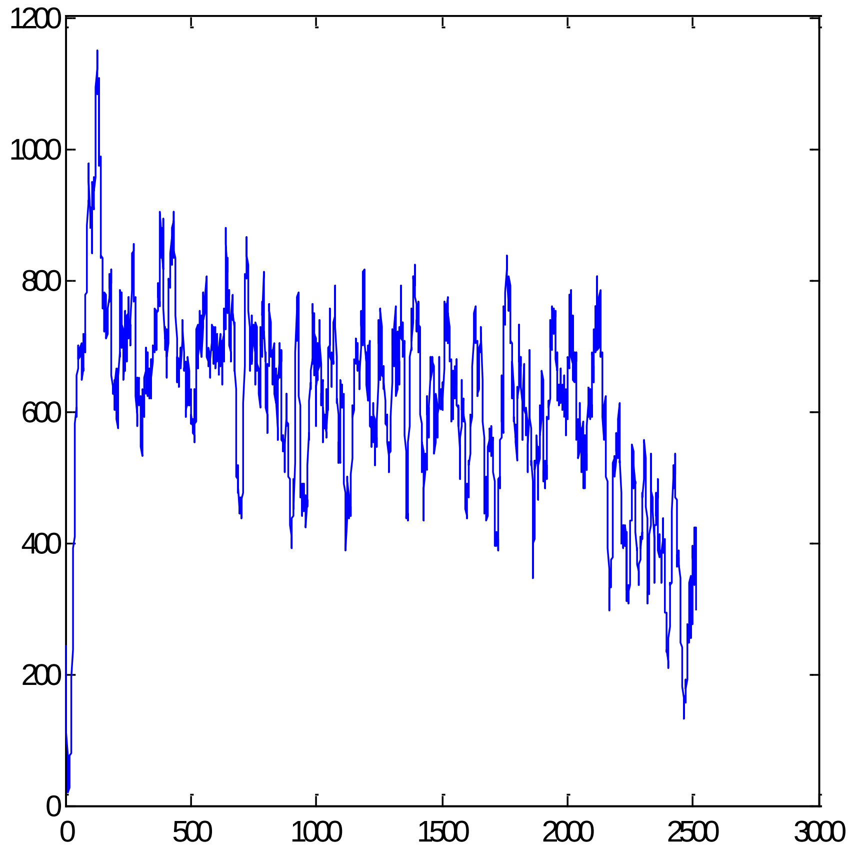

Figure 7: Portfolio Holdings across Time

This figure shows the number of holdings every day in the portfolio constructed with the signals generated by patterns.

Figure 7 shows the number of holdings across time. We can find that, on each day, there are on average 613 holdings. The 25% quartile holding is 528 stocks, and the 75% quartile holds 704 stocks.

From the portfolio holdings we can obtain the daily return of the portfolio r_t. To adjust the risk, we use a two-step method. First, regress the returns of each stock to the *MKT* factor, *SMB* factor and *HML* factor to obtain that stock's beta for each factor β_{is}, β_{iv}

and β_{im}. After that, we can obtain the time-series of the factor loadings of this portfolio, which is the average of the factor loadings of all the stocks in our portfolio since the portfolio is equally weighted.

$$\beta_{t,j} = \frac{\sum_{i=1}^{N_t} \beta_{i,j}}{N_t} \tag{3}$$

for $j = s, v, m$, respectively.

With the above knowledge we define our alpha as follows:

$$\alpha_t = r_t - R_{f,t} - \beta_{m,t}(R_{m,t} - R_{f,t}) - \beta_{s,t} * SMB_t - \beta_{v,t} * HML_t, \tag{4}$$

where r_t is the return of our constructed portfolio, R_f is the risk-free rate and $\beta_{m,t}$ $\beta_{s,t}$ and $\beta_{v,t}$ are the average loadings on the MKT, SMB and HML factors of all stocks in the portfolio for day *t* respectively.

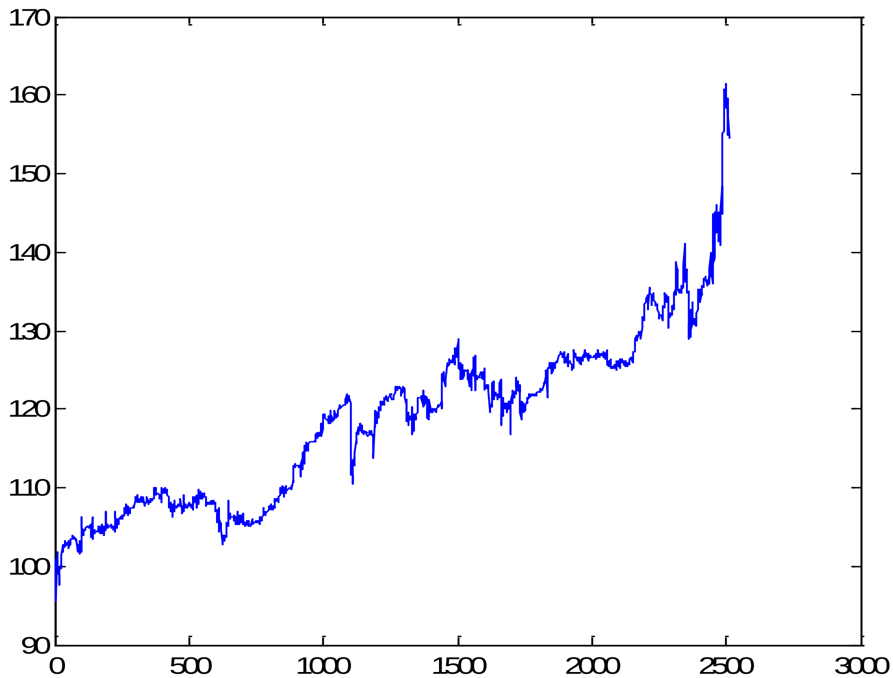

Figure 8: Cumulative Alphas

This figure shows Fama-French-3-factor adjusted cumulative returns of the portfolio constructed by the indications of the patterns. The sample period runs from June 1999 to December 2008. Alpha is the intercept in a time-series regression of daily excess return. The explanatory variables are the monthly returns from the market portfolio (MKT) and size (SMB) and book-to-market (HML) factor-mimicking portfolios.

