An empirical investigation of technical analysis in fixed income markets

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Abstract

The aim of this thesis is to evaluate the effectiveness of technical analytic indicators in the fixed income markets. Technical analysis is a widely used methodology by investors in the equity and foreign exchange markets, but the empirical evidence on the profitability of technical trading systems in the bond markets is sparse. Therefore, this thesis serves as a coherent and systematic examination of technical trading systems in the government bond futures and bond yield markets.

We investigate three aspects of technical analysis. First, we evaluate the profitability of 7,991 technical trading systems in eight bond futures contracts. Our results provide mixed conclusions on the profitability these technical systems, since the results vary across different futures markets, even adjusting for data snooping effects and transaction costs. In addition, we find the profitability of the trading systems has declined in recent periods. Second, we examine the informativeness of technical chart patterns in the government benchmark bond yield and yield spread markets. We apply the nonparametric regression methodology, including the Nadaraya-Watson and local polynomial regression, to identify twelve chart patterns commonly taught by chartists. The empirical results show no incremental information are contained within these chart patterns that investors can systematically exploit to earn excess returns. Furthermore, we find that bond yield spreads are fundamentally different to price series such as equity prices or currencies. Lastly, we categorize and evaluate five type of price gaps in the financial markets for the first time. We apply our price gap categorisation to twenty-eight futures contracts. Our results support the Gap-Fill hypothesis and find that some price gaps may provide additional information to investors by exhibiting returns that are statistically different to the unconditional returns over a short period of time.

In conclusion, this thesis provides empirical evidence that broadly support the usage of technical analysis in the financial markets.

Contents

List of Tables

List of Figures

Acknowledgements

American economist Fisher Black once mentioned that *"By its nature, research involves many false starts and blind alleys."* This thesis is no exception. After two 'false starts' in the first two years of my doctorate program, I finally began my research on technical analysis after I met Professor David Barr in 2004. I take this opportunity to thank him for his excellent supervision and guidance during the last two years, and for sharing many of his experiences with me.

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Chapter 1

Introduction

Modern financial markets are complex and fascinating. One important characteristic of the modern financial system is the presence of organized market place for buying and selling financial assets. In these early stock exchanges, detailed financial price data of stocks and commodities are recorded daily, either updated on ticker tapes or chalk boards as brokers and dealers conduct transactions.[1]

Long before the advent of the efficient market hypothesis, market practitioners have already begun creating simple statistical methods to analyze these financial data. In 1884, Charles Dow developed the Dow Theory and created the Dow Industrial Index to track the broad movements of the US stock market[2], 29 years before Louis Bachelier (1900) applied the Random Walk theory to describe the movements of stock prices! Based on Dow's work and other early pioneers, a new field in finance has grown rapidly, one that uses price and volume data solely to predict future stock prices. Today, this field is known as *technical analysis*.

What roles do technical analysts perform? In summary, the practice of technical analysis is defined by Pring (1991, p.2) to be:

> The technical approach to investment is essentially a reflection of the idea that prices move in trends that are determined by the changing attitudes of investors toward a variety of economic, monetary, political, and psychological forces. The art of technical analysis, for it is an art, is to identify a trend reversal at a relatively early stage and ride on that trend until the weight of the evidence shows or proves that the trend has reversed.

[1]See, for example, Michie (1999) for an account of the historical development of the London stock exchange.

[2]See Lynch and Rothchild (1995, p.70) for a description on the creation of the Dow Jones Industrial Index.

This definition shows that technical analysis encompasses wide-ranging fields, with the most important strategies being *contrary* and *trend-following*. To some extent, technical analysis also include some analyses of investors psychology, an area that has only begun in the academic finance in earnest, popularly known as *behavioural finance*.

As far as academics are concerned, they have always rejected technical analysis, as Campbell, Lo and Mackinlay (1997, p.43) succinctly describe this view:

> Historically, technical analysis has been the "black sheep" of the academic community. Regarded by many academics as a pursuit that lies somewhere between astrology and voodoo, technical analysis has never enjoyed the same degree of acceptance that, for example, fundamental analysis has received.

However, this view has begun to change in recent decades, possibly due to the fact that using fundamental information to predict the level of asset prices has become notoriously difficult, and many technical oriented traders have profited from this using approach.[3] Moreover, modern media may have assisted in the distribution of "technical" knowledge in reports and periodicals, as described by Robert Shiller (2000, 2002). For example, a typical investment report from brokerage firms or news agencies may have the following titled: *"Balancing the fundamentals: Technical analysis offers investors other ways to read market tea leaves."*[4] Because of these developments, technical analysis has now become indispensable to a large proportion of traders and fund managers. It is common to see investors adopting a 'hybrid' approach, one that includes both technical and fundamental inputs into their investment decisions.

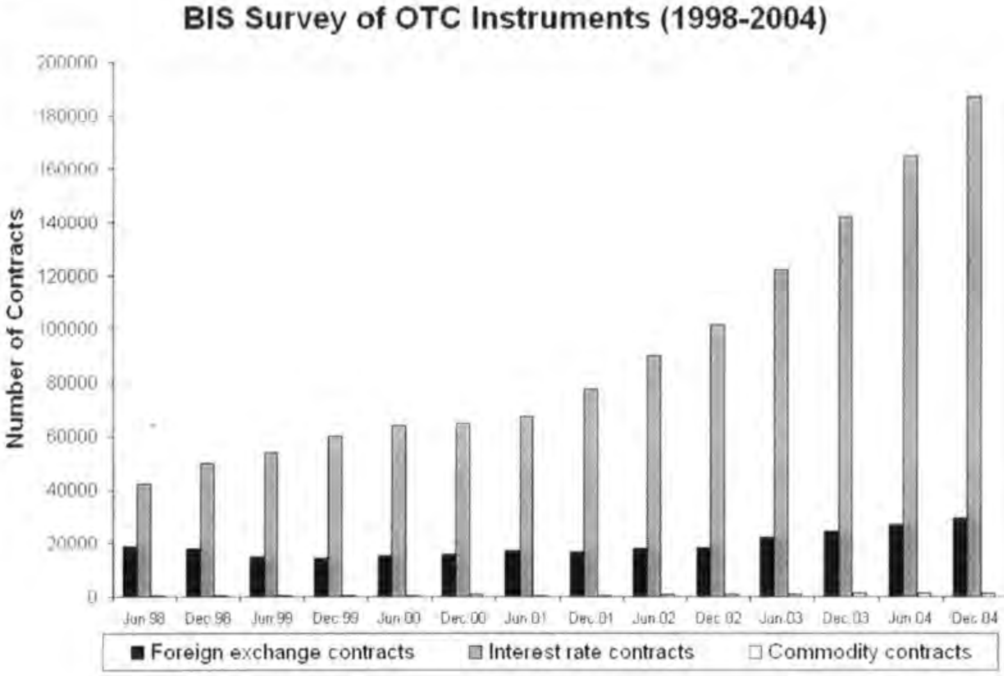
Given the widespread knowledge of technical analysis, it is generally assumed that technical analysis is equally applied to all asset classes, including equity, currency, commodities and fixed income markets. Even though the finance literature has produced an extensive amount of research on technical analysis in the equity and currency markets, the evidence for fixed income markets is less clear and established. Therefore, the objective of this thesis is to evaluate the effectiveness of technical analysis in trading fixed income securities.

In the bond world, quantitative models reign supreme. To provide partial evidence for this fact, Figure 1.1 presents the biannual survey results conducted by the Bank of

[3]If one views that technical analysis should belong to voodoo science, the results obtained by Yuan, Zheng and Zhu (2006) will be even more perplexing. They find that *"stock returns are lower on the days around a full moon than on the days around a new moon."*

[4]International Herald Tribune, 18 February 2006, p.14.

Figure 1.1: A BIS Survey of Assets By Classes in the Over-The-Counter (OTC) Markets



International Settlement (BIS) of the Over-The-Counter (OTC) derivatives trading since the late nineties (BIS, 2004, 2005). The growth rate of OTC markets for interest rate derivatives contracts shown in this figure is astonishingly high and dominate the foreign exchange and commodity derivatives by a large margin. Fixed income markets are unique among the asset markets mainly because of *cash flow*. Unlike equities or commodities, bond markets have a fixed, or at least a partially fixed, known cash flow projected some time into the future. This cash feature is attractive to investors because they can buy and sell fixed income instruments to hedge their cash flow requirements.[5] For traders and arbitrageurs, fixed cash flow makes it fairly straightforward to compute the relative value of various fixed income securities and replicate it with other securities. As a result, arbitrageurs perceive bond markets to contain little fundamental risk.[6] The combination of above factors means that traders are more reliant on quantitative models, such as Heath, Jarrow and Morton

[5]For example, government and corporate bonds are frequently traded by pension funds and insurance firms to hedge their business liabilities, a process known as *immunization*.

[6]Even though many events and studies have proved otherwise. The collapsed of Long-Term Capital Management in September 1998 is a good example of the huge capital losses incurred in arbitraging swap spread markets. Duarte, Longstaff and Yu (2005) investigate whether such arbitrage activities amount to picking 'nickels in front of a steamroller'. The main result from their study shows the excess returns from a number fixed income arbitrage strategies are positively skewed, even after controlling for leverage effect and the possibility of a unrealized "peso" event. This means that there are economically viable benefits to arbitrageurs.

(1992) and Brace, Gaterek and Musiela (1997) frameworks for relative trading and derivatives hedging rather than using technical analysis in forecasting interest rates and bond yields. Hence, it would be very interesting to test how effective is technical analysis in the fixed income markets in terms of supporting investment strategies.

For the rest of this chapter, we summarise and discuss the current state of affairs in technical analysis with applications to the fixed income markets. The objective here is not to provide a literature review of technical analysis since it has already been comprehensively written by Park and Irwin (2004). Rather, we distill a number of major results from the literature into several stylized facts. For this purpose, we first provide an overview of the technical analytic indicators. Next, we describe and discuss three stylized facts about these technical indicators. Lastly, we discuss the scope of technical analysis in the fixed income markets.

1.1 Technical Analysis: Facts and Fantasies

1.1.1 An Overview of the Technical Indicators

Developing and implementing technical trading systems require vast amount of efforts from traders, not to mention the critical need to keep abreast of the financial markets developments that may have an impact on the trading systems. Generally, technical analysis is an umbrella term for a myriad of indicators. There are numerous technical indicators and methods for investors to choose from. For a more thorough discussions of many of these methods, see Edwards and Magee (1966), Murphy (1986), Schwager (1996), Pring (1991), Bulkowski (2005) and Kaufman (2005). The following is a brief listing of the fundamental building blocks of technical indicators:

1. **Technical Theories.** The advocation of technical theories marks the beginning of technical analysis. The key theories include Dow Theory, Fibonacci theory, Elliot Wave Theory (Prechter (1980)), Kondratieff Wave theory (Kondratieff (1984)) and Gann Lines. Many technical analysts use these theories as a tool to track the overall performance of the markets over a period of time. The length of historical analysis varies among theories and analysts. See Brown, Goetzmann and Kumar (1998) for an analysis of the Dow hypothesis.

2. **Technical Charts and Chart Patterns.** Charting is the foundation of technical analysis. The major chart types include line, bar, point-and-figure and candlesticks. Many chart patterns have been developed for each of these charts in order to analyse the price actions. The major price patterns for line and bar charts include Head-and-Shoulders, Triangles, Broadening, Rectangles, Flags,

Double and Triple formation, (Bulkowski (2005)) while some of the major patterns in candlestick charts are Takuri, Kubitsuri, Kabuse, Kirikomi, Tsutsumi, Hoshi, Narabi Kuro, Tasumi and Doji (Nison (1991)). Lastly, the major patterns in point-and-figure charts include Bullish signals, Bearish signals, Catapults formation, Long tail, Broadening formation, Relative Strength and Bullish Percent (Dorsey (2001)). No comparison has been made to see which charting method produces better investment results.

3. **Trend Following Indicators.** This area provides the most popular technical indicators among technical analysts and traders. Major trend-following strategies include filters (Alexander (1961, 1964)). moving average and its variants, channel breakout, support and resistance, and swing trading.[7] In addition, the price distribution trading systems attempt to capture price trends based on the moments of the financial prices, with indicators such as skewness and kurtosis.

4. **Breath Indicators.** Breath indicators analyse the volume aspect of the financial markets, usually in a manner that complements trend-following indicators or chart patterns. Indicators include volume, On-Balance volume, Accumulator and Advance-Decline system. (See Kaufman (2005))

5. **Short-term Momentum Indicators.** This category includes indicators like moving average convergence-divergence (MACD), momentum, Stochastics, relative strength index (RSI), rate-of-change, percent R (%R), among many others, to track the short-term price movements.

6. **Sentiment Indicators.** These indicators attempt to measure the broad market psychology. Sentiment indicators include short-interest ratio, insider trading news reports, grouping of advisory services, mutual funds cash/asset ratio, analysis of margin debt, put/call ratio, surveys of investment managers' views, investment newsletter sentiment, short interest. Barron's confident index and CBOE volatility index (fear gauge). Davis (2003) provides some interesting examples of contrarian indicators.

7. **Cycles and Seasons.** Observing that financial markets exhibit cycles, technical analysts use a number of wave-based mathematical tools such as Fourier system to model these cycles. Studies of current business cycles are frequently couched in the framework of Dow theory or Kondratieff wave theory.

[7] Kaufman (2005, p.153) defines 'price swing' to be "a sustained price movements." Thus, swing trading attempts to capture these price swings.

8. **Econometric Models.** Recent advancements in econometrics techniques have popularised the usage of advance statistical tools in analyzing market behaviour. Models that technical analysts have employed include linear regression, ARIMA models, stochastic volatility models such as AutoRegressive Conditional Heteroskedasticity (ARCH, Engle (1982)) and Generalized AutoRegressive Conditional Heteroskedasticity (GARCH, Bollerslev. (1986)), and state space models like Kalman Filter. How profitable these models are is yet to be empirically verified.

9. **Network Models.** Advancing computer technology has made complicated models like neural network, genetic algorithm, and chaos system popular among sophisticated traders, as these network models are able to handle complex, nonlinear multivariate relationships among numerous financial variables. However, the majority of the empirical research of these methodologies generally found negative results about their profitability. Neural network, in particular, has been shown to generate inconsistent profits over time. (See, for example, White (1988), Trippi and Turban (1992), Allen and Karjalainen (1999) and Ready (2002)). Whether these methods are as widely used as simple indicators like moving average is not known.[8]

In summary, the number of technical analytic tools available to investors is enormous. It is common for traders to combine one or more of the above indicators into a single and coherent trading system. Pring (1991, p.9), for instance, recommends that, *"No single indicator can ever be expected to signal trend reversals, and so it is essential to use a number of them together to build up a consensus."* Pruitt and White (1988) and Pruitt, Tse and White (1992) combine several technical indicators, including Cumulative volume, RelatIve Strength and Moving Average indicators and assess their profitability. This strategy is commonly known as CRISMA. They find this system earned annualized mean excess returns of 1.0 to 5.2 percent after transaction costs in US equity markets over period 1986-1988, which outperformed the buy-hold strategy. But Goodacre, Bosher and Dove (1999) apply this strategy to UK equity market over 1987-1996 and find little evidence of high excess return after taking transaction costs and risk into account. Similarly, Goodacre and Kohn-Spreyer (2001) discover this system generates little profits in the US market in the nineties after adding transaction costs and risk. But CRISMA system is only one possible

[8]The difficulties in using neural network for trading purpose are due to (i) Sophisticated mathematical methods involved, (ii) No a priori hypothesis on selected explanatory variables. The repercussion is that neural network provides no explanation as to why the forecasts are inaccurate and when the network will likely to provide good forecasts, and (iii) Neural network are prone to overtraining and faulty optimization. (See, for example, McNelis (2005))

combination. There are many other combinations. Moreover, many technical analysts have developed many new indicators that not listed here due to their proprietary nature. Thus it is difficult for us to test all indicators and their combinations.

1.1.2 Some Stylized Facts of Technical Analysis

The literature on technical analysis is a large and growing one. This section provides some stylized facts distilled from this voluminous literature:

Stylized Fact 1: Increasing Usage of Technical Analysis. An increasing number of traders and investors is using technical analysis to compliment their trading activities and investment strategies. This can be due better computing facilities and data availability. To prove this fact, various survey studies conducted by Group of Thirty (1986), Brorsen and Irwin (1987), Frankel and Froot (1990), Taylor and Hellen (1992), Menkhoff (1997), Lui and Mole (1998), Cheung and Wong (2000), Cheung, Chinn and Marsh (2000), Cheung and Chinn (2001) and Oberlechner (2001) have confirmed such a trend in the financial community. But whether increasing usage of technical indictors will lead to a decrease in the profitability of these strategies is difficult to verify since many other factors may influence the overall results.

Stylized Fact 2: Profitability of Technical Analysis is Still Inconclusive. A voluminous amount of empirical studies have researched on the profitability of technical trading systems. Unfortunately, the conclusion from these studies is far from certain. Early empirical studies by Cootner (1964), Van Horne and Parker (1967, 1968), Alexander (1961, 1964), Fama and Blume (1966), Jensen and Benington (1970), Dryden (1970a, 1970b) and James (1968) find that technical rules such as filter and moving average rules generate inconsistent profits. For instance, James (1968, p.326) concludes:

> What seems abundantly clear, however, is that when records of individual stocks (as opposed to averages or indices of stock price) are examined, this survey detected little reason to believe that investors' position will be benefited by the use of monthly moving average.

The collapsed of Bretton Wood system in the early seventies, however, contributed to higher price volatility in the financial markets. In light of these developments, a number of studies find technical indicators to be profitable in the currencies markets, including Dooley and Schafer (1983), Schulmeister (1987) and Sweeney (1986, 1988), Levich and Thomas (1993), Silber (1994), Taylor

(1994), Menkhoff and Schlumberger (1997), Lee and Mathur (1996a, 1996b), Kho (1996), Szakmary and Mathur (1997), Chang and Osler (1999), LeBaron (1999), Maillet and Michel (2000), Okunev and White (2003), Lee, Gleason and Mathur (2001), Lee, Pan and Liu (2001), Martin (2001), Neely (2002), Saacke (2002) and Sapp (2004). They report that a variety of technical rules are consistently profitable in the currency markets, even during central bank intervention. In the equity markets, Brock, Lakonishok and LeBaron (1992), Bessembinder and Chan (1995), Huang (1995), Wong (1995), Raj and Thurston (1996), Mills (1991, 1997), Hudson, Dempsey and Keasey (1996), Gencay and Stengos (1997), Ito (1999), Ratner and Leal (1999), Coutt and Cheung (2000), Gunasekarage and Power (2001) and Ready (2002) have found on average that technical indicators yield positive returns in developed and developing capital markets. But many of these studies conclude that these technical strategies become unprofitable once transactions costs and bid-ask spreads are included. On the whole, the profitability of technical strategies is found to be weaker in equity markets than in currency markets. In fixed income markets, few studies has empirically tested the profitability of technical analysis.

Fact 3: Suitability of Technical Analysis Differs Among Traders. The profitability of technical trading system depends on the traders' psychological makeup and compatibility. Two issues are certain here. One, not everyone is suited to be a trader and two, not every trader can be a profitable technical trader. (See, for example, Schwager (1990, 1992) and Steenbarger (2002)) Recently, academic studies by Lo and Repin (2002) and Lo, Repinz and Steenbargery (2005) have begun to focus on the behavioral reaction of traders during trading hours. However, this is an area that demands further research.

Discussions

Stylized Fact 1: Although the first stylized fact is clear and unambiguous, academics are intrigued as to why analysts and traders use technical analysis at all. To resolve this puzzling behaviour, a number of theoretical models have been proposed, mostly within the noisy rational expectations equilibrium framework. These models assume that the current asset prices do not fully reveal all available information because of market noise. Consequently, technical analysis can aid investors in disentangling information from these market noise. Formal models by Brown and Jennings (1989) and Grundy and McNichols (1989) show that a series of price patterns help traders to make better judgement of the underlying asset through learning behaviour. In a similar framework, Blume, Easley and O'Hara (1994) consider the role of volume and price together, arguing that volume provide important information to traders, one that is unique from prices. Overall, the economic impact of an increasing number of technical investors in the financial market is yet unclear.

Stylized Fact 2: The second stylized fact, on the other hand, is still controversial. A corollary of efficient market hypothesis (EMH) implies that profitability of technical trading systems equates market inefficiency and vice versa, as strongly advocated by Fama (1970). Since in an efficient market, prices reflect all available information. Technical rules that rely on historical prices should not be able to consistently produce superior results in comparison to passive trading strategies after adjusting for risk and transaction costs. (See, for example, Roberts (1967) and Pinches (1970)) Many early empirical studies on US equity markets indeed confirm this hypothesis by documenting the fact that moving average and filter rules are unprofitable. This led to the conclusion that technical strategies cannot help investors in earning excess returns consistently and that financial markets are efficient, as Jensen and Bennington (1970, p.470) summarise this view:

> Likewise given enough computer time, we are sure that we can find a mechanical trading rule which works on a table of random numbers - provided of course that we are allowed to test the same rule on the same table of numbers which we used to discover the rule. We realize of course that the rule would prove useless on any other table of random numbers, and this is exactly the issue with Levy's (1971) results.

However, there is a possible flaw to this conclusion. There are hundreds, if not thousands, of possible technical strategies for traders to choose from, with many new ones being developed daily and old ones discarded. Since it is virtually impossible to test all trading systems, is it correct to deduce that the whole financial market is efficient (or inefficient) based on a small subset of trading strategies tested on a small subset of securities? As Timmermann and Granger (2004) recently point out that empirical tests of EMH need to have access to the full set of forecasting models available at any given point in time and the search technology used to select the best forecasting model. None of the above studies, however, fully satisfies these requirements. Furthermore, Grossman and Stiglitz (1980) identify that a perfectly efficient market is impossible due to the costs involved in gathering information and interpreting these information.

Besides, it is well known that academic research suffers from the so-called *publication bias*—only unusual and significant results get published. The exclusion of many other technical indicators may affect the conclusion that financial markets are efficient. There are two opposing effects caused by this bias. One, the excluded technical indicators are unprofitable, which strengthens the case for market efficiency since the indicators that are profitable are likely to be due to data snooping.[9] Two, the excluded indicators are profitable but not known to researchers. In this situation, the case for an efficient market is weaken.[10]

As many empirical studies subsequently show that the profitability of technical indicators varies across financial markets and time periods, it appears that financial markets may exhibit time-varying efficiency across time, across asset markets and across different countries, as Neftci and Policano (1984, p.138) conclude from their tests on trend-following indicators in the futures markets:

> A disturbing point was the way results varied across commodities and across contracts for the same commodity. One set of parameters which yield a significant dummy in one case, was found to be insignificant in other cases.

Furthermore, many tests of technical system do not take into account that technical traders can change their trading strategies change over time by incorporating new market characteristics. Traders are not static users of systems but evolutionary. Time to time, they even override trading signals from the trading systems. This is to ensure the profitability of their technical system and their survivability over the long run. Recently, Andrew Lo (2004) has coined such evolutionary behavior *Adaptive Market Hypothesis* (AMH). This hypothesis postulates that the survivability of market participants is the most important objective in the traders' mind, even though other objectives, such as profit and utility maximisation, are important. In fact, the well known fund manager George Soros (1987) exhibits this type of mentality, as he states the objective of his Quantum Fund to be: *"Generally speaking, I am more concerned with preserving the Fund's capital than its recent profits, so that I tend to be more liberal with self-imposed limits when my investment concepts seem to be working."* (p.145)

Only recently has research begun to recognize these facts by testing more technical strategies and to account for the possible effects of data snooping. For example, Sullivan, Timmermann and White (1999) tested 7,846 technical strategies, while Hsu

[9] White (2000, p.1097) defines data snooping to be *"Data snooping occurs when a given set of data is used more than once for purposes of inference or model selection."*

[10] One stylized fact in the mutual fund industry is that the majority of fund managers are unable to outperform passive investment strategies, especially when transaction costs are added into the evaluation. (See, for example, Malkiel (1995, 2003)) Whether mutual fund managers use technical analysis in selecting securities is not known.

and Kuan (2005) tested 39,832 strategies. Moreover, studies like Pesaran and Timmermann (1995)have adopted the idea of "recursive modeling" to account for the fact that technical strategies change over time. Recently, White (2000) and Hansen (2005) develop variants of the stationary bootstrap procedure in an attempt ameliorate the data mining problem.

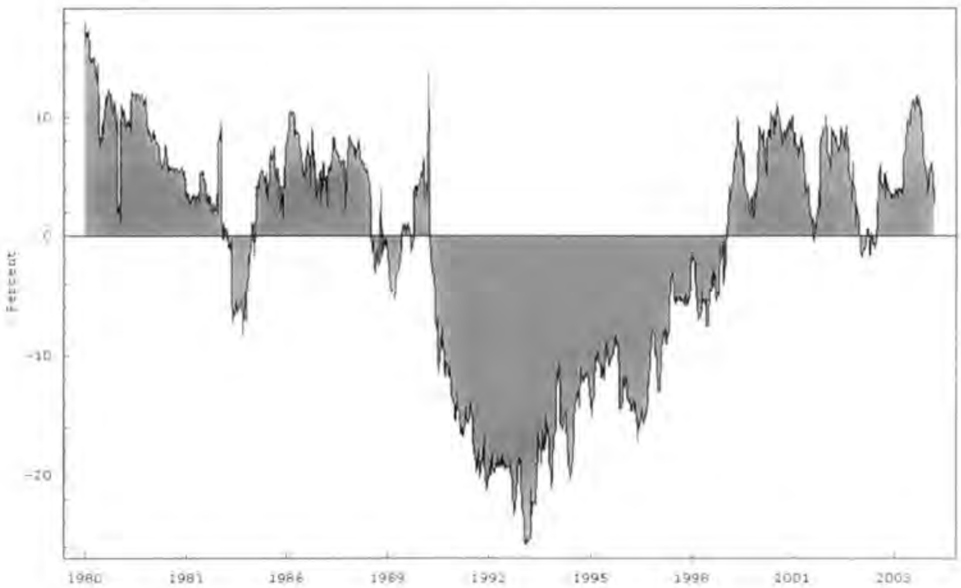
However, even with such a huge number of strategies and adoption of complicated bootstrap methodologies in the evaluation procedure, we are still no closer to answering whether financial markets are efficient. This is because the results of these studies seem to vary over time, asset markets and strategies. (See Chapter 2 for more discussions of these bootstrap studies.) To give a simple example of time-varying market efficiency, Figure 1.2 displays the first-order autocorrelation coefficients (in percentage) of the weekly US 30-year Treasury bond futures returns over 1980-2005. The simple Random Walk hypothesis asserts that all financial returns are serially uncorrelated, which implies that all correlation coefficients should not be statistically different from zero.[11] However, the coefficients in Figure 1.2 seem to refute this assertion. If the values of autocorrelation coefficients are crude proxies for market efficiency, then it is obvious that this efficiency varies through time. In fact, Andrew Lo (2004, p.18) has described that market efficiency is dependent on the competition and other variables within any given market:

> Market efficiency cannot be evaluated in a vacuum, but is highly context-dependent and dynamic, just as insect populations advance and decline as a function of the seasons, the number of predators and prey they face, and their abilities to adapt to an ever-changing environment.

Another important point that many researchers neglected when evaluating technical trading strategies is that technical strategies constitute only a portion of the overall trading system. There are many aspects of the trading system which are very important, such as risk management and capital management, not to mention the personality of traders involved, all of which can drastically affect the final profits. Practical issues like stop loss, position sizing, risk-reward ratio, markets to trade and leverage level need to be addressed. Since these factors vary widely across market participants, it is difficult to impose a set of homogeneous and realistic assumptions across all markets participants for modelling purpose. A prime example is the leverage level of a fund. Theory tells us that starting with too much capital may hamper a trader's performance by being over-capitalized, but if it is unable to sustain a string of losses, an otherwise profitable technical trading system may still be terminated

[11]See Campbell, Lo and Mackinlay (1997, p.42) for further discussion about testing for $H_0 : \hat{\rho}_1 = 0$.

Figure 1.2: First-Order Autocorrelation Coefficients of the US 30-year Bond Futures Weekly Returns Using 3-year Rolling Windows from January 1978 to February 2005.



prematurely, as in the arbitrage scenario envisioned by Shleifer and Vishy (1997). The optimal leverage level of a fund depends on a number of factors, such as appetite (or perhaps disregard?) for risk. So how should one manages his/her leverage level? Theoretically, Grossman and Vila (1992) solve for the dynamic optimal trading strategy of an investor who faces some form of leverage constraint. Their model assumes that investors have constant relative risk aversion, which may not be reflective of actual market participants.[12] Liu and Longstaff (2000) study the optimal investment strategy in a market where there are arbitrage opportunities. They find the optimal leverage for arbitrageurs is determined largely by the volatility and speed of convergence of the pair trades, and the characteristics of the margin requirements. In Duarte, Longstaff and Yu (2005), they also find that the amount of capital allocated to fixed income arbitrage is correlated to the strategy excess returns. They suggest that having (p.22) *"intermediate levels of capital may actually improve liquidity and enable trades to converge more rapidly."* However, no such study has been carried out on technical strategies and so we do not know what are the effects of time-varying leverage on the final results and whether an optimal leverage level exists.

[12]Along the same line, Getmansky, Lo and Makarov (2004) develop an econometric model with dynamic leverage characteristic to model hedge funds returns. The exogenous factors are market volatility and prices. De Souza and Smirnov (2004), for example, model the leverage as a function of the net asset value of a fund with barriers. In trading underlying Treasury securities, high leverage is attainable via repo financing, that is, using the Treasury securities as collateral for funding over a short-term horizon.

Stylized Fact 3: The third stylized fact is perhaps the most important: Not every trader uses technical trading systems, and not every trader who uses them can be successful. Two important but controversial issues need to be addressed here: (1) Can a successful technical trading system be publicized and still remain successful? and (2) What makes a successful technical trader and what are their characteristics? Regarding the first issue, there are plenty of evidence presented in Schwager (1990, 1992). For example, two highly successful technical traders, William Eckhardt and Richard Dennis, debated on whether a profitable technical trading system can be taught to a group of inexperience traders and remain profitable for these new traders. To settle this issue, they taught a number of trainees traders about their highly successful technical systems and supply these newly minted traders with capital ranging from \$500,000 to \$1,000,000 for them to begin trading with their method. (These trainees are the so-called *Turtles* traders.) After two successive experiments, the trading results accumulated by these traders were labelled as "outstanding success" by William Eckhardt. (Schwager (1990, p.128)), which perhaps settled the question that successful technical trading system can be taught from one generation to another, and still remain profitable.

However, would exposing the successful trading system render them ineffective since many investors will be using the same indicators? The answer to this question is unclear, as from the above-mentioned experiment, it appears that the technical system will remain successful. Another such strategy that survive public scrutiny is the *momentum* strategy initially documented by Jegadeesh and Titman (1993), which is still found to be profitable nine years later in Jegadeesh and Titman (2001).[13] However, observations from arbitrage activities are less supportive as the burgeoning hedge fund sector may add impetus for relative mispricing of securities to disappear quickly, especially in the fixed income sector.[14]

[13] By and large, the momentum strategy in Jegadeesh and Titman's (1993, 2001) study and the trend-following strategy in the above-mentioned experiment are similar, in the sense that both strategies chase after recent price trends. De Long et al. (1990) have modeled such a feedback mechanism between asset prices and market participants' psychology. The basic observation is that the higher the asset prices, the more bullish market participants becomes, and vice versa. Studies by DeBondt (1993), Griffin, Harris and Topaloglu (2003) and Brunnermeier and Nagel (2004) confirm this trend chasing behaviour by showing that forecasters and institutional investors do chase after trends once the trend is detectable in asset prices, and attempt to time the market by reducing their holding before the bubble burst. Abreu and Brunnermeier (2003) develop a theoretical framework that model the dynamics of asset prices when informed and rational agents ride a price bubble until it reaches a critical level.

[14] Riskless arbitrage depends fundamentally on the Law of One Price, which implies that two securities with similar payoff structure should have the same price. The more capital is put to execute these arbitrage strategies, especially on the relative value strategies in the fixed income market, the faster the convergence between the two securities will take place. The positions for arbitrage or convergence will be exactly opposite to that of trend-following technical trading system.

The second issue about the characteristics that underpin successful technical traders is harder to validate because the behavior of traders who use technical trading systems ranges so widely. For example, Lo, Repin and Steenbargery (2005) find little correlation between a trader's personality traits and the trading performance in their survey of 80 traders. Moreover, it is well known that many biases affect traders, such as loss aversion biases (Odean, 1998) and overconfidence biases (Daniel, Hirshleifer and Subrahmanyam (2001)). How to control for this biases when evaluating the profitability of trading system remains a rich avenue for future research.

Moreover, academic studies do not incorporate that fact different market participants will inevitably gravitate to the trading model that best suit their personality, no matter whether it is fundamental system or technical system. For example, some traders, such as day traders, prefer short-term trading horizon and consequently they built their trading model accordingly to capture short-term price movements. On the other hand, some traders are inclined towards long-term positional trade.[15] Their trading model will try to capture trends in financial markets over a longer time frame. More research is definitely needed in understanding how to match a trader's behavior to the optimal trading style and what kind of traders use technical tools successfully.

Recently, progress has been made in linking the emotion states of a trader with their trading performance by Lo and Repin (2002), Steenbarger (2002), Fento-O'Creevey et al. (2004) and Lo, Repin and Steenbargery (2005). They find that the emotional responses to stress and financial losses of traders are vital and important ingredients in ensuring the survivability of traders. Perhaps one way that traders express their survivability (by reducing the stress caused by trading activities) is to choose a trading system that accentuates mental calmness and ensuring optimal performance during trading hours. This can only be achieved if the trading system they use is compatible with their mind-set and personality.

1.2 Active Bond Portfolio Management and the Quest For Bond Yields

1.2.1 Active Bond Portfolio Management

Within the universe of bond portfolio management, there are two main types of strategies in generating portfolio yields: *active* and *passive* management. Since pas-

Thus, it is difficult for us to judge whether more trend-following investors will sway the financial markets toward increased market efficiency or whether they will accentuate the price trends.

[15] Unsurprisingly, even the word 'long-term' can mean different time frame to different traders.

sive bond managers attempt to match the returns of the portfolio to a particular index without any active input, technical analysis generally does not serve any purpose in this area.[16] On the other hand, active bond managers strive to outperform a targeted benchmark with a focus on maximizing portfolio yield, and subjected to a targeted average maturity or credit quality of the portfolio. This is an area where technical analysis may provide value to bond managers and traders.

Broadly speaking, there are four main types of active bond portfolio management approaches, which we briefly described below (See, for example, Fabozzi (2001, 2005)):

1. **Directional Approach**. This approach attempts to profit from the expected trend in interest rate by adjusting the duration length of the bond portfolio to capitalize on the directional views, or by acquiring unhedged positions in bond futures. A simple strategy is to increase the portfolio duration if interest rates are expected to increase and reduce portfolio duration if interest rates are expected to decrease. This relies greatly on the market timing ability of the manager. For obvious reason, this strategy entails high market risk and thus constitutes only a portion of the activity of the overall bond portfolio.

2. **Yield Curve Approach**. Since the yield curve is dynamical over time, it can generate a variety of possible shapes. Fund managers who attempt to exploit the movements of the yield curve adjust the maturity profile of their bond portfolio to capture the shifts in the yield curve shapes. The strategies below are some approaches that adjust the maturity profile of the bond portfolio to reflect the views of the fund managers on different yield curve shapes:

   (a) **Ladder** - An equal investment in each issuing maturity along the yield curve. This bets on the parallel shifts of the yield curve.

   (b) **Bullet** - An investment at one maturity on the yield curve, betting on the movement in a particular point on the yield curve.

   (c) **Barbell** - An investment in two non-adjacent maturities with the same duration as an intermediate maturity. This bets on the curvature of the yield

[16] More specifically, passive strategies include buy-and-hold and indexing. By indexing it means that the bond manager strives to replicate the performance of the index, such as the Lehman Brother, Merrill Lynch or JP Morgan bond index. Depending on the selection of the securities in their portfolio, there will be *tracking error* between the portfolio return and the benchmark return. Furthermore, since replicating the index is costly, for example, Lehman Aggregate Index includes 5,000 bonds, managers can select a subset of securities to track the index movements. See Evans and Archer (1968) and McEnally and Boardman (1979). Obviously, asset managers can elect to mix both passive and active management into a hybrid system whereby the managers are allowed a measured deviation from the benchmark in terms of cash flow, sector or credit quality.

curve. In comparison to bullet strategy, barbells outperform bullet during yield curve flattening and underperform during yield curve steepening.

(d) **Butterfly** - An investment in three sections of the yield curve with the two ends having the same position and opposite to the middle section. There are a number of weighting schemes available to trades, including Nelson-Siegel (1987) model. Grieves (1999) and Fabozzi, Martellini and Priaulet (2005), who discussed several weighting methods and the profitability of this strategy.

(e) **Riding the yield curve** - This strategy aims at enhancing the portfolio yield by holding securities with a longer maturity in an upward sloping term structure. For this strategy to be profitable, it assumes that the yield curve shape does not change over the holding period, tantamount to a bet on parallel yield curve shifts. Dyl and Joehnk (1981), Grieves and Marcus (1992), Ang, Alles and Allen (1998), Grieves et al. (1999) and Bieri and Chincarini (2005) empirically investigate this strategy in the US and international Treasury markets. All in all, they find this strategy enhances the bond portfolio's return on average compared to the buy-and-hold strategy with only a modicum increase in risk.[17]

3. **Yield Spread Approach**. A yield spread strategy attempts to profit from the spread between different bond sectors or bond markets, such as the spread between the natural resource corporate bonds and the government bonds. A number of risk factors can affect this spread such as the credit ratings of the issuer and/or some industry specific risk factors. In other words, to trade yield spread profitably, traders have to estimate accurately how these factors may alter the dynamics of yield on both sides of the trade. (The bonds of the same maturity between two countries are usually called *sovereign spread.*) The following spreads are utilized by fund managers to earn extra yield:

   (a) Sector Spread - Bond yield spread between different industry sectors.