The cumulative alpha is presented in Figure 8. On average, this strategy generates about 47 basis points per month after we control the *MKT*, *SMB* and *HML* factors. This is a significant result since it means a 5.64% yearly additional returns to the stock market and is at similar level of magnitude of most other identified factors in the equities market. This result clearly demonstrated the abnormal returns after we control the traditional Fama-French factors.

In this chapter, we analyze the average returns generated by the chart patterns as well as the aggregate alpha after we control for the common factors. In the next chapter, we will study the chart patterns from another perspective, utilizing the bootstrap method to investigate popular time series models. This can help us to better understand how different market price models can catch these complex graphical chart patterns.

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CHAPTER 4

BOOTSTRAP MODELS

4.1 Introduction

Bootstrap methods introduced by Efron (1979) and further developed by Freedman (1984) and Freedman and Peters (1984a, 1984b) were originally used to approximate bias and find the standard error of an estimator in a complex statistical model. However, in the recent finance literature, it became a popular method for technical trading strategy analysis after Brock, Lakonishok, and LeBaron (1992), Kho (1996), and Karolyi and Kho (2004). Since the work by Freedman and Peters (1984a, 1984b), it has been popular to simulate a time series to contain unknown statistical properties of various null return-generating models. This method requires fitting the original time series with various statistical models and keeping the estimated coefficients and residuals. After that, the residuals are standardized, scrambled, and combined with the coefficient estimations to form a new time series. Since this does not require any prior distribution assumption, it is useful for leptokurtic, autocorrelated, and conditionally heteroskedastic time series problems while the *t*-ratio assumes normal, stationary, and time-independent distribution, in contrast to most financial time series. As Diciccio and Efron (1996) explained, “Monte Carlo techniques are often required for the extraction process, but that is not essential to the basic idea of the bootstrap.”

Bootstrapping provides a convenient tool for checking whether different market data-generating processes invented in econometrics and financial engineering truly reflect the dynamics of market movements. In addition to some widely used and representative time series models from previous literature, such as random walk, AR (1), and GARCH-M, the Heston (1993) stochastic volatility model is also investigated here to see if this modern mathematical finance model serves as a better proxy of the true data-generating process of the real market. The Heston model was built to estimate derivatives prices, so until now, most of its validation checks have been established merely on its power in options price calibration. The bootstrap method provides another way to test whether this model has the ability to simulate the real market. A model is estimated and simulated here using the same pattern-testing method used in the real market to investigate the models' performance in a simulated market.

Two methods have been used to do bootstrap sampling: with and without replacement. The majority of the technical analysis literature employs sampling with replacement by default (Brock, Lakonishok and LeBron (1992); Levich and Thomas (1993); Lo, Mamaysky and Wang (2000)). However, there is no specific implementation of the bootstrap paradigm universally superior to others (Young (1994)). In addition, Bickel et al. (1997) and Politis and Romano (1994) point out that, under some conditions, sampling without replacement provides better consistency of estimators. Therefore, we will employ bootstrap sampling both with and without replacement.

In the previous chapter we use the entire stock database. However, if we keep all the stocks in the bootstrap analysis then the result would be a mix of two dimensions: the differences can either be caused by a different return generating process or just caused by different stocks. Since our focus is to investigate the bootstrap result of different return generating processes, we choose the median performing stock to do the bootstrap analysis. [2] In our sample the stock whose chart patterns generated the median profitability is identified as DIS.

The bootstrap procedure is conducted as follows:

1) Estimate model coefficients from the stock time series.

2) Scramble the standardized error using the bootstrap method with both with replacement and without replacement methods.

3) Regenerate a thousand times for the stock price series from the model parameters and standardized errors.

4) Use the same technical rule as in the time series to identify patterns.

5) Calculate the returns generated by the patterns found in the new time series, standardize them and compare them with the standardized returns generated in the original market data.

6) To facilitate comparison among different models, also use simulated *p*-values for the profits generated by simulation of various market processes. The reported

[2] I thank Professor Karolyi for the suggestion to use a representative stock time series to do the analysis.

empirical *p*-values are the percentages by which the generated profit is higher than or equal to the profit generated by the market price process.

Following Brock et al. (1992), we summarize the estimation of different models in one table (Table 4). The table reports the estimation results for all of the models we implement (random walk with drift, AR (1), GARCH-M and stochastic volatility). The results of the following four models will be reported from Table 5 to Table 12. A graphic summary of the tables is reported in Figure 9.

4.2 Random Walk

The random walk model is the benchmark in the literature on technical analysis. According to Jensen (1978), this model is frequently used to check whether the patterns in random innovation can generate similar or higher profit than patterns from real market data. It is also interesting since Aronson (2007) suspected that even if we draw the random walk graph, people can still identify various triangles, rectangles, broadening, and other chart patterns. Thus, we need to determine whether the "patterns" identified in a random walk model contain similar information as that in the patterns found in real markets.

Table 4: Parameter Estimates

This table contains parameter estimates for Random Walk with Drift, AR(1), GARCH-M and Heston models. Parameter are simulated on all daily returns series in the data sample. The AR(1) is estimated by OLS. The GARCH-M and Heston stochastic volatility models are estimated using maximum likelihood. R_t is the compounded return and σ is the conditional standard deviation. The numbers in parenthesis are t-ratios.

Panel A: Random Walk with Drift Estimates

$R_t = a + \varepsilon_t, \quad \varepsilon_t \sim IID(0, \sigma^2)$

a
0.00014
(3.24)

Panel B: AR(1) Parameter Estimates

$$R_t = a + \rho * R_{t-1} + \varepsilon_t$$

a	ρ
0.00013	0.05206
(2.309)	(3.751)

Panel C: GARCH-M Parameter Estimation

$$R_t = a + \gamma\sigma_t^2 + b\varepsilon_{t-1} + \varepsilon_t$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 e_{t-1}^2 + \beta\sigma_{t-1}^2$$

$$\varepsilon_t = \sigma_t z_t, \ z_t \sim N(0,1)$$

a	γ	b	α_0	α_1	β
0.0011	0.9962	-0.0285	0.0056	0.1186	0.8350
(1.03)	(63.27)	(-15.39)	(3.38)	(51.42)	(231.12)

Panel D: Stochastic Volatility Parameter Estimation

$$X_t = d\begin{bmatrix} S_t \\ Y_t \end{bmatrix} = \begin{bmatrix} a + bY_t \\ \kappa(\gamma - Y_t) \end{bmatrix} dt + \begin{bmatrix} \sqrt{(1-\rho^2)Y_t} & \rho\sqrt{Y_t} \\ 0 & \sigma\sqrt{Y_t} \end{bmatrix} d\begin{bmatrix} W_1^p(t) \\ W_2^p(t) \end{bmatrix}$$

κ	γ	σ	ρ	a	b
3.26	0.13	0.29	-0.67	-0.01	0.29
(11.04)	(3.82)	(37.61)	(-12.16)	(-2.38)	(4.28)

Here, we use the definition of random walk model 1 from Campbell, Lo, and MacKinlay (1997):

$$R_t = a + \varepsilon_t, \quad \varepsilon_t \sim IID(0, \sigma^2) \tag{5}$$

where a is the drift term for each security, and ε_t is the independently and identically distributed innovation.