   (b) Country Spread - Yield spread between similar bonds in different countries.

   (c) Currency Spread - Similar bonds denominated in different currencies.

   (d) Yield Curve Spread - Two different maturities on the same yield curve.

4. **Individual Security Approach**. This strategy is mainly based on a relative basis, meaning that fund managers identify undervalued or overvalued fixed income securities relative to comparable bond of similar characteristics.

[17]To an extent, this strategy trades on the empirical regularity that yield curve are upward sloping most of the time. (See, for example, Brown and Schaefer (1994))

5. **Volatility Approach**. This strategy positions the bond portfolio to take advantage of the time-varying volatility property of interest rates. For example, fund managers adjust the convexity of a portfolio by holding convex assets like puttable bond if volatility is expected to increase and sell callable bonds (negative convex assets) if volatility is expected to decrease. Other instruments that are explicitly exposed to volatility are exchange traded bond options.

For all the above investment approaches, the specific element lacking in each strategy is the *timing* of trades, and this is where technical analysis may offer invaluable help to traders. By using specific technical indicators, the null hypothesis is that traders is able to improve the individual trade profitability, and hence improve the overall trading performance. Until now, this application has never been investigated in a systematic way across various fixed income markets. Thus, the main interest of this thesis is to test the various aspects of technical analysis tools in the fixed income markets, and especially in government bond futures markets and government bond yield markets in a coherent manner.

1.2.2 Technical Analysis in the Fixed Income Markets

> *"Economists are as perplexed as anyone by the behaviour of the stock market."*
>
> — Robert Hall, 2001 Richard T.Ely Lecture

What can technical analysis contribute to the fixed income market? At first impression, the role of technical analysis in fixed income markets are somewhat limited. On one side of the field are macro-economists who examine extensively the term structure of interest rates using the expectation hypothesis approach. (See, for example, Campbell and Shiller (1987) and Fama and Bliss (1987)) Occupying the other half of the field are sophisticated stochastic models built for pricing fixed income derivatives, with the key building block being the models of latent (unobservable) factors with no-arbitrage restriction. (See, for example, Heath, Jarrow and Morton (1992), Duffie and Kan (1996), and Dai and Singleton (2000))

A brief analysis of both approaches shows that neither side is reliable in predicting future interest rates. The core theory in the first approach is the expectations theory of the term structure of interest rates, which carry the implication that the forward interest rates are unbiased forecasts of future interest rates. Empirically, the predictive power of the forward rate is much less significant than what the expectations theory suggest. For example, Fildes and Fitzgerald (1980), Shiller, Campbell and Shoenholtz (1983), Fama (1984, 2006), Fama and Bliss (1987), Walz and Spencer (1989) and Shiller (1990) have empirically confirmed this observation in many countries.[18] Apart from forward rates, yield spreads (the yield curve slope) have been investigated by many researchers on whether it can forecast changes in spot interest rates. The answer to this, however, is more positive. For example, Campbell and Shiller (1991), Hardouvelis (1994), Engsted (1996), and Campbell, Lo and Mackinlay (1997) have all provided evidence that the yield spread may contain some information that account for the changes in future spot rates, especially as the maturities increases. Other economic factors, such as the real rate expectations, inflation expectations and risk premiums, are found to have time-varying impacts on the movements of short-term interest rates and bond yields. (Ilmanen (1995)) At the moment, the literature does not seem to offer a method which separates these different effects. Thus we argue that analysing directly on these bond yields using technical indicators may yield better investment results.

For the second approach, it is surprising that given the plethora of existing stochastic models, very few studies have shown them to able to provide accurate forecast for future interest rate. Stochastic model are factor-based models, factors here refer to some unknown economic impact on interest rates commonly modelled with Brownian motion. According to Litterman and Scheinkman (1991) and Knez, Litterman and Scheinkman (1994), the three most common factors are labeled as "level", "slope" and "curvature", which describe the movements of the yield curve over time. Contrary to the economic approach, these factors are purely statistical and does not explain the nature of factors.[19] Even though these models are useful in pricing interest rate derivatives, their forecasting capability in forecasting future yields is somewhat limited. Duffee (2002) supported this fact by documenting the fact the three-factor affine term structure models (ATSM) by Dai and Singleton (2000) are particularly poor at forecasting future bond yields. What is surprising is that he shows that ATSM cannot outperform a simple random walk model in terms of forecast errors for both in- and out-of-sample tests. He argues that ATSM cannot fit the distribution of yields and the observed patterns of predictability in the excess holding period returns on US Treasury bills and bonds data.

[18] On the other hand, Longstaff (2000) provides some support for the expectations hypothesis at the very short end of the yield curve. From the overnight, weekly and monthly repo rates data, he finds the term rates are unbiased estimators of the average overnight rate realised over the same period. There is no statistically risk premium in the weekly and monthly rates. See also Dai and Singleton (2002).

[19] The particular technique they employ to extract the factors in bond returns is the principal component analysis, which provides no economic intuition. For example, the first factor in Litterman and Scheinkman's (1991) study accounts for an average of 89.5 percent of the observed variation in yield changes across maturities. See Bliss (1997) for more intuitive explanation of these factor term structure models.

Recently, some studies have attempted to combine both the economic and statistical approaches to improve the overall fit of the model to yield curve data. For example, Ang and Piazzesi (2003) develop the no-arbitrage model of the term structure of interest rates that includes inflation and macroeconomic activity, in addition to the level, slope and curvature factors. They find that the inclusion of the two additional economic factors improve the model's ability to forecast the dynamics of the yield curve. Similar results are obtained by Evans and Marshall (2002). Still, the overall view is that the first approach does not produce convincing proof that the bond markets obey the rational expectation models conjectured by economists, especially regarding the predictability of future interest rate changes using forward rate. The second approach plays only a limited role in active bond portfolio management since they seemed to provide miserable forecasts.

The final approach for forecasting bond yields and trading fixed income securities may be technical analysis. Given the above evidence that both the economic and stochastic modelling approach cannot provide accurate forecasts, can technical analysis replace (or compliment) the above methodologies? This approach has not been examined in the fixed income markets and it will be interesting to see what they can offer.

Several studies have provided partial evidence on the inefficiency of fixed income markets, which provide some motivations for our work here. A potential anomaly is the calendar effects. For example, Johnston, Kracaw and McConnell (1991) discover two significant weekly seasonal effects in the US GNMA, T-bond, T-note and T-bill futures returns, including the negative Monday effect and positive Tuesday effect, which could have significantly impacted trading performance. In addition, De Vassal (1998) finds that the bond yields tend to increase before the monthly auctions and drift downwards after the auction, and since 1980 interest yield volatility is highest on Friday in US bond markets. However, he did not test whether such predictability are exploitable for traders. Other studies on the seasonal effects in the bond markets include Scheneeweis and Woolridge (1979), Smirlock (1985), Clayton, Delozier and Ehrhardt (1989) and Smith (2002). Erb, Harvey and Viskanta (1994, 1996) find that forming bond portfolios based on *Institutional Investor* risk ratings generate risk-adjusted abnormal, unhedged returns in the range of 500 basis points per year, suggesting that bond markets respond to the level of recent changes in various measures of economic risk. At shorter horizon, Cohen and Shin (2003) find that in US Treasury markets, trade and price movements show positive feedback symptoms during market stress. A short-term trend-following strategy may earn high returns. Furthermore, Ilmanen and Byrne (2003) point out that it is possible to make abnormal returns by trading Treasury bonds before the announcement of important economic variables like non-farm payroll as there seems to be some momentum effects in bond yield movement right up to the announcement day.[20]

Moreover, researchers have discovered some models that might help investors in forecasting future interest rates. For example, Diebold and Li (2003) recently show that there is some form of predictability in the US yield curve using the simple Nelson-Siegel (1987) model.[21] They use this model to forecast the future bond yields with both in- and out-sample tests. They find the model's one-year forecasts outperform a random walk and show the Nelsons-Siegel model are able to outperform (in terms of root-mean square error) even the best model from Duffee (2002). Encouraged by this result, Fabozzi, Martellini and Priaulet (2005) use this model to identify whether the predictability in the model parameters generate any significant improvement in trading results using butterfly strategies in the US swap markets. In addition, they utilize the *recursive modeling* techniques developed by Pesaran and Timmerman (1995) and the *thick modeling* proposed by Granger and Jeon (2004) with a number of economically motivated explanatory variables. The results they obtained are statistically significant since they are able to find that these variables are able to predict the beta parameters in the Nelson-Siegel model and able to make statistically significant gains over the buy-hold strategy.

Despite none of the above studies evaluates technical rules directly, it does seem to suggest that there are some form of inefficiency in the fixed income markets that may have trading significance. This thesis thus sought shed some lights on this issue by evaluating technical trading systems directly in fixed income markets. Specifically, we investigate three areas in the bond markets[22]:

[20]The news announcement effects in the bond markets has been investigated by several studies. Fleming and Remolona (1997, 1999a, 1999b) document that a number economic releases cause significant price movements in the US bond markets. Important economic factors include Consumer Price Index, Durable Goods Order, Housing Starts, Jobless rate, Nonfarm Payroll and Producer Price Index, among others. Goldberg and Leonard (2003) find that US economic announcements also affect Germany bond markets. On intraday basis. Balduzzi. Elton and Green (2001) examine the effects of economic announcements on price, volume and price volatility. Unexpected component of the news causes price volatility. However, none of them investigates whether the news-effect can generate abnormal trading performance.

[21]The Nelson-Siegel model is: $r_{t,\theta} = \beta_0 + \beta_1 \left[\frac{1-\exp(-\theta/t)}{\exp(\theta/t)}\right] + \beta_2 \left[\frac{1-\exp(-\theta/t)}{\exp(\theta/t)} - \exp(-\theta/t)\right]$, where $r_{t,\theta}$ is the rate at time zero with maturity θ. The physical interpretation of the parameter set $(\beta_0, \beta_1, \beta_2)$ is often denoted as the level, slope and curvature of the yield curve. Dolan (1999) provides some analysis of this model and shows that the slope parameter is predictable in several countries.

[22]All the tests in this thesis do not make use of any fundamental information, thus the problem associated with unreliable economic information and inaccurate company data is avoided. The underlying principles of technical analysis are (1) All information are already discounted in the prices. Therefore, no fundamental information are needed. Chestnut (1965, p.12) summarises this

- Can technical trading systems exploit the predictability in the yield curve and interest rates in the government bond futures markets? Our study evaluate the weak-formed EMH in the bond markets directly by testing the moving average and volatility strategies, augment with extensive bootstrapping methodology that can account for the data snooping problem.
- Can chart patterns provide any incremental information to bond and relative value traders in the government bond markets? Since chart patterns are more subjective than technical trading systems, we use various smoothing techniques to extract the chart patterns mechanically. The smoothing estimators include the nonparametric kernel regression and local polynomial regression.
- Can investors use price gaps to initiate technical strategy in a profitable way? A price gap here is defined to be the vertical empty space create by the highlow price in the current period and the high/low price in the next trading period. Our examination attempt to answer several questions at once. (1) Are price gaps filled in the future? (2) Is there any extra information contained in the price gaps that is exploitable by traders?

1.3 The Scope of the Thesis

The rest of this thesis is as follows.

Chapter 2 investigates the profitability of a large number of technical trading systems in the bond futures markets systematically. For preliminary examination, we examine three moving average technical rules, augment with the standard test statistics and non-parametric bootstrap methodology. In the second part, we examine 7,991 technical trading systems using White's (2000) Reality Check bootstrap procedure to explore the significance of technical profits.

Chapter 3 evaluates the predictive power of technical patterns in the benchmark government bond yield markets using a smoothing algorithm known as non-

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principle:

> ...[W]e do not need to know why one stock is stronger than another in order to act profitably upon the knowledge of the fact. The market itself is continually weighting and recording the effects of all the bullish information and all the bearish information about every stock. No one in possession of inside information can profit from it unless he buys or sells the stock. The moment he does, his buy or sell orders have their effect upon the price. That effect is revealed in the market action of the stock.

(2) History always repeat itself. Thus, all chart patterns will occur in the future, albeit in different forms. See, for example, Robert Levy (1966), who has written a lucid argument on the practice of technical analysis.

parametric kernel regression. This method was developed by Lo, Mamaysky and Wang (2000). Although this kernel methodology has been applied to the equity markets, to our knowledge this is the first time it has been applied to the bond yield and bond yield spread data. Furthermore, we improve upon the non-parametric kernel method by developing a new methodology known as local linear regression to detect chart patterns.

Chapter 4 attempts to verify the Gap-Fill hypothesis advocated by technical analysts. This is the first systematic study of price gaps in the financial markets. We first categorize the various price gaps into five commonly taught price gaps, and examine whether these price gaps exhibit any significant information that is exploitable by technical traders by comparing the conditional returns against the unconditional returns. We explore this hypothesis in the futures markets, including equity, fixed income, currencies and commodities contracts.

Chapter 5 concludes.

Chapter 2

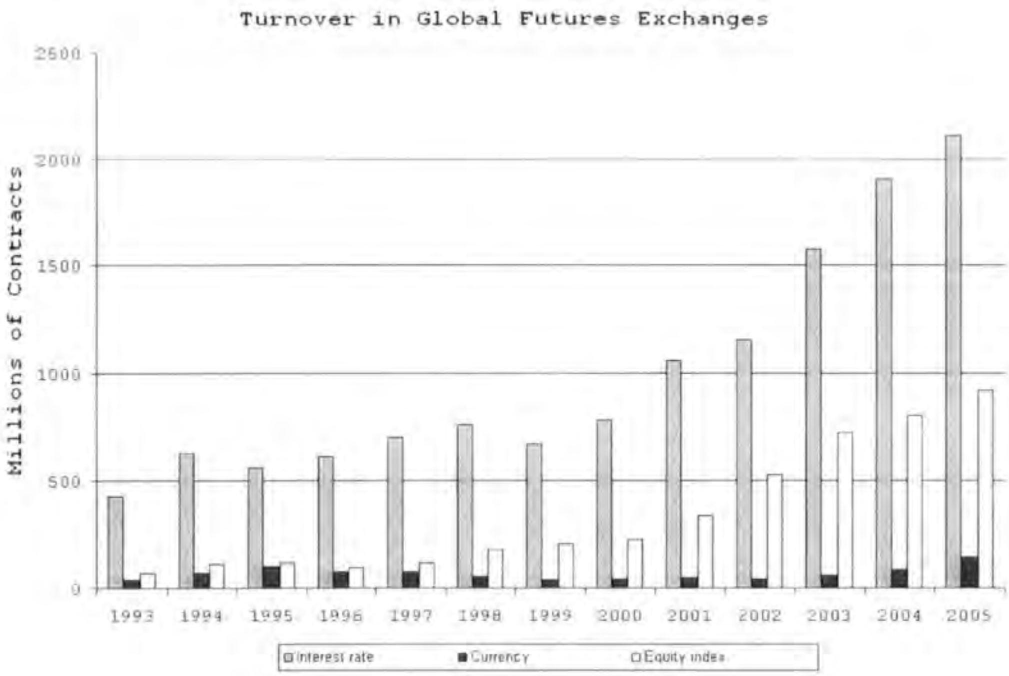
An Empirical Evaluation of Technical Trading Systems in Bond Futures Markets

2.1 Introduction

This Chapter investigates the profitability of technical trading systems in the bond futures markets. Bond futures are popular trading vehicles employed by institutional investors and traders to manage their interest rate exposure. They are popular because of the low trading costs, higher liquidity and extra gearing. The first interest rate futures contract was introduced by International Monetary Market (IMM) in January 1976 with the 90-day Treasury Bill as the underlying asset, followed shortly by the 30-year Treasury bond futures introduced by Chicago Board of Trade (CBOT) in 1977. Since its introduction, trading in interest rate futures has grown rapidly and now constitutes a large segment of exchange-traded futures contracts in many developed capital markets. The annual Bank of International Settlements' (BIS) survey of the notional amount of futures trading worldwide in Figure 2.1 clearly shows the popularity of interest rate futures contracts as compared to equity and currency futures.

A large proportion of futures traders employ a variety of technical trading systems to speculate on the movements of futures prices. Many examinations on the profitability of technical trading strategies claim that some technical trading rules can provide genuine value to investors. (See, for example, Brock, Lakonishok and LeBaron (1992), Levich and Thomas (1993) and LeBaron (1999)) On the other hand, there is also a large proportion of empirical evidence which show that technical trading rules are unprofitable once transaction costs are factored into the rules. The leading skeptic

Figure 2.1: A Survey of Global Futures Markets (BIS) by Turnover



on this side is Fama (1970, 1991) and Malkiel (1986, 2003). Until now, this debate has not been settled.

Given the prominence of fixed income futures contracts as previously mentioned, it is somewhat surprising that little evidence is known about the profitability of technical trading systems in this particular asset class. The majority of the research are concentrated on the profitability of trading systems in the equity and currency markets. There is little published research concerning the usefulness of trading systems in the fixed income market.[1] Thus the question, *"Are fixed income markets efficient?"* remains sorely unanswered.

A number of papers, however, have suggested the bond markets exhibit *weak-form inefficiency*. Hamilton (1996), for instance, finds that short-term interest rates do not behave like a martingale. This makes short rate partially predictable. Becker, Finnerty and Kopecky (1995) examine the intra-day movement of Eurodollar and US Treasury bond futures when there are important news announcements. Contrary to the prediction of market efficiency, they show that both futures experienced a substantial delay in responding to macroeconomic news and both futures contracts

[1] Many studies concentrate on the arbitrage efficiency of the bond market. See, for example, Vignola and Dale (1980), Elton, Gruber and Rentzler (1983), Kolb and Gay (1985) and Huang and Ederington (1993).

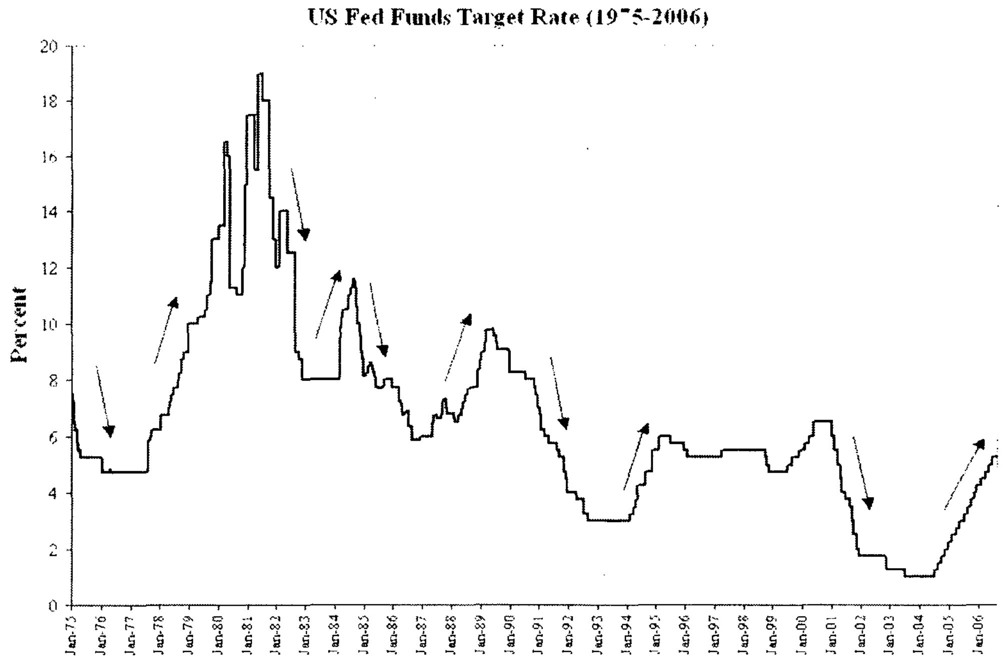
show large variation in responding to news shocks. They conclude that interest rate futures are informationally inefficient. De Vassal (1998) shows that interest rates changes are related to time patterns. such as Friday effect and seasonal patterns. This predictability may benefit bond traders. Furthermore, Papageorgiou and Skinner (2002) demonstrate that a simple probit-type model can predict the direction of 5-, 7-, 10- and 20-year US constant maturity Treasury yields sixty percent of the time. Reisman and Zohar (2004) find significant predictive power in the US Treasury yield data, which they claim can increase a bond portfolio's return dramatically. All these studies provide evidence that there are some form of predictability in the fixed income markets, which can be exploited by astute investors.[2] This predictability in rates can be seen in the US federal funds rate in Figure 2.1, which indicates that Federal Reserve does not act randomly. The probability of a 10-rate increases in a row is much higher than getting 10 heads in a row from 10 coin tosses. Empirically, such cyclical behaviour in rates is observed by Melnik and Kraus (1969, 1971), who estimate a short-run cycle of eighteen months to twenty-four months in both ninety-day US T-bill rate and ten-year US government bond yield rate. The issue now is whether traders can employ trend-following technical trading strategies to exploit these cyclical trends in the bond markets.

To partially answer this question, we evaluate the profitability of a large number of technical trading systems in the fixed income futures markets. For preliminary investigation, we test the profitability of three moving average systems. This is a useful acid test since moving average system is claimed to be one of the more profitable trading systems and is a widely viewed technical indicator by traders. For example, Lui and Mole (1998, p.544) find the following in their survey of foreign exchange traders, *"Interest rate news is found to be a relatively important fundamental factor, while moving average and/or other trend following systems are the most used technical techniques."* For statistical inference on the profitability of the moving average strategy, we use the standard t-test and nonparametric bootstrap. (Levich and Thomas (1993))

However, active search for trading opportunities often give rise to spurious or exaggerated findings, as Lo and Mackinlay point out (1990, p.432) *"The more scrutiny a collection of data is subjected to, the more likely will interesting (spurious) patterns*

[2]A study by Brandt and Kovajecz (2004) find that price discovery occurs in the US Treasury bond market and that this process is tilted towards the on-the-run securities. They find that orderflow imbalances account for a substantial portion of the daily fluctuations of the yield curve and liquidity seems to determine the orderflow. Some active bond strategies, such as butterfly, can take advantage of these price movements. But their study is mainly concentrated on the underlying Treasury bond markets and not the fixed income futures markets.

Figure 2.2: Trends in Interest Rates Over Time (see arrows)



emerge." This is especially true when evaluating technical trading systems because they are quite simple to develop, as Michael Jensen draws attention to the data snooping problem (1968, p.81):

> If we begin to test various mechanical trading rules on the data we can be virtually certain that if we try enough rules with enough variants we will eventually find one or more which would have yielded profits (even adjusted for any risk differentials) superior to buy-and-hold policy.

But eliminating this problem is virtually impossible, as Campbell, Lo and Mackinlay (1997, p.523) argue:

> Unfortunately, there are no simple remedies to these two problems since the procedures that give rise to them are the same procedures that produce genuine empirical discoveries. The source of both problems is the inability to perform controlled experiments and, consequently, the heavy reliance on statistical inference for our understanding of the data.

Thus, we use a recent statistical procedure developed in the literature, known as the *Reality Check*, to account for the possibility of data mining. This procedure was developed by White (2000) and has been applied to evaluate the profitability of technical trading systems in the Dow Jones Industrial Index (DJIA) by Sullivan, White and Timmermann (1999, thereafter STW). Over a period of more than 100 years of data (1896-1986), they conclude that the best technical trading system cannot beat the benchmark index once the data mining issue is pressed into the evaluation procedure, especially in the recent decades from 1986-1996 using S&P 500 futures contract. In another paper, Sullivan, White and Timmermann (2001) apply the same method to examine the calendar effects in DJIA index, and they find that the profitability of these calendar strategies is drastically weakened when the data mining effects are accounted for.

However, Qi and Wu (2001) apply the Reality Check procedure to seven currency pairs and find contrary evidence. They discover that technical trading systems have value to currency traders even after taking data snooping and transaction costs issues into account. Similarly, Hsu and Kuan (2005) apply this procedure to four US markets, including DJIA, S&P500, Russell 2000 and Nasdaq indices. Interestingly, they find that they cannot reject the data mining problem in "older" markets, such as DJIA and S&P500, but technical trading systems have value to investors in "younger" markets, such as Nasdaq and Russell 2000. Recently, Kosowski et al. (2005) apply the White's Reality Check procedure to the universe of fund managers in order to determine whether skill is the driving force of high alpha fund managers. On the whole, they find results which support active management. Our study here attempts to determine whether this is the case for bond futures markets.

Given the possible combination of technical trading systems is limitless, we are able to evaluate only a subset of the universe of systems. In total, we investigate 7,991 technical trading strategies, which is a large number in comparison to many previous studies. The basic four categories in our universe of trading strategies include the moving average system, Donchian breakout system, Wilder volatility system and price distribution system.[3] Similar to the above-mentioned studies apply the Reality Check procedure to this set of trading systems in an attempt to detect the possibility of data snooping.

The rest of this Chapter is as follows: Section 2.2 describes the bond futures data used in our study, including a discussion on the long-memory tests using the traditional and Lo's (1991) modified Rescaled-Range (R/S) statistic. The first part of Section 2.3 evaluates the profitability of three moving average systems using the standard test statistics and nonparametric bootstrap. The second part proceed to

[3]The Wilder volatility trading system is closely related to the 'Turtle' trading strategy discussed in Chapter 1. The 'Turtle' strategy is the technical trading system that is being taught to a number of inexperience traders.

examine a larger set of trading systems using White's Reality Check procedure. All the empirical evidence are given in Section 2.4. Lastly, Section 2.5 concludes.

2.2 Bond Futures Data and Long Memory Tests

2.2.1 Bond Futures Markets and Data Adjustments

We focus our attention on six markets, namely, US, UK, Germany, Japan, Australia and Canada government bond futures markets. Since trading futures contract entails margin requirement and subjected to the marked-to-market procedure, we collect daily rather than weekly futures data.

For US markets, we select three of the most popular bond futures currently traded in CBOT: 5-year Treasury Note futures, 10-year Treasury Bond futures and 30-year Treasury-Bond futures. For UK and Germany, we choose the 10-year long-gilts futures and the 10-year Bund futures respectively.[4] For Japan, we include the JGB futures, and for Australia, we gather data on the popular 3-year and 10-year government bond futures contracts traded in Sydney Futures Exchange (SFE). Lastly, we also include the 10-year Canadian bond futures. All bond futures have the same expiry months in March, June, September and December.

In reaction to recent decline in global nominal interest rates, futures exchanges have reduced the coupon rate of the deliverable bonds. The coupon rate of many deliverable bonds is now 6 percent. We split the sample data according to the periods with the same notional coupon rate. This allows us to have bond futures prices derived from a similar basket of bonds. Apart from the long-gilts futures, other bond futures have experienced only a small number of changes to the notional coupon rate. In US and Canada, for example, there was only one change, in 1999 and 2000 respectively, while in UK, changes occurred in 1988, 1998 and 2004 respectively. For the rest of the markets, there was no change to the coupon rate. A summary of the bond futures markets is given in Table 2.1. In total, our data set contains eight bond futures and fifteen subperiods to which we apply the technical trading strategies. Each futures series includes the daily high, low and closing futures prices from *Datastream* and *Ecowin*.

Unlike spot markets, futures contracts expire. There will be a price gap between the two futures contracts when rolling over from one futures contract to another,

[4]Germany has a number of popular bond futures contracts traded in EUREX. They are Bobl, Bund, Buxl and Schatz futures contracts. Specifically, Bobl futures are 5-year Federal Notes, Bund futures are the benchmark 10-year bond futures, Buxl is the 20- to 30-year government bond futures and Schatz futures are the 2-year bond futures.

assuming not taking delivery of the underlying asset. Without adjusting for these price gaps, the trading signals generated by the data will be spurious. To solve this issue, we follow the standard procedure in creating the gap-adjusted bond futures price data by deducting the price gaps from all the historical prices. (See, for example, Levich and Thomas (1993) and Kho (1996)) Starting from the latest price in 29 February 2005, if a price gap during rollover exists, we deduct this difference in price from all historical prices before this rollover day, a procedure known as slicing. Our chosen rollover day is the last trading day before the delivery month. That is, the last trading day in February, May, August and November. We assume that there is no liquidity problem during rollover. We avoid rolling over on the delivery day in the delivery month for two reasons. One reason is the presence of quality and timing options in the delivery month, which may complicate the bond futures pricing.[5] The other reason is that there are evidence of excessive volatility in futures price during delivery date. (See, for example, Ma, Mercer and Walker (1992)).

Table 2.1 presents the summary statistics of the annualized daily bond futures returns, taken to be the first log-difference of the artificially constructed bond futures prices.[6] The annualized daily mean return varies by contracts. The smallest mean return is Australia 10Y bond futures at 0.619 percent and the largest is US30YTB (1999-2005) at 8.176 percent. It is noticeable that Australia reports the lowest annualized standard deviation of at 1.525 and 1.561 percent for 3-Y and 10-Y bond futures respectively. We also note from US market that the volatility of bond futures is proportional to its maturity, the higher the maturity, the larger the standard deviation. This is inconsistent to Fisher's (1896) observation that short-term rates are more variable than long-term rates.[7]

It is clear from the normality tests that bond futures returns display the fat-tailed phenomena commonly seen across all asset classes. One possible explanation for the non-normal returns is the clustering effects induced by the release of macroeconomic

[5]Bond futures contract does not have one underlying (deliverable) asset. Rather, it has a basket of underlying securities (as defined by the futures exchange). Valuation of bond futures typically use the cost-of-carry model, relating the bond futures price to the cheapest-to-deliver bond. There are several options available to the bond futures seller. For example, the *timing option*, where the short seller may deliver the bond on any business day in the delivery month, and *quality option*, where the short seller has the opportunity to deliver any bond that has at least fifteen years to maturity or first call. See Chance and Hemler (1993) for a review of these options and Carr and Chen (1997) for a valuation of the quality option embedded in bond futures. Interestingly, Rendleman (2004) shows that if interest rates are significantly above or below 6 percent, the delivery option has little influence on the pricing of Treasury bond futures.

[6]The annualized mean returns X_A is computed as: $X_A = 252 \times T^{-1} \sum_{t=1}^{T} X_t$ and the annualized standard deviation σ_A is given by: $\sigma_A = \sqrt{252} \times \sqrt{T^{-1} \sum_{t=1}^{T} (X_t - \bar{X})^2}$

[7]We did not apply the trading rules to the UK gilt market after 2003 because of insufficient data. Some trading systems require 250 historical trading days before the first signal is generated.

news. For example, Fleming and Remolona (1999a, 1999b) and Furfine (2001) find empirical evidence that show most of the large movements in bond markets are associated with macroeconomic news shocks in the US treasury markets. Ahn, Jun and Cheung (2002) find the macroeconomic announcements from Germany and US are important sources of volatility for Germany Bund futures contracts. Durenard and Veradas (2002) further document that macro-economic news surprises do affect the US Treasury bond futures price movements, especially when the forecast error of the market participants are large. Moreover, they find these unexpected macroeconomic effects to depend on business cycle because the news effect on bond futures prices is dependent on the business cycle. Collectively, this body of work shows that whenever there is a concentration of news shocks permeating the bond markets, these information shocks generate excessive volatility across the yield curve and cause the bond returns to behave outside the normal distribution.

2.2.2 Long Memory in Bond Futures Returns

Long memory has been associated with the profitability of technical trading rules, as Levich and Thomas (1993, p.469) highlight this possible connection in their study of trading systems in the currency markets, *"...the link between serial dependency in the data and the profitability of technical rules is a question."* As a small part of our investigation, we examine whether the persistence of asset returns are linked to the profitability of technical trading systems. Long memory in asset returns can be captured by the Rescaled-Range statistics (R/S) developed by Hurst (1951) and Mandelbrot and Wallis (1969a, 1969b, 1969c).[8] Earlier studies by Olszewski (1998, 2001) show that there may be a positive link between the R/S statistic and trend following system in a number of futures contracts. Overall, he finds that there using R/S statistic as a filter for future out-of-sample trading yield higher profits, and concludes that (p.701):

> ...when the R/S statistics used to filter trade, the profitability of the system is improved overall....Furthermore, the R/S statistics seem to provide insights into why momentum-based trading system is profitable in some but not other markets.

[8]Basically, a time series X_t has long memory if there is a real number $\alpha \in (0, 1)$ and a constant $c_\rho > 0$ such that $\lim_{k\to\infty} \frac{\rho(k)}{c_\rho k^{-\alpha}} = 1$, where $\rho(k)$ is the sample autocorrelation. (See Beran (1994, p.42)).

Table 2.1: Summary Statistics of Annualized Daily Bond Futures Return.

Futures Market	Sample Period	Coupon (Percent)	Obs.	Mean	Standard Deviation	Skew	Kurtosis	Normality Test	Autocorrelation ρ_1	ρ_5	ρ_{10}
					US						
5YT-Note	05/88-11/99	8.0	2883	2.4888	4.4857	-0.1354	2.1707	333.83***	0.0680*	-0.0093	0.0283
5YT-Note	12/99-02/05	6.0	1313	5.0072	4.9935	-0.2664	1.3450	67.508***	0.0453	0.0074	-0.0497
10YT-Bond	09/83-11/99	8.0	4327	6.4089	10.1888	0.2409	3.0608	846.71***	0.0393	-0.0229	0.0089
10YT-Bond	12/99-02/05	6.0	1312	6.8065	7.5874	-0.3439	1.0455	46.465***	0.0198	-0.0129	-0.0307
30YT-Bond	10/77-11/99	8.0	5569	2.6932	25.7079	0.0714	2.4135	766.34***	0.0201*	-0.0036	-0.0130
30YT-Bond	12/99-02/05	6.0	1311	8.1762	11.5490	-0.3655	0.8045	36.080***	0.0018	0.0280	-0.0232
					UK						
LG1	12/82-02/88	12.0	1383	2.5050	9.9280	-0.0339	1.8203	126.60***	-0.0080	0.0541*	-0.0088
LG2	09/88-09/98	9.0	2467	2.4597	8.5667	-0.2070	3.3881	553.91***	-0.0004	0.0154	0.0053
LG3	10/98-09/03	7.0	1461	0.8286	5.8090	-0.3578	1.4538	80.552***	0.0655*	-0.0372	0.0168
					Germany						
10Y G-Bond	12/90-02/05	6.0	3789	1.9723	5.5715	-0.3720	1.0642	57.338***	-0.0388	-0.0381	0.0088
					Japan						
JGB	12/86-02/05	6.0	4370	5.9999	8.8590	-0.4355	5.4427	1727.8***	0.0091	0.0320*	0.0232
					Australia						
3YG-Bond	12/89-02/05	6.0	3840	1.1612	1.5251	0.2016	4.2875	1224.9***	-0.0240	0.0011	-0.0141
10YG-Bond	12/84-02/05	6.0	5078	0.6192	1.5614	-0.3244	3.9209	1256.7***	-0.0452	0.0281	-0.0163
					Canada						
10YG-Bond	12/89-01/00	8.0	2565	3.9003	7.8407	-0.1894	2.7228	312.46***	0.0135*	-0.0039	-0.0459
10YG-Bond	02/00-02/05	6.0	1245	5.1455	6.3996	-0.3479	0.8874	31.593***	0.0772	0.0019	0.0215

Source: Datastream and Ecowin

Long memory in financial markets is estimated by the classical R/S statistic:

$$Q_T = \frac{1}{S_T}\left[\max_{1\le k\le T}\sum_{j=1}^{k}(X_j-\bar{X}) - \min_{1\le k\le T}\sum_{j=1}^{k}(X_j-\bar{X})\right] \tag{2.1}$$

where $S_T^2 = \frac{1}{T}\sum_{j=1}^{T}\left(X_j-\bar{X}\right)^2$ is the sample variance, X_t is the futures return and $\bar{X}$ is the sample mean. The first and second term in (2.1) are the maximum and minimum (over k) of the partial sums of the first k deviations of X_j from the sample mean respectively. If $k = T$, then the final sum is equal to zero. Given some volatility, a small R/S statistic means that the returns data do not wander far from the mean value. On the contrary, a large R/S statistic says that the range of partial sums is large and mean reverts slowly towards the mean value.

Since the original R/S statistic has no reliable distributional basis for statistical inference, Lo (1991) improves the R/S statistic by incorporating short-range memory effects and derives an asymptotic sampling theory of the R/S statistic:[9]

$$Q_T(q) = \frac{1}{S_T(q)}\left[\max_{1\le k\le T}\sum_{j=1}^{k}(X_j-\bar{X}) - \min_{1\le k\le T}\sum_{j=1}^{k}(X_j-\bar{X})\right] \tag{2.2}$$

where the denominator is now:

$$S_T^2(q) = \frac{1}{T}\sum_{j=1}^{T}(X_j-\bar{X})^2 + \frac{2}{\sqrt{T}}\sum_{j=1}^{q}w_j(q)\left[\sum_{i=j+1}^{T}(X_i-\bar{X})(X_{i-j}-\bar{X})\right] \tag{2.3}$$

and w_j are the Barlett weights:

$$w_j(q) = 1 - \frac{j}{q+1}, \qquad q < T \tag{2.4}$$

The second squared term in (2.3) is the weighted autocovariance. Essentially, the critical difference between Lo's R/S and classical R/S statistic is the inclusion of the weighted autocovariance, which accounts for short range memory effects in asset returns. When $q = 0$, the modified Lo's R/S statistic corresponds to the classical R/S statistic. The null hypothesis of Lo's modified R/S statistics is *no* long-memory and the critical values of Q_T and $Q_T(q)$ are adopted from Lo (1991, p.1288, Table II). For ease of comparison, we tabulate the critical values in Table 2.2. For example, if the value of $Q_T(q)$ is larger than 1.7470, then the null hypothesis of no long memory is rejected at 5 percent significance level. Similarly, if the value of $Q_T(q)$ is less than 0.8610, then the alternative hypothesis of anti-persistence (or negative persistency) is

[9] For recent improvements to Lo's statistic, see Kwiatkwaski et al. (1992) and Giraitis et al (2003).

Table 2.2: Fractiles of the Limiting Distribution of the V Statistic Under the Assumption of No Long Memory

$Prob(V < v)$	0.005	0.025	0.050	0.100	0.200	0.300	0.400	0.500
v	0.721	0.809	0.861	0.927	1.018	1.090	1.157	1.223
$Prob(V < v)$	0.543	0.600	0.700	0.800	0.900	0.950	0.975	0.995
v	$\sqrt{\pi/2}$	1.294	1.374	1.473	1.620	1.747	1.862	2.098

Source: Lo (1991, p.1288, Table II)

accepted. Returns which display anti-persistence mean that large bond price movements in a given direction is likely to be followed by price movements in the opposite direction. As T increases without bound, the R/S statistic converges (in distribution) to a well-defined random variable V when properly normalized:

$$\frac{1}{\sqrt{T}}Q_T(q) \Rightarrow V \tag{2.5}$$

where $\Rightarrow$ denotes weak convergence and V is the range of a Brownian bridge on a unit interval.

Table 2.3 presents the results for both classical R/S and Lo's R/S tests on the bond futures returns and their percentage differenced. For the modified Lo's statistics, the number in the bracket is the bias in percentage, calculated as: $[Q_T/Q_T(q) - 1] \times 100$. Since the Lo's R/S statistic has no optimal q a priori, four value of $q = 25, 50, 100, 250$ are computed to assess the bias between the classical R/S statistics and the Lo's statistic.

The classical R/S statistic in Table 2.3 (Column 2) shows a varied picture about the persistence within the bond futures returns. The largest R/S statistic is 1.7130 while the lowest is 0.8009. Among the classical R/S statistic, only US 30YTN(77-99) displays statistical significant positive persistence returns. The rest of the contracts show no strong bias towards positive or negative persistence. Our result here is consistent with Fung and Lo (1993) and Booth and Tse (1995), who find no evidence of long memory in both Eurodollar and US T-Bill futures contracts. A study by Connolly, Guner and Hightower (2001) also find that the excess weekly return of the US Treasury Bill display no long-term memory, but not the gross weekly returns. They suggest that the persistence in gross returns is due to the persistence in inflation rate.

A comparison between the classical and Lo's R/S statistics shows an interesting observation. Classical R/S statistics which has anti-persistence (< 1.223) display contrary evidence when the value of q for Lo's R/S statistic increases. For example, USLG1 (1983-1988) has a classical R/S statistic of 0.8931 (anti-persistence), but rises to 1.9872 when $q = 250$, a statistically significant persistence value. Such effects can also be seen in US10YB (1999-2005), US30YTB (1999-2005) and CAN10YGB (2000-2005). This conflicting evidence implies that long memory is present in these bond futures returns, but this characteristic is masked by short-term anti-persistence effects.

We also note that the classical R/S statistics for US bond futures have declined recently, meaning that bond futures are becomingly less persistence and increasingly behaving like a random walk. This suggests that the past movements of the futures prices cannot predict future changes and trading based on historical rates are probably going to be futile and unprofitable. For Canada futures contract CAN10YTB (2000-2005), this decrease is even more pronounced. This implies that long-term trend-following rule might be unprofitable. Instead, a mean-reverting trading system may be more appropriate for these futures contracts. To verify whether this hypothesis true, we proceed to evaluate the technical trading systems in the next section, where our universe of trading strategies include both trend following and counter-trend systems.

2.3 Technical Trading in Bond Futures Markets: Preliminary Evaluation and Implementing Reality Check

2.3.1 Preliminary Evaluation: Moving Average Systems

For preliminary evaluation, we investigate the profitability of three simple moving average technical trading systems. The trading signals Z_t from the moving average systems are emitted when two moving averages of prices crossover. In particular, the signals Z_t from the single, dual and triple moving average trading rule are given by:

$$Z_t = \text{Sgn}\left(\frac{1}{n}\sum_{s=0}^{n-1} F_{t-s} - \frac{1}{m}\sum_{s=0}^{m-1} F_{t-s}\right) \tag{2.6}$$

$$Z_t = \text{Sgn}\left(F_t - \frac{1}{\sum_{i=1}^{3} w_i} \times \left[\left(\frac{1}{n}\sum_{s=0}^{n-1} F^1_{t-s}\right) w_1 + \left(\frac{1}{m}\sum_{s=0}^{m-1} F^2_{t-s}\right) w_2 + \left(\frac{1}{r}\sum_{s=0}^{r-1} F^3_{t-s}\right) w_3\right]\right) \tag{2.7}$$

where F_t is the futures price at time t and Sgn$(\cdot)$ is the signum function. More specifically, $Z_t = +1$ (long signal) if Sgn$(\cdot) > 0$ and $Z_t = -1$ (sell signal) if Sgn$(\cdot) < 0$. We multiply these signals to the futures returns X_t. The first term in Equation (2.6) is the shorter n-day moving average and the second term is the longer m-day moving average. The parameters (n, m, r) control the smoothness of the moving average. If $n = 1$, then equation (2.6) becomes the *single* moving average system. If $n > 1$, the equation (2.6) becomes the *dual* moving average system. Equation (2.7) extends the single and dual moving average to triple moving average system, where (w_1, w_2, w_3) are the weights assigned to the moving averages.[10] For the single moving average, we set the parameter values at $n = 1$ and $m = 50$. For dual moving average system, our parameters are $n = 10$ and $m = 150$. For the triple moving average system, the parameter values are $n = 10, m = 100$ and $r = 200$. As long as the shorter moving average remains above or below the longer moving average, we shall remain with the position given by signal Z_t. In this section we do not apply any time or price filter.

Standard Statistical Tests and Nonparametric Bootstrap

For a simple measurement of the statistical significance of moving average system's profitability, we use the standard test statistic. (See, for example, Brock, Lakonishok and LeBaron (1992)) Let $\bar{X}_B$ and $\bar{X}_S$ be the overall average buy and sell return respectively, given as:

$$\bar{X}_i = \frac{\sum^{n_i} X_t}{n_i}, \qquad i = \text{B,S} \tag{2.8}$$

where $\sum^{n_B} X_t$ and $\sum^{n_S} X_t$ is the sum of all daily returns produced by the buy and sell signals respectively and where n_B and n_S is the number of buy and sell days. For buy signals, the null hypothesis is $H_0 : \bar{X}_B = 0$ against $H_1 : \bar{X}_B > 0$ because we

[10] Apart from the arithmetic moving average, another method of computing the moving average is the geometric moving average: $\left(\prod_{s=0}^{m-1} F_{t-s}\right)^{1/m}$. However, since Acar (1993) has shown that these two averages are approximately similar (assuming the near equality of arithmetic and geometric returns), we shall use the arithmetic moving average in our preliminary investigations. Another widely used moving average is the exponential smoothed moving average (ESMA). The computation of ESMA depends on the exponential constant C, which has the formula $C = 2/(m+1)$, where m is the moving average lag. Specifically, ESMA has formula: $ESMA_{t+1} = (F_t - ESMA_t) \times C + ESMA_t$, where F_t is the futures price at time t. The advantage of ESMA over the arithmetic moving average is that it is easier to compute and constitutes a form of weighted moving average, which put more emphasis on recent data. Broadly speaking, moving average rules belong to a set of rules that obey the Markov time principle proposed by Neftci (1991). A Markov time τ is defined as: $\tau < t \in \Im_t$, $\forall t \in T$, which means that at each time point t, τ is adapted to the filtration set $\Im_t$ of the economic agents without utilizing future information. In other words, technical rules like moving average do not require market participants to generate forecasts. Further theoretical analysis of the moving average rules can be found in Acar and Satchell (1997), Kuo (1998) and Chiarella, He and Hommes (2003).

expect long positions to earn positive returns. For short positions, the null hypothesis is $H_0 : \bar{X}_B = 0$ against $H_1 : \bar{X}_B < 0$ because short positions are expected to earn negative returns. In addition, we test the joint effect of buy and sell signals. The null hypothesis for this buy-sell spread is $H_0 : \bar{X}_D = 0$ against $H_1 : \bar{X}_D > 0$. The corresponding test statistics for the buy, sell and buy-sell signals are:

$$t_i = \frac{\bar{X}_i}{\sigma/\sqrt{n_i}}, \qquad i = \text{B,S} \tag{2.9a}$$

$$t_D = \frac{\bar{X}_D}{(\sigma/\sqrt{n_B} + \sigma/\sqrt{n_S})} \tag{2.9b}$$

respectively, where σ is the standard deviation of the whole sample. The critical values for the above tests are derived from normality assumption. (See, for example, Wong, Manzur and Chew (2003, p.547)) Basically, if the t-statistic is larger than 1.645, we reject the buy and buy-sell spread null hypothesis at 5 percent level, and if the t-statistic is smaller than -1.645, we reject the sell null hypothesis at 5 percent level.[11]

In addition to the standard test statistic, we also provide the results from nonparametric bootstrap. Bootstrapping is a simulation procedure used to test the significance of the trading system with a fixed number of random permutations of the original data series. (Efron (1979) and Freedman and Peters (1984a, 1984b)). We apply the simple nonparametric bootstrap with replacement. Nonparametric here refers to the fact that we are not imposing any form of statistical distribution on the time series.[12] The sampling procedure is as follows: First, given n returns from a particular strategy, we scramble these returns to form a new n-dimensional array. We multiply this bootstrapped array of returns by the first bond futures price. This way, the starting points for all bootstrap futures price series are the same as the actual futures price. Second, we apply the same trading strategy to this scrambled futures prices to form the empirical distribution of the trading profits. We then compare the actual profits to this distribution. The procedure is repeated 500 times for each trading rule.[13]

[11] The detail rejection criteria of the null hypothesis is as follows: For significance level 5%-10%: $1.6449 > T > 1.2816$, for significance level 1%-5%, $2.3263 > T > 1.6449$ and for significance level 1%, $T > 2.3263$, where T is the value of test statistic. See Wong, Manzur and Chew (2003).

[12] Brock, Lakonishok and LeBaron (1992) fit four statistical models to the US stock index data. The models are random walk model, autoregressive $AR(1)$ model, GARCH-in-Mean model and Exponential GARCH model. The bootstrapping procedure involves randomly shuffling the error series obtained from the fitting. See also Levish and Thomas (1993), Boswijk, Giffoen and Hommes (2001) and Kwon and Kish (2003).

[13] It is possible to increase the number of bootstraps. According to Efron and Tibshirani (1986), 500 replications are sufficiently close to the true estimator. We have extended the number of bootstraps

A simple null hypothesis for the nonparametric bootstrap can be stated as follows: if there is no information in the original series, then the profits from the trading system should not be significantly different from the profits obtained with the shuffled series. We set the rejection point of this hypothesis at α significance level. (We choose $\alpha = 10$ percent)

Since our preliminary evaluation evaluated only three moving average systems, drawing inferences from such a small set of technical trading systems is unreliable even though we implement the nonparametric bootstrap. We have not account for the possibility of data snooping effects. Furthermore, the traditional test statistics assume normal empirical returns, which may not accurately reflect the true distribution of bond futures returns, as Merton (1987, p.107) argues:

> Is it reasonable to use standard t-statistics as a valid measure of significance when the test is conducted on the same data used by many earlier studies whose results influenced the choice of theory to be tested?

To address these issues and determine whether technical systems have genuine value to investors, we apply the White's Reality Check to a larger set of technical trading systems.

2.3.2 White's Reality Check

This section extends the examination of the technical trading systems in the bond futures markets by employing White's (2000) *Reality Check* procedure. Extending the work by Diebold and Mariano (1995) and West (1996), White's test evaluates the distribution of a performance measure accounting for the full set of models that lead to the best performing model among the following $(L \times 1)$ vector of performance statistic:

$$\mathrm{f}_k = \frac{1}{n}\sum_{t=R}^{T} f_t, \qquad k = 1, ..., L \tag{2.10}$$

where L is the number of trading systems, n is the number of prediction periods indexed from R through T, i.e., $n = T - R + 1$ and f_t is the observed performance measure for period t. k is the index for the number of trading models. The first trading signal is generated at $R = 251$ because some technical rules require 250 days of previous prices in order to provide the first trading signal. The value of T and n differ for each bond futures contracts.

to 2000 and find the mean bootstrapped profits to be close to the mean profits with 500 replications.

The rate of return for k^{th} trading rule at time t is computed as:

$$f_{k,t} = \ln\left[\frac{X_{t+1}S_k(\beta_k)}{X_{t+1}S_0(\beta_0)}\right], \qquad k = 1, ..., L \tag{2.11}$$

for $t = 251, ..., T$, where X_{t+1} is the futures price return. $S_0(\cdot)$ and $S_k(\cdot)$ are the signal functions that convert prices into market positions for the system parameters β_k. The signal function has three possible values: +1 for long position, 0 for neutral position and -1 for short position. Following Brock, Lakonishok and LeBaron (1992) and STW, our benchmark trading rule is the null system, which is always out of the market. Consequently, S_0 is zero for all t.

The null hypothesis is that the best technical system is no better than the performance of the benchmark:

$$H_0 : \max_{k=1,...,L} [E(f_k)] \leq 0 \tag{2.12}$$

where the expectation $E(\cdot)$ is evaluated with the simple arithmetic average $\bar{f}_k = n^{-1}\sum_{t=R}^{T} f_{k,t}$. Rejection of this null hypothesis lead to conclusion that the best trading rule is superior to the chosen benchmark.

White (2000) shows that the null hypothesis (2.12) can be tested by applying the stationary bootstrap of Politis and Romano (1994) and West (1996) to the observed values of $f_{k,t}$. First, we resample the empirical returns $f_{k,t}$ from Equation (2.11) for each trading rule k, one (or more) observation at a time with replacement and denote the resulting series as $f^*_{k,t}$. We repeat this procedure B times, yielding B bootstrapped mean return for each trading rule K, $\bar{f}^*_{k,t} = \frac{1}{n}\sum_{t=R}^{T} f^*_{k,t}$. Second, we repeat this sampling procedure over all L trading rules, $k = 1, ..., L$. Thirdly, we construct the following statistics:

$$\bar{V} = \max_{k=1,...,L} \left[\sqrt{n}\left(\bar{f}_k\right)\right] \tag{2.13}$$

$$\bar{V}^*_{k,i} = \max_{k=1,...,L} \left[\sqrt{n}\left(\bar{f}^*_{k,i} - \bar{f}_k\right)\right], \quad i = 1, ..., B \tag{2.14}$$

and denote the sorted values of $\bar{V}^*_{k,i}$ as $\bar{V}^*_{k,1}, \bar{V}^*_{k,2}, ..., \bar{V}^*_{k,B}$. We seek to find M such that $\bar{V}^*_{k,M} \leq \bar{V} \leq \bar{V}^*_{k,M+1}$. Lastly, White's Reality check p-value is obtained by comparing $\bar{V}$ to the quantiles of $\bar{V}^*_i$, calculated as $P = 1 - M/B$. By using the maximum value over all L models, the Reality Check p-value incorporates the effects of data snooping from L trading systems.

Consistent with STW and White (2000), we implement the stationary bootstrap in our study. The stationary bootstrap requires the value of the smoothing parameter

q that determines the length of the block resampling procedure, where $0 < q \leq 1$. (See STW (1999, p.1689)) The average length of the sampling block follows the geometric distribution, and is equal to $1/q$. If $q = 1.0$, then the stationary bootstrap becomes the ordinary bootstrap. In this chapter, we use $q = 0.1$ for all contracts, meaning the average block is 10.[14]

The above hypothesis (2.12) can be extended to examine the superiority of the best trading system based on Sharpe ratio.

$$H_0 : \max_{k=1,\dots,L} [g(E(X_k)) \leq g(E(X_0))] \tag{2.15}$$

where G is the Sharpe ratio, in the form:

$$g(E(X_{k,t+1})) = \frac{E(X_{k,t+1}) - r_{f,t+1}}{\sqrt{E(X^2_{k,t+1}) - (E(X_{k,t+1}))^2}} \tag{2.16}$$

where the expectations are evaluated with arithmetic average and where $r_{f,t+1}$ is the risk-free rate at time $t+1$.[15] The relevant statistic are:

$$\bar{f}_k = g(\bar{h}_k) - g(\bar{h}_0) \tag{2.17}$$

where $\bar{h}_0$ and $\bar{h}_k$ are average rates of returns over the prediction sample for the benchmark and the kth trading rule respectively, that is, $\bar{h}_k = n^{-1}\sum_{t=R}^{T} h_{k,t+1}$ over the trading rules $k = 0, ..., L$. The above stationary bootstrap procedure is applied to evaluate the Sharpe ratio by generating B bootstrapped values of $\bar{f}_k$, which we denote as $\bar{f}^*_{k,i}$:

$$\bar{f}^*_{k,i} = g(\bar{h}^*_{k,i}) - g(\bar{h}^*_{0,i}), \qquad i = 1, ..., B \tag{2.18}$$

$$\bar{h}^*_{k,i} = \frac{1}{n}\sum_{t=R}^{T} h^*_{k,t+1,i}, \qquad i = 1, ..., B \tag{2.19}$$

[14]The stationary bootstrap procedure is as follows: (1) First set $t = R$ and draw a random number from the empirical returns $R, ..., T$. (2) Increase t by 1. If $t > T$, stop. Else, draw a standard uniform random variable $U \in [0, 1]$. If $U < q$, draw a block θ_t randomly, independently and uniformly from $R, ..., T$. Else if $U \geq q$, expand the block θ_t by setting $\theta_t = \theta_{t-1} + 1$. If $\theta_t > T$, reset $\theta_t = R$. (3) Repeat Step 2. STW examine $q = 0.01, 0.1, 0.5$ and find their original results are sufficiently robust to different values of q. See also Qi and Wu (2001). Thus, there is no need to further check for different values of q here.

[15]The risk-free rate is different for each sample country. We take the interest rate closest to the policy rate for each country and convert the annualized rates into daily rates using the formula $r_d = Ln(1 + r_{ann})/252$, where r_d and r_{ann} are the daily and annualized interest rates respectively. We assumed there are 252 trading days in a year.

The Universe of Trading Strategies

We now discuss the universe of technical trading systems available to a trader. In financial markets, the number of possible combinations of trading system is unlimited and it is impossible to test them all. Furthermore, public access to proprietary trading strategies is limited. In response to these considerations, we focus on trading systems that are publicly available and widely used. We acknowledge that the issue of the size of the 'universe' of trading strategies in White's Reality Check is always a concern. But STW (p.1684) defended the choice in their study as long as two issues are satisfied:

> The omitted trading rules cannot improve substantially the best performing trading rule drawn from the current universe, and the omitted trading rules should generate payoffs that are largely orthogonal to the payoffs of the included trading rule so that they will increase the effective span.

We choose four major trading systems, which are (1) Moving average, (2) Donchian Breakout, (3) Wilder volatility and (4) Price distribution systems. These systems have all been documented in the literature extensively and are still widely used by trading professionals in various guises. Altogether, we test 7,991 trading systems.

As a robustness check on the span of our universe of trading rules, we randomly select 250 trading rules from the full universe and form the covariance matrix of returns from these 250 rules. The size of the covariance matrix is therefore 250×250. We then apply the principal component analysis to this matrix. The intuition here is that the greater the number of nonzero eigenvalues, the larger is the effective span of the trading systems.[16] Figure 2.3 plots the eigenvalues (sorted in descending order) along the x-axis. This figure provides some evidence that our universe of trading rules has nonzero eigenvalues. This procedure is repeated several times, with similar results. Therefore, we are assured that our universe of trading rules has a sufficient span as discussed by STW.[17] We now describe the trading systems in detailed.

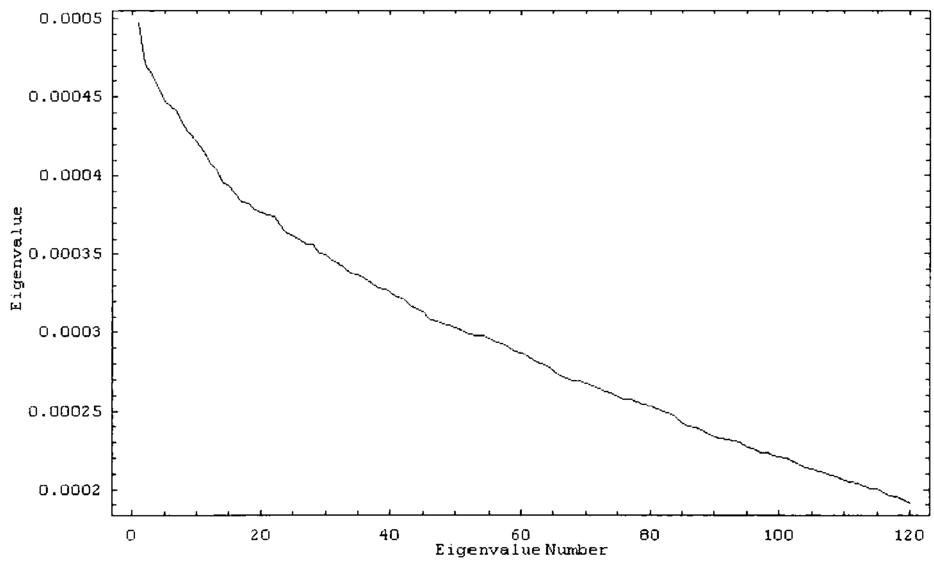
A. Moving Average Systems

The preliminary section has evaluated only three moving average systems. We now extend the number of moving average systems to be tested. We test the single, dual and triple moving average systems. Furthermore, we apply price and time filter in order to obtain trading signals. The parameter values for the three moving averages

[16]This is only a subset of the universe of trading rules. Due to computational constraint, we are unable to increase the size of the matrix. But we are allowed to repeat this exercise several times.

[17]However, We are unable to check whether the omitted trading rule has higher returns than our universe of trading rules since there is an infinite combination of trading rules available.

Figure 2.3: Checking the Span of the Universe of Technical Trading Systems from 250 randomly selected rules. After computing the covariance matrix of the returns from the 250 trading rules, we apply principal component analysis this (250×250) covariance matrix to obtain the eigenvalues. The following Figure plots the sorted eigenvalues.



are: n, m, r = [5, 10, 15, 20, 25, 30, 50, 60, 75, 100, 125, 150, 200, 250]. We apply four time filers, Time Filter = [2,3,4,5] days and four price filters, Price Filter = [0.001,0.005,0.01,0.02] percent. Altogether, we test 3,751 moving average systems.

B. Donchian Breakout Systems

The Donchian Breakout rule is also known as *support and resistance rule* (in STW) or *trading range break* (in Brock, Lakonishok and LeBaron (1992)). This is an old technical rule, discussed as early as in Wyckoff (1910) but reformulated and popularised by Donchian (1957), hence our preferred description.

The classical n-day Donchian rule dictates that a long position is taken if the current price exceeds the highest price in the previous n trading days and a short position is taken if the current price declines below the lowest of the previous n days. Whenever a new signal is generated, we liquidate the old position simultaneously. Thus, the system stays in the market throughout. The modified Donchian rule generates a buy signal if the current price rises above the maximum price in the previous n trading days and exit the market if the current price falls below the low of m previous trading days, where $m < n$. Accordingly, the system is not necessarily in the market throughout. We apply the following parameters to the Donchian classical and modified system n = [3, 5, 10, 15, 20, 25, 30, 40, 50, 60, 75, 80, 90, 100]. In addition, we apply the price filter for each Donchian system, Price Filter = $[0.001, 0.005, 0.01, 0.02]$. We test 924 Donchian systems altogether.

C. Wilder Volatility Systems

Wilder volatility system is another popular technical rule advocated by practitioners. The basic premise of this rule assumes that the price range (as measured by the difference between the high, low and closing price) can detect changes in price trends. (See Patel (1998))

First, we define the true range (TR) at time t to be the maximum of:

$$TR_t = \max\left(H_t - L_t, H_t - C_{t-1}, L_t - C_{t-1}\right) \tag{2.20}$$

where H_t, L_t and C_{t-1} are the day t high, low and day $t-1$ close price respectively. The W-day average true range (ATR) is the average of the W previous TR. For the initial trading signal, we record the initial trend so that we can pick a point to enter the market when this initial trend reverse. For example, increasing closing prices imply initial increasing trend and we take a short position should this initial trend reverses. Conversely, decreasing close prices imply a decreasing initial trend and we enter into a long position when this initial trend reverses. The point where we enter the market is known as *Stop and Reverse* (SAR). For initial downtrend, the time t SAR_t is the sum of time $t-1$ ATR_{t-1} and the lowest closing price in the previous W trading days. If the current close price is higher than SAR_t, a buy signal is generated. After the initial entry signal is emitted, the rest of the trading signals are mechanically updated. We examine this system with the following parameters, W = [7, 10, 15, 20, 25, 30, 35, 40, 50, 60, 75, 90, 100, 120, 150, 180, 200, 225, 250], and three price filters of $0.1\%, 0.25\%, 0.5\%$, yielding a total of 76 systems.

D. Price Distribution Systems

Price distribution system is based on the skewness and kurtosis of a time series. The underlying principle of this system captures the fact that if there is a price trend, then this trend will cause the skewness and kurtosis to deviate from the Gaussian distribution. By measuring the skewness and kurtosis we can detect the beginning of a trend. (See Kaufman (2005))

When prices are platykurtic, prices must be trending since more prices are detected on the tails of the Gaussian curve. On the contrary, if prices are leptokurtic, prices concentrate together, a typical trendless period. Hence, when kurtosis is low, we employ the trend following strategy, and when kurtosis is high, we turn to a mean-reverting strategy. After deciding which strategy to use, we then decide which position to take. If positive skewness is observed, we take a long position. If negative skewness is recorded, we take a short position. Lastly, higher volatility (as measured by TR in the previous section) must be observed before a position is taken.

The system is as follows: Let K and S be the value for kurtosis and skewness respectively and V for the minimum volatility. For the trend following system, we enter into a *long* position when $K < 0$, $S > 0$, $TR > V$ and we enter into a *short* position when $K < 0$, $S < 0$, $TR > V$. For mean-reverting systems, we go *long* when $K > 0$, $S < 0$, $TR > V$ and go *short* if $K < 0$, $S < 0$, $TR > V$. We supply the following kurtosis K and skew S parameters S, K = [5, 7, 8, 10, 15, 20, 25, 30, 40, 50, 75, 90, 100, 125, 180, 200, 250] and the minimum volatility level V is V =[0, 0.25, 0.50, 0.75, 1.00] percent. Altogether, we test 3,240 systems.

2.4 Empirical Evidence

2.4.1 Preliminary Results from Moving Average Systems

The empirical results for single, dual and triple moving average system are tabulated in Table 2.4 Panel A, Panel B and Panel C respectively. Column 2 and 3 are the annualized buy and sell mean return and its corresponding test statistics from Equation (2.9a), Column 4 and 5 are the annualized average daily standard deviations of buy and sell signals, Column 6 is the coefficient for the Buy-Sell spread and its associated test statistics. Lastly, Column 7 presents the nonparametric bootstrap results, in terms of the ranking of the moving average profits among the 500 bootstrap profits. For example, a value of 490 means that the moving average profit is higher than 489 of the bootstrap profits, a statistically significant value.

For the single 50-day moving average system, the empirical results report significant positive buy signals in a number of markets, including US, UK, Japan, Australia and Canada. Most mean buy returns are statistically significant in US, rejecting the null hypothesis that buy signals yield zero returns. However, the sell signals are not as good as the buy signals. More than half of the sell mean returns are positive, implying that holding short positions results in losses. UK long-gilts futures is the only contract to show negative sell returns in three sub-periods. For the Buy-Sell spread statistic, the results are mixed. This is because the Buy-Sell spread statistic is a linear combination of buy and sell signals. By adding the profitable buy signals to unprofitable sell signals cancels out the profits. For example, the buy mean return for US 5YTN (1999-2005) is significantly profitable with t-statistic of 2.409, but after adding the unprofitable sell mean return, the Buy-Sell spread statistic turned insignificant with t-statistic of 1.074. UK, Australia and Japan futures contracts all show statistically significant Buy-Sell test statistics. We also note that the return's volatility for buy signals is consistently lower than sell signals.[18]

Turning to the nonparametric bootstrap of the single moving average system in Column 7, the results shows that a number of futures contracts have a high ranking among the 500 bootstraps, including US 5YTN futures, US 10YTB futures, JGB futures and Australia 3YGB futures. All but US 30YTB futures (1999-2005), Bund futures and Canadian (2000-2005) futures have rankings higher than 400. This result is consistent with the standard test statistics reported earlier.

Moving onto the dual moving average system, the results look similar to the single moving average system. Most of the buy test statistics are still significant, but none of the sell signals is. Four out of six buy mean returns in US are statistically significant. The results for UK long gilts futures have deteriorated as compared to the previous system, as we find only one significant Buy-Sell spread statistic against three in the previous system. Moreover, most of the recent periods in US and Canada are unprofitable too. Australia is the only country to report significant buy signals and Buy-Sell spread statistics for both 3-Y and 10-Y futures, suggesting that technical trading system has some value in the Australian market. Interestingly, the Bund futures and JGB futures produce results opposite to the previous system. The results from the nonparametric bootstrap is similar to the conclusions derived from the standard test statistics.

To explain why buy signals are more profitable than sell signals, we hypothesize that this is due to the declining policy rates during our sample period, which led to an increase in bond futures prices. The profitable buy signals capture this increase while sell signals are results of whipsaws occurring to the trend following moving average systems.

Lastly, it is noticeable that the results for the triple moving average system in Panel C are not as good as the previous two systems. This shows that a change in the way we apply the basic indicator (moving average) can result in a big difference in trading profits. Altogether, there are only five significant buy-sell spread statistics. For US bond futures, most of the significant buy-sell statistic are concentrated in the *pre*-1999 period. UK long gilts futures do not report any significant test statistics in

[18] We are unable to test whether the so-called 'leverage effect' hypothesis by Black (1976) is applicable to our situation here.

all three sub-periods, including most buy and all sell signals. For Bund and JGB futures, the buy signals are statistically significant but not the Buy-Sell spread statistic. Similar to the previous system, Australia has produced both significant buy signals and Buy-Sell spread statistic.

The nonparametric bootstrap results displays similar conclusion about the profitability of the trading systems. The lowest ranking of the nonparametric bootstrap among all contracts is Canadian 10YGB (2000-2005), attaining a rank of only 47. Clearly, a loss as large as this is puzzling. In an efficient market, the economic profits is likely to be zero. There should not be any systematic technique in generating capital losses. One possible explanation for this result may be due to the anti-persistency characteristic found earlier. For example, in Table 2.3 the lowest classical R/S statistic is display by Canada 10YGB (2000-2005) at 0.8009. Since the moving average system is a trend-following system, this anti-persistency characteristic will cause the moving average system to generate losses. A counter-trend technical trading strategy is more appropriate for this futures contract over the sample period 2000-2005. This shall be investigated in our expanded universe of trading strategies in the next section.

In summary of the empirical evidence so far, we find the preliminary results show some promising results. But we are unsure whether this is due to data snooping or technical indicators have genuine value to traders. Moreover, the results presented here are only valid historically, providing a snapshot of what we can reasonably expect from these trading systems. The profits seem to vary over time and over different futures contracts. This confirms Stylized Fact 2 mentioned earlier in Chapter 1: it is difficult to conclude whether technical trading systems provide genuine value to investors.

Table 2.3: Long Memory Tests of Bond Futures Returns. Column 2 is the Classical R/S Statistic, and Column 3-6 are the Lo's R/S Statistic under four different values of q.

Futures Contracts	Classical		Lo's R/S Statistics		
	R/S Statistics	$q = 25$	$q = 50$	$q = 100$	$q = 250$
US5YTN(88-99)	1.3471	1.3141	1.2271	1.2208	1.2387
		(2.51%)	(9.78%)	(12.18%)	(8.75%)
US5YTN(99-05)	1.2256	1.2255	1.2607	1.3839	1.5692
		(0.01%)	(-2.79%)	(-11.14%)	(-21.90%)
US10YTN(83-99)	1.2962	1.2585	1.2104	1.1967	1.1544
		(3.00%)	(7.09%)	(8.32%)	(12.29%)
US10YTN(99-05)	1.0227	1.0487	1.1093	1.2637	1.5675
		(-2.47%)	(-7.80%)	(-19.07%)	(-34.75%)
US30YTB(77-99)	1.7130	1.6429*	1.5922	1.6242*	1.5279
		(4.27%)	(7.59%)	(5.40%)	(11.12%)
US30YTB(99-05)	0.8367	0.8490*	0.9370	1.1496	1.5607
		(-1.44%)	(-10.70%)	(-27.21%)	(-46.49%)
UKLG1(83-88)	0.8931	0.8566*	0.8368*	0.9300	1.9872*
		(4.26%)	(6.73%)	(-3.96%)	(-55.05%)
UKLG2(88-98)	1.3291	1.3459	1.3217	1.3198	1.2362
		(-1.19%)	(0.62%)	(0.77%)	(7.57%)
UKLG3(98-03)	1.1033	1.1025	1.5775	1.1185	1.2519
		(0.07%)	(4.96%)	(1.36%)	(-11.87%)
GER10YB(98-05)	1.0593	1.1038	1.1302	1.1357	1.1604
		(-4.03%)	(-6.27%)	(6.73%)	(-8.07%)
JAPJGB(86-05)	1.4430	1.3045	1.2309	1.2872	1.4501
		(10.62%)	(17.22%)	(12.10%)	(-0.49%)
AUS3YGB(89-05)	1.3792	1.3519	1.2869	1.2404	1.2304
		(2.03%)	(7.18%)	(11.20%)	(12.12%)
AUS10YGB(84-05)	1.2423	1.2624	1.2368	1.2283	1.2455
		(-1.59%)	(0.45%)	(1.14%)	(-0.25%)
CAN10YGB(90-00)	1.3059	1.2613	1.2183	1.1954	1.2660
		(3.57%)	(7.20%)	(9.25%)	(3.16%)
CAN10YGB(00-05)	0.8009	0.8973	1.0084	1.2421	1.9237*
		(10.75%)	(-20.58%)	(-35.52%)	(58.37%)

Table 2.4: Preliminary Results of the Moving Average Systems. Column 2-3 are the Buy/Sell mean return, followed by the Buy/Sell standard deviation and the Buy-Sell Spread. Column 7 is the Ranking from the nonparametric bootstrap. Numbers in parenthesis are the t-statistics.