Table 5: Random Walk without Replacement

This table describes simulation tests from random walk model bootstraps without replacement. The stock's price history is scanned for any occurrence of the eight technical indicators. The average returns for all patterns for different holding periods and their corresponding simulated p-values are reported.

Patterns	Day1	Day3	Day5	Day10	Day15	Day20	Day25	Day30
BOTop	-0.0000	0.0000	0.0002	0.0001	0.0000	0.0001	0.0002	-0.0000
p-value	[0.000]	[0.000]	[0.002]	[0.000]	[0.000]	[0.000]	[0.010]	[0.003]
BOBtm	0.0001	0.0000	0.0002	0.0001	0.0002	0.0003	0.0000	-0.0001
p-value	[0.000]	[0.000]	[0.001]	[0.000]	[0.002]	[0.012]	[0.000]	[0.000]
TRTop	-0.0001	-0.0000	-0.0003	-0.0002	-0.0002	0.0000	0.0001	0.0000
p-value	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.003]
TRBtm	-0.0002	0.0001	0.0002	0.0004	0.0003	0.0003	0.0002	-0.0000
p-value	[0.000]	[0.000]	[0.000]	[0.003]	[0.001]	[0.012]	[0.008]	[0.000]
RETop	0.0001	-0.0001	-0.0001	-0.0003	-0.0001	0.0000	0.0002	0.0002
p-value	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.005]	[0.027]	[0.033]
REBtm	0.0003	0.0004	0.0004	0.0003	0.0002	0.0002	0.0002	0.0001
p-value	[0.005]	[0.012]	[0.023]	[0.002]	[0.003]	[0.019]	[0.021]	[0.003]
HSTop	-0.0000	-0.0002	-0.0002	-0.0003	-0.0002	-0.0002	-0.0000	0.0000
p-value	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.004]	[0.011]
HSBtm	0.0000	0.0002	0.0002	0.0001	0.0002	0.0002	0.0002	0.0000
p-value	[0.042]	[0.016]	[0.015]	[0.018]	[0.022]	[0.080]	[0.049]	[0.000]

Table 6: Random Walk with Replacement

This table describes simulation tests from random walk model bootstraps with replacement. The stock's price history is scanned for any occurrence of the eight technical indicators. The average returns for all patterns for different holding periods and their corresponding simulated *p*-values are reported.

Patterns	Day1	Day3	Day5	Day10	Day15	Day20	Day25	Day30
BOTop	0.0000	0.0001	0.0001	0.0002	0.0002	0.0001	0.0000	-0.0001
p-value	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.005]	[0.000]
BOBtm	-0.0001	-0.0001	-0.0002	-0.0003	-0.0002	-0.0001	-0.0001	-0.0001
p-value	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
TRTop	0.0000	0.0001	0.0000	-0.0001	-0.0001	0.0001	-0.0001	-0.0001
p-value	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
TRBtm	0.0000	0.0001	0.0002	0.0004	0.0004	0.0004	0.0003	0.0003
p-value	[0.000]	[0.001]	[0.000]	[0.002]	[0.043]	[0.046]	[0.029]	[0.015]
RETop	0.0000	0.0000	0.0001	0.0002	0.0001	0.0000	-0.0001	0.0000
p-value	[0.000]	[0.000]	[0.000]	[0.000]	[0.002]	[0.000]	[0.000]	[0.000]
REBtm	0.0002	0.0004	0.0007	0.0005	0.0005	0.0003	0.0003	0.0001
p-value	[0.001]	[0.010]	[0.041]	[0.031]	[0.071]	[0.058]	[0.048]	[0.001]
HSTop	0.0001	0.0000	-0.0001	0.0000	-0.0001	-0.0001	-0.0001	0.0000
p-value	[0.002]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.003]
HSBtm	0.0001	0.0002	0.0001	0.0001	0.0000	0.0001	0.0002	0.0002
p-value	[0.103]	[0.018]	[0.006]	[0.011]	[0.003]	[0.018]	[0.042]	[0.026]

Table 5 and 6 display the results of random walk with drift simulations. The results of the without replacement method is reported in Table 5 and the result with replacement is reported in Table 6. On the left side are eight different strategies and each column represents a holding period (from 1 day to 30 days). For each strategy, the average return until the specified holding periods is reported. Below the average return is the simulated *p*-value, the percentage that simulated time series generated a higher return than the original price series. The reported numbers show that, for both replacement methods, few patterns identified in the simulated random walks generate larger returns than the original pattern. Some of them even generate negative returns. The results show that the random walk model has little power to explain the abnormal returns identified and is insufficient for modeling the return generating process.

4.3 AR (1) Model

The autoregressive process model is also widely used to describe the market dynamics. As Conrad and Kaul (1989) reported, the return of the first-order autocorrelation is positive, and the higher order autocorrelation is almost zero. Thus, the first-order autoregressive model (AR (1)) is a common specification for the market dynamics.

The AR (1) model is specified as follows:

$$R_t = a + \rho R_{t-1} + \varepsilon_t \tag{6}$$

where R_t is stock's return on day t and ε_t is the independent and identically distributed innovation. The parameters (a, ρ) and the residuals e_t are estimated from each stock time series using OLS. The residuals are then resampled both with replacement and without replacement methods, and the ARs are generated using the estimated parameters and scrambled standardized residuals.

Table 7: AR(1) Model without Replacement

This table describes simulation tests from AR(1) model bootstraps without replacement. The AR(1) residual series is resampled with replacement and simulated using the AR(1) estimated parameters. The average returns for all patterns for different holding periods and their corresponding simulated *p*-values are reported.