Futures Market	Buy Mean (t-stat)	Sell Mean (t-stat)	Buy S.D.	Sell S.D.	Buy-Sell Spread (t-stat)	Rank
Panel A: 50-Day Moving Average System						
US5YTN(88-99)	4.863	-0.671	4.445	4.451	5.533	497
	(2.793)***	(-0.330)			(4.186)***	
US5YTN(00-05)	6.351	3.960	4.934	5.174	2.391	370
	(2.409)***	(0.960)			(1.074)	
US10YTB(83-99)	8.333	0.802	9.274	10.416	7.531	472
	(2.742)***	(0.215)			(2.478)***	
US10YTB(99-05)	8.351	6.426	7.089	8.611	1.925	315
	(2.117)**	(1.007)			(0.573)	
US30YTB(77-99)	12.606	-7.459	22.370	29.051	20.065	483
	(1.682)**	(-0.931)			(3.667)***	
US30YTB(99-05)	7.899	9.093	10.878	12.603	-1.195	243
	(1.291)	(0.993)			(-0.235)	
UKLG1(83-88)	9.725	-6.145	9.051	10.245	15.870	487
	(1.716)*	(-0.999)			(3.807)***	
UKLG2 (88-98)	4.784	-0.681	7.678	9.740	5.465	430
	(1.343)*	(-0.157)			(1.984)**	
UKLG3 (98-03)	2.966	1.657	5.738	5.907	4.623	423
	(0.869)	(-0.471)			(1.888)**	
GER10YB(90-05)	2.211	3.502	5.004	6.053	-1.291	189
	(1.243)	(1.537)			(-0.920)	
JAPJGB(86-05)	11.007	-5.451	7.089	11.549	16.458	500
	(4.209)***	(-1.483)**			(7.725)***	
AUS3YGB(89-05)	1.740	0.173	1.408	1.683	1.567	493

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Futures Market	Buy Mean (t-stat)	Sell Mean (t-stat)	Buy S.D.	Sell S.D.	Buy-Sell Spread (t-stat)	Rank
	(3.563)***	(0.268)			(4.028)***	
AUS10YGB(84-05)	0.928	0.185	1.418	1.731	0.743	429
	(2.057)**	(0.342)			(2.143)**	
CAN10YGB(90-00)	7.374	0.235	7.302	8.553	7.139	475
	(2.290)**	(0.061)			(2.888)***	
CAN10YGB(00-05)	4.458	7.881	6.041	7.060	-3.302	163
	(1.315)*	(1.486)			(-1.134)	
Panel B: 10/150-Day Moving Average System						
US5YTN(88-99)	4.774	-1.276	4.329	4.621	6.051	494
	(2.867)***	(-0.563)			(4.510)***	
US5YTN(00-05)	4.137	11.697	5.002	5.252	-7.561	72
	(1.619)*	(2.011)			(3.232)	
US10YTB(83-99)	8.082	-0.739	9.033	10.622	8.821	483
	(2.779)***	(-0.185)			(3.745)***	
US10YTB(99-05)	4.375	18.678	7.416	7.994	-14.303	53
	(1.131)	(2.300)			(-4.095)	
US30YTB(77-99)	11.864	-8.002	20.453	31.949	19.867	485
	(1.619)**	(-0.933)			(3.566)***	
US30YTB(99-05)	4.402	15.887	11.273	11.953	-11.485	117
	(0.708)	(1.549)			(-2.150)	
UKLG1(83-88)	-1.002	7.726	8.632	11.181	-8.728	114
	(-0.181)	(1.096)			(-2.001)	
UKLG2(88-98)	5.480	-2.399	7.215	10.919	7.880	460
	(1.559)*	(-0.494)			(2.767)***	
UKLG3(98-03)	-1.502	0.491	5.684	6.001	-1.993	235
	(-0.456)	(0.123)			(-0.785)	
GER10YB(90-05)	3.955	0.204	4.886	5.941	3.751	456

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Futures Market	Buy Mean (t-stat)	Sell Mean (t-stat)	Buy S.D.	Sell S.D.	Buy-Sell Spread (t-stat)	Rank
	(2.385)***	(0.083)			(2.731)***	
JAPJGB(86-05)	5.118	4.618	6.517	12.627	0.499	298
	(2.111)**	(1.140)			(0.240)	
AUS3YGB(89-05)	1.718	-0.055	1.468	1.619	1.773	492
	(3.690)***	(-0.074)			(4.501)***	
AUS10YGB(84-05)	1.455	-0.117	1.456	1.718	1.108	471
	(2.256)**	(-0.202)			(3.162)***	
CAN10YGB(90-00)	4.621	6.244	7.143	8.333	-1.624	234
	(1.559)*	(1.474)			(-0.668)	
CAN10YGB(00-05)	2.801	14.543	6.422	6.494	-11.743	35
	(0.809)	(2.165)			(-1.134)	
Panel C: 10/100/200-Day Moving Average System						
US5YTN(88-99)	4.244	-0.013	4.339	4.628	4.257	482
	(2.560)***	(-0.006)			(3.138)***	
US5YTN(00-05)	5.090	6.768	5.063	5.353	-1.678	254
	(1.917)**	(1.145)			(-0.693)	
US10YTB(83-99)	7.665	0.811	8.992	10.598	6.853	456
	(2.637)***	(0.202)			(2.908)***	
US10YTB(99-05)	5.600	13.068	7.339	8.630	7.468	150
	(1.398)*	(1.583)			(-2.072)	
US30YTB(77-99)	8.696	-4.275	21.050	31.669	12.972	446
	(1.180)	(-0.493)			(3.309)**	
US30YTB(99-05)	5.794	13.130	11.083	12.889	-7.339	182
	(0.910)	(1.212)			(-1.337)	
UKLG1(83-88)	0.834	2.967	8.649	11.369	-2.123	247
	(0.149)	(0.399)			(-0.475)	
UKLG2(88-98)	3.999	0.268	7.343	10.831	3.731	407

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Futures Market	Buy Mean (t-stat)	Sell Mean (t-stat)	Buy S.D.	Sell S.D.	Buy-Sell Spread (t-stat)	Rank
	(1.113)*	(0.055)			(1.039)	
UKLG3(98-03)	0.011	-2.087	5.440	5.990	2.098	366
	(0.003)	(-0.544)			(0.829)	
GER10YB(90-05)	2.670	2.594	4.866	5.993	0.076	288
	(1.594)*	(1.054)			(0.055)	
JAPJGB (86-05)	6.250	5.298	6.594	11.459	0.952	317
	(2.740)***	(1.336)			(0.481)	
AUS3YGB(89-05)	1.519	0.451	1.473	1.683	1.068	457
	(3.194)***	(0.621)			(2.684)***	
AUS10YGB(84-05)	1.103	-0.207	1.416	1.782	1.310	478
	(2.511)**	(-0.351)			(3.717)***	
CAN10YGB(90-00)	4.206	3.376	7.075	8.453	2.830	387
	(2.118)**	(0.761)			(1.158)	
CAN10YGB(00-05)	1.448	17.190	6.422	7.140	-15.746	24
	(0.405)	(2.443)			(-4.943)	

*** - significant at 1 percent level, ** - significant at 5 percent level, - * significant at 10 percent level

Volatility and Moving Average Profits

Results in Table 2.4 highlight the fact that technical profits have declined in recent years, as shown by the sub-period tests on US, UK and Canada futures contracts. Our results are consistent with Ready (2002), Kidd and Brorsen (2004) and Olson (2004), who all report findings that technical profits have decreased over time. For example, Olson (2004) finds the moving average rule produces three percent annualized risk-adjusted profit in the eighties, which declined to zero percent in the nineties. Similarly, Ready (2002) finds the moving average rules in Brock, Lakonishok and LeBaron's (1992) study on US DJIA had performed quite poorly after 1986.

A plausible explanation for this decline in profitability is the decline of the volatility of bond futures return itself. Recall that moving average system is a form of trend following strategy, with nonlinear option-like payoff. (See, for example, Fung and Hsieh (2001)) This means that trend following systems tend to perform better during periods of high volatility. During periods of decreasing or low volatility, the ability of moving average system in generating significant returns is drastically reduced because it generates too many small and unprofitable trades, a period known as *whipsaw*. Pedersen and de Zwart (2004), for example, demonstrate that if the volatility of an exchange rate series is low, then the moving average rule cannot generate high profitability due to the absence of trends. They determine this result using a large number of simulations. It is plausible that it might occur in our dataset.[19]

To provide some evidence for this, Figure 2.4(a) plots the 50-day moving average variance of the 30-year US Treasury bond futures return. It clearly shows that bond futures returns have declined substantially since the volatile periods in the early eighties and has remained very low for the last 10 years. Thus, trend following systems exhibit lower profits recently.

To see further how volatility affects the trend following system profits, we fit the geometric Brownian motion model to the US (1978-1999) futures returns and conduct a number of simulation trials.[20] For each volatility value (holding the drift parameter constant), we simulate ten trials. Figure 2.4(b) shows the relationship between increasing volatility and the possibility of higher moving average profits. As volatility increases, the range of annualized returns from the 50-day moving average system

[19]Skewness and kurtosis also have positive effects on trend following strategies, such as moving average rule. This is due to the option-like feature of the moving average payoff function.

[20]The geometric Brownian motion model is: $dF_t = \mu F_t + \sigma F_t dW_t$, where W_t is the standard Brownian motion and F_t is the futures price. To generate simulated prices, we first estimate the drift and diffusion coefficients by maximum likelihood and the simulate prices using estimated drift parameter value while varying the volatility parameter value.

increases. Our point here is not to suggest that increased volatility will definitely increase the profits from trend following trading rules. But increased volatility will increase the probability of price trends occurring in the markets, and *if* the trend following trading system is able capture the trend correctly, then it will lead to higher profits. Otherwise, higher volatility may just increases the chances of whipsaw and reduces the profits of the trend-following systems. This can be seen in Figure 2.4(b), an increase in volatility increases the possibility of generating large losses from the moving average system.

Another possible explanation for the lower technical profits is due to a more efficient market. For instance, a recent study by Fong and Yong (2005) demonstrate that even in a highly speculative bubble, such as the internet stocks during period 1998-2002, investors who use trend-following rules like moving average systems are unable to earn statistically significant returns. Lo and Mackinlay (1999) suggest that the widespread "statistical arbitrage" activities may have contributed to the lower technical profits. Furthermore, the proliferation of the moving average system and the a decrease in computer cost has made it harder for these systems to generate significant returns since virtually every investors will use this tool. By the time a price trend is properly defined, most traders may already taken a position and there is no additional impetus to carry the trend forward. As a result, the market retreats in the opposite direction and the trader suffers a loss.[21]

In short, we still cannot determine conclusively the variables that cause the recent decline in technical profits.

Next, Figure 2.5 shows the positive relationship between long memory effects and moving average system profits. The slope in each figure depicts the relationship between the R/S statistics in Table 2.3 (x-axis) and the annualized Buy-Sell return in Table 2.4 (y-axis) for each trading system. The positive slope here captures the observation that the more persistence the returns, the larger moving average system profits. This positive relationship holds for all three moving average systems. In other words, the R/S statistic may be able to act as a form of filter that increases the profitability of trend following systems. For example, if for any subperiods one

[21]But it is perhaps unrealistic to presume that the traders have used the same technical system unchanged over the last two decades. Traders have probably altered their techniques dramatically over the sample period so as to adapt to the changing market conditions (such as decreasing volatility and increase program trading), while the simple rules that we test here have been held constant throughout. Barberis and Shleifer (2003) develop a model whereby investors categorise risky assets into different styles and move funds among these styles in accordance to the relative performance of each style. In other words, investors engaged in "style-chasing". Teo and Woo (2004) provide empirical evidence that confirm this fact in the US equity and mutual fund markets.

estimate that the R/S statistic is low, then a counter trend technical rule will likely to benefit than a trend following rule. But the cutoff point which determine how 'low' the R/S statistic should be before investors switch from trend following strategy to counter trend strategy vary according to different markets. Moreover, even with strong positive persistence, the technical profits vary according to the parameters of the trading rule. The evidence in Figure 2.5 suggests that 1.200 is a reasonable cutoff point for the three moving average systems, implying that as the R/S statistics drop below 1.200, trend following traders might want to reconsider their position for the next out-of-sample time period, either by switching to counter trend strategy or reducing their capital commitments to trend following trading signals.[22] Our results here are consistent with the results given by Olszewski (1998, 2001).

Figure 2.6 provides some observations about the cumulative wealth effects of the 50-day moving average system over two sub-periods (1977-1999, 1999-2005). On the left-hand scale is the wealth over time and on the right-hand scale is the futures price. The initial wealth is assumed to be 100. It is striking how the moving average profits can be consistent in the first period and become more volatile in the second period. The same technical rule which is profitable in one period may generate losses in the next period. This indicates that there is a need to recalibrate the trading system to more recent data in order to avoid the problem of structural change in the financial markets, changes that may render the trading systems ineffective in out-of-sample trading. The procedure of varying the trading system's parameters over time is known as *optimization* in the markets. But whether this has any positive effect on the performance of the trading system is still controversial. For example, Pardo (1986) argues that because of the continuing changes in the financial markets, traders must periodically check and re-optimize the trading systems as the markets evolve.[23] But Lukac and Brorsen (1989, p.58) empirically test the value of optimization and refute the claim that optimization has any incremental value:

> ...there appears to be very little difference between any of the strategies, again suggesting that the value of optimisation is very limited. Reoptimization strategy did not hurt the mean profits or performance from the systems. But, the value of reoptimization strategies is less that what many users of optimization expect.

Even the length of historical period to which we calibrate the trading system is arbitrarily selected. For example, Lui and Mole (1998) find in their survey that the

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[22]From Table 2.2, 1.223 is the value that separates between negative and positive persistence.

[23]There are other ways to improve the trading results. For example, Ilmanen and Sayood (2002) suggest the following ways to increase trading profits, such as smarter indicator weightings, adding new predictors, improving breadth by adding new trading rules, or smarter ways of combining trades.

most common length of historical period used by foreign exchange dealers in Hong Kong is 12 months. But financial markets evolve over time and so do the optimal moving average parameters. Traders with a short trading horizon will prefer a shorter historical calibration period, and vice versa.

It is noticeable from 2.6(b) that even though the trading system may be able to produce substantial profits at some point in the past, the drawdown value may be unacceptable to many investors.[24] The issue here is how we can incorporate appropriate risk management techniques into the trading system to avoid giving back all these profits when the system fails. For instance, one needs to minimize the capital commitments when the position is suffering losses. Reducing the size of positions during losses ensures that the fund does not deplete its capital holding onto losing position, a crucial tactical move in light of the daily marking-to-market procedure in futures markets. The other method for improving method is to devise trading systems that capture only trends and ignore the whipsaws. For example, adding filters to the moving average system, such as price or time filter, may reduce unprofitable and marginal trades.[25] Another technique is the usage of stop-loss orders. While the simpler part is placing these stop-loss orders, the more difficult part is knowing *where* to place the stop-loss orders. From the technical analysis perspective, there is a number of potential choices, such as putting the stop-loss on major support/resistance level, round numbers, trendlines, previous high/close/low prices, and on significant retracement level, possibly based on Fibonacci ratio or Elliot Wave.[26]

Even with these measures, trend following systems may not always necessarily be profitable. This is because in actual trading, human biases complicate matters. For example, taking losses during whipsaws is an action that traders tend to avoid. Consequently, this resulted in larger losses and smaller profits over time. See, for example, Shefrin and Statman (1985) for a description of this disposition effect and

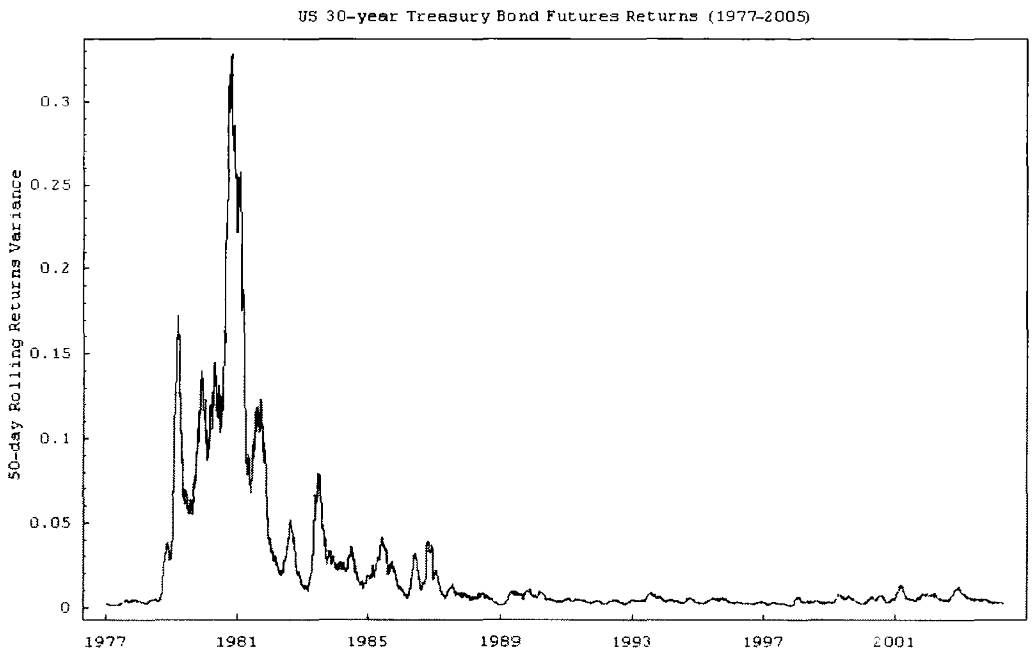
[24]Under the Commodity Futures Trading Commissions' (CTFC) mandatory disclosure rules, managed futures advisors are obliged to disclose this drawdown figure. How useful this figure for potential investors in evaluating traders is still debatable. For a discussion on the drawdown issue, see, for example, Acar and James (1997).

[25]From the perspective of technical analysis, a marginal trade is a trade that has poor risk-reward ratio. This risk-reward ratio depends on two elements: (1) Price objective, and (2) A subjective probability on whether the current price will reach this price objective in the future. Depending on the trading system that one is using and their risk appetite, the recommended risk-reward ratio is usually 3-1 or more. See Pring (1992) and Kaufmann (2005).

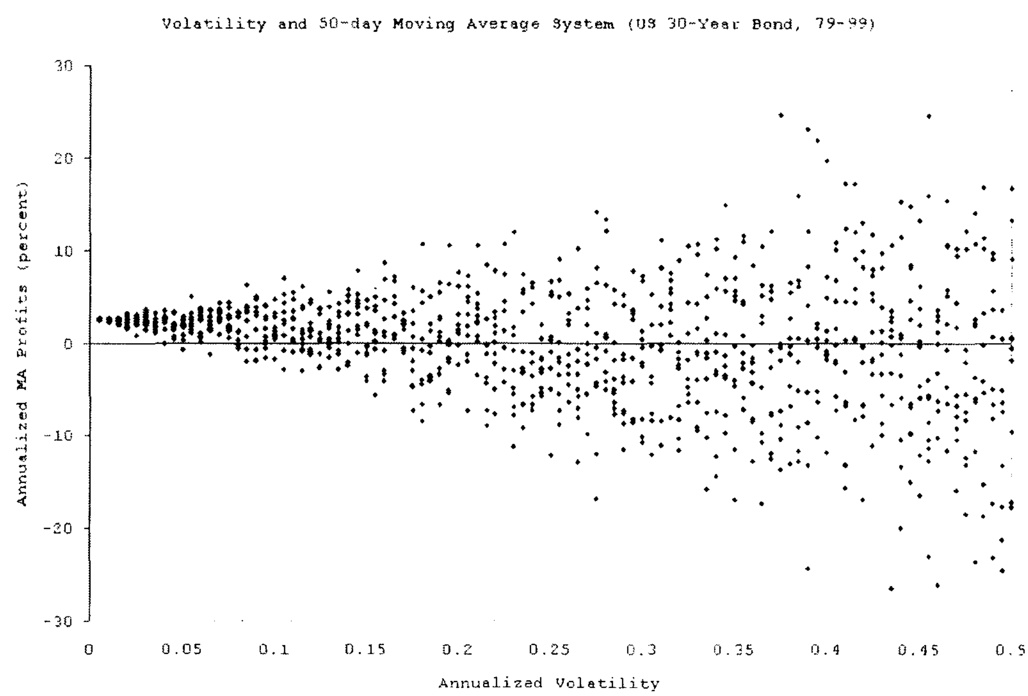
[26]A support level is an area where prices reverse its downward movements and a resistance level is an area where prices meet opposition to a further rise. The support and resistance lines are usually drawn horizontally. Trendlines are slanted support/resistance level. See, for example, Edwards and Magee (1966). Empirically, Osler (2003) finds that there is a clustering effect on predictable support and resistance levels in the currency markets and prices tend to reverse at these levels. Furthermore, price trends are usually more rapid after crossing these levels. This strongly suggests that currency traders do place trading orders according to the technical indicators. See also Osler (2000).

Odean (1998) for some empirical evidence. Recently, Coval and Shumway (2005) collect some trading results from CBOT traders and find that CBOT traders become more risk-seeking and aggressive in setting prices in the afternoon session if they had suffer losses in the morning trading session. Such behaviors may cause the traders to frequently override trading signals from technical system or over-leverage their position. It will be an interesting avenue for future research on how human biases will affect technical trading profits.

Figure 2.4: Volatility and Trend Following Trading System Profits



(a) Declining Volatility in Bond Futures Returns



(b) Simulation and Moving Average Profits.

Figure 2.5: Long Memory and Trend-Following Trading System Profits. The x-axis is the R/S statistic and y-axis is the Buy-Sell Spread statistic.

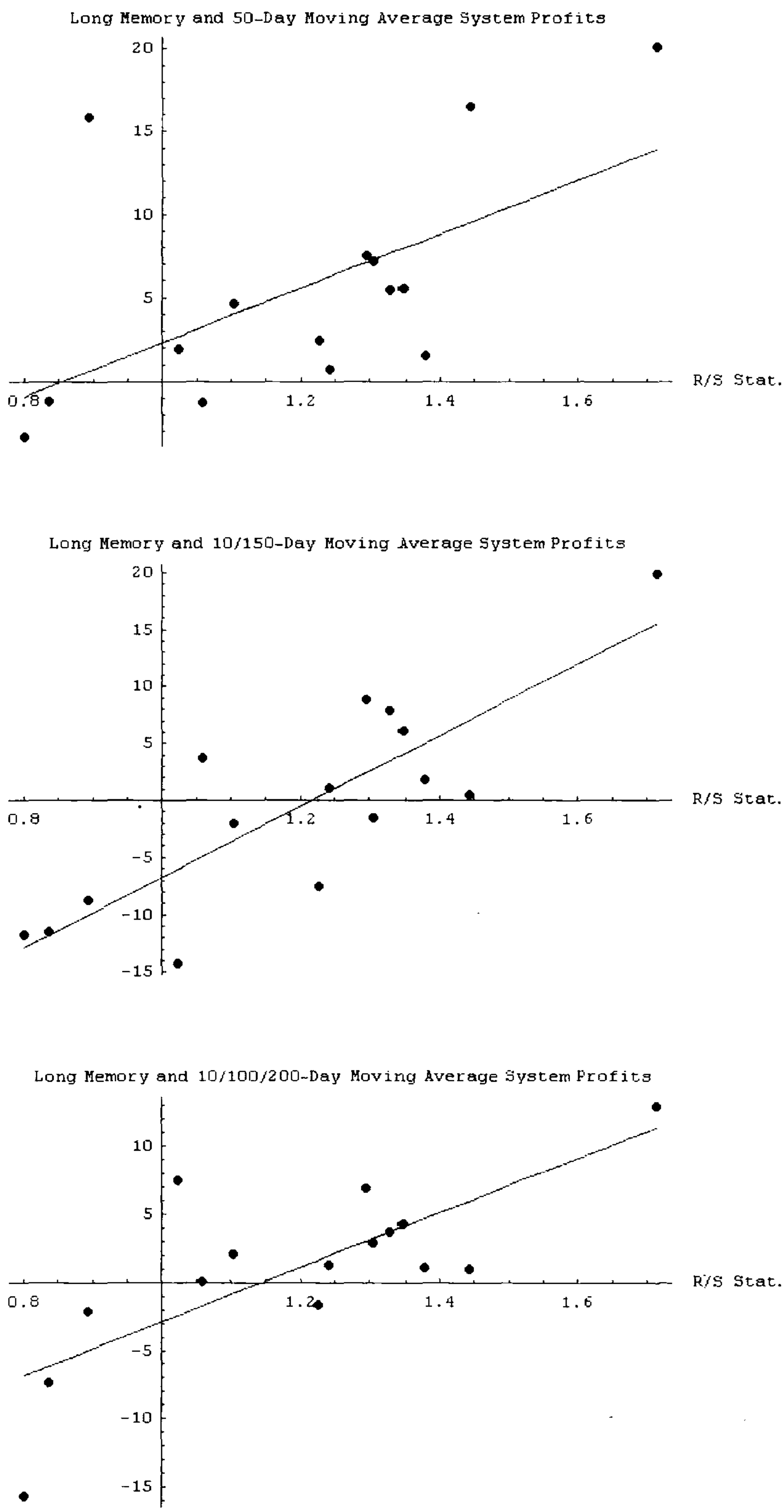
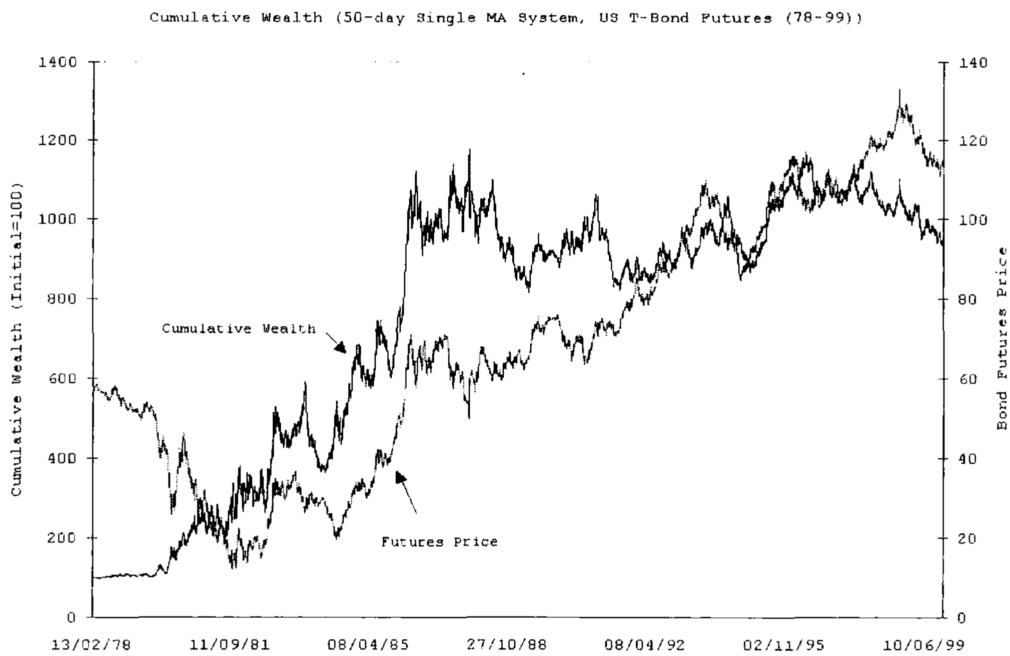
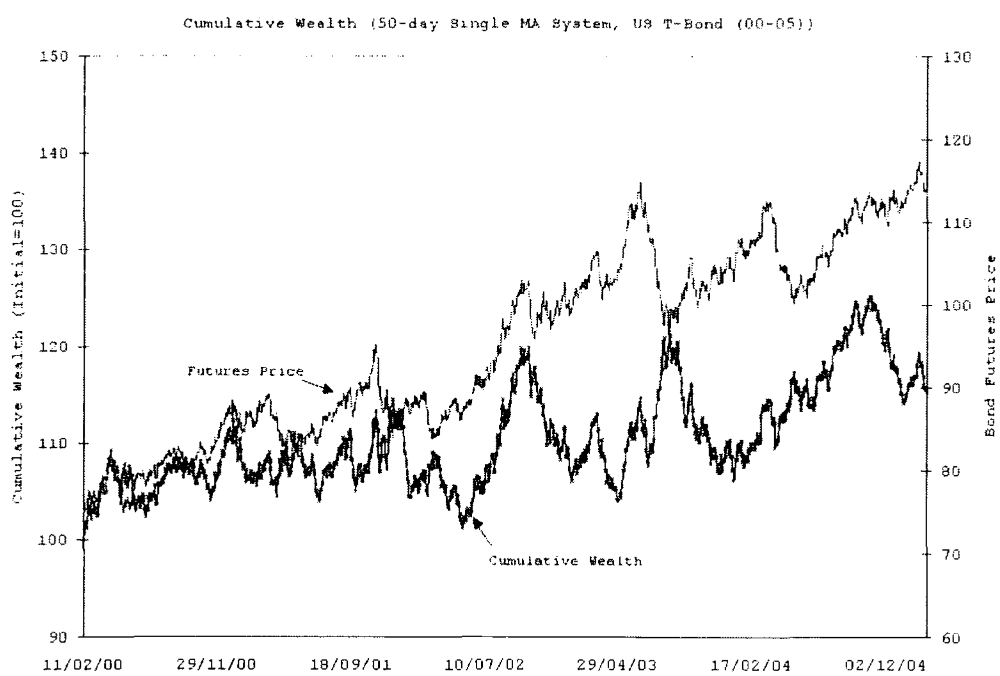


Figure 2.6: Technical Trading System and Cumulative Wealth



(a) US 30-Year T-Bond (1988-1999)



(b) US 30-Year T-Bond (1999-2005)

2.4.2 Results from White's Reality Check

We now discuss the empirical results from applying White's Reality Check to bond futures. The performance results of the best trading system for each futures contract are reported in Table 2.5, along with White's Reality Check p-value, the nominal p-value and the best technical system. The nominal p-value is the result of applying the bootstrap methodology to the best trading rule only, thereby ignoring the effects of data mining. In other words, the difference between these two p-values represents the magnitude of data snooping on the performance measure f_k. In the last column in Table 2.5 is the number of trades recorded for the best trading system.

The results show that the annualized mean return for the best technical trading system varies substantially across markets, from 1.039 percent (Australia 10-Y) to 18.192 percent (US 30-Y, 1977-1999). A number of the best trading systems come from the triple moving average with time filter. Thus, adding the time filter seems to improve the profitability of the moving average trading system. For the US 5-Y T-Notes futures (1999-2005), US 10-Y T-Bond futures (1999-2005) and UK long-gilts futures (1988-1998), the best rule is the dual moving average, while for Canadian 10-Y futures (1990-2000) the best rule is the 5-day single moving average. A number of futures contracts display p-values above the 10 percent significant level (> 0.10), indicating that the best technical system does not perform better than the null benchmark. For example, such as the Australia 10YGB (1984-2005), where the p-value is statistically insignificant at 0.228. This result is contrary to the preliminary results discussed earlier, where we find that Australia 10YGB has significant buy-sell test statistic for all three moving average systems.

On the other hand, the futures contracts that reject the null hypothesis (2.12) include the US 5-Y (1988-1999), US 10-Y (1983-1999), US 30-Y (1977-1999), Germany Bund futures, Australia 3-Y and Canada 10-Y (1990-2000). This shows that the best technical trading system has genuine value to traders for these markets even after accounting for data snooping effects.

A comparison between the nominal p-values and White's p-values show a large difference between them. All nominal p-value indicates that the best trading system is statistically significant among the 500 bootstraps since all nominal p-values are below 0.10. This indicates data snooping effects are important and affects the conclusion about the profitability of technical trading system. For example, the UK long gilts futures (1983-1988) contract has a nominal p-value of 0.000. Taken at face value, this means that the triple moving average with time filter system is statistically significant at 1 percent and we can reject the null hypothesis (2.12). However, once we employ White's procedure to account for data snooping effects, the p-value rises to 0.298, clearly refuting the earlier conclusion. A similar pattern appears in other bond futures markets,

Furthermore, we notice that the White's p-values are consistently higher in recent periods than earlier periods. Recall that we discussed about a decrease in the profitability of the moving average system in recent periods in the previous section. This fact, apparently, appears here. An example of this decline is given by UK long-gilts futures for the three subperiods (1983-1988,1988-1998,1998-2003), where the best mean annualized return are 10.435 percent, 6.796 percent and 4.819 percent respectively, a marked decline of more than 50 percent. We conjecture that this lower profitability may have resulted in higher White's p-values. A contradiction to this hypothesis is shown by US5YTN, where the White's p-value are much higher for US5YTN (1999-2005) than US5YTN (1988-1909) even though the mean returns is higher as well. Thus this evidence may rule out the explanation that lower returns increase p-values.

How do our results here fared as compared to other asset classes? In STW, they obtain White's p-value to be 0.000 for DJIA over 100-year period (1897-1986). However, in the out-of-sample test using S&P 500 futures over period 1984-1996, they obtain White's p-value to be 0.90 even though the best mean return is 9.4 percent per annum. They claim that technical trading systems provide no useful value to traders over the more recent period, thus refuting Brock, Lakonishok and LeBaron's (1992) earlier claim that technical rules have value to investors. In another test, Sullivan, Timmermann and White (2001) find White's p-value to be 0.243 for DJIA for the best calendar rule and 0.874 for the out-of-sample tests, again showing the best calender rule is unable to beat the benchmark. On the contrary, Qi and Wu (2001) find White's p-value to be zero for seven currency pairs, was able to reject the null hypothesis (2.12) after including transaction costs. Recently, Hsu and Kuan (2005) apply White's Reality Check to NASDAQ and Russell 2000 Index and find the best trading system be statistically significant ($p = 0.00$) with annualized returns of 39.19 percent and 47.10 percent respectively. Most of these studies find the best rule to be the moving average system.

It is interesting that the results for the White's test vary so much across different markets. For future research, it would be interesting to find out why the null hypothesis (2.12) are rejected in some asset classes and not others. Kho (1996, p.287), for example, pinpoints the source of technical profits in currency markets to the time-varying risk premium and conclude that:

> Periods of higher or lower returns identified by the technical rules largely

correspond to those of higher or lower conditional expected returns, due to high or low risk premia and volatility. Thus, large parts of the technical rule profits are a natural consequence of time-varying risk premia and volatility.

This finding strengthens Fama's (1991) argument that market efficiency does not preclude a degree of forecastability due to time-varying risk premia. More recently, Mifre (2002) also finds that commodity futures exhibit time-varying risk premia when testing the performance of abnormal returns with a number of economic factors. For bond markets, Ilmanen (1995) analyzes the predictability variation in the monthly excess return of long-term government bonds over period (1978-1993) in US, UK, Germany, Japan, France and Canada with four economic factors, which are inverse relative wealth, bond beta, term spread and real bond yield. What he finds is that these variables can forecast international bond returns to some extent, and consequently, dynamic trading strategies can exploit these return predictability and earn annualized excess return between 3 to 8 percent. Without a complete macro-economic model, we cannot determine the origins of the time-varying profits in our tests here. [27]

An important issue when evaluating technical trading systems is assessing the effects of transaction costs on trading profits. From the number of trades given by the preliminary moving average trading systems, (See Column 10 of Table 2.4), it is evident that the number of trades is relatively low. For example, US 30-Y T-Bond futures (1977-1999) produces a total of 354 trades over the last 22 years, which is equivalent to 1.34 trade per month. Australia 10-Y futures (1984-2005) has an equivalent of 1.5 trades per month for 21 years. A characteristic of the moving average rule is that the number of trades are not evenly spread throughout the sample period. For instance, when the bond futures prices are trending, the trading signal can remain unchanged for as long as a year. When the market enters into a choppy period, the number of trades rises quickly and some trading signals can be as short as a day.

Table 2.6 presents the Reality Check results with transaction costs. Since it is difficult to estimate the exact historical transaction costs, we assume two cost values.

[27] If investors are rational, then the bond return predictability captured by trading systems will be a result of time-varying bond risk premiums. This implies that bond returns are high when bonds returns command high risk premiums. In particular, high risk premiums come from (i) Highly risk-averse investors or (ii) Bonds are deemed to be very risky. Empirical tests of bond asset pricing model includes Campbell, Kazemi and Nanisetty (1999). However, since we cannot observed directly on the expectations of these investors, we can never know to what extent bond risk premiums reflect the time-varying risk premiums or systematic forecast errors. Some studies employ the survey-type study to proxy for the market's expectations. See, for example, Froot (1989).

Panel A display the results assuming cost of 0.25 percent per transaction while panel B show the results assuming cost of 0.5 percent per transaction. This assumed transaction costs will not be very accurate for several reasons. First, transaction costs vary across market participants.[28] Second, transaction costs vary across different futures markets. Third, transaction costs vary across different times, especially during market stress. For example, Fleming (2004) explores the relationship of the bid-ask spread in the US treasury market using tick data. He finds that the liquidity (as proxied by the spread) increased heavily during the market stress, such as the equity market decline in October 1997, LTCM's collapse in 1998, and the market disruption around Treasury's quarterly refunding in February 2000. He finds variables such as quote size, trade size on-/off-the-run spread are only modest proxies for liquidity. The basic Reality Check results in Table 2.5 provide us with some estimates on the breakeven costs. For example, for US 30YTB(1977-1999) over a period of 21 years, the best mean return is 18.19 percent with 628 trades recorded. The breakeven costs is thus $(18.19 \times 21)/628 \approx 0.61$ percent. This figure may be too high to reflect the actual costs.[29] For bond markets, transactions costs further varies with the age and size of the bonds.[30]

Table 2.6 shows that the best trading system with transaction costs are similar to previous results without transaction costs. Moreover, the mean returns are not drastically reduced by transaction costs. For example, most of the previously significant p-values previously are still significant even after 0.5 percent transaction costs are added, while the contracts that have insignificant p-values have only marginally higher p-values than without transaction costs. The only exception is Bund futures contract, which generated statistically insignificant p-value after transaction costs are included. Its basic White's p-value is 0.082, rising to 0.084 after 0.25 percent cost are added and 0.134 after 0.5 percent costs are added.

One possible reason to that fact that transaction costs have no major impact on the baseline results is due to the low number of trades from the best trading system.

[28] Sweeney (1988), for example, studies the profitability of filter rules on 30 Dow Jones stocks and find that the profits vary across market participants. Floor traders can generate substantial profits with the filter rules, while institutional money managers can only break-even. Other investors outside this group generate losses.

[29] For example, Chakravarty and Sarkar (2003) examine the transaction costs in three US bond markets. They find that the mean daily bid-ask spread per \$100 par value is 23 cents for municipal bonds, 21 cents for corporate bonds and 8 cents for Treasury bonds. For bond futures markets, this spread is arguably lower due to greater competition. For example, a common bid-ask spread estimate by CBOT is one sixty-fourth of a point – \$15.625 on a \$100,000 transaction.

[30] For example, Alexander, Edwards and Ferri (2000) and Sarig and Wara (1989) find younger corporate bonds are more actively traded and Babbel et al. (2004) show that on-the-run Treasury bonds have smaller spreads. Moreover, credit ratings can also affect the size of bid-ask spread. Different securities have inherently different liquidity and therefore bid-ask spread.

For example, there are only four trades recorded for both US5YTN (1999-2005) and US10YTN (1999-2005) over a period of six years. Consequently, adding 0.5 percent transaction costs is likely to reduce only a tiny fraction of the mean returns.

Table 2.7 summarizes the results on the best trading rules under the Sharpe ratio criterion, which evaluate the superiority of the best trading rule with the average excess returns per unit risk. Unlike Qi and Wu (2001), some of the best trading systems are different to the ones given by the mean return criterion. For example, the best trading rule for US30YTB (1977-1999) is the mean-reverting price distribution system rather than the triple moving average system. The majority of the p-values that are statistically significant under the mean return criterion is also significant under the Sharpe ratio criterion. An interesting observation is that for Bund and JGB futures, the p-value for the mean return criterion is 0.082 and 0.650 respectively. But the p-value for the Sharpe ratio criterion has changed to 0.242 and 0.032 respectively, a switch in statistical significance. An explanation for this change in statistical significance may be due to the relatively low capital costs in Japan, which resulted in higher Sharpe ratio and lower p-values than Bund futures.

The overall conclusion from the White's tests reflects the preliminary empirical results documented earlier. One, there are technical trading systems that seem to have genuine value to investors from a universe of 7,991 trading rules. This can be seen by the statistically significant p-values for both mean return and Sharpe ratio criterion that reject the null hypothesis that best trading rule cannot beat the null benchmark. Furthermore, the addition of transaction costs did not change this conclusion since there was only a marginal increase in the p-values. Two, we also find that the p-values are higher in recent periods, which carry the implication that technical rule has less investment significance to investors for this sample period. However, the Reality Check procedure cannot determine the reason behind this cause.

Table 2.5: Best Trading System and Mean Return Criterion. Column 2 is the mean return from the best rule. Column 3 and 4 is the p-value from the nominal (apply bootstrap once) and White's p-value. Column 5 is the best trading system while Column 6 is the number of trades.

Bond Futures Contracts	Mean Return	Nominal p-value	White's p-value	Best Performing Technical Trading System	Number of Trades
US5YTN(88-99)	5.0082	0.000	0.004	Triple MA Time Filter (20,150,200,4)	26
US5YTN(00-05)	6.6583	0.002	0.162	Dual MA (200,250)	4
US10YTB(83-99)	7.8770	0.000	0.072	Triple MA Time Filter (20,125,250,4)	58
US10YTB(99-05)	9.2505	0.002	0.114	Dual MA Time Filter (200,250,3)	4
US30YTB(77-99)	18.1924	0.000	0.030	Triple MA Price Filter (5,15,25,0.001)	628
US30YTB(99-05)	10.1001	0.004	0.958	Triple MA (10,15,50)	112
UKLG1(83-88)	10.4257	0.000	0.298	Triple MA Time Filter (5,10,20,4)	88
UKLG2(88-98)	6.7960	0.010	0.700	Dual MA Price Filter (100,150,0.005)	6
UKLG3(98-03)	4.8186	0.032	0.998	Triple MA Time Filer (20,25,30,5)	52
GER10YB(90-05)	4.1788	0.002	0.082	Triple MA Time Filter (10,100,200,4)	62
JAPJGB(86-05)	7.3889	0.014	0.650	Triple MA Price Filter (5,20,60,0.001)	269
AUS3YGB(89-05)	1.5071	0.000	0.022	Triple MA Time Filter (5,30,75,3)	142
AUS10YGB(84-05)	1.0386	0.000	0.228	Triple MA Time Filter (20,25,100,2)	247
CAN10YGB(90-00)	9.5727	0.000	0.000	Single MA (5)	602
CAN10YGB(00-05)	6.8299	0.002	0.456	Triple MA Price Filter (5,20,25,0.005)	41

Table 2.6: Best Trading System and Mean Return Criterion with Transaction Costs. We apply two transaction costs values: 0.25% and 0.50%.

Bond Futures Contracts	Mean Return	Nominal p-value	White's p-value	Best Performing Technical Trading System	Number of Trades
Panel A: One-way Transaction Cost = 0.25 **percent**					
US5YTN(88-99)	5.0022	0.000	0.000	Triple MA Time Filter (20,150,200,4)	26
US5YTN(00-05)	6.6583	0.002	0.174	Dual MA (200,250)	4
US10YTB(83-99)	7.8681	0.000	0.048	Triple MA Time Filter (20,125,250,4)	58
US10YTB(99-05)	9.2481	0.004	0.166	Dual MA Time Filter (200,250,3)	4
US30YTB(77-99)	18.1210	0.000	0.028	Triple MA Price Filter (5,15,25,0.001)	628
US30YTB(99-05)	10.0441	0.012	0.952	Triple MA (10,15,50)	112
UKLG1(83-88)	10.3859	0.002	0.346	Triple MA Time Filter (5,10,20,4)	88
UKLG2(88-98)	6.7943	0.006	0.730	Dual MA Price Filter (100,150,0.005)	6
UKLG3(98-03)	4.7954	0.030	0.996	Triple MA Time Filer (20,25,30,5)	52
GER10YB(90-05)	4.1682	0.002	0.084	Triple MA Time Filter (10,100,200,4)	62
JAPJGB(86-05)	7.3490	0.022	0.696	Triple MA Price Filter (5,20,60,0.001)	269
AUS3YGB(89-05)	1.4829	0.000	0.008	Triple MA Time Filter (5,30,75,3)	142
AUS10YGB(84-05)	1.0072	0.004	0.244	Triple MA Time Filter (20,25,100,2)	247
CAN10YGB(90-00)	9.4269	0.000	0.000	Single MA (5)	602
CAN10YGB(00-05)	6.8130	0.000	0.440	Triple MA Price Filter (5,20,25,0.005)	41
Panel B: One-way Transaction Cost = 0.50 **percent**					
US5YTN(88-99)	4.9963	0.000	0.002	Triple MA Time Filter (20,150,200,4)	26
US5YTN(00-05)	6.6583	0.006	0.174	Dual MA (200,250)	4
US10YTB(83-99)	7.8592	0.000	0.046	Triple MA Time Filter (20,125,250,4)	58
US10YTB(99-05)	9.2458	0.002	0.142	Dual MA Time Filter (200,250,3)	4
US30YTB(77-99)	18.0495	0.000	0.036	Triple MA Price Filter (5,15,25,0.001)	628
US30YTB(99-05)	9.9881	0.022	0.946	Triple MA (10,15,50)	112
UKLG1(83-88)	10.3462	0.006	0.382	Triple MA Time Filter (5,10,20,4)	88

continued next page

(continued)

UKLG2(88-98)	6.7926	0.004	0.740	Dual MA Price Filter (100,150,0.005)	6
UKLG3(98-03)	4.7721	0.040	0.998	Triple MA Time Filer (20,25,30,5)	52
GER10YB(90-05)	4.1576	0.006	0.134	Triple MA Time Filter (10,100,200,4)	62
JAPJGB(86-05)	7.3091	0.010	0.728	Triple MA Price Filter (5,20,60,0.001)	269
AUS3YGB(89-05)	1.4587	0.000	0.024	Triple MA Time Filter (5,30,75,3)	142
AUS10YGB(84-05)	0.9759	0.006	0.350	Triple MA Time Filter (20,25,100,2)	247
CAN10YGB(90-00)	9.2812	0.000	0.000	Single MA (5)	602
CAN10YGB(00-05)	6.7960	0.006	0.480	Triple MA Price Filter (5,20,25,0.005)	41

Table 2.7: Best Trading System and Sharpe Ratio Criterion

Bond Futures Contracts	Sharpe Ratio	Nominal p-value	White's p-value	Best Performing Technical Trading System	Number of Trades
US5YTN(88-99)	0.0717	0.001	0.002	Triple MA Time Filter (20,150,200,4)	26
US5YTN(00-05)	0.0807	0.000	0.404	Dual MA (200,250)	4
US10YTB(83-99)	0.0527	0.000	0.048	Triple MA Time Filter (20,125,250,4)	58
US10YTB(99-05)	0.0757	0.004	0.388	Dual MA Time Filter (200,250,3)	4
US30YTB(77-99)	0.0440	0.000	0.024	Price Distribution Mean Reverting (8,30,0.01)	297
US30YTB(99-05)	0.0763	0.000	0.418	Price Distribution Mean Reverting (15,10,0.01)	131
UKLG1(83-88)	0.0820	0.000	0.068	Price Distribution Mean Reverting (50,200,0.000)	13
UKLG2(88-98)	0.0522	0.002	0.766	Price Distribution Trend-Following (8,75,0.0075)	518
UKLG3(98-03)	0.0936	0.000	0.396	Price Distribution Mean Revering (7,90,0.000)	75
GER10YB(90-05)	0.0482	0.000	0.242	Triple MA Time Filter (10,100,200,4)	60
JAPJGB(86-05)	0.0568	0.000	0.032	Price Distribution Trend-Following (20,7,0.025)	696
AUS3YGB(89-05)	0.0626	0.000	0.012	Triple MA Time Filter (5,30,75,3)	142
AUS10YGB(84-05)	0.0423	0.002	0.174	Triple MA Time Filter (20,25,100,2)	247
CAN10YGB(90-00)	0.0770	0.000	0.000	Single MA (5)	602
CAN10YGB(00-05)	0.0754	0.003	0.486	Price Distribution Mean Reverting (30,15,0.005)	107

2.4.3 Data Mining Effects

Figure 2.7 to 2.14 shows the White's p-value as a function of the trading strategy. Each figure demonstrates how the effects of data mining may propagate over the number technical trading systems. The sequential ordering of the technical rules is unimportant since only the terminal value of the highest mean return and the terminal Reality Check p-value matter to our final assessment. (See STW for more details). All figures include the sequentially updated highest mean return (thin black line, with corresponding left-hand scale), the annualized mean return from each strategy (dots, with corresponding left-hand scale) and the White's p-value (thick black line, with corresponding right-hand scale).

For US markets, there are two distinct phases of White's p-value, *pre-* and *post-*1999. In *pre*-1999, the White's p-values are generally smaller and below 0.01. But *post*-1999 period produces higher White's p-values. It is interesting to see how the effects of data mining enters into the evaluation procedure. When additional trading systems do not lead to an improvement over previously best performing trading system, the p-value for the null hypothesis (2.12) that the best model does not outperform the benchmark increases. This accounts for the fact that the best rule has been selected from a large universe of trading system. This can be seen in the *post*-1999 period. For example, the US30YTB (1999-2005) has a p-value below 0.600 at model 200. But the p-value rises steadily while we evaluate more trading rules. At model 4,500 until 7,991, the p-value stays above 0.900, which reject the null hypothesis (2.12).

For UK, the effects are similar. White's p-values generally increase faster in recent sub-periods, implying that the value of technical trading system decreases overtime. For example, the White p-value rises fairly slowly in the period 1983-1988, especially after trading system 4,500. For subperiod 1988-1998, the p-value shows a steady increase throughout the evaluation until model 4,500. For the subperiod 1998-2003, the p-value stays near 1.0 for nearly all the trading systems, dipping occasionally when there is a new maximum mean return.

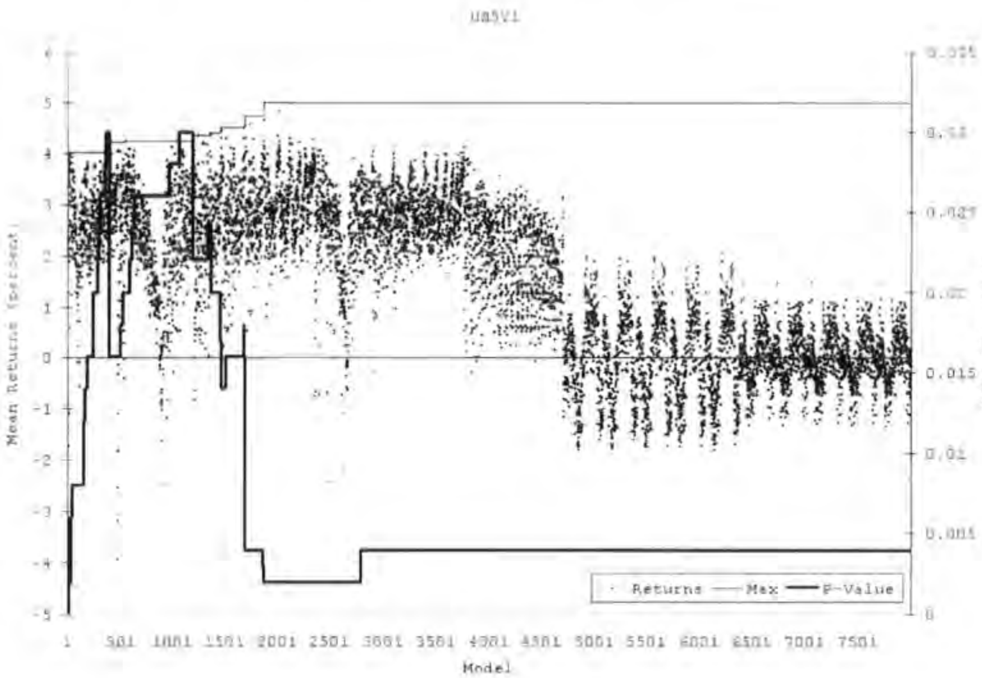
On the other hand, Bund futures shows significant p-value throughout all technical systems. As seen from Figure 2.12, an improvement over the previously best-performing system results in a drop in the White's p-values. For JGB futures, however, it seems that the economic value of trading systems is low after considering the universe of trading systems. The results for Australia futures are consistent with the preliminary results shown earlier. The White's p-values are consistently low throughout the technical systems, especially for 3-Y futures. Lastly, the Canadian futures over period (1990-2000) shows that the White's p-value is effectively zero for all strategies. This is because the best rule for this market is the first system we evaluate. For Canadian futures (2000-2005), the p-value generally drops when a new maximum mean return emerge, and rises slowly after no new maximum mean return is found. This result is consistent with the earlier observations.

Moving onto the Sharpe ration criterion, Figure 2.15 to Figure 2.22 display the p-value for the Sharpe ratio criterion over 7,991 trading systems. Similar to the mean return criterion, the thin line is the maximum Sharpe ratio and the thick black line is the p-value for each system. Each dot represents the Sharpe ratio from each trading strategy.

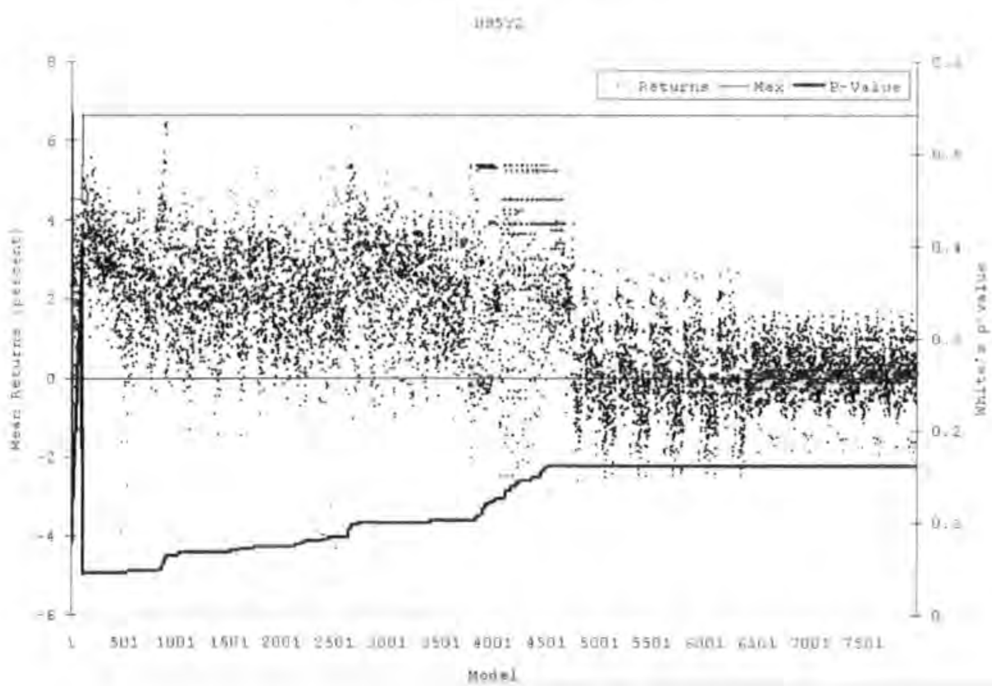
The effects of data snooping described earlier can also be seen from these figures. For example, the US30YTB (1999-2005) shows the p-values increases steadily from model 200 to model 4500. After which, an increase in the maximum Sharpe ratio causes the value of p-value to decrease substantially from more than 0.90 to less that 0.50. Such effects are also exhibited by other contracts. By comparing the maximum Sharpe ratio and the maximum mean return, it is noted that some of the best trading system for the mean return criterion is different to the Sharpe ratio criterion. For example, the best trading rule underlying the best mean return for US30YTB (1999-2005) is the Triple moving average with time filter. while the best rule for the highest Sharpe ratio criterion is price distribution system. What this implies is that even though the triple moving average system gives the highest mean return, it may not necessarily has the highest excess return per unit risk.

Recently, Hansen (2005) argues that including poor performing trading rules into White's (2000) Reality Check procedure may erode its statistical power. Hansen develops an alternative procedure known as the superior predictive ability (SPA) procedure that reduces this problem. In Hansen, Lunde and Nason (2005), they use this procedure to re-examine the calender effects investigated by STW (2001) and find contrary evidence to STW (2001). They conclude that calender effects are statistically significant in a number of markets, even though they find the calendar effects have diminished since later 1980s. It will be for a work for future research in implementing the SPA procedure in the bond futures markets.

Figure 2.7: Best Trading System and Mean Return Criterion: US 5-Year T-Note. The dots are the mean return from each trading rule (left-scale). The thin line is rolling maximum return (left-scale) and the thick line is White's p-value (right scale).

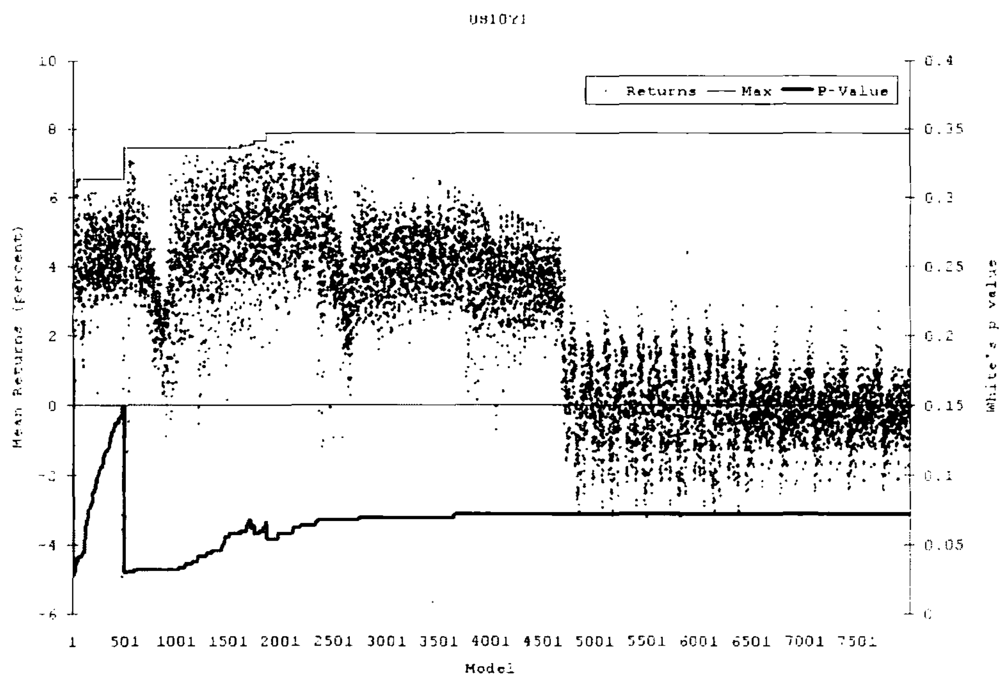


(a) US 5YTN (1988-1999)

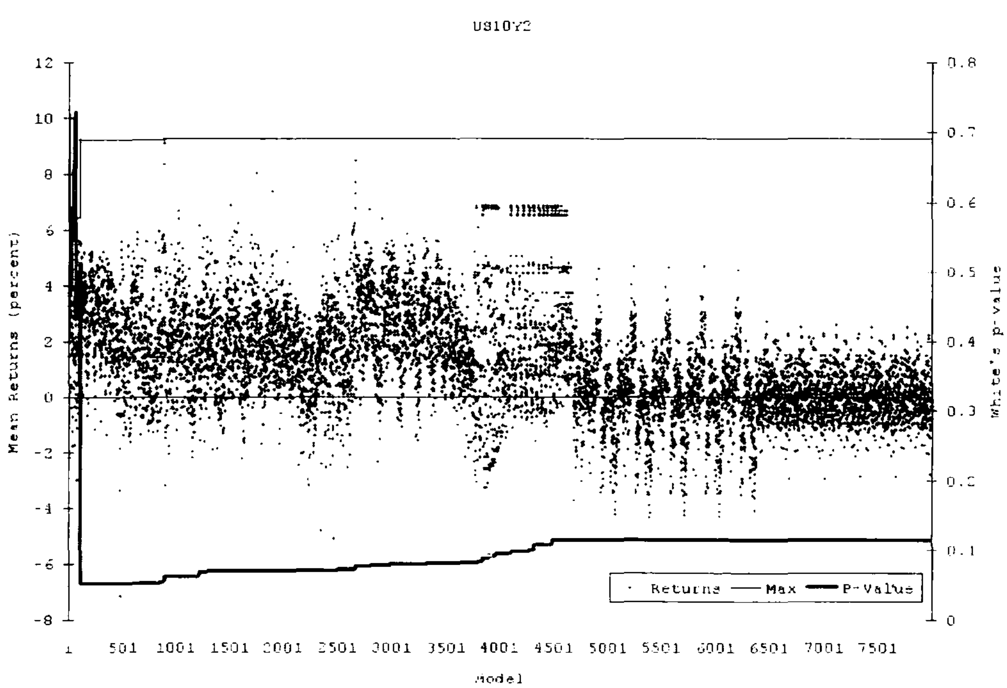


(b) US 5YTN (1999-2005)

Figure 2.8: Best Trading System and Mean Return Criterion: US 10-Year T-Bond

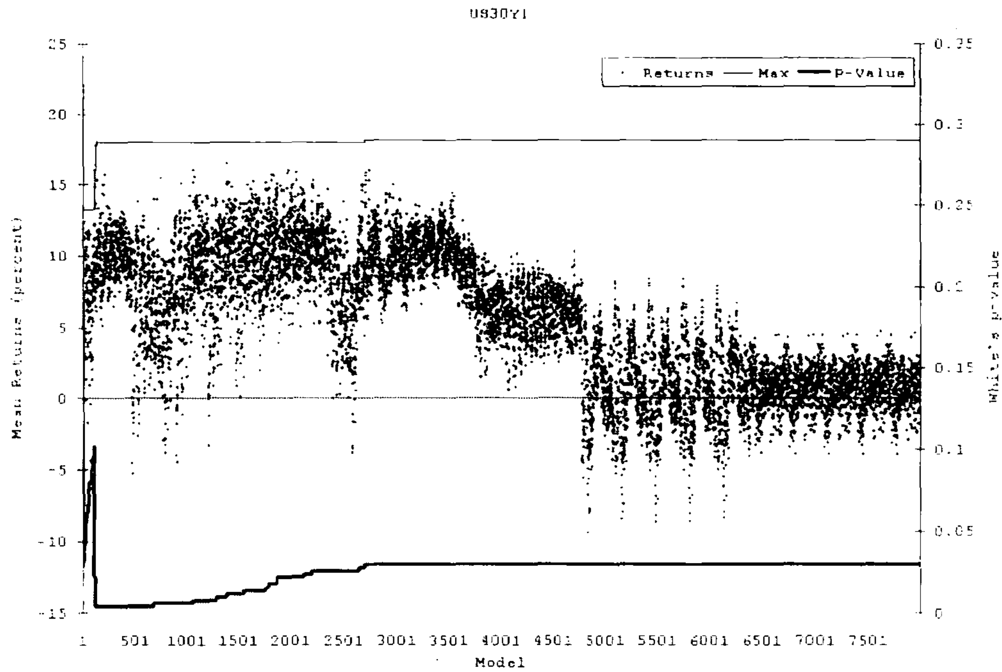


(a) US 10YTN (1983-1999)

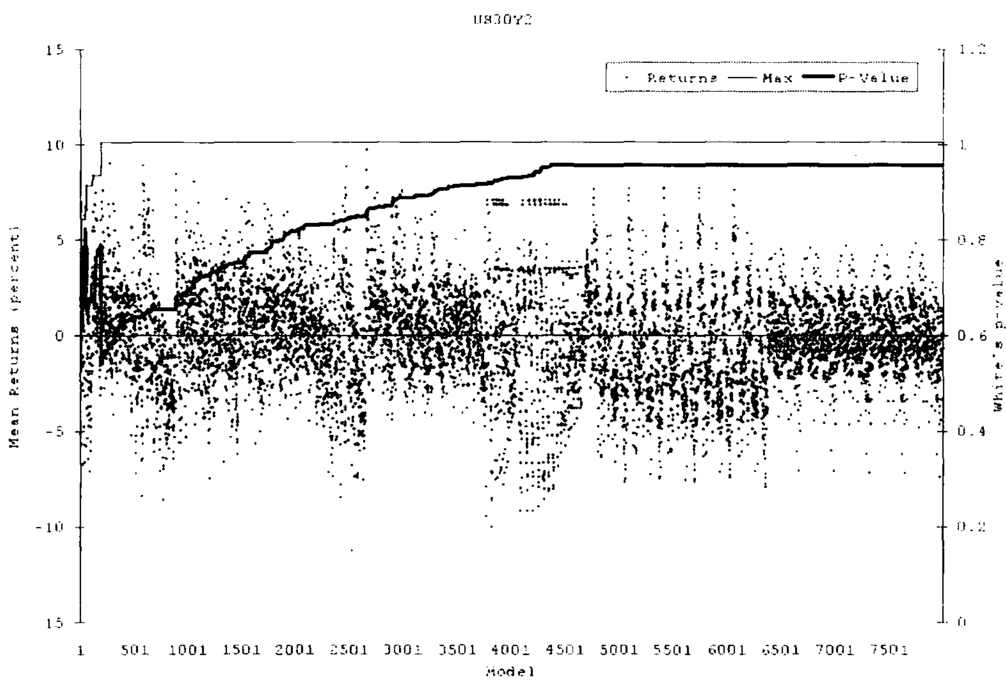


(b) US 10YTN (1999-2005)

Figure 2.9: Best Trading System and Mean Return Criterion: US 30-Year T-Bond

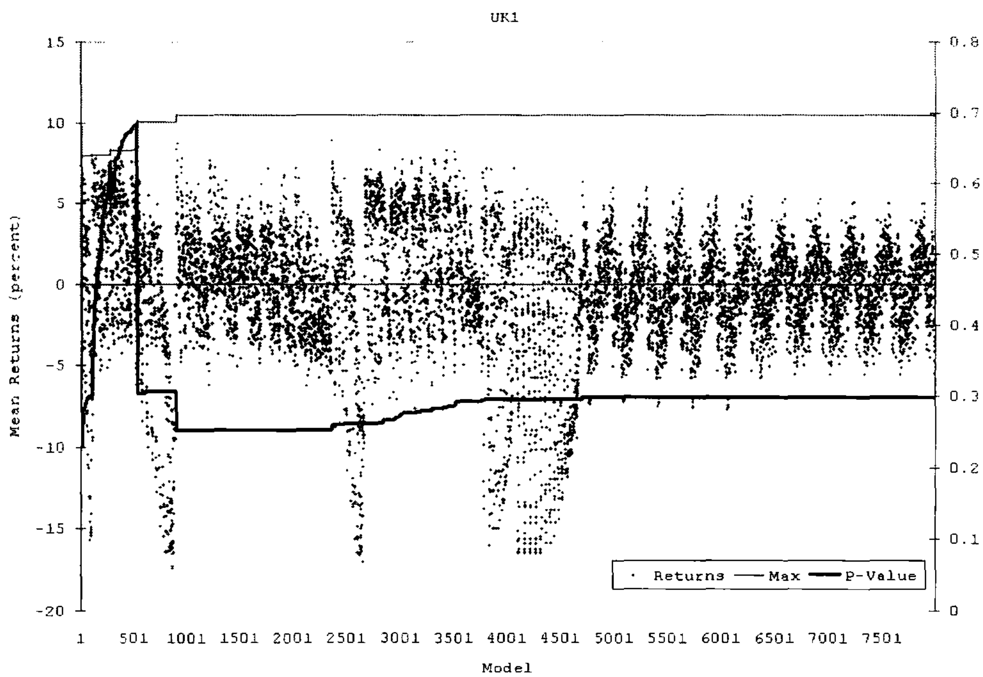


(a) US 30YTB (1977-1999)

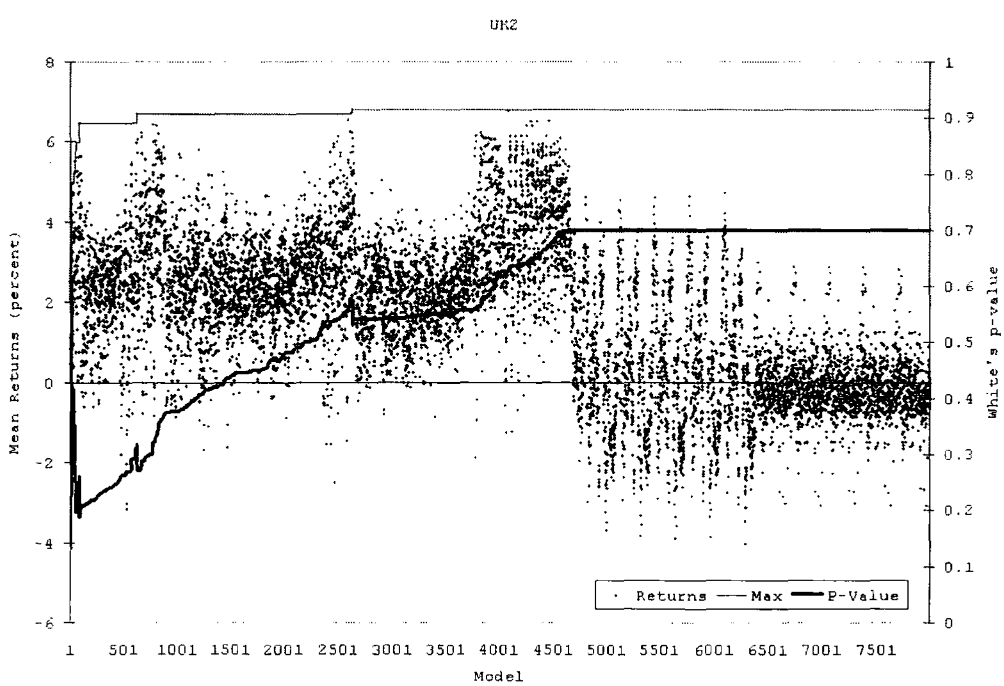


(b) US 30YTB (1999-2005)

Figure 2.10: Best Trading System and Mean Return Criterion: UK Long Gilts (LG)

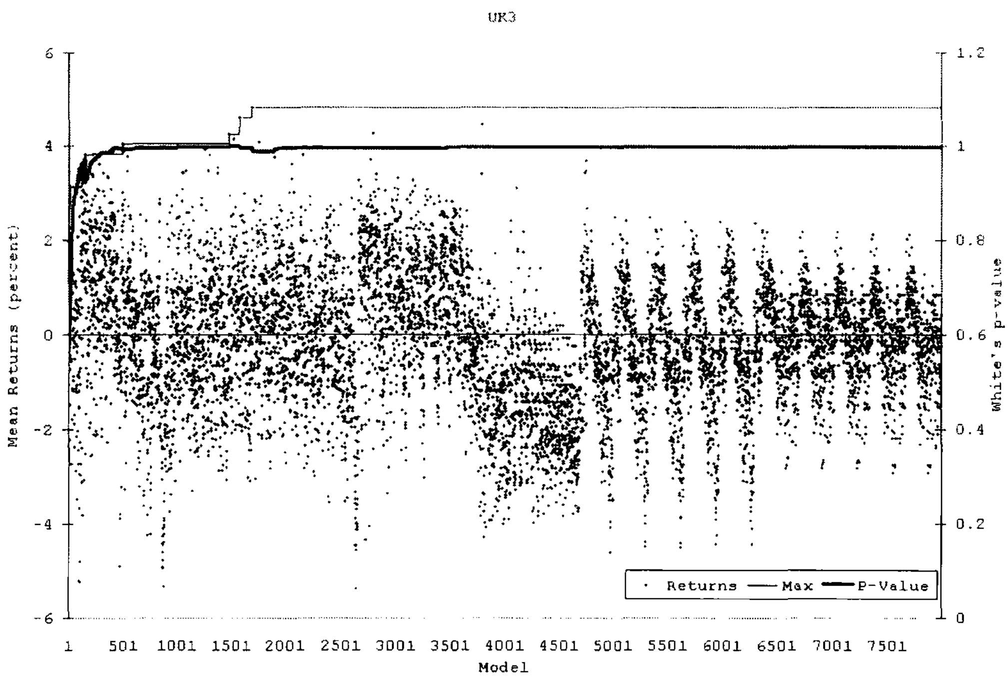


(a) UK LG1 (1983-1988)



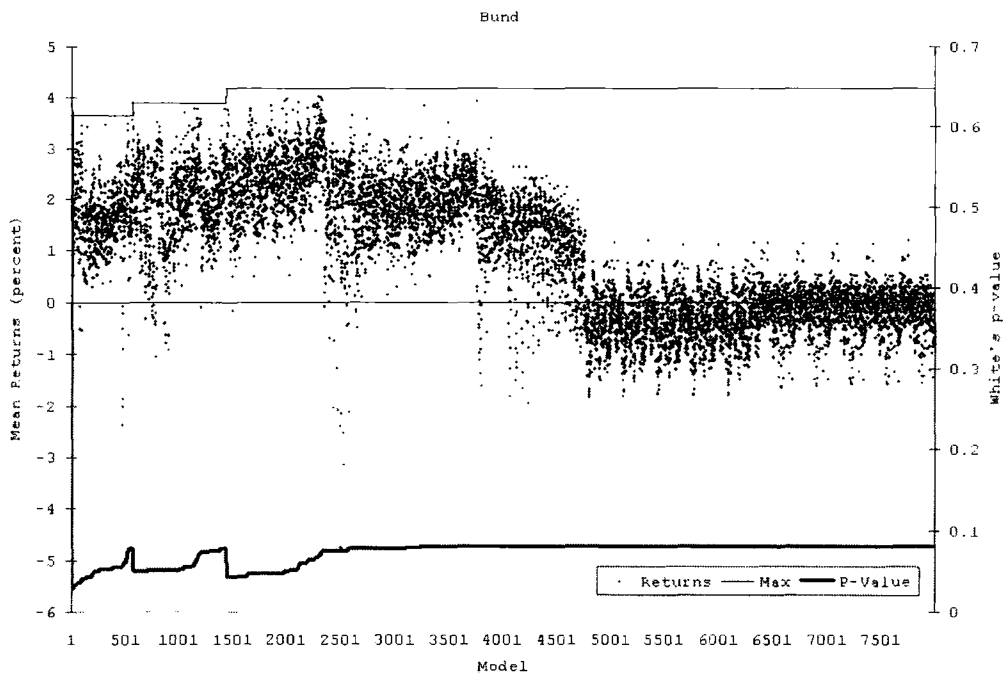
(b) UK LG2 (1988-1998)

Figure 2.11: Best Trading System and Mean Return Criterion: UK Long Gilts (LG) (continued)

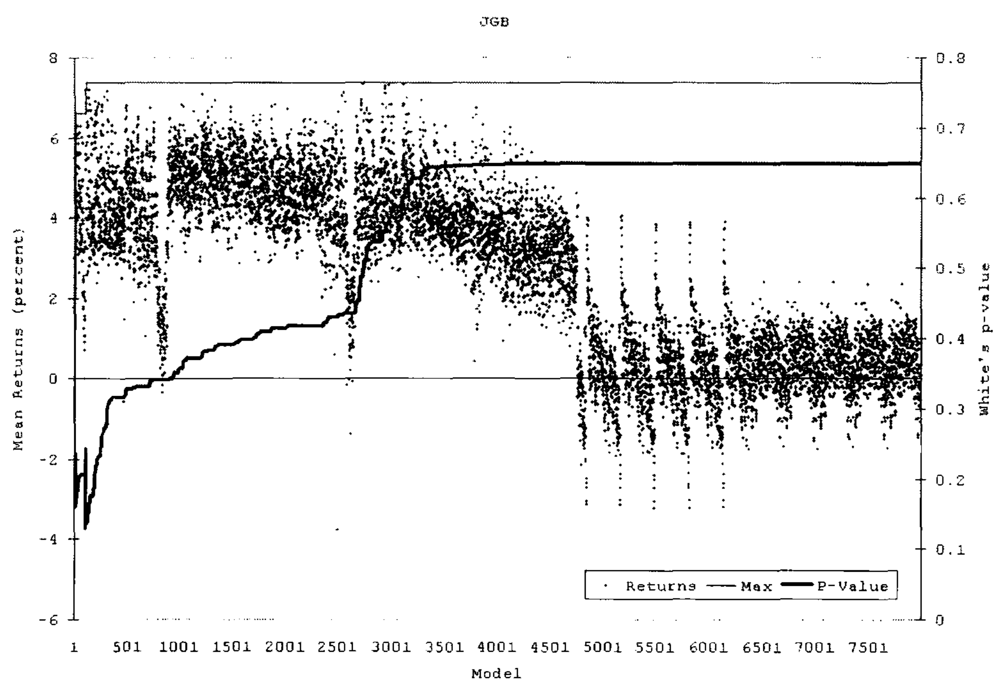


(a) UK LG3 (1998-2003)