Patterns	Day1	Day3	Day5	Day10	Day15	Day20	Day25	Day30
BOTop	0.0010	0.0015	0.0008	0.0006	0.0007	0.0006	0.0005	0.0003
p-value	[0.002]	[0.028]	[0.014]	[0.013]	[0.042]	[0.061]	[0.046]	[0.028]
BOBtm	0.0011	0.0032	0.0027	0.0014	0.0013	0.0011	0.0010	0.0006
p-value	[0.032]	[0.085]	[0.048]	[0.031]	[0.138]	[0.129]	[0.138]	[0.103]
TRTop	0.0009	0.0021	0.0017	0.0012	0.0010	0.0005	0.0001	0.0000
p-value	[0.005]	[0.042]	[0.020]	[0.069]	[0.077]	[0.025]	[0.004]	[0.002]
TRBtm	0.0014	0.0017	0.0021	0.0013	0.0006	0.0004	0.0001	0.0000
p-value	[0.218]	[0.137]	[0.143]	[0.088]	[0.080]	[0.051]	[0.017]	[0.000]
RETop	0.0000	0.0010	0.0005	0.0004	0.0003	0.0002	0.0002	0.0001
p-value	[0.001]	[0.051]	[0.032]	[0.030]	[0.029]	[0.026]	[0.022]	[0.010]
REBtm	0.0005	0.0012	0.0009	0.0008	0.0007	0.0005	0.0002	-0.0002
p-value	[0.014]	[0.072]	[0.061]	[0.059]	[0.108]	[0.110]	[0.028]	[0.000]
HSTop	0.0005	0.0010	0.0008	0.0003	0.0003	0.0001	0.0000	-0.0001
p-value	[0.026]	[0.072]	[0.074]	[0.043]	[0.112]	[0.033]	[0.005]	[0.000]
HSBtm	0.0001	0.0004	0.0006	0.0004	0.0003	0.0002	0.0001	-0.0001
p-value	[0.163]	[0.046]	[0.085]	[0.104]	[0.133]	[0.067]	[0.012]	[0.000]

Table 8: AR(1) Model with Replacement

This table describes simulation tests from AR(1) model bootstraps with replacement. The AR(1) residual series is resampled with replacement and simulated using the AR(1) estimated parameters. The average returns for all patterns for different holding periods and their corresponding simulated *p*-values are reported.

Patterns	Day1	Day3	Day5	Day10	Day15	Day20	Day25	Day30
BOTop	0.0012	0.0014	0.0011	0.0008	0.0008	0.0007	0.0005	0.0003
p-value	[0.007]	[0.021]	[0.026]	[0.021]	[0.058]	[0.084]	[0.044]	[0.032]
BOBtm	0.0006	0.0022	0.0025	0.0015	0.0014	0.0011	0.0011	0.0006
p-value	[0.009]	[0.033]	[0.042]	[0.040]	[0.166]	[0.132]	[0.170]	[0.105]
TRTop	0.0014	0.0025	0.0019	0.0012	0.0008	0.0006	0.0002	0.0000
p-value	[0.027]	[0.065]	[0.028]	[0.064]	[0.053]	[0.032]	[0.010]	[0.008]
TRBtm	0.0017	0.0019	0.0027	0.0015	0.0006	0.0004	0.0002	0.0000
p-value	[0.325]	[0.168]	[0.237]	[0.104]	[0.086]	[0.057]	[0.033]	[0.004]
RETop	0.0004	0.0010	0.0008	0.0006	0.0004	0.0003	0.0003	-0.0001
p-value	[0.019]	[0.043]	[0.093]	[0.088]	[0.055]	[0.066]	[0.112]	[0.002]
REBtm	0.0006	0.0015	0.0009	0.0010	0.0007	0.0006	0.0002	0.0001
p-value	[0.027]	[0.096]	[0.063]	[0.087]	[0.105]	[0.165]	[0.030]	[0.006]
HSTop	0.0010	0.0011	0.0012	0.0005	0.0003	0.0002	0.0002	0.0002
p-value	[0.081]	[0.093]	[0.155]	[0.087]	[0.115]	[0.080]	[0.058]	[0.063]
HSBtm	0.0001	0.0006	0.0007	0.0005	0.0004	0.0002	0.0002	0.0000
p-value	[0.190]	[0.085]	[0.128]	[0.132]	[0.172]	[0.078]	[0.055]	[0.004]

The results show that this specification explains more of the abnormal returns than the random walk model, especially at the start of the holding days. Since the returns over short periods of time are positively correlated, part of the abnormal returns produced by technical patterns might be related with the trend generated from the final breakout. Another observation is that resampling with replacement generates higher returns and *p*-values across all holding days, which is consistent with Jagedeesh and Titman (2001) found.

However, the majority of the returns are not explained by this first-order autoregressive factor.

4.4 GARCH-M Model

The GARCH-in-Mean model was developed by Schwarz (1978) and Engel, Lilien and Robins (1987). One characteristic of the GARCH-M model is that the conditional variance σ_t^2 is a linear combination of the square of the last period's conditional variance and the square of the last period's errors. It thus implies a positive serial correlation in the conditional volatility, widely known as the volatility cluster. Also, the conditional returns are combinations of the conditional variance and past innovations. Compared with the AR(1) model, the GARCH-M model contains relatively rich specifications about e market dynamics through the return and volatility interactions. Since the technical patterns obtained are usually generated during important market movements, it is reasonable to look for evidence of whether the abnormal return can be explained by the volatility clusters.

The GARCH-M model, as Schwarz (1978) described, can be summarized as follows:

$$R_t = a + \gamma\sigma_t^2 + b\varepsilon_{t-1} + \varepsilon_t$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 e_{t-1}^2 + \beta\sigma_{t-1}^2 \qquad (7)$$

$$\varepsilon_t = \sigma_t z_t,\ z_t \sim N(0,1)$$

where ε_t follows conditional normal distribution with mean zero and conditional variance σ_t^2, and z_t follows *i.i.d.* standard normal distribution. σ_t^2 is a linear combination of the last period's conditional variance and of the square of the last period's errors. This specification is richer than the AR (1) process by incorporating positive series correlation in the conditional second moment of the return process. The conditional returns are a linear function of the conditional variance and the past disturbance. Under this data-generating process, volatility changes over time, and the expected returns are a function of volatility in addition to the past returns as specified in the AR (1) model. This is a rich specification and is popular in financial econometrics literature. The parameters and standardized residuals are estimated from the return series using maximum likelihood. The standardized residuals are resampled with and without replacement and are used along with the estimated parameters to generate the GARCH-M series.