Figure 2.12: Best Trading System and Mean Return Criterion: Bund and JGB

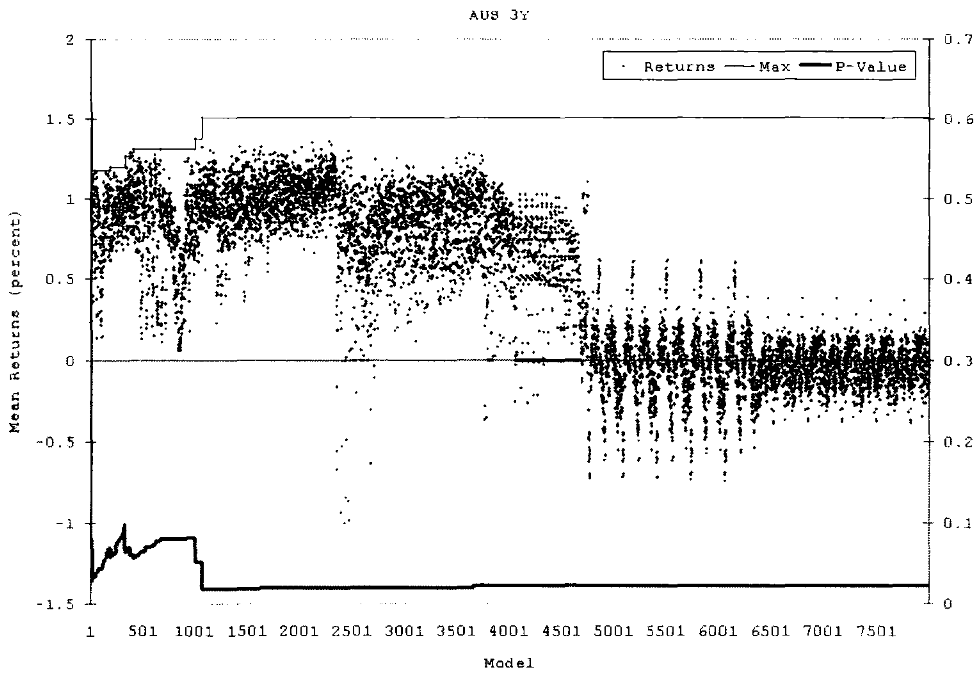


(a) Germany 10YB (1990-2005)

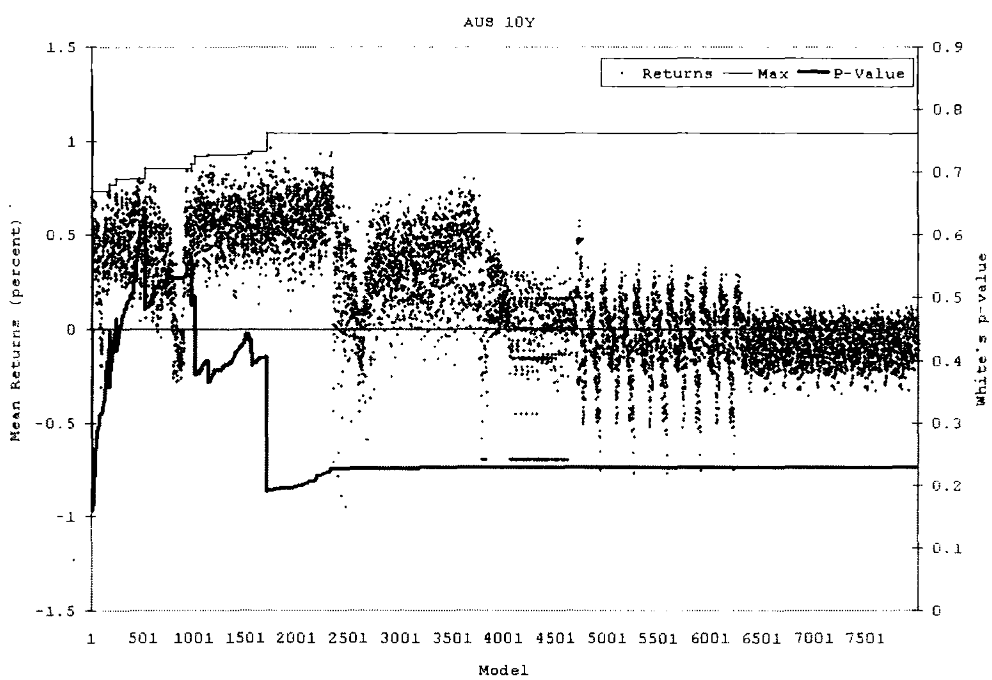


(b) JGB (1986-2005)

Figure 2.13: Best Trading System and Mean Return Criterion: Australia Bond

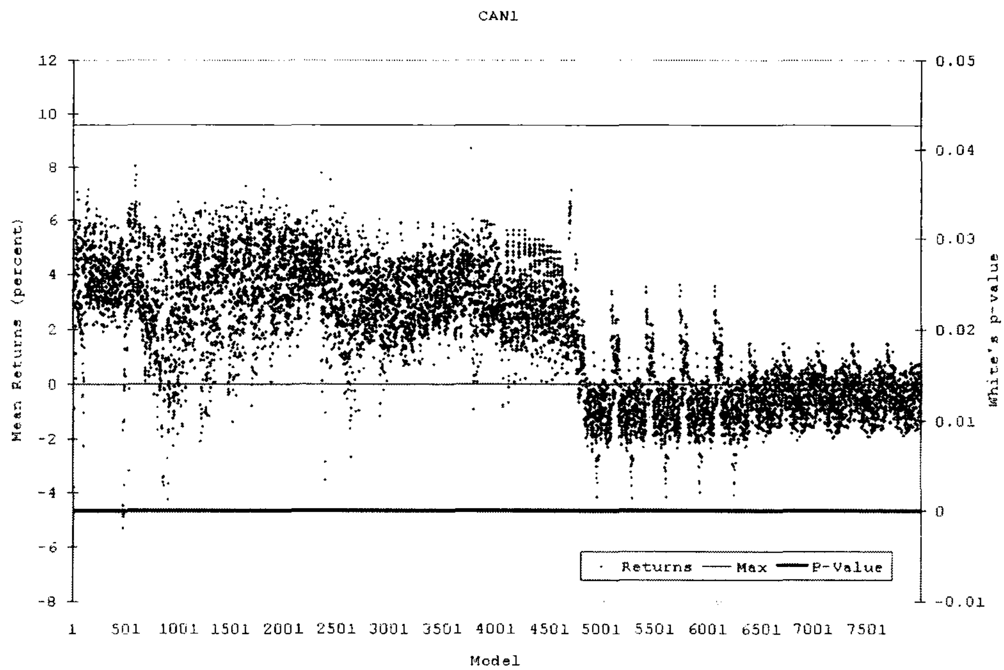


(a) Australia 3YGB (1989-2005)

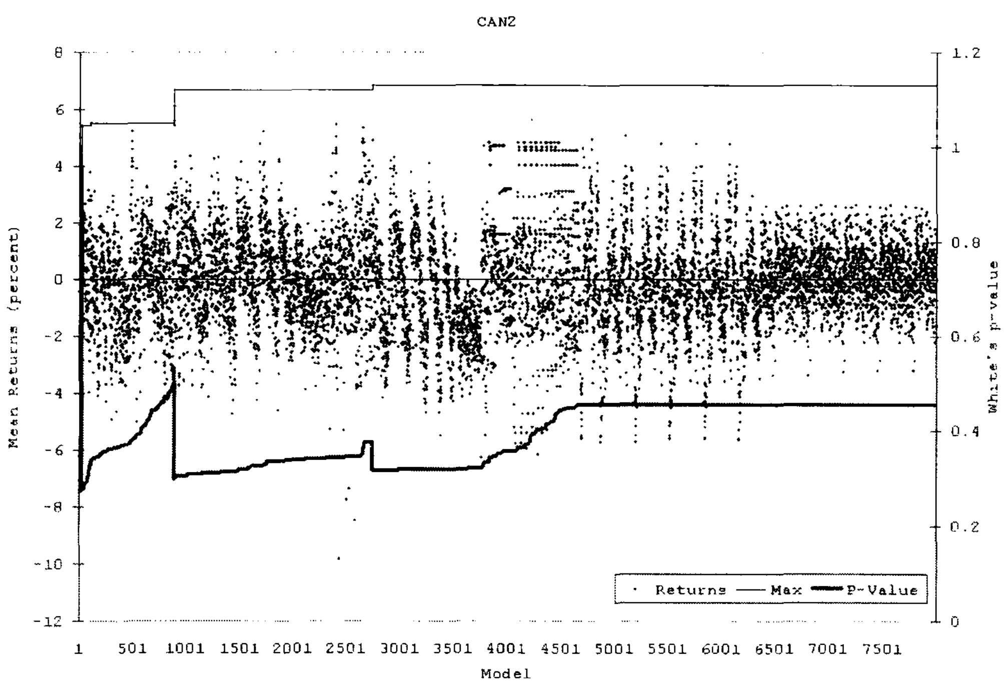


(b) Australia 10YGB (1986-2005)

Figure 2.14: Best Trading System and Mean Return Criterion: Canada Bond

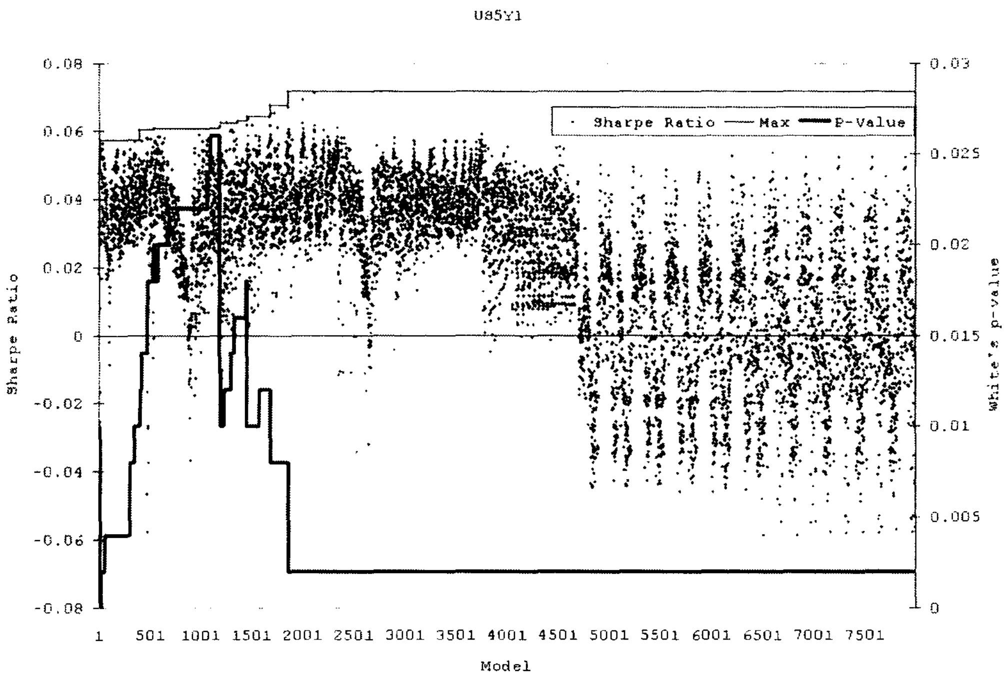


(a) Canada 10YGB (1990-2000)

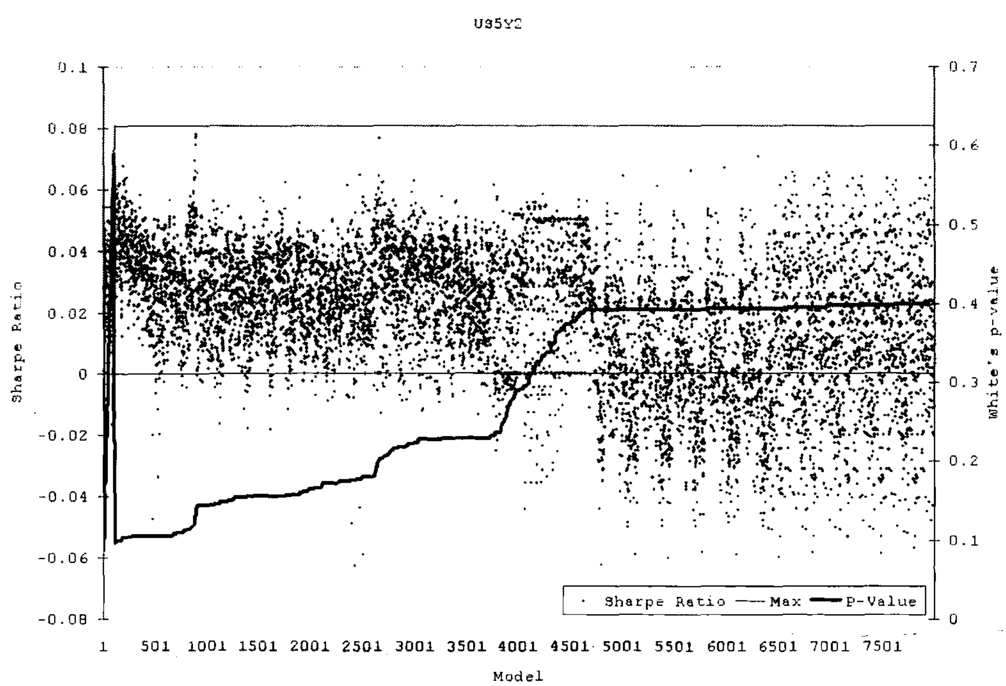


(b) Canada 10YGB (2000-2005)

Figure 2.15: Best Technical Trading System and Sharpe Ratio Criterion: US 5-Year T-Note. The dots are the Sharpe ratio from each trading rule (left scale). The thin line is the best rolling Sharpe ratio (left scale) and the thick line is White's p-value (right scale).

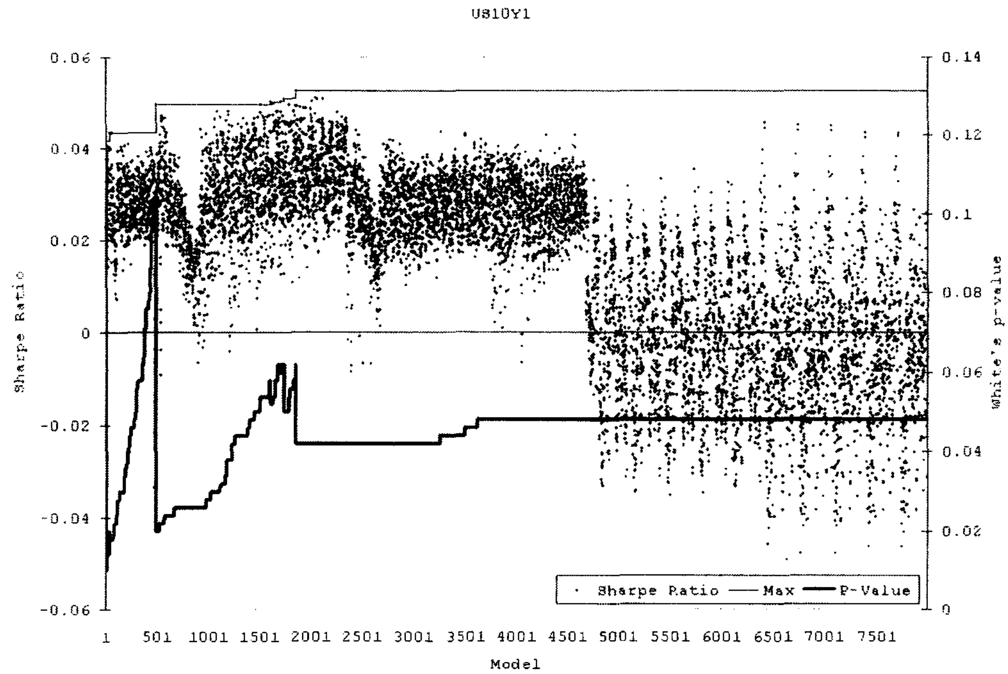


(a) US 5YTN (1988-1999)

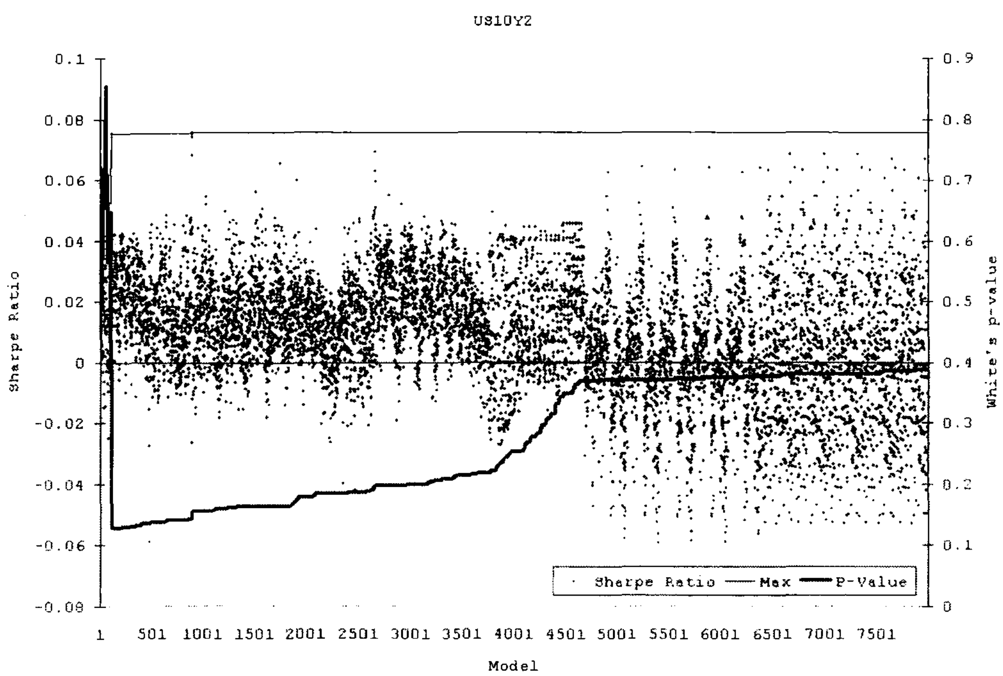


(b) US 5YTN (1999-2005)

Figure 2.16: Best Technical Trading System and Sharpe Ratio Criterion: US10-Year T-Bond

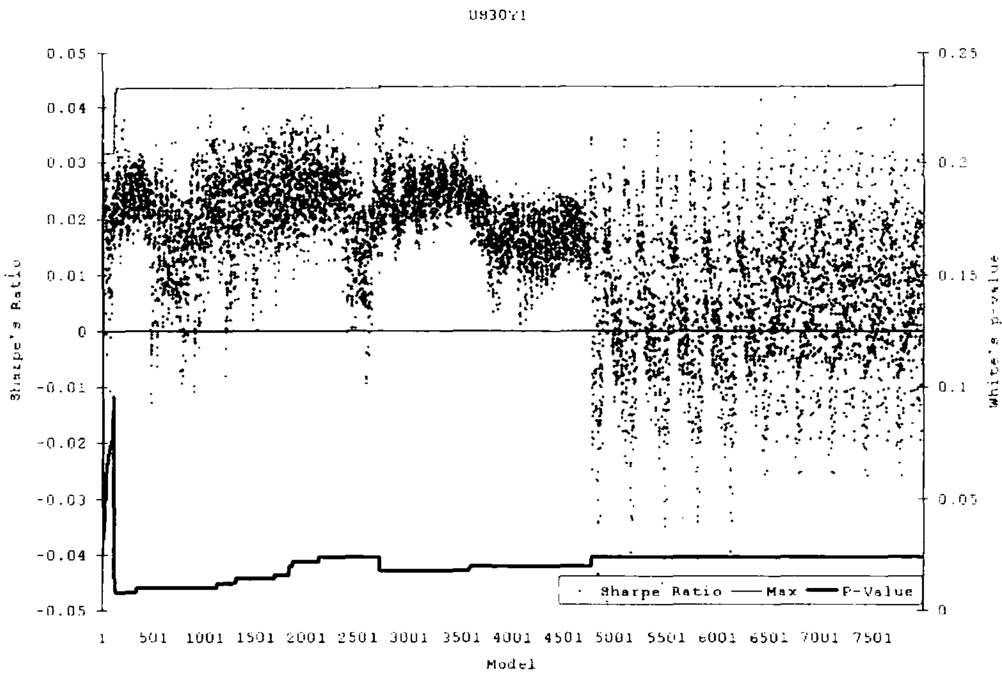


(a) US 10YTN (1983-1999)

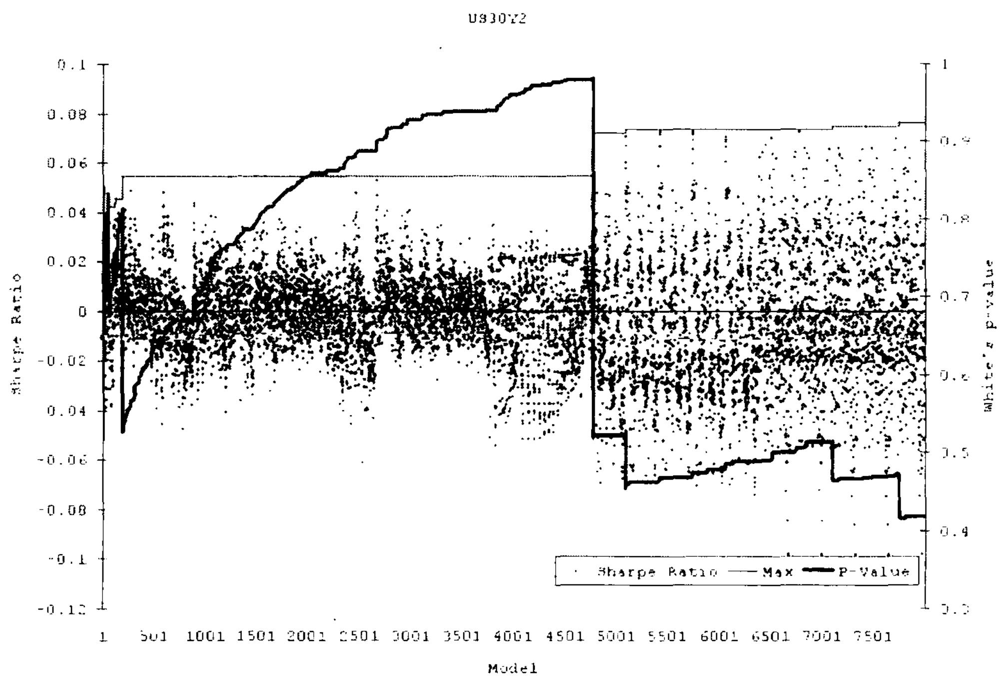


(b) US 10YTN (1999-2005)

Figure 2.17: Best Technical Trading System and Sharpe Ratio Criterion: US 30-Year T-Bond

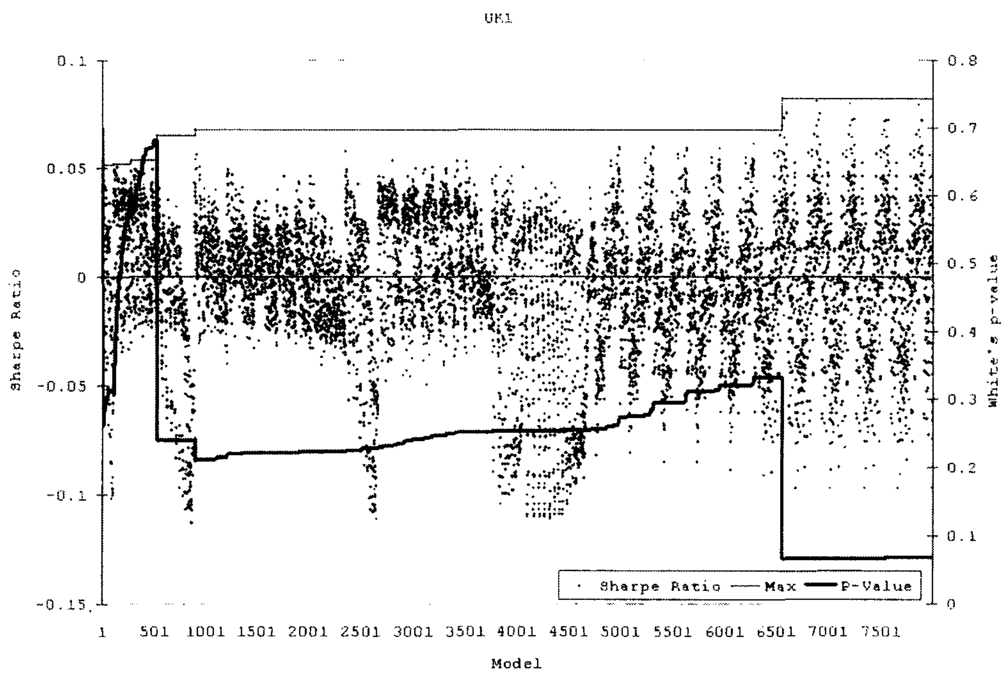


(a) US 30YTB (1977-1999)

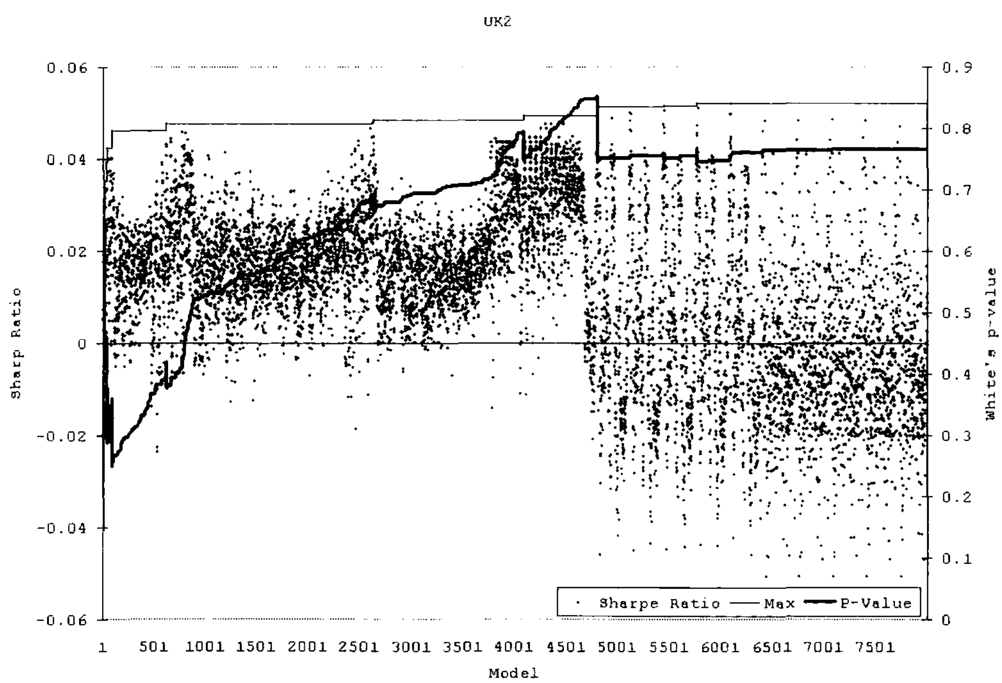


(b) US 30YTB (1999-2005)

Figure 2.18: Best Technical Trading System and Sharpe Ratio Criterion: UK Long Gilts (LG)

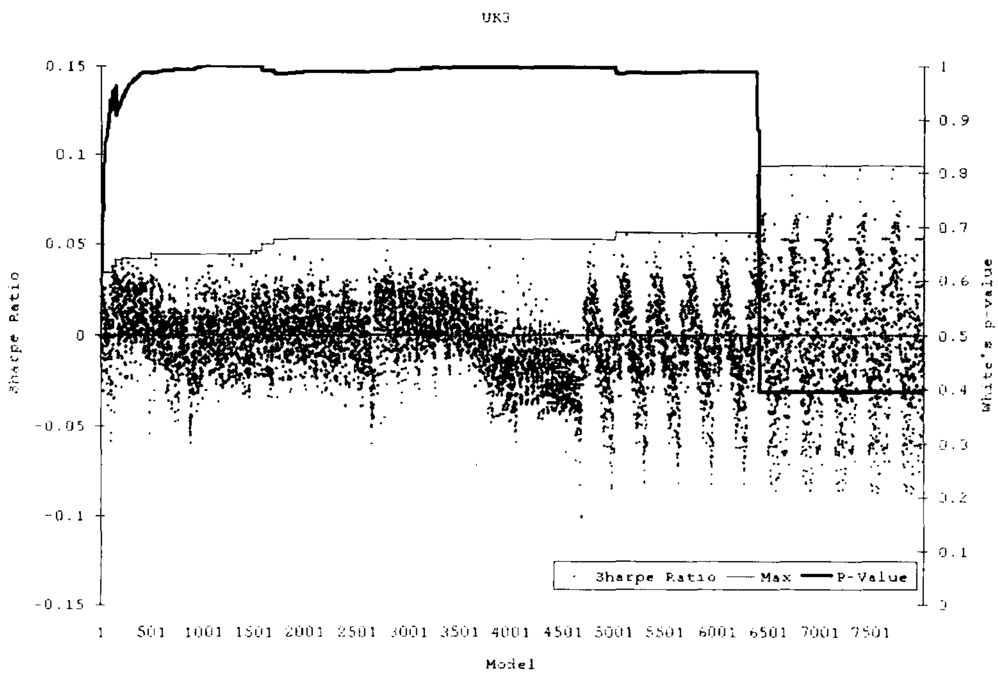


(a) UK LG1 (1983-1988)



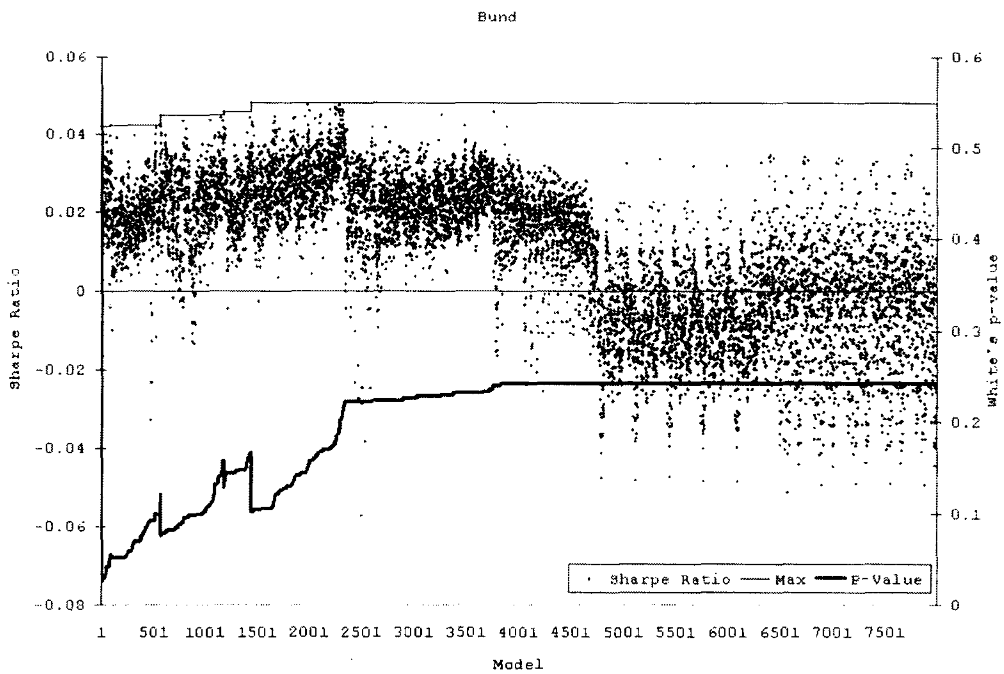
(b) UK LG2 (1988-1998)

Figure 2.19: Best Technical Trading System and Sharpe Ratio Criterion: UK Long Gilts (LG) (continued)

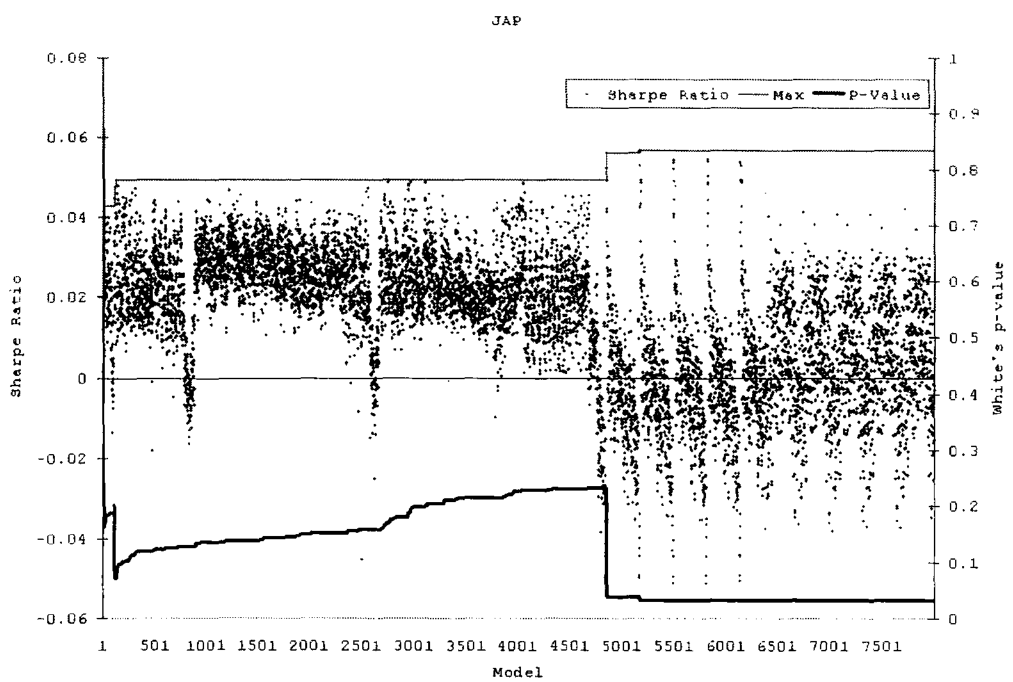


(a) UK LG3 (1998-2003)

Figure 2.20: Best Technical Trading System and Sharpe Ratio Criterion: Bund and JGB

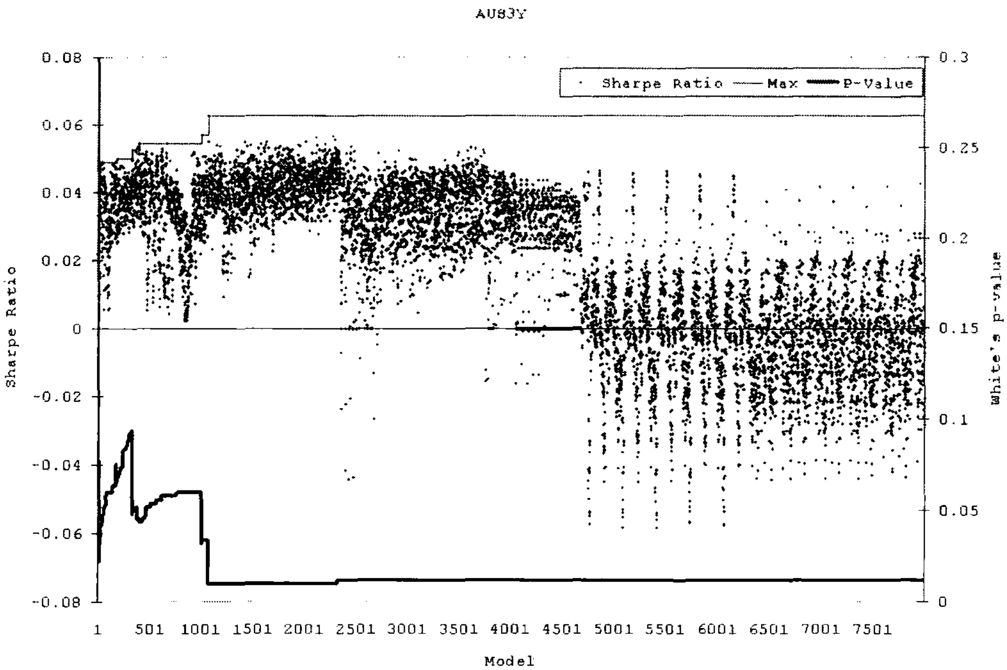


(a) Germany 10YB (1990-2005)

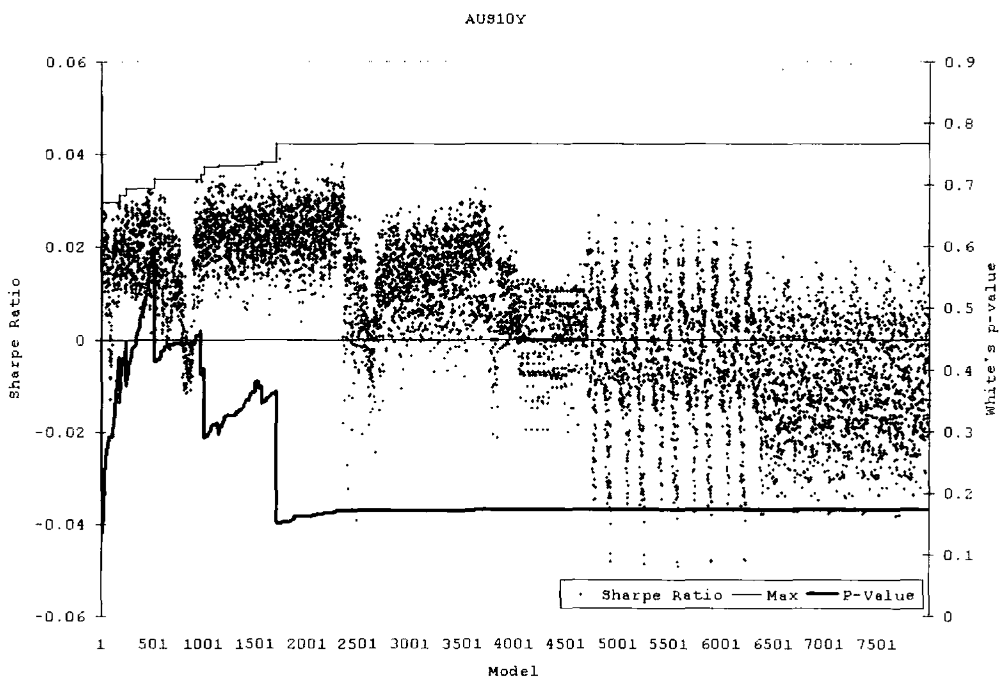


(b) JGB (1986-2005)

Figure 2.21: Best Technical Trading System and Sharpe Ratio Criterion: Australia Bond

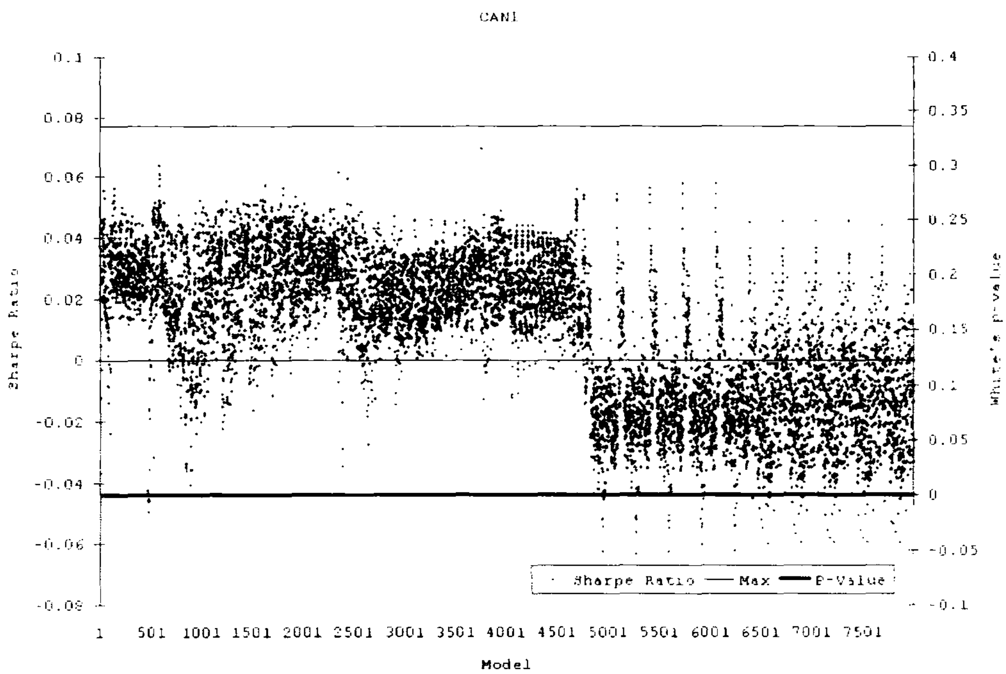


(a) Australia 3YGB (1989-2005)

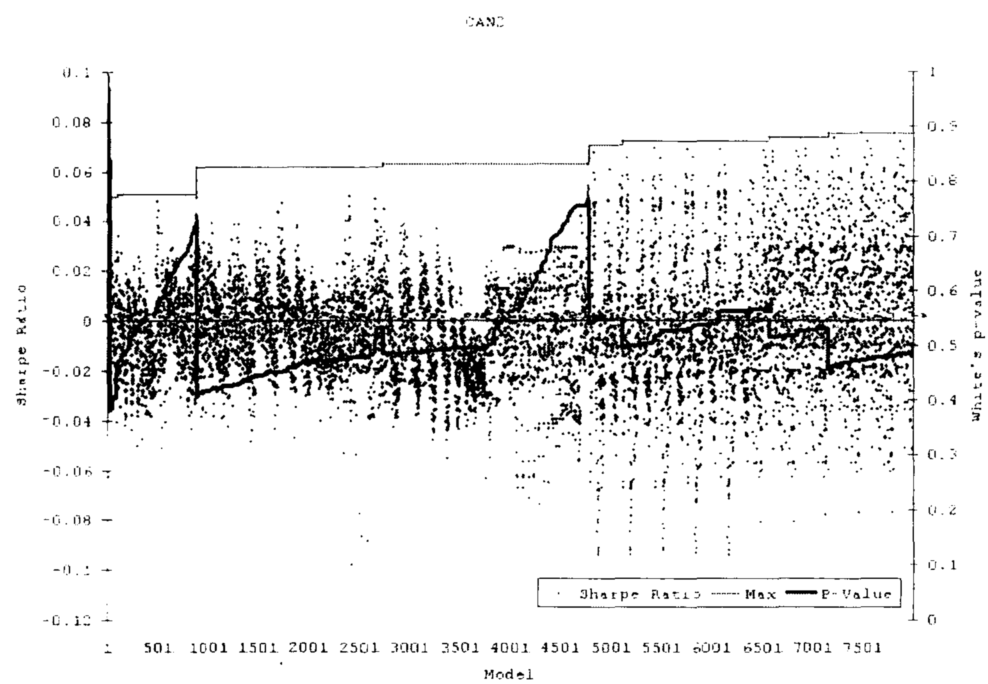


(b) Australia 10YGB (1986-2005)

Figure 2.22: Best Technical Trading System and Sharpe Ratio Criterion: Canada



(a) Canada 10YGB (1990-2000)



(b) Canada 10YGB (2000-2005)

2.5 Conclusion

This chapter evaluates the profitability of technical trading systems in the fixed income derivatives markets, namely, the bond futures markets, across six markets. For preliminary investigation, we test the profitability of three moving average systems. The results shows some promising results. We find that the single 50-day moving average system is statistically profitable in a number of futures markets. This lead us to further examine more trading systems.

In the second part of our examination, we evaluate 7,991 trading systems. The universe of trading systems include the moving average, breakout, volatility and price distribution systems. Moreover, we employ White's Reality Check procedure to account for the possibility of data mining. By using the highest trading system return and comparing it with the maximum sorted bootstrapped empirical returns, this procedure ameliorates the danger of data mining.

Overall, we find that some bond futures contracts exhibit statistically significant returns, which led us to reject the null hypothesis that trading system has no value to bond investors. For example, we find US30YTB (1977-1999) produces annualized mean returns of 18.12 percent after transaction costs, and with statistically significant p-value. However, White's Reality Check does not explain why some contracts have more statistically significant returns than the rest. On a broader perspective, it does not explain why some asset class are more profitable than others. For example. Qi and Wu (2001) find that technical trading systems are statistically significant in the currency markets while STW argue that the equity markets are more efficient using the same procedure. More research is required to address this difference.

Our results also highlight the possibility that technical trading systems have become less profitable in recent periods. This is shown by both moving average tests and Reality Check results. This finding is consistent with the results from a number of recent studies that find lower technical profits in currency and equity markets. However, whether this due to a more efficient financial market is yet to be determined. Some researchers have suggested that this unprofitability is due to lower volatility in asset prices. This is a plausible explanation since the number of discernable trends in asset prices is lower when the volatility is low. As most trading systems belongs to trend following (such as moving average rule), this may cause these systems to be unprofitable.

Returning to the issue on whether trend following strategies can profitably exploit the trends in interest rates, the answers are mixed. Although trends exist in policy rates, these trends may not map directly to the longer-maturity bond futures markets because of market noise. These noise give rise to noisy trading signals that cause the trend following signals to be unprofitable. Because of this, we argue that adjustments to the trading systems are needed in order to capture the trends, such as adding risk and capital managements techniques to the trading systems. One interesting question for future research is to examine the informational content of policy rates on the technical profits, whether movements in policy rates will have any impact on technical profits. For example, LeBaron (1999) finds that central bank interventions are associated with high technical profits in the currency markets.

In conclusion, our results here indicate that technical trading systems may provide some value to bond traders. But in view of the data mining problem and time varying technical profits, we argue that a consistently profitable technical system that provide genuine value to traders is quite difficult to uncover. We do not suggest that it is not possible to do, as we have argued in Chapter 1. But with an ever advancing technology and increasing speculative capital roaming the global capital markets in search for profits, this task will become immeasurably harder over time.

Chapter 3

An Empirical Investigation of Technical Charting in the Bond Markets

3.1 Introduction

Chart analysis is the cornerstone of technical analysis. Unlike the technical trading systems analysed in Chapter 2, technical chart patterns are more subjective and open to varied interpretations. This makes unanimous identification of chart patterns problematic. According to Efficient Market Hypothesis (EMH), technical chart patterns should not be consistently profitable over time, as Jegadeesh (2000, p.1766) points out:

> Perhaps the most important reason why charting techniques have not been more widely accepted is that they are built on weak foundations. For instance, chartists believe that selected patterns in the history of stock prices tend to repeat. However, there does not seem to be a plausible explanation as to why these patterns should indeed be expected to repeat.

In this Chapter, we investigate the informativeness of technical patterns in the bond markets. It is claimed that the yields of fixed income securities appear to contain repetitive patterns over time, and to be able to take advantage of these recurring patterns, fixed income traders may need to understand the technical behavior of bond yields. Thus, bond yields and bond yield spreads present a new and interesting application of technical charting. In particular, we wish to answer the following consequential questions: (i) Do technical chart patterns exist in the bond yield and bond yield spread markets? and (ii) If they do, can bond and relative value traders exploit these chart patterns in any way? Our results will have important implications for EMH since the government bond market is one of the most competitive financial markets, a characteristic which ensures that any anomaly which contributes to excess returns will disappear fairly quickly.

To answer the above questions, we apply and extend the pattern recognition tool proposed by Lo, Mamasky and Wang (2000, thereafter LMW) in identifying various chart patterns commonly prescribed by technical analysts. The main statistical tool they proposed is the *nonparametric kernel regression*, which has been used in the fixed income markets to construct the cross-sectional yield curve and to estimate stochastic interest rate models.[1] By framing the chart patterns in such a way that is recognizable by the kernel regression, LMW were able to use the nonparametric kernel regressions to match a number of pre-defined technical chart patterns and therefore identify patterns like Head-and-Shoulders with ease. The key contribution of their work is *automating* the process of identifying chart patterns in stock prices. In this Chapter, we improve upon the nonparametric Nadaraya-Watson kernel regression proposed by developing the *local polynomial regression*, which is known to ameliorate several biases embedded in the Nadaraya-Watson regression.

There are many types of trading strategies in fixed income markets. The most straightforward trading strategy is directional trades, which bet on the direction of the interest rates. (See Chapter 2) Another prominent strategy is the spread strategy, which belongs to the *relative value* strategy. An example of the relative value strategy is the swap spread strategy between interest rate swaps and government securities, a popular relative value trade among hedge funds and proprietary desks of institutional investors. Other examples of bond spreads include the yield spreads between different maturities along the same yield curve, or between the spreads between mortgage-based securities (MBS) and US Treasuries.[2]

However, most analyses of these spreads depend either on fundamental factors or quantitative models. For instance, one popular method used to measure the relative

[1] Nonparametric statistical methods have the attractive feature of being *distribution-free*, thereby avoiding any specification bias. For yield curve construction, Tanggaard (1992) compare the cross-sectional yield curve constructed using Nelsen-Siegel (1987) method and nonparametric kernel regression. They find the latter method provides a good fit to the yield data. See Gourieroux and Scaillet (1994) and Linton et al. (2001) for further advances in this area. On the other hand, Ait-Sahalia (1996), Stanton (1997) and Johannes (2004) develop various nonparametric statistical methods to estimate the continuous-time interest rate model.

[2] See, for example, Duffie and Singleton (1997) and Brown, In and Fang (2002) for some empirical analysis of the swap spreads. Another popular spread strategy is the TED spread, which is the spread between the US Treasury Bills and Eurodollar. See Fung and Hsieh (2002) for some analyses of different types of fixed-income spread returns.

cheapness of LIBOR-based swap spread is the so-called rich/cheap analysis, which is based on contemporaneous market variables such as the implied volatility of S&P 100 index and yield curve slope. (See, for example, Prendergast (2000)) The quantitative method approach in analysing bond spread include the contingent claim models developed by Merton (1974) and Black and Cox (1976). (See, for example, Duffie and Singleton (2003) for a comprehensive review of these models.) In this chapter, we take another route by analyzing the bond yields and bond yield spreads via technical chart patterns.

We apply the nonparametric Nadaraya-Watson and local polynomial regressions to seven government bond markets, including US, UK, Germany, Japan, Australia, Canada and Hong Kong. The availability of bond yield data varies according to the sophistication of the respective debt markets. For example, the US bond yield data starts from 1962 while the Hong Kong bond yield begins only in 1992. In total, we evaluate twelve chart patterns, including Head-and-Shoulders, Broadening, Triangle, Rectangle, Double and Triple chart patterns.

The rest of this chapter is as follows: The next section provides a brief review of the technical charting literature. In the first part of Section 3.3, we briefly describe the nonparametric kernel regression and the local polynomial regression. In the second part, we provide the characterization of various chart patterns. Section 3.4 discusses the bond yield data and statistical tests underlying our examinations of the informativeness of chart patterns. Next, Section 3.5 presents the empirical evidence. Lastly, Section 3.6 concludes.

3.2 Literature Review on Technical Charting

There are many types of charts available to investors, including bar charts, line charts, point-and-figure charts and candlestick charts. Each type of chart has different interpretations of the asset prices and therefore different trading implications.[3] In this Chapter, we shall mainly analyse line charts and the patterns within them.

Chart patterns have been known to investors for a long time. (See Shabacker (1930) and Edwards and Magee (1966)) The advent of modern technology such as

[3]Historically, rice traders in Japan was the first to introduce the *candlestick* chart. (Nison (1991)) Recently, Marshall, Young and Rose (2005) investigate the predictive property of candlestick charting in the US active stocks over the period 1992-2002. Using the bootstrap methodology as in Brock, Lakonishok and LeBaron (1992), they report low predictive power of the various candlestick patterns commonly advocated by technical analysts. Thus, their results support the EMH and conclude that investors who based their trading decisions solely on candlestick patterns are unlikely to gain financially from this activity. See also Fock, Klein and Zwergel (2005).

computer has led to the idea of automating the identification of chart patterns. Girmes and Damant (1975) use the gradient smoothing technique to find the Head-and-Shoulders pattern in stock prices. Interestingly, they find five times as many Head-and-Shoulders pattern in the actual stock prices than in simulated data. This implies that the movements of stock prices are subjected to more human intervention than, say, a random walk. But Levy (1971) tests the predictive power of thirty-two 'five-point chart patterns' and concludes that (p.318) *"after taking transaction costs into account, none of the thirty-two patterns showed any evidence of profitable forecasting ability in either (bullish or bearish) direction."*

Similarly, Olser (1998) tests the Head-and-Shoulders pattern in the US equity market by random selecting 100 stocks from the CRSP (Center of the Research on Securities Prices) with historical prices going back to 1962. She finds this pattern lacks predictive power. Dempster and Jones (1998, 2002) automate the detection of Head-and-Shoulders and Channel technical pattern using a fixed number of local maxima and minima in the currency markets. They test their algorithm on the intra-day spot exchange rate data obtained from the industry vendors. Contrary to expectations of market practitioners, they find that both patterns produce trading losses. Their study supports the notion that chart patterns are simply indistinguishable from noise.

Along the same line, Chang and Osler (1999) use a percentage method to define the Head-and-Shoulders pattern on six currencies pairs. Their empirical results indicate mix results, with four out of six currencies found to be unprofitable. But dollar-yen and dollar-mark currency pairs are profitable, even after adjusting for interest rate differential, risk and transaction costs. Dawson and Steeley (2003) evaluate ten chart patterns in the UK equity market over the sample period 1986-2001 using the kernel regression methodology. They find that no excess profit can be earned using these technical patterns. Given these negative evidence on the profitability of chart patterns, the fact that market practitioners continue to use them is a puzzling behaviour, as Chang and Osler aptly describe such activity as "methodical madness".

However, such negative views on technical charting may not necessarily be correct. From their empirical results on US equity markets, even LMW admit that using technical chart patterns as additional inputs to the investment process may be useful (p.1753):

> We find that certain technical patterns, when applied to many stocks over many time periods, do provide incremental information, especially for Nasdaq stocks. Although this does not necessarily imply that technical

analysis can be used to generate "excess" trading profits, it does raise the possibility that technical analysis can add value to the investment process.

Using the same methodology as LMW, Savin, Weller and Zvingelis (2003) find that the Head-and-Shoulders pattern has explanatory power in predicting excess returns in the US equity markets. They also determine that trading using this pattern yield 7-8 percent risk-adjusted return per year over the period 1989-1999. The factor risk-measure they use is the three factor Fama-French model augment with a momentum factor. Bulkowski (2005) has produced an extensive "Encyclopedia" on technical chart patterns and argue that (p.7), *"Investing using chart formations is an exercise in probability."* He claims that the most profitable chart pattern in both bull and bear markets is the Flag pattern, with an average rise in prices of 69 percent and 42 percent respectively!

So far, no empirical study evaluates the profitability of chart patterns in the bond markets. Thus, we contribute to the literature on technical analysis by applying the nonparametric kernel regression to examine the informativeness of chart patterns in the government bond yields and bond yield spread markets. The literature on yield spread trading is sparse. Typically, bond yield spreads are used to determine whether there exist a relationship between these spreads and country risk premium, or whether the expectations hypothesis of the term structure is validated.[4] A number of strategies has already been devised to speculate on the yield spread movements, such as the butterfly, barbell or the credit spread strategy. (See, for example, Fabozzi (2001))

Only recently has research began to examine the trading opportunities offered by yield spread trading. Dolan (1999) provides a preliminary analysis of the predictability of the yield curve shapes. By choosing the Nelson-Siegel (1987) model as the benchmark tool, he shows that the model parameters are predictable over time, which may have investment significance in the selection of bond portfolios. Using the same model, Diebold and Li (2003) provide evidence that the parameter which capture the bond yield spread movement is predictable in the US bond markets. Encouraged by this development, Fabozzi, Martellini and Priaulet (2005) apply the Nelson and Siegel model to fit US swap curve over period 1994-2003 and test their impact on the butterfly strategy.[5] Furthermore, they incorporate the technique of "recursive modeling" developed by Pesaran and Timmermann (1995) and "thick modeling" proposed by

[4] For the first topic, see, for example, Angeloni and Short (1980), Feder and Ross (1982) and Scholtens (1999). For the expectation hypothesis, see, for example, Cox, Ingersoll and Ross (1981), Campbell and Shiller (1987) and Longstaff (2000a, b).

[5] See Chapter 1 and Fabozzi (2001, 2005) for more details about this strategy.

Granger and Jeon (2004) to improve the forecast of these parameters with a number of external economic factors. They show that the combination of above techniques enable them to generate significant portfolio outperformance.[6] This studies provide some evidence that yield spread may be predictable.

In addition to these developments, several research efforts have initiated modeling the sovereign yield spread using econometrics models. For instance, Duffie, Pedersen and Singleton (2003) estimate the Russian yield spread relative to US treasuries during the 1998 Russian debt default using multifactor affine model. Koutmos (2002) models the dynamics of the MBS spreads using a two-factor stochastic model. But despite the plethora of arbitrage-free yield curve models in the literature, it is not sure whether any of them have good forecasting property. Duffee (2002), for example, documents the fact that the three-factor affine term structure model cannot outperform a simple random walk model in forecasting future interest rates.

In summary, it would be interesting to see whether technical chart patterns can provide an alternative approach in forecasting bond yield spreads.

3.3 Identification of Technical Charts Patterns

3.3.1 Nonparametric Kernel Regression

Financial asset prices are filled with "noise". (Black (1986)) The presence of these market noise complicates the analysis of price movements since the underlying true signals are obscured by these noise. To identify the true signals from the noisy data, one has to smooth the asset prices in some way. Press et al. (2002, p.655), for instance, have aptly describe the potential of smoothing:

> Data smoothing is probably most justified when it is used simply as a graphical technique, to guide the eye through a forest of data points all with large error bars; or as a means of making initial *rough* estimates of simple parameters from a graph.

For this purpose, we turn to nonparametric smoothing methodologies such as kernel regression and local polynomial regression. Nonparametric method has the advantage

[6] Relatedly, Krishnamurthy (2002) examines the spread between the new bond and old government bonds. He finds that the average profit are close to zero once the difference in repo market financing rates between the two bonds is taken into account, and liquidity does seem to play an important role in the variation of the new- and old-bond spread. To an extent, his research analyses the convergence properties of the spread over time.

of being distribution-free, thereby avoiding any specification bias imposed upon the asset prices.

It is assumed that the bond yields, y, is generated by the function $f(\cdot)$:

$$y = f(x) + \epsilon \tag{3.1}$$

where $f(x)$ is an arbitrary fixed but unknown nonlinear function of the state variable x and ϵ's are independent and identical white noise, i.e., $E(\epsilon) = 0$ and $Var(\epsilon) = 1$. For any arbitrary x, a smoothed estimator of $f(x)$ may be expressed as:

$$\hat{f}(x) = \frac{1}{T}\sum_{t=1}^{T} \omega_t(x) y_t \tag{3.2}$$

where the weights $\omega_t(x)$ are large for those y_t paired with x_t near focal point x_0 and small for those y_t paired with x far from focal point x_0. The weight function $\omega_t(x)$ is constructed from a probability density function $K(x)$, also known as a *kernel*, with the following properties:

$$K(x) \geq 0 \qquad \int K(u)du = 1 \tag{3.3}$$

The idea of the kernel $K_h(\cdot)$ is to multiply different weights to the data so that the data closer to the focus point x_0 has more influence than the data further away from the focus point x_0. (See, for example, Rosenblatt (1956), Silverman (1986), Hardle (1990), Campbell, Lo and Mackinlay (1997, Chapter 12) for a comprehensive review of these concepts.) By rescaling the kernel with respect to a parameter $h > 0$, we can change its spread:

$$K_h(u) = \frac{1}{h}K(u/h) \qquad \int K_h(u)du = 1 \tag{3.4}$$

The weight function ω_t is defined as:

$$\omega_{t,h} = K_h(x - x_t)/g_h(x) \tag{3.5}$$

$$g_h(x) = \frac{1}{T}\sum_{t=1}^{T} K_h(x - x_t) \tag{3.6}$$

Substituting equation (3.5) and (3.6) into (3.2) yields the *Nadaraya-Watson* kernel estimator $\hat{f}_{NW}(x)$ of $f(x)$:

$$\begin{aligned} \hat{f}_{NW}(x) &= \frac{1}{T}\sum_{t=1}^{T}\omega_{t,h}(x)y_t \\ &= \frac{\sum_{t=1}^{T} K_h(x-x_t)y_t}{\sum_{t=1}^{T} K_h(x-x_t)} \end{aligned} \tag{3.7}$$

This expression allow us to estimate the kernel regression in any fixed length window of size d. In empirical form, this can be written as:

$$\hat{f}_{NW}(\tau) = \frac{\sum_{s=t}^{t+d-1} K_h(\tau-s)y_s}{\sum_{s=t}^{t+d-1} K_h(\tau-s)} \quad t = 1, ..., T-(d+H-1) \tag{3.8}$$

where d is the size of the fixed length window, T is the total number of data in a bond yield series and H is the holding period to which we measure the conditional bond returns. In other words, we apply the Nadaraya-Watson estimator to a series of fixed length rolling windows from t to $t+d-1$, where t begins from 1 and ends at $T-(d+H-1)$. The rationale for this sub-window is to prevent the detection of technical patterns of varying duration from fitting a single kernel regression to the entire data set. What remains to be specified is the kernel function $K_h(\cdot)$ and the bandwidth parameter, which we shall discuss in Section 3.3.3.

Assuming $\hat{f}_{NW}(\tau)$ is a differentiable function of τ, once the function $\hat{f}_{NW}(\tau)$ is obtained, the local extrema can be readily identified by find times $(\tau-1)$ such that $\text{Sgn}(\hat{f}'_{NW}(\tau-1) = -\text{Sgn}\hat{f}'_{NW}(\tau)$, where $\hat{f}'_{NW}(\tau)$ denotes the derivative of $\hat{f}_{NW}(\tau)$ with respect to τ and $\text{Sgn}(\cdot)$ is the signum function. If the signs of $\hat{f}'_{NW}(\tau-1)$ and $\hat{f}'_{NW}(\tau)$ are $+1$ and -1 respectively, then we have found a local maximum, and if they are -1 and $+1$ then we have found a local minimum. With this procedure we are able to identify all the extrema in a given fixed-length window. A useful consequence of the above algorithm is that the series of extrema alternates between minima and maxima. That is, if the k^{th} is the extremum is a maximum, then it is always the case that $(k+1)^{th}$ is a minimum and vice versa. We label all extrema found in the window to be $(e_1, ..., e_m)$.

However, it is well-known that the Nadaraya-Watson estimator (3.7) suffers from a number of weaknesses. For example, the Nadaraya-Watson estimators have large bias order at the boundary region. Even though many ad-hoc proposals such as the ***boundary kernel methods*** have been proposed to alleviate this problem, they are less efficient than local linear fit. (See, for example, Fan and Gijbels (1996)) Thus, we shall extend the usage of kernel regression in technical analysis by turning to the local polynomial regression, which has the advantage of similar bias order along the boundary and in the interior. This reduces the need to use specific boundary kernels. Another advantage of the local polynomial regression is that we can estimate the regression parameters using least squares. (See, for example, Fan and Gijbels (1996, Chapter 3) and Hastie, Tibshirani and Friedman (2001, Chapter 5) for further discussion of these issues.)

3.3.2 Local Polynomial Regression

The starting point for local polynomial regression is similar to the nonparametric kernel regression. Assuming that the bond yields and bond yield spreads are generated by some nonlinear function $f(\cdot)$ as in equation (3.1), and further assume that the $(p+1)^{th}$ derivative of $f(x)$ at focal point x_0 exists, we can approximate the unknown regression function $f(x)$ locally by a polynomial of order p. A Taylor expansion for x in the neighborhood of x_0 gives:

$$f_{LP}(x) \approx f(x_0) + f'(x_0)(x - x_0) + \frac{f''(x_0)}{2}(x - x_0)^2 + \ldots + \frac{f^{(p)}x_0}{p}(x - x_0)^p \quad (3.9)$$

This polynomial is fitted locally by a weighted least square regression, minimizing the following function:

$$\min_{\beta} \sum_{i=1}^{d} \left[y_i - \sum_{j=0}^{p} \beta_j (x_i - x_0)^j \right]^2 K_h \left(\frac{x_i - x_0}{h} \right) \quad (3.10)$$

where $K_h(\cdot)$ is the kernel function assigning weights to each datum point, and h is the bandwidth parameter controlling the size of the local neighborhood. Let $\hat{\beta}_j, j = 0, ..., p$ be the solution to this least squares problem, it is clear from the Taylor expansion that $\hat{f}_j(x_0) = j!\hat{\beta}_j$ is an estimator for $f^{(j)}(x_0)$, for $j = 0, 1, ..., p$. Denote $\mathbf{X}$ as the $(d \times p)$ design matrix:

$$\mathbf{X} = \begin{pmatrix} 1 & (x_1 - x_0) & \cdots & (x_1 - x_0)^p \\ 1 & (x_2 - x_0) & \cdots & (x_2 - x_0)^p \\ \vdots & \vdots & \ddots & \vdots \\ 1 & (x_d - x_0) & \cdots & (x_d - x_0)^p \end{pmatrix} \quad (3.11)$$

and let $\mathbf{W}$ be the $(d \times d)$ diagonal matrix of weights:

$$\mathbf{W} = \text{diag}\{K_h \left(\frac{x_i - x_0}{h} \right)\} \quad i = 1, ..., d \quad (3.12)$$

The weighted least square problem (4.3) can be written as:

$$\min_{\beta}(\mathbf{y} - \mathbf{X}\beta)'\mathbf{W}(\mathbf{y} - \mathbf{X}\beta) \tag{3.13}$$

where $\hat{\beta} = (\beta_0, \beta_1, ..., \beta_p)'$ is the vector of parameters and $\mathbf{y}$ is the vector of bond yields or bond yield spreads. The solution is provided by weighted least squares theory and is given by:

$$\hat{\beta} = (\mathbf{X}'\mathbf{W}\mathbf{X})^{-1}\mathbf{X}'\mathbf{W}\mathbf{y} \tag{3.14}$$

if $(\mathbf{X}'\mathbf{W}\mathbf{X})$ is invertible. The estimator $\hat{f}_{LP}(\cdot)$ is the intercept term $\hat{\beta}_0$. To ensure that $(\mathbf{X}'\mathbf{W}\mathbf{X})$ is invertible, at least $(p+1)$ different points with positive weights are required.

After all the $\hat{\beta}_0$'s are computed, we can determine the extrema in this window by checking the signs of $\{\hat{f}'_{LP}(\tau)\}_{\tau=1}^{\tau=45}$. $\hat{f}'_{LP}(\cdot)$ is simply given by parameter $\hat{\beta}_1$ in (4.7). All extrema are obtained by checking for the sign of $\hat{f}'_{LP}(\tau)$ against $\hat{f}'_{LP}(\tau - 1)$. If $\hat{f}'_{LP}(\tau) > 0$ and $\hat{f}'_{LP}(\tau - 1) < 0$, a minimum extrema is found at $(\tau - 1)$. On the contrary, if $\hat{f}'_{LP}(\tau) < 0$ and $\hat{f}'_{LP}(\tau - 1) > 0$, a maximum extrema is found at $(\tau - 1)$. If both $\hat{f}'_{LP}(\tau) = 0$ and $\hat{f}'_{LP}(\tau - 1) = 0$, we work backwards for each $\beta_{1,\tau}$ to determine whether the current stationary point is a maximum or minimum since the extrema always gives an alternating sequence between maximum and minimum. As before, we label all extrema in a rolling window to be $(e_1, ..., e_m)$.

Asymptotic results prescribe that odd p has a clear advantage over even p, in the sense that the conditional bias for odd values of p are simpler that even values of p. (See Simonoff (1996) and Fan and Gijbels (1996)) Consequently, we shall use the first order only, $p = 1$, for all polynomial regressions.

In equation (4.7), $\mathbf{X}$ is a matrix of time point $1, 2, ..., d$. The parameter d is the window of bond yields/bond yield spreads to which we apply (4.7) to each data point τ in that window in order to obtain d smoothed bond yields. In this chapter, we shall fixed $d = 45$, meaning that both the local polynomial and kernel regressions are applied to bond yields at interval $\{y_t, ..., y_{t-44}\}$ in a series of rolling window. The first window starts at $t = 1$ and ends at $d + H - 1$, where H is the holding period. (See equation (3.8)) Our fixed-length window is larger than in LMW's study because bond markets may take a longer time frame to display the pattern.[7] Here, we set

[7]This may be due to the lower government bond price volatility relative to stock prices. Some estimates of the yield volatility σ are given in the Appendix I.

$H = 1$, which has carries the intuition that the market practitioners would take 1-day to realize the completion of the chart pattern.

To identify the chart patterns, the pattern must be completed with $d - H$ days. In addition, the last extrema e_m must occur on the day $d - H$. Without this requirement, the same pattern would be recorded several times while rolling the window forward. The strategy for our estimation is as follow: (1) First estimate a 45-day window of smoothed prices using kernel and local polynomial regression. (2) Check whether an extrema has occurred at day 44. (3) If an extrema exists on this day, the next step is to check whether a chart pattern has occurred. If not, move on to the next window. (4) If a chart pattern is confirmed, then the one-day conditional bond return is measured from day 45 ($d + 1$) to day 46 ($d + 2$). This way, we have a clean out-of-sample bond return to measure the informativeness of the technical chart patterns. If no chart patten is confirmed, we move on to the next fixed-length window.

3.3.3 Nonparametric Kernel Function and Bandwidth Determination

As Jegadeesh (2000) points out, the nonparametric kernel smoothing method developed by LMW does depend on a number of parameters that may be detrimental in the quest of objectifying chart patterns. Similar criticism applies to our nonparametric local polynomial regression. There is no optimal solution in solving this since each chart pattern will, in practice, be unique to some extent.

Two parameters plays an important role in nonparametric regression, which are the kernel function $K(\cdot)$ and the bandwidth value h. In this section, we shall briefly describe the kernel function and the choice of the bandwidth value, followed by a discussion of the chart patterns in the next section.

There exist a number of possible kernel functions, including uniform, Gaussian, Epanechnikov and Biweight. Rather than following LMW and Dawson and Steely (2003), who use the Gaussian kernel,[8] we choose to use the Epanechnikov kernel (Epanechnikov (1969)):

$$K(z) = \frac{3}{4}(1 - z^2)_+ \tag{3.15}$$

This choice is based on results by Fan and Gijbels (1996, Theorem 3.4) and Fan et al. (1995), who prove that Epanechnikov kernel is the optimal kernel for all orders of

[8] The Gaussian kernel is defined as: $K_h(x) = \frac{1}{h\sqrt{2\pi}} \exp(-x^2/2h^2)$. For other kernel choices, see Silverman (1986) and Hardle (1990).

p in the local polynomial regression, that is, it is the weight function that minimizes the asymptotic mean squared error of the local polynomial estimators. To be consistent for both nonparametric regression, this kernel function is also applied to the Nadaraya-Watson estimators.

The bandwidth parameter h plays a more important role than the kernel function $K(\cdot)$. The reasons for this straightforward: if h is large, then averaging will occur over a larger neighborhoods of the y_ts, leading to an overly smooth kernel estimates, on the other hand, if h is small, the average will occur over a small neighborhood of the y_ts, resulting in a choppy function that does not filter out the noise in the yields, depriving us of the power of the smoothing methods.

There are numerous methods in computing the bandwidth parameter value, including the rule-of-thumb, cross-validation, nearest neighbors and plug-in methods. (See Simonoff (1996), Fan and Gijbels (1996) and Jones, Marion and Sheather (1996) for some extensive discussion of these methods.) In this chapter, we use the bandwidth parameter derived from the popular cross validation method, which minimizes the following function:

$$\hat{h}_{CV} = \frac{1}{d}\sum_{t=1}^{d}\left(y_t - \hat{f}_t\right)^2 \qquad (3.16)$$

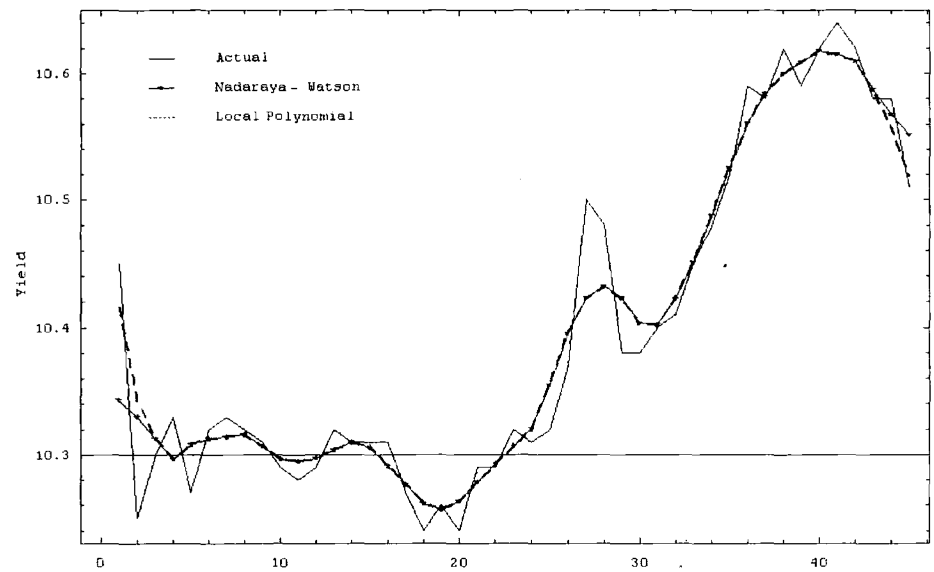
where

$$\hat{f}_{h,t} = \frac{1}{d}\sum_{\tau\neq t}^{d}\omega_{\tau,h}y_\tau \qquad (3.17)$$

which is the omit the τ^{th} observation from local regression at the focal value y_i. Omitting the τ^{th} makes the fitted value independent of the observed value y_i.

Figure 3.1 presents a graphical example of applying both the Nadaraya-Watson estimator $\hat{f}_{NW}$ (line with asterisk) and the local polynomial regression estimate $\hat{f}_{LP}$ (thick dashed line) to the bond yields over a period of 45 days. The kernel function used in this example is the Epanechnikov kernel and the bandwidth parameter value is derived from the cross-validated method with no adjustment being made. Some interesting properties can be seen here. First, the boundary bias for Nadaraya-Watson estimates is obvious. In the interior, both Nadaraya-Watson and local polynomial regression estimates are similar, but as we examine the estimates on the left and right boundary, large discrepancies appear between these two estimates. At both boundaries, the local polynomial regression tracks the actual bond yields better than the Nadaraya-Watson estimates, which tend to over-smooth the actual bond yields.

Figure 3.1: A Comparison of Nadaraya-Watson Estimators $\hat{f}_{NW}$ and Local Polynomial Regression $\hat{f}_{LP}$ with Cross-Validated Bandwidth Parameter and Epanechnikov Kernel Function



Correcting this boundary bias is important because we are always measuring $\hat{f}'(\cdot)$ near the right boundary. If the Nadaraya-Watson estimates over-smooth the actual bond yields, then the regression estimates might not capture the extrema e_m even if one exists.

Second, the bandwidth parameter $\hat{h}_{CV}$ obtained from cross-validation method may over-smooth the actual bond yields, especially during day 26-30. Consequently there is a need to reduce the value of the bandwidth parameter value obtained from the cross-validation procedure. Furthermore, choosing a smaller bandwidth value can reduce the boundary bias for Nadaraya-Watson estimator. We examine various bandwidth adjustments, and it is decided that the final bandwidth adjustment is fixed at $\hat{h}_{CV} \times 0.45$ for both bond yields and bond yield spreads. This is a local bandwidth parameter whose values may vary over different fixed-length rolling window.[9]

[9]Since a global bandwidth parameter value will not reflect any local yield movements, a local bandwidth parameter can resolve this deficiency. But such adjustment are by no means perfect. Even LMW admit (p.1714) that selecting the appropriate bandwidth parameter is a challenging task, "*...this an ad hoc approach, and it remains an important challenge for future research to develop a more rigorous procedure.*" They rely on a trial and error approach and some practical advice from professional technical analysts to fix the bandwidth at $\hat{h}_{CV} \times 0.3$.