Table 9: GARCH-M model without Replacement

This table describes simulation tests from GARCH-M model bootstraps without replacement. The GARCH-M returns series are simulated using the estimated parameters and standardized residuals. The average returns for all patterns for different holding periods and their corresponding simulated *p*-values are reported.

Patterns	Day1	Day3	Day5	Day10	Day15	Day20	Day25	Day30
BOTop	0.0022	0.0025	0.0028	0.0014	0.0013	0.0011	0.0007	0.0002
p-value	[0.021]	[0.039]	[0.053]	[0.089]	[0.145]	[0.167]	[0.098]	[0.053]
BOBtm	0.0024	0.0048	0.0025	0.0020	0.0010	0.0009	0.0006	0.0005
p-value	[0.045]	[0.114]	[0.040]	[0.073]	[0.097]	[0.088]	[0.082]	[0.069]
TRTop	0.0022	0.0031	0.0030	0.0013	0.0013	0.0009	0.0007	0.0003
p-value	[0.096]	[0.125]	[0.031]	[0.087]	[0.098]	[0.049]	[0.057]	[0.052]
TRBtm	0.0020	0.0022	0.0023	0.0023	0.0015	0.0006	0.0004	0.0003
p-value	[0.423]	[0.214]	[0.185]	[0.266]	[0.245]	[0.096]	[0.070]	[0.038]
RETop	0.0011	0.0023	0.0017	0.0006	0.0004	0.0003	0.0003	0.0002
p-value	[0.067]	[0.159]	[0.220]	[0.092]	[0.052]	[0.068]	[0.118]	[0.233]
REBtm	0.0013	0.0022	0.0019	0.0010	0.0009	0.0007	0.0004	0.0002
p-value	[0.068]	[0.130]	[0.142]	[0.092]	[0.188]	[0.191]	[0.073]	[0.038]
HSTop	0.0012	0.0016	0.0013	0.0007	0.0005	0.0002	0.0001	0.0000
p-value	[0.114]	[0.217]	[0.176]	[0.193]	[0.141]	[0.085]	[0.022]	[0.019]
HSBtm	0.0002	0.0011	0.0008	0.0005	0.0006	0.0003	0.0002	0.0001
p-value	[0.314]	[0.193]	[0.157]	[0.136]	[0.210]	[0.193]	[0.058]	[0.027]

Table 10: GARCH-M model with Replacement

This table describes simulation tests from GARCH-M model bootstraps with replacement. The GARCH-M returns series are simulated using the estimated parameters and standardized residuals. The average returns for all patterns for different holding periods and their corresponding simulated *p*-values are reported.

Patterns	Day1	Day3	Day5	Day10	Day15	Day20	Day25	Day30
BOTop	0.0028	0.0030	0.0029	0.0014	0.0014	0.0011	0.0007	0.0002
p-value	[0.030]	[0.058]	[0.059]	[0.092]	[0.163]	[0.162]	[0.096]	[0.060]
BOBtm	0.0026	0.0048	0.0030	0.0022	0.0010	0.0010	0.0006	0.0005
p-value	[0.062]	[0.120]	[0.060]	[0.102]	[0.103]	[0.117]	[0.091]	[0.072]
TRTop	0.0023	0.0035	0.0031	0.0013	0.00013	0.0008	0.0006	0.0003
p-value	[0.101]	[0.142]	[0.039]	[0.085]	[0.091]	[0.035]	[0.039]	[0.049]
TRBtm	0.0021	0.0028	0.0026	0.0025	0.0017	0.0007	0.0004	0.0003
p-value	[0.452]	[0.276]	[0.211]	[0.291]	[0.307]	[0.121]	[0.075]	[0.032]
RETop	0.0013	0.0023	0.0021	0.0010	0.0005	0.0003	0.0004	0.0002
p-value	[0.086]	[0.160]	[0.261]	[0.135]	[0.094]	[0.070]	[0.146]	[0.245]
REBtm	0.0013	0.0026	0.0019	0.0009	0.0010	0.0007	0.0005	0.0002
p-value	[0.066]	[0.173]	[0.140]	[0.074]	[0.201]	[0.189]	[0.081]	[0.040]
HSTop	0.0016	0.0018	0.0016	0.0007	0.0006	0.0004	0.0002	0.0001
p-value	[0.195]	[0.263]	[0.202]	[0.195]	[0.166]	[0.175]	[0.051]	[0.121]
HSBtm	0.0002	0.0010	0.0012	0.0006	0.0005	0.0003	0.0001	0.0000
p-value	[0.308]	[0.158]	[0.280]	[0.162]	[0.197]	[0.186]	[0.026]	[0.009]

The results show that, with the volatility cluster structure embedded, the GARCH-M model in general generates higher returns than the AR(1) model across different strategies and holding periods. The average returns from most patterns and most holding periods are improved. An average *p*-value of 0.119 and 0.135 are generated for the without replacement and with replacement method, respectively. This is substantially larger than the AR(1) model, which validates that conditional volatility explains a larger proportion of the abnormal returns.

4.5 Heston Model

The Heston model is motivated by widespread evidence that implied volatility is neither constant nor deterministic through time, across strike prices, and across maturities, but rather it is stochastic. Also, the distribution of risky asset returns has tails longer than that of a normal distribution. Both of the empirical stylized facts can be addressed by stochastic volatility models with correlated price and volatility innovation. The stochastic volatility options pricing model were developed by Johnson and Shanno (1987), Wiggins (1987), Hull and White (1987, 1988), Scott (1987), Stein and Stein (1991), and Heston (1993). These models provide better explanations for the empirical features of the joint time series of the stocks and derivatives prices that cannot be captured by simpler models. Among them, Heston (1993) arrived at a semi-closed-form solution based on the characteristic function of the price distribution, which became a popular model in stochastic volatility. According to Papanicolaou and Sircar (2013),

“Heston (1993) is the industry standard among stochastic volatility models. Its parameters are known to have clear and specific controls on the implied volatility skew/smile, and it can mimic the implied volatilities of around-the-money options with a fair degree of accuracy.”

This model explicitly incorporates the effect of volatility on the change in the variance process as well as the correlation between the price innovation and the volatility innovation. In other words, it models the volatility of volatility. In addition, it uses implied volatility, which is considered by Poon and Granger (2003) as a better proxy for volatility forecast than the historical volatility. We try to determine whether this structure successfully captures the market dynamics with bootstrapping.

The estimation choice is between the maximum likelihood and method of moments. The benefit of maximum likelihood is that it is an efficient estimator and can achieve the Cramér Rao lower bound; the disadvantage is that it requires full specification of the data-generating process. On the other side, the method of moments can tolerate the partially specified data-generating process, but its error is typically larger than Cramér Rao, and some moments may not be known in closed form. In addition, the approximation process is usually more time consuming than the maximum likelihood method. For our purpose, since the closed-form analytical solution has already been provided by Heston (1993), a MLE estimation is a better choice.

To perform the maximum likelihood estimation we need to identify the likelihood function of the state vector $X_t = [S; h]'$ where S_t is the time series of the stock price and h_t is the implied volatility time series. This approach has the advantage of using all available information in the estimation procedure. The implied volatility data is downloaded from the IVolatility database.

In a general form, a two-vector state variable stochastic volatility model can be represented as a function in which the price is a function of a vector of state variables $X_t$that follow a multivariate diffusion process:

$$dX_t = \mu^P(X_t)dt + \sigma(X_t)dW_t^P, \tag{8}$$

where X_t is a two-dimensional vector of stock price and volatility variables $[S_t, h_t]'$, W_t^P is a two-dimensional canonical Brownian motion under the objective probability measure P, and $\mu^P(X_t)$ is a two-dimensional function of X_t.

$$dX_t = d\begin{bmatrix} s_t \\ h_t \end{bmatrix} = \begin{bmatrix} a + bh_t \\ \kappa(\gamma - h_t) \end{bmatrix} dt + \begin{bmatrix} \sqrt{(1-\rho^2)h_t} & \rho\sqrt{h_t} \\ 0 & \sigma\sqrt{h_t} \end{bmatrix} d\begin{bmatrix} W_1^p(t) \\ W_2^p(t) \end{bmatrix} \tag{9}$$

There are six parameters to be estimated: $a, b, \rho, \kappa, \gamma, \sigma$.

The next target is to obtain the log-likelihood function of the observable market data set $X_t = [S; h]'$. When applied to the Heston model, the log-likelihood function given in Ait-Sahalia and Kimmel (2010) can be written in the form of the following power series in Δ: (Δ is the sampling frequency per year).

$$l_x(x|x_0;\theta) = -\frac{\ln(2\pi\Delta)}{2} - D(x;\theta) + \frac{1}{\Delta}C_X^{(-1)}(x|x_0;\theta) + C_X^{(0)}(x|x_0;\theta) + \Delta C_X^{(1)}(x|x_0;\theta) \quad (10)$$

where $l_x(\Delta, x|x_0;\theta)$ represents the log likelihood of the conditional density of x given x_0 and parameter vector θ under P measure. D *and* $C_X^{(k)}$ are coefficients for each Δ_k.

The coefficients for the log-likelihood function in (10), $C_X^{(-1)}, C_X^{(0)}, C_X^{(1)}$ *and* D are functions of our *6*-dim parameter set. The functional form of these coefficients is provided by Ait-Sahalia and Kimmer (2010) and is attached in the Appendix. Then our task is simplified into finding the optimal parameter combination to maximize the log likelihood function l_x, which takes the shape of a 6-dim geometric "surface" sitting above a 6-dim hyperplane spanned by the parameter vector. Optimizing the above log likelihood function with the traditional Nelder-Mead simplex (direct search) method that is widely used in mathematical finance literature (Bates (2006)) and we obtain the estimation result in Panel D of Table 4.

The value -0.67 for ρ reflects the empirical regularity that innovations to volatility and stock price are generally strongly negatively correlated. The long-term value of the variance γ 0.13 with a speed of mean reversion coefficient κ of approximately 3.26 gives a 2.5 month half-life of volatility mean-reversion process, a reasonable number in the volatility market. After we obtain the estimates the standardized residuals are calculated and scrambled with the bootstrapping method. Then we regenerate a thousand time series for the stock price series from the model parameters and scrambled standardized residuals both with and without replacement. After that the same technical pattern recognition algorithms are implemented in these simulated time series to identify patterns. Then I calculate the returns generated by the patterns found in the new time series and obtain the fraction of simulations generating a return larger than those from the actual series.

Table 11 and Table 12 present the returns and the percentage of the fraction of simulations generating a mean larger than those from the actual return series (Sim. *p*-value) for different models.

Table 11: Heston model without Replacement

This table describes simulation tests from Heston model bootstraps without replacement. The stochastic volatility returns series are simulated using the estimated parameters and standardized residuals. The average returns for all patterns for different holding periods and their corresponding simulated *p*-values are reported.

Patterns	Day1	Day3	Day5	Day10	Day15	Day20	Day25	Day30
BOTop	0.0052	0.0054	0.0052	0.0034	0.0014	0.0009	0.0008	0.0004
p-value	[0.083]	[0.117]	[0.116]	[0.256]	[0.189]	[0.111]	[0.108]	[0.121]
BOBtm	0.0030	0.0076	0.0065	0.0030	0.0019	0.0016	0.0012	0.0008
p-value	[0.121]	[0.212]	[0.278]	[0.260]	[0.149]	[0.173]	[0.194]	[0.129]
TRTop	0.0052	0.0059	0.0054	0.0019	0.0017	0.0011	0.0005	0.0004
p-value	[0.268]	[0.244]	[0.098]	[0.121]	[0.151]	[0.070]	[0.023]	[0.075]
TRBtm	0.0026	0.0041	0.0050	0.0026	0.0020	0.0016	0.0010	0.0008
p-value	[0.598]	[0.401]	[0.314]	[0.308]	[0.361]	[0.269]	[0.145]	[0.082]
RETop	0.0019	0.0024	0.0029	0.0018	0.0009	0.0005	0.0005	0.0005
p-value	[0.115]	[0.170]	[0.315]	[0.274]	[0.096]	[0.088]	[0.170]	[0.376]
REBtm	0.0013	0.0025	0.0028	0.0010	0.0008	0.0005	0.0004	0.0003
p-value	[0.072]	[0.167]	[0.252]	[0.095]	[0.139]	[0.122]	[0.069]	[0.050]
HSTop	0.0018	0.0027	0.0027	0.0010	0.0010	0.0008	0.0006	0.0003
p-value	[0.264]	[0.366]	[0.358]	[0.244]	[0.223]	[0.339]	[0.418]	[0.296]
HSBtm	0.0003	0.0020	0.0019	0.0011	0.0010	0.0010	0.0008	0.0006
p-value	[0.471]	[0.513]	[0.505]	[0.374]	[0.432]	[0.457]	[0.311]	[0.292]

Table 12: Heston model with Replacement

This table describes simulation tests from Heston model bootstraps with replacement. The stochastic volatility returns series are simulated using the estimated parameters and standardized residuals. The average returns for all patterns for different holding periods and their corresponding simulated *p*-values are reported.

Patterns	Day1	Day3	Day5	Day10	Day15	Day20	Day25	Day30
BOTop	0.0055	0.0063	0.0058	0.0019	0.0015	0.0011	0.0008	0.0005
p-value	[0.103]	[0.147]	[0.139]	[0.112]	[0.198]	[0.163]	[0.128]	[0.170]
BOBtm	0.0039	0.0068	0.0062	0.0032	0.0021	0.0017	0.0013	0.0010
p-value	[0.185]	[0.163]	[0.210]	[0.322]	[0.197]	[0.221]	[0.242]	[0.203]
TRTop	0.0043	0.0066	0.0062	0.0021	0.0021	0.0012	0.0006	0.0004
p-value	[0.235]	[0.273]	[0.080]	[0.165]	[0.231]	[0.096]	[0.032]	[0.077]
TRBtm	0.0025	0.0042	0.0039	0.0018	0.0021	0.0017	0.0015	0.0004
p-value	[0.573]	[0.426]	[0.290]	[0.213]	[0.414]	[0.320]	[0.271]	[0.051]
RETop	0.0025	0.0029	0.0032	0.0007	0.0010	0.0007	0.0006	0.0003
p-value	[0.142]	[0.217]	[0.428]	[0.109]	[0.129]	[0.144]	[0.251]	[0.141]
REBtm	0.0023	0.0035	0.0031	0.0011	0.0009	0.0006	0.0004	0.0004
p-value	[0.159]	[0.296]	[0.314]	[0.112]	[0.185]	[0.163]	[0.075]	[0.084]
HSTop	0.0020	0.0025	0.0028	0.0012	0.0011	0.0008	0.0006	0.0004
p-value	[0.301]	[0.329]	[0.401]	[0.369]	[0.313]	[0.342]	[0.409]	[0.443]
HSBtm	0.0007	0.0022	0.0021	0.0014	0.0009	0.0010	0.0009	0.0006
p-value	[0.802]	[0.587]	[0.518]	[0.594]	[0.403]	[0.431]	[0.437]	[0.395]

From Table 11 and Table 12, one can see that, across all strategies, a significant amount of the abnormal returns associated with the technical patterns is explained by the introduction of the two related Brownian motion structures and implied volatility as specified by the Heston model. Across different patterns and holding days the average *p*-value arrives 0.227 and 0.262 for without resampling and resampling methods, respectively. Both of them are higher than the *p*-values generated by the GARCH-M models.

Figure 9 summarizes the average *p*-values across all eight patterns. The *p*-value indicates the percentage that the returns generated by the patterns in the model-based simulation is higher than the returns generated by the patterns in the market. The closer the value is to 0.5 means the better a model can mimic the return generating process by the market. This figure demonstrates that across all holding periods from one day to thirty days, the *p*-value generated by the Heston model is better than the GARCH-M model and other simpler models.

We also notice that with some exceptions in the random walk model, bootstrap with replacement generates a higher chance of returns. This echoes what Jegadesh and Titman (2001) presented, although the differences here are not as striking as theirs. This paper is not intend to investigate which method overwhelms another. The key point here is that our result is robust to the choice of resampling methods. Under both resampling methods, the Heston model dominates the GARCH-M model as well as other models we tested.

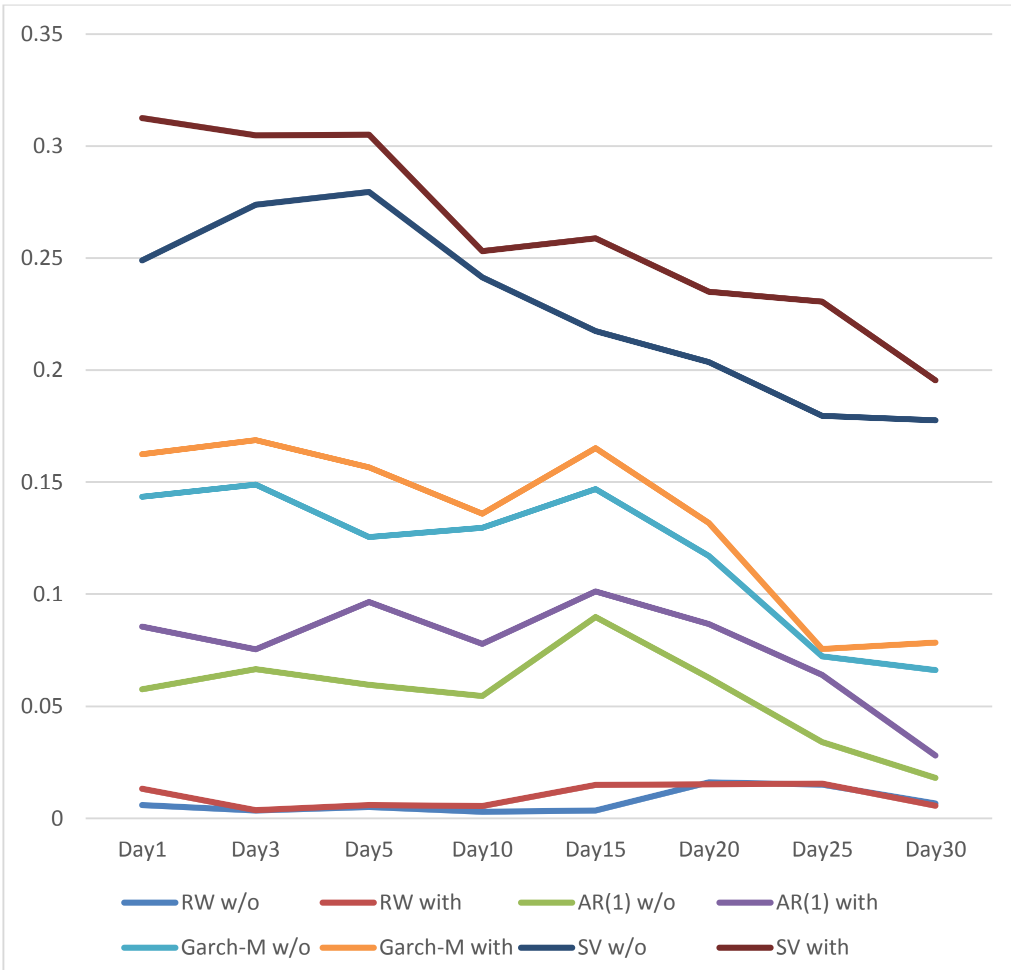

Figure 9: Average Simulated P-value across Days

In addition, notice that the inverse head-and-shoulder pattern returns can be replicated by the Heston model quite well. Investigating theoretical corresponding relationships between the specific non-linear structure and the model specifications is beyond the scope of this thesis, however, it may serve as a fruitful future research direction.

Although a considerable part still remain to be explained by more complex structures, the Heston model does perform better than the classic econometrics models, such as AR(1) and GARCH-M. These results not only support the insights of Fama and Blume (1966) and Neftci (1991) that technical analysis may capture the nonlinear properties of stock prices left unexploited by linear models, but they also indicate that some of the abnormal returns are generated from more complex volatility structures, as specified by the stochastic volatility models in the mathematical finance literature, than the traditional volatility cluster phenomenon specified by the generalized autoregressive conditional heteroskedasticity (GARCH-M) models.

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CHAPTER 5

CONCLUSION

This thesis investigates empirical evidence for the profitability of the chart patterns widely used by market practitioners in identifying market trend movements. The first chapter summarizes my contributions and provides a fundamental understanding of the previous works on technical analysis, especially those on chart patterns. The second chapter provides definitions of chart patterns, their recognition methods and trading strategy designs.

The third chapter presents an empirical analysis of the profitability of the chart patterns identified above. We take positions after the patterns end and hold them from one day to thirty days, observing their average returns across all patterns of the same type. Further, the aggregate returns are calculated by allocating our initial investment evenly to all stocks that generate patterns, and then calculating the return time series across the whole data sample after controlling for the three Fama-French factors. The results show that although the abnormal returns are reduced by controlling the three-factor model, there are still substantial abnormal returns remaining.

Based on the discoveries of the first three chapters, the fourth chapter investigates whether the econometric models and mathematical finance models that are widely used to simulate stock prices can generate similar patterns to the actual market data, and in particular, whether these patterns generate similar abnormal returns as the real market. The results reveal that although these abnormal returns cannot be fully explained by first-order autocorrelation or changing volatility, a stochastic volatility model from the mathematical finance literature does explain a substantial part of the abnormal returns by simulating more complex volatility innovation structures.

Appendix: the log-likelihood function detail from Ait-Sahalia and Kimmer(2010)

$$D(x;\theta) = \ln\big((1-\rho^2)\sigma x_2\big)/2;\ \ a_1 = a;\ a_2 = \kappa\gamma;\ b_1 = \rho\gamma - 0.5; b_2 = \gamma\sigma - \kappa$$

$$\begin{aligned}
C_x^{(-1)}(x|x_0;\theta) = &-\frac{(x_2-x_{20})^2 - 2\rho\sigma(x_2-x_{20})(x_1-x_{10}) + \sigma^2(x_1-x_{10})^2}{2(1-\rho^2)\sigma^2 x_{20}} \\
&+\frac{(x_2-x_{20})^3}{4(1-\rho^2)\sigma^2 x_{20}^2} - \frac{\rho(x_2-x_{20})^2(x_1-x_{10})}{2(1-\rho^2)\sigma x_{20}} + \frac{(x_2-x_{20})(x_1-x_{10})^2}{4(1-\rho^2)x_{20}^2} \\
&+\frac{(7\rho-8\rho^3)(x_2-x_{20})^3(x_1-x_{10})}{24(1-\rho^2)^3\sigma x_{20}^3} \\
&-\frac{(7-10\rho^2)(x_2-x_{20})^2(x_1-x_{10})^2}{48(1-\rho^2)^2 x_{20}^3} - \frac{\rho\sigma(x_2-x_{20})(x_1-x_{10})^3}{24(1-\rho^2)^2 x_{20}^3} \\
&+\frac{\sigma^2(x_1-x_{10})^4}{96(1-\rho^2)^2 x_{20}^3} - \frac{(15-16\rho^2)(x_2-x_{20})^4}{96(1-\rho^2)^2\sigma^2 x_{20}^3}
\end{aligned}$$

$$\begin{aligned}
C_x^{(0)}(x|x_0;\theta) = &\frac{(x_2-x_{20})(x_{20}b_2 - \rho\sigma x_{20}b_1 - \rho\sigma a_1 + a_2)}{(1-\rho^2)\sigma^2 x_{20}} \\
&-\frac{(x_1-x_{10})(\rho x_{20}b_2 - \sigma x_{20}b_1 - \sigma a_1 + \rho a_2)}{(1-\rho^2)\sigma x_{20}} - \frac{\sigma^2(x_1-x_{10})^2}{24(1-\rho^2)x_{20}^2} \\
&-\frac{(x_2-x_{20})^2(\alpha(\alpha - 12\rho\alpha_{1)+}12a_2)}{24(1-\rho^2)\sigma^2 x_{20}^2} \\
&+\frac{(x_2-x_{20})(x_1-x_{10})(\rho\sigma^2 - 6\sigma a_1 + 6\sigma a_2)}{12\sigma x_{20}^2(1-\rho^2)}
\end{aligned}$$

$$\begin{aligned}
C_x^{(0)}(x|x_0;\theta) = &\frac{\rho\sigma a_2 b_1 + \rho\sigma a_1 b_2 - \sigma^2 a_1 b_1 - a_2 b_2}{(1-\rho^2)\sigma^2} + \frac{(2\rho\sigma b_1 b_2 - \sigma^2 {b_1}^2 - {b_2}^2)x_{20}}{2(1-\rho^2)\sigma^2} \\
&-\frac{\sigma^4 - \rho^2\sigma^4 + 6\sigma^2 {a_1}^2 - 6\sigma^2 {a_2}^2 + 6\rho^2\sigma^2 a_2 - 12\rho\sigma a_1 a_2 + 6{a_2}^2}{12(1-\rho^2)\sigma^2 x_{20}}
\end{aligned}$$