3.3.4 Technical Chart Patterns

We apply the nonparametric kernel to six pairs of technical patterns that are commonly taught in classic technical analysis texts. (See, for example, Edward and Magee (1966), Schwager (1996), Kaufman (2005) and Bulkowski (2005)) They are Head and Shoulders Top (HSTOP) and Bottom (HSBOT), Broadening Top (BTOP) and Bottom (BBOT), Triangle Top (TTOP) and Bottom (BBOT), Rectangle Top (RTOP) and Bottom (RBOT), Double Top (DTOP) and Bottom (DBOT) and Triple Top (TPTOP) and Triple Bottom (TPBOT).

From the nonparametric algorithm described in the previous section, we would have identified m local extrema in a given fixed length window. Denoting all the m extrema by $(e_1, e_2, ..., e_m)$ and $(t_1^*, t_2^*, ..., t_m^*)$ the dates on which these extrema occur, the last five extrema are labeled as $(e_{m-4}, e_{m-3}, e_{m-2}, e_{m-1}, e_m)$. The technical patterns are identified by framing conditions on these extrema.

Head-and-Shoulders Pattern

Head-and-Shoulders Top (HSTOP) and Bottom (HSBOT) are popular technical patterns that have been regularly detected and examined by practitioners and researchers. (See Osler (1998), Change and Osler (1999) and Dempster and Jones (1998)) Basically, HSTOP and HSBOT consist of five local extrema, including the left shoulder, the head, and the right shoulder. Thus, five extrema are able to define a Head-and-Shoulders pattern in the following way:

HSTOP1 e_m is a maximum

HSTOP2 $e_{m-2} > e_{m-4}$, $e_{m-2} > e_m$, $e_{m-4} > e_{m-3}$, and $e_m > e_{m-1}$

HSTOP3 $\max |e_i - \bar{e}| = 0.010 \times \bar{e}$, where $i = m-4, m$ and $\bar{e} = (e_{m-4} + e_m)/2$

HSTOP4 $\max |e_i - \bar{e}| = 0.010 \times \bar{e}$, where $i = m-3, m-1$ and $\bar{e} = (e_{m-3} + e_{m-1})/2$

and

HSBOT1 e_m is a minimum

HSBOT2 $e_{m-2} < e_{m-4}$, $e_{m-2} < e_m$, $e_{m-3} > e_{m-4}$, and $e_{m-1} > e_m$

HSBOT3 $\max |e_i - \bar{e}| = 0.010 \times \bar{e}$, where $i = m-4, m$ and $\bar{e} = (e_{m-4} + e_m)/2$

HSBOT4 $\max |e_i - \bar{e}| = 0.010 \times \bar{e}$, where $i = m-3, m-1$ and $\bar{e} = (e_{m-3} + e_{m-1})/2$

Broadening Pattern

BTOP and BBOT are characterized by a sequence of five consecutive local extrema such that:

BTOP1 e_m is a maximum

BTOP2 $e_{m-4} < e_{m-2} < e_m$ and $e_{m-3} > e_{m-1}$

and

BBOT1 e_m is a minimum

BBOT2 $e_{m-4} > e_{m-2} > e_m$ and $e_{m-3} < e_{m-1}$

Triangle Pattern

A symmetrical triangle occurs when the trading range of the asset prices gradually decreases, which is exactly opposite to the Broadening pattern. Typically, a 'breakout' from a symmetrical triangle often signifies the initiation of a medium term price trend. Symmetrical Triangle Top (TTOP) and Triangle Bottom (TBOT) are characterized by the following:

TTOP1 e_m is a maximum

TTOP2 $e_{m-4} > e_{m-2} > e_m$ and $e_{m-3} < e_{m-1}$

and

TBOT1 e_m is a minimum

TBOT2 $e_{m-4} < e_{m-2} < e_m$ and $e_{m-3} > e_{m-1}$

Rectangle Pattern

The Rectangle formation is also one of the frequently taught and observed patterns in asset prices. The following conditions satisfy the rectangle Top (RTOP) and Bottom (RBOT) respectively:

RTOP1 e_m is a maximum

RTOP2 $\max|e_i - \bar{e}| = 0.010 \times \bar{e}$, where $i = m-4, m-2, m$ and $\bar{e} = (e_{m-4} + e_{m-2} + e_m)/3$

RTOP3 $\max|e_i - \bar{e}| = 0.010 \times \bar{e}$, where $i = m-3, m-1$ and $\bar{e} = (e_{m-3} + e_{m-1})/2$

RTOP4 $\min(e_{m-4}, e_{m-2}, e_m) > \max(e_{m-3}, e_{m-1})$

and

RBOT1 e_m is a minimum

RBOT2 $\max|e_i - \bar{e}| = 0.010 \times \bar{e}$, where $i = m-4, m-2, m$ and $\bar{e} = (e_{m-4} + e_{m-2} + e_m)/3$

RBOT3 $\max|e_i - \bar{e}| = 0.010 \times \bar{e}$, where $i = m-3, m-1$ and $\bar{e} = (e_{m-3} + e_{m-1})/2$

RBOT4 $\max(e_{m-4}, e_{m-2}, e_m) < \min(e_{m-3}, e_{m-1})$

Double Pattern

Double top (DTOP) and double bottom (DBOT) are characterized by the local extremum e_m and local extrema e_a and e_b such that:

$$e_a = \sup\{P^*_{t_k} : t^*_k > t^*_m\} \quad k = 1, ..., d-1 \tag{3.18a}$$

$$e_b = \inf\{P^*_{t_k} : t^*_k > t^*_m\} \quad k = 1, ..., d-1 \tag{3.18b}$$

The above equations mean that we compare the highest maxima extrema recorded in a rolling window with last extrema. Given these two extrema, Double Top (DTOP) and Bottom (DBOT) can be characterized by:

DTOP1 e_m is a maximum

DTOP2 $\max|e_i - \bar{e}| = 0.010 \times \bar{e}$, where $i = (m, a)$ and $\bar{e} = (e_m + e_a)/2$

DTOP3 $t^*_a - t_m > 20$ days

and

DBOT1 e_m is a minimum

DBOT2 $\max|e_i - \bar{e}| = 0.010 \times \bar{e}$, where $i = (m, b)$ and $\bar{e} = (e_m + e_b)/2$

DBOT3 $t^*_b - t_m > 20$ days

Triple Pattern

Triple Top (TPTOP) and Bottom (TPBOT) are rare formations in the asset prices. Typically, a TPTOP consists of three highest local maxima that occur around the same value. Similarly, TPBOT also has three lowest minor bottoms that are generally of the same value. To detect TPTOP, we first record all the extrema in a fixed-length window and we pick out the highest three maxima, one of which must be the last extrema e_m. Next, we compare whether the yields are within a stipulated band (say, 1.0 percent) of one another. Lastly, the time difference between the first and last extrema are assumed to be more than five weeks (25 days). The following conditions define TPTOP and TPBOT respectively:

TPTOP1 e_m is a maximum

TPTOP2 Select three highest maxima ($e_{\max 1} > e_{\max 2} > e_{\max 3}$) with corresponding times at ($t_{\max 1}, t_{\max 2}, t_{\max 3}$) respectively. One of which extrema must be e_m.

TPTOP3 $\max |e_i - \bar{e}| = 0.010 \times \bar{e}$ for $i = (\max 1, \max 2, \max 3)$, where

$$\bar{e} = \frac{e_{\max 1} + e_{\max 2} + e_{\max 3}}{3}$$

TPTOP4 $t_{\max 3} - t_{\max 1} > 25$ days

and

TPBOT1 e_m is a minimum

TPBOT2 Select three lowest maxima ($e_{\min 1} < e_{\min 2} < e_{\min 3}$) with corresponding times at ($t_{\min 1}, t_{\min 2}, t_{\min 3}$) respectively. One of the extrema must be e_5.

TPBOT3 $\max |e_i - \bar{e}| = 0.010 \times \bar{e}$ for $i = (\min 1, \min 2, \min 3)$, where

$$\bar{e} = \frac{e_{\min 1} + e_{\min 2} + e_{\min 3}}{3}$$

TPBOT4 $t_{\min 3} - t_{\min 1} > 25$ days

3.4 Bond Yield Data, Return Measurement and Information Tests

3.4.1 Government Benchmark Bond Yield Data

To evaluate the usefulness of technical chart patterns, we apply the smoothing methods described in the previous section to the US, UK, Germany, Japan, Australia, Canada and Hong Kong government benchmark bond yield markets. Benchmark bonds are usually the most liquid government bonds among a basket of similar maturity bonds. Consequently, benchmark bonds are viewed as reference points for many investors and used as pricing benchmarks for other financial assets, such as corporate bonds. The benchmark bonds are frequently replaced because the maturity of bonds shortens due to the time decay factor. New replacements are needed to ensure the benchmark bonds stay within the maturity bracket, such as 2-year or 10-year. All benchmark bonds are coupon bonds.

We tabulate the basic information on the bond yield data in Table 3.4.1. All data are obtained from *Ecowin*. In Panel A, the second column is the maturity of the bond yield, and the third column is the various yield spread pairs. Each country has different maturity sectors. There are 34 bond yields with 204,816 data in total. Not all of the maturities have equal number of data, for example, the 1-year maturity bond yield data may start in 1962 while the 5-year maturity bond yield data begins in 1979. To extract the yield spread between these two time series, we begin with the later date. If a missing data among the two yield data is encountered while matching with the two date series, the series without the missing data on that particular date is dropped. Altogether, we have extracted 43 yield spreads series of different maturities, with a total of 262,170 data points. These spreads are chosen because of their popularity with bond and relative value traders. One interesting avenue for future research is to apply the statistical algorithm in this chapter to credit spreads between different industry sectors, such as between the motor industry and the government bond sector, or the emerging market spreads.[10]

The summary statistics of the bond yield and bond yield spreads are tabulated in Appendix I. The results basically confirm the stylized facts documented by Diebold and Li (2003). For example, the average yield curve for all countries is upward sloping and concave, as shown by the increasing bond yield mean value and the positive mean yield spreads for all bond yield spreads. Furthermore, the standard deviation σ from fitting the Vasicek model (see next section) shows that the shorter maturities bond yields are more volatile than the long maturities bond yields. The autocorrelation $\rho(100)$ in the last column implies that bond yields are highly persistent, a fact observed by Chapman and Pearson (2001). They estimated that the US monthly bond yields' autocorrelation are in excess of 0.98. They suggest that this persistence in bond yields may be due to the sluggish adjustment of interest rates to fundamental factors. From the maximum and minimum bond yield in Column 6 and 7, there seem to be substantial variation of the sample bond yield data. For example, the 2-year Japanese government benchmark bond yield has a maximum of 8.49 percent and a minimum of 0.01 percent during the sample period 1986-2006. On the other hand,

[10]Stanton (1997) and Bhanot (2001) have estimated the continuous-time model using nonparametric methods on credit spreads. But so far, no charting algorithm has been to credit spreads. Most of the credit spread models are derived from the quantitative approach with option pricing methodology. See, for example, Merton (1974) and Duffie and Singleton (2003) for more details.

the variation of the yield spread data, though not as huge as the bond yield, is still fairly large. This points to the fact that the movement of the term structure of bond yields is non-parallel.

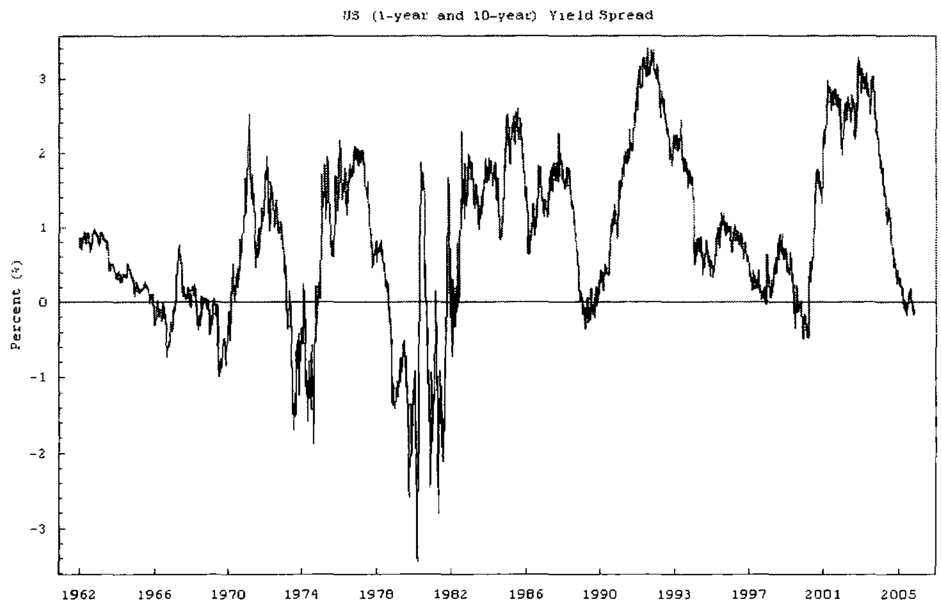
Table 3.1: Government Benchmark Bond Yield Data. Column 2 is the bond yield maturity. Column 3 is yield spread pairs, followed by the number of data.

Panel A: Bond Yield and Bond Yield Spread

Markets	Bond Yield Maturities (yr)	Yield Spread Pairs (Short,Long)	Obs. (Bond Yield)	Obs. (Yield Spread)
US	1, 2, 3, 5, 7, 10, 30	(1,5),(1,7),(1,10),(1,30),(2,5),(2,7),(2,10),(2,30) (3,7),(3,10),(5,10),(5,30),(10,30)	69,245(7)	116,147(13)
UK	2, 5, 7, 10	(2,5),(2,7),(2,10),(5,10)	27,848 (4)	27,848 (4)
Germany	2, 3, 5, 7, 10	(2,5),(2,7),(2,10),(3,7),(3,10),(5,10)	25,500 (5)	30,104 (6)
Japan	2, 3, 5, 10	(2,5),(2,10),(3,10),(5,10)	21,000 (4)	21,000 (4)
Australia	2, 3, 5, 10	(2,5),(2,10)(3,10),(5,10)	20,548 (4)	20,548 (4)
Canada	2, 3, 5, 7, 10	(2,5),(2,7),(2,10),(3,7),(3,10),(5,10)	25,785 (5)	30,942 (6)
Hong Kong	2, 3, 5, 7, 10	(2,5),(2,7),(2,10),(3,7),(3,10),(5,10)	14,890 (5)	15,581 (6)
Total			204,816 (34)	262,170 (43)

Source: Econwin

Figure 3.2: A Historical View of US (1,10)-year Yield Spread



According to a number of empirical studies on yield spread and the economic cycles, the historical yield spread data appear to contain some predictive power for the business cycle in many countries, and seem to suggest that each inversion of the bond yield curve tends to precede an occurrence of economic recession. Harvey (1991), for example, reports that the US yield spread provides warnings for the economic recessions in 1973 and early eighties, and in various out-of-sample tests. Estrella and Hardouvelis (1991) also find the yield spread has predictive power for cumulative changes in the real output for up to 4 years and recession 5 to 7 quarters ahead. Hu (1993), Davis and Henry (1994), Estrella and Mishkin (1998), Bernard and Gerlach (1998) and Kanagasabapathy and Rajan (2002) have all provided empirical evidence on the predictive power of the yield spread on the real economic output in a number of countries, such as UK, Germany and India.

To illustrate, Figure 3.2 shows the US government benchmark ten- and one-year bond yield spread since 1962. A positive spread implies an upward sloping term structure of bond yields while a negative spread describes a downward sloping term structure. It is noticeable that the spread is quite volatile over time, which is contrary to the assumption of constant yield curve spread. There were six major occasions where the spread is negative (not including the current one in 2006), in year 1967, 1969, 1973, 1979, 1989 and 2000. If we match the dates in which these negative spread occurred and the economic cycles, the spread seems to coincide with the onset of economic downturn.[11]

Given this attractive convergence and partially predictable property of yield spreads, is it possible to trade profitably on this pattern consistently over time? The answer is probably no. This is simply because such convergence trades between yields of different maturities are risky. These trades do not have the same risk profile as riskless arbitrage. For example, suppose the 1- and 10-year US Treasury yield spread is currently at 2 percent. Historical data tells us that such a steep yield curve will revert to near zero percent level at some point in the future, as shown in Figure 3.2. However, before the spread tightens, it may widen to 3 percent, as it occurred in 1992 and 2002. A converging spread trade involving a long position in 10-year sector and a short position in 1-year sector will thus incur large capital losses in the short-term. Over a the long period of time, the spread trade may be profitable, but in the short-run, the trader may have to liquidate the positions before the gains are reaped, especially when the positions are highly leveraged, as Jay Ritter (2002) comments, *"Being right in the long run is no consolation if you lost everything in the short-run."*[12] Leverage in yield spread trading constitute a critical component for a spread trader or a hedge fund. Fixed income spread traders typically make use of high leverage (with collateral known as *hair-cut*) to amplify their returns. However, in the event of extreme market turbulence, such as the 1998 Russian default episode, such high leverage can destabilize the orderly liquidation of spread positions, especially when a large proportion of traders have similar risk exposures. Hence, the timing of the spread trades is very important. Perhaps technical analysis of the spread can aid traders in initiating spread trades.

3.4.2 Sampling Conditional and Unconditional Bond Returns

Returns are an important part in our investigation of the effectiveness of technical charts. In LMW and Dawson and Steeley (2003), the conditional returns of the stock prices are measured once a chart patten is detected using the return formula: $\ln\left(\frac{y_t}{y_{t-1}}\right)$. However, this is not possible here because we do not have the associated price series for the benchmark bond yield. Rather, we utilized the following relationship between the change in bond yield and the modified duration D^* to obtain the bond returns:

$$r_t^{BY} = \frac{\Delta P}{P} = \Delta y \times D^* \times (-1) \tag{3.19}$$

[11]One can refer to the dates on the US business cycle expansions and contraction provided by the National Bureau of Economic Research (NBER) found in www.nber.org.

[12]Readers may realize that this situation is aptly applicable to arbitrage activities as well.

where $\Delta P = P_t - P_{t-1}$ is the change in bond price and $\Delta y = y_t - y_{t-1}$ is the change in bond yield from time $t-1$ to t. $\frac{\Delta P}{P}$ is the percentage bond price change, taken to be the bond return r_t^{BY} at time t. (For more details. see Appendix II) Effectively, the bond yield is the exogenous variable that drives bond returns. Because of this fact we can apply the charting algorithm to the bond yield rather than the bond price.

Since yield spread trading is based on the assumption that two sections of the yield curve exhibit non-parallel movements, either diverging (steepening yield curve) or converging (flattening yield curve) over time, when a trader forecasts that the spread between the long- and short-end of the yield curve will diverge further in the future, a *long* spread position is established by buying the shorter maturity bond and selling the longer maturity bond to lock in on the yield spread. On the other hand, if the trader forecast that the spread will tighten in the future, a *short* spread position is entered by selling the longer maturity bond and buying the longer maturity bond. Arguably, this yield spread reflects the market's credit situation and the required bond risk premium. A yield spread portfolio requires that both positions are duration-neutral or dollar-value of a basis point (DV01) neutral so that the spread portfolio is not expose to the *level* of the yield curve.

Thus, the bond yield spread portfolio shall include two positions with opposite weights. The conditional portfolio return is a linear combination of the two weights assigned to the long and short position, given by:

$$r_t^{YS} = w_1 r_t^{BY1} + w_2 r_t^{BY2} \tag{3.20}$$

where r_t^{BY1} and r_t^{BY2} are given by the previous equation, representing the bond return from each segment of the portfolio multiplied by the weight. While spread trades may entail less market risk than outright directional trade, such undertaking still expose traders to the slope factor of the yield curve. To maintain an equal dollar value of both positions so that this portfolio is insensitive to the *level* of yield curve, the trader has to adjust the portfolio so that it is duration-neutral. For a *long spread* position, the weights for (w_1, w_2) are $(+w_1, -w_2)$ since the trader is betting on the divergence of yield spread. If a trader enters into a *short spread* position, the weights (w_1, w_2) will have signs $(+w_1, -w_2)$. To ensure that the spread portfolio is neutral of the direction of the bond yield, the weights are adjusted using the duration of the short and long segment of the portfolio.[13]

[13]For example, suppose the duration of the 2-year and 10-year bond are 1.7 and 6.8 respectively, and a long spread strategy is initiated. That is, buy 2-year bond and sell 10-year bond. To maintain the same return from each bond following a parallel shift in the yield curve, the bond with larger duration will have a smaller weight while the bond with smaller duration will have a larger weight.

After applying the nonparametric chart algorithm to each yield data, we have twelve sets of conditional yield returns upon detection of each chart pattern. For each bond yield and yield spread series, we also construct the *unconditional* yield returns and compare them to the conditional yield returns. To make comparison easier across different markets, both the conditional and unconditional yield returns are standardized by subtracting the mean and dividing by the standard deviation:

$$Z_{i,t} = \frac{r_{i,t} - \text{Mean}(r_{i,t})}{\text{S.D.}(r_{i,t})} \tag{3.21}$$

where the mean and standard deviation are computed for each individual yield series. Moreover, to increase the power of the statistical tests, we join all the bond yield and bond yield spread series for the information tests describe in the next section.

3.4.3 Information and Statistical Tests

To conclude whether chart patterns contain any particular information compared to the unconditional yields returns, we follow the procedure proposed by LMW, who advocated the goodness-of-fit test and the Kolmogorov-Smirnov test. The null hypothesis for these tests is that if chart patterns are informative, conditioning on them would alter the empirical distribution of the bond returns. On the other hand, if the information contained in the pattern has been incorporated into the returns, then the normalized conditional and unconditional bond returns should be similar.

For the goodness-of-fit test, the procedure is to compare the quantiles of the conditional bond returns with their unconditional counterparts. The first step is to compute the deciles of unconditional returns and tabulate the relative frequency $\hat{\delta}_j$ of conditional returns that fall into decile j of the unconditional returns, $j = 1, ..., 10$:

$$\hat{\delta}_j = \frac{\text{Number of conditional bond returns in decile } j}{\text{total number of conditional bond returns}} \tag{3.22}$$

The null hypothesis is that bond returns are independently and identically distributed and thus the conditional and unconditional bond returns distribution are identical. The corresponding goodness-of-fit test statistics Q is given by:

$$\sqrt{T}(\hat{\delta}_j - 0.10) \sim N(0, 0.10(1 - 0.10)) \tag{3.23}$$

To see this, assume a positive shift of $\Delta y = 0.1$ and by equation (3.19), the return for 2-year and 10-year bonds is -0.17 and -0.68 respectively. Substituting these two components into equation (3.20), equate it to zero and use $w_1 + w_2 = 1.0$, the weight for 2-year bond and 10-year bond is 0.80 and 0.20 respectively. This means that four-fifth of the capital is invested in the 2-year bond and one-fifth in 10-year bond. In other words, buy four units of 2-year for every unit of 10-year bond sold. The only exposure of this portfolio is non-parallel shifts of the yield curve.

$$Q = \sum_{j=1}^{10} \frac{(T_j - 0.10T)^2}{0.10T} \sim \chi_9^2 \tag{3.24}$$

where n_j is the number of observations that fall in decile j and the T is the total number of observations and (4.13) is the asymptotic Z-values for each bin.

For the Kolmogorov-Smirnov test, the statistical basis is derived from the cumulative distribution function $F_1(z)$ and $F_2(z)$ with the null hypothesis that $F_1 = F_2$. Denote the empirical cumulative distribution function $\hat{F}_j(z)$ of both samples:

$$\hat{F}_j(z) = \frac{1}{T_i} \sum_{k=1}^{T_i} I(Z_{ik} \leq z), \quad i = 1, 2 \tag{3.25}$$

where $I(\cdot)$ is the indicator function and $(Z_{1t})_{t=1}^{T_1}$ and $(Z_{2t})_{t=1}^{T_2}$ are the two IID samples. The Kolmogorov-Smirnov statistic is given by the expression:

$$\gamma = \left(\frac{T_1 T_2}{T_1 + T_2}\right)^{1/2} \sup |\hat{F}_1(z) - \hat{F}_2(z)| \tag{3.26}$$

and the p-values are given by:

$$\text{Prob}(\gamma \leq x) = \sum_{k=-\infty}^{\infty} (-1)^k \exp(-2k^2 x^2), \quad x > 0 \tag{3.27}$$

Under the null hypothesis, the statistic γ should be small. 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. (See Press et al. (2002, Section 14.3) and DeGroot (1986))

Apart from the Goodness-of-fit and Kolmogorov-Smirnov test, a simple t-statistic tests whether the conditional mean returns are statistically significant different from zero. The formula for the test-statistic is:

$$t = \frac{\bar{z}}{\sigma / \sqrt{T_z}} \tag{3.28}$$

where $\bar{z}$ is the mean normalized conditional returns, σ is the standard deviation of the normalized unconditional returns, and T_z is the number of observations for the conditional returns $\bar{z}$ for a particular chart pattern. We apply equation (3.28) to all bond yield and bond yield spread mean returns.

3.4.4 Conditioning on Moving Average

Moving average is one of the most frequently cited technical indicators that has predictive value for asset prices. (See, for example, Brock, Lakonishok and LeBaron (1992), Levich and Thomas (1993) and Chapter 2) Therefore, for each chart pattern, we will compute the 45-day moving average and include it as a further conditioning variable. The total number of chart patterns is thus separated into two categories, one where the last extrema e_m is above the moving average and the other below the moving average. Including moving average as an indicator has a further advantage because we can use it to filter 'incorrect' patterns detected by the kernel regression. For example, to quantify a Head-and-Shoulders Top, the formation must at least be above the 45-day moving average since it is a 'top', while a Head-and-Shoulders Bottom must be at least below the 45-day moving average since it is a 'bottom' pattern.

3.4.5 Simulation Using 1-Factor Vasicek Model

In addition to the raw bond yield data, we also apply the smoothing algorithm to simulated prices for comparison purpose. In particular, we conduct simulation trials using the Vasicek (1977) yield curve model, a popular and widely used model in pricing fixed income derivatives. We choose this model because it is simple and intuitive. By its Gaussian property, the Ornstein-Uhlenbeck process is able to generate negative values, which models the yield spread better then the square-root model.[14] The Vasicek model is given by:

$$dy_t = \lambda(\mu - y_t)dt + \sigma dW_t \tag{3.29}$$

where W_t is the standard Brownian motion and y_t is the yield at time t. The parameter λ governs the speed of mean reversion to the long run equilibrium μ and σ is the volatility parameter. Given the discrete time counterpart to model (3.29) is:

$$y_t = \mu(1 - e^{-\lambda}) + e^{-\lambda} y_{t-1} + \sigma \left(\frac{1 - e^{-2\lambda}}{2\lambda} \right)^{\frac{1}{2}} \varepsilon_t$$

where ε_t is the standardized Gaussian white noise. The maximum likelihood estimates of parameters (μ, λ, σ) are:

$$\hat{\mu} = \frac{1}{T} \sum_{t=1}^{T} y_t = \bar{y} \tag{3.30}$$

[14]The square-root process is: $dy_t = \lambda(\mu - y_t)dt + \sigma\sqrt{y_t}dW_t$. See Cox, Ingersoll and Ross (1985)

$$
\begin{aligned}
\hat{\rho} &= \frac{\frac{1}{T}\sum_{t=1}^{T}(y_t - \bar{y})(y_{t-1} - \bar{y})}{\sum_{t=1}^{T}(y_t - \bar{y})^2} \\
\hat{\eta}^2 &= \frac{1}{T}\sum_{t=1}^{T}[y_t - \bar{y} - \rho(y_{t-1} - \bar{y})]^2 \\
\hat{\lambda} &= -\log(\hat{\rho}) \qquad (3.31) \\
\hat{\sigma} &= -\left(\frac{2\log\hat{\rho}}{1-(\rho)^2}\right)\hat{\eta}^2 \qquad (3.32)
\end{aligned}
$$

where $\bar{y}$ is the sample mean and T is the number of observations over $t = 1, ..., T$. (See, for example, Gourieroux and Jasiak (2001, Section 12.1) or Brigo and Mercurio (2001, p.54))

The value of each parameter is estimated for each yield series. (The full results are given in Appendix I (Table 3.12)). A causal comparison between the bond yield and the bond yield spread series shows some interesting characteristics. First, the parameter μ for bond yield is much larger than yield spread. This is expected since the level of bond yields is higher than yield spread. Second, a comparison of the parameter λ shows that it is larger for yield spread than for bond yield. This is intuitive because yield spreads tend to exhibit more reversals than bond yield, and as a result, the speed to which yield spreads move toward their mean value is faster than bond yield. Lastly, a comparison of σ between the bond yield and yield spread indicates that the volatility for bond yield is larger than yield spread.

Given these parameter values, an independent price series is simulated for each bond yield and bond yield spread series. Next, we apply the pattern recognition algorithm to detect the occurrence of each of these technical patterns in each simulated series. We do this procedure only once for each series since the purpose here is not to construct a distribution of conditional yield returns but to provide a comparison between the simulate series and the actual yields.[15]

3.4.6 Graphical Examples of the Nonparametric Kernel Charting Algorithm

This section presents some graphical examples of the technical chart patterns defined in Section 3.3.4. The nonparametric local polynomial regression is applied to the US (10-1)-year government benchmark bond yield spreads over period 1962-2006. The

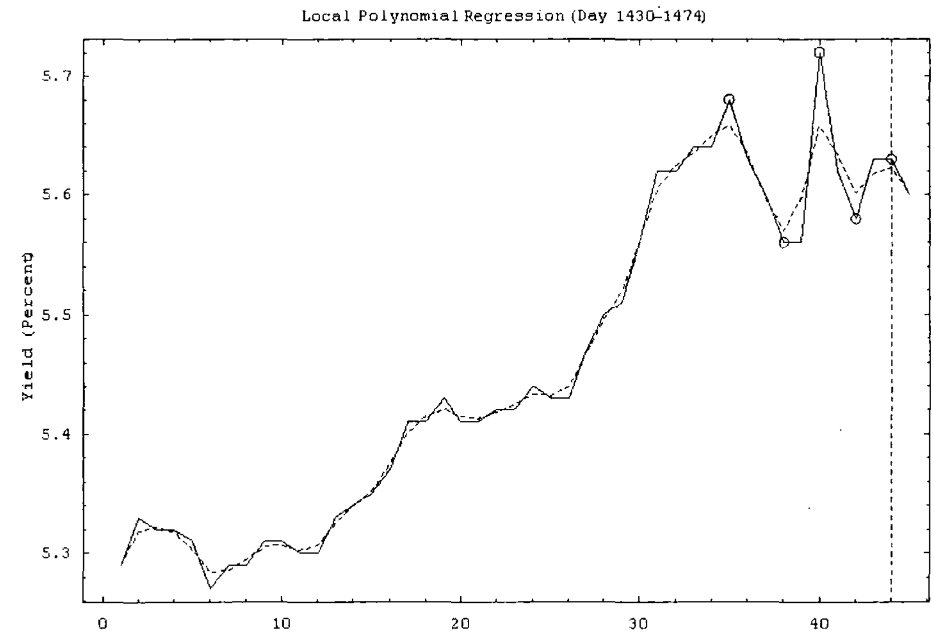
[15]The primary reason for not conducting more simulation is because of time constraint. To complete a cycle of simulating and applying the nonparametric kernel regression to 240,000 data takes approximately 48 hours in *Mathematica*. Hence conducting 1000 simulations is not feasible. To a large extent, this problem also exists in LMW and Dawson and Steely's (2003).

fixed-length window for each pattern is 45 trading days, with a requirement that the last extrema e_m must occurred on day $d-1$ before we measure the conditional bond return. For all chart patterns, the kernel bandwidth parameter value is fixed at $\hat{h}_{CV} \times 0.45$. The solid line in each figure is the actual bond yield spreads, and the dashed line is the kernel estimate $\hat{f}_{LP}(\cdot)$.

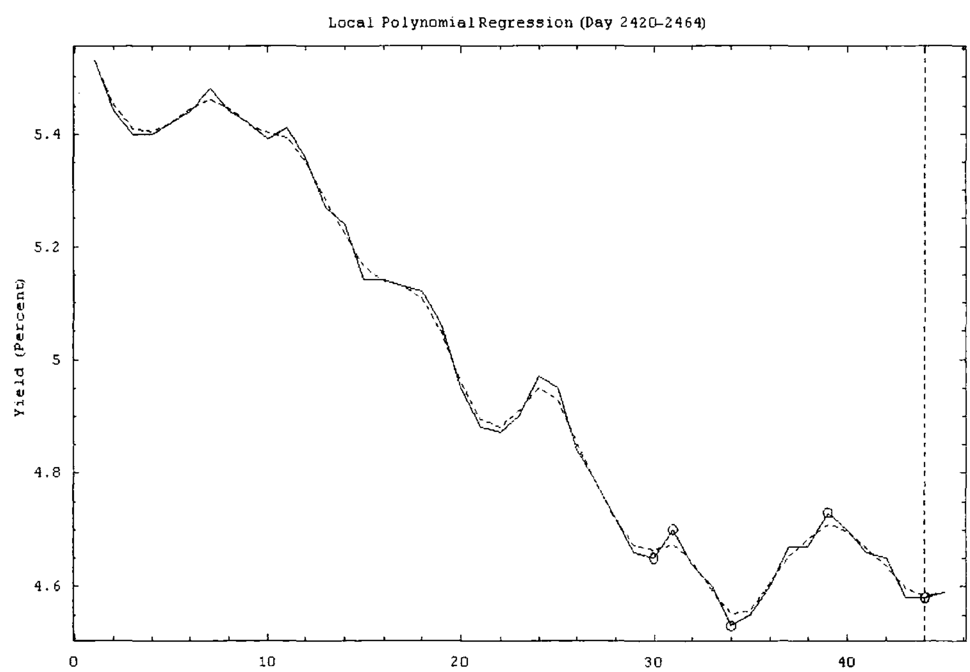
A casual inspection of the pictorial representations show some matching properties between the technical pattern and the nonparametric kernel regressions. However, these are merely illustrative examples and not meant to be conclusive. As a matter of fact, one critical weakness of the nonparametric estimators shown in these figures is that the extrema of the smoothed prices and the actual yields do not coincide.[16] A number of the extrema of the local polynomial regression are situated at one or more days away from the turning point in the actual bond yield. As a result, even though the yields obtained from the dates at which these extrema $(e_{m-4}, e_{m-3}, e_{m-2}, e_{m-1}, e_m)$ satisfy the chart pattern conditions, they may not represent the actual turning point. To ameliorate this problem, one can (i) tighten the definitions of the chart patterns, or (ii) reduce the bandwidth parameter value further. The consequence of the first action is that a lesser number of pattern count is detected, which is detrimental to our statistical tests since the power of the tests would be diminished substantially. The result of the second remedy, on the other hand, greatly reduces the advantage of the smoothing methodology advocated in this chapter, since there is little differences between the smoothed yields and the actual yields (even though the local peaks of both the smooth and actual yield now match). Given the considerable needs to balance both sides of the arguments, we shall use the original algorithm specified in Section 3.3.4.

[16]The same problem exists in LMW's estimation. If one refers to the graphic examples given in LMW closely, not all extrema of the kernel regression occur on the same day as the actual closing price. Furthermore, it is noticeable that the last extrema of the Triangle Top (p.1723) and Double Top (p.1725) does not occur on day 35 (vertical line) in the 35-day rolling window, which is contrary to their stated algorithm on page 1719 *"...we require that the final extremum that completes a pattern occurs on day 35."*

Figure 3.3: An Illustration of Head-and-Shoulders Pattern. The thin line is the actual bond yield while the dotted line is the Local Polynomial Regression. The empty circles are the last five extrema which satisfied the Head-and-Shoulders conditions.

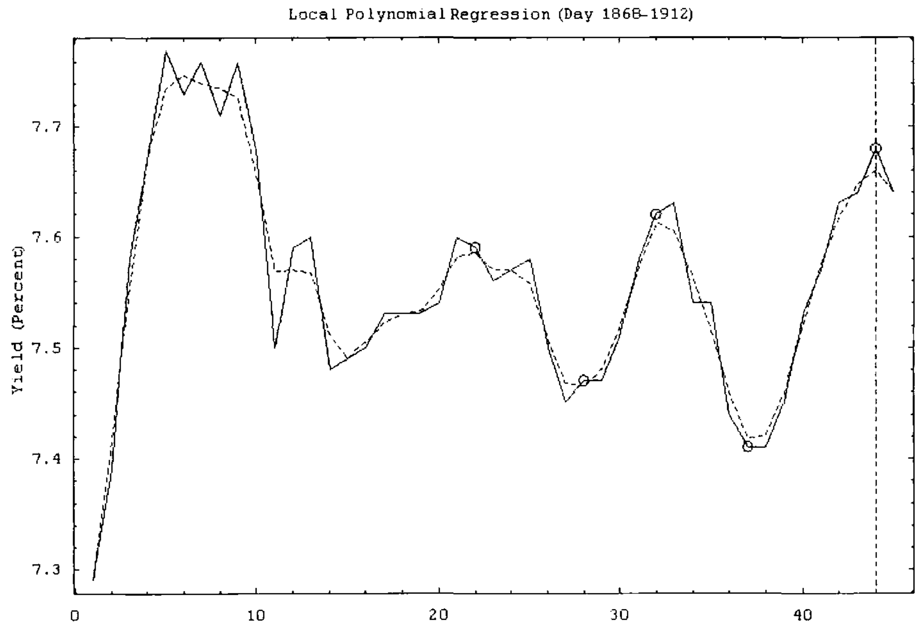


(a) Head-and-Shoulders Top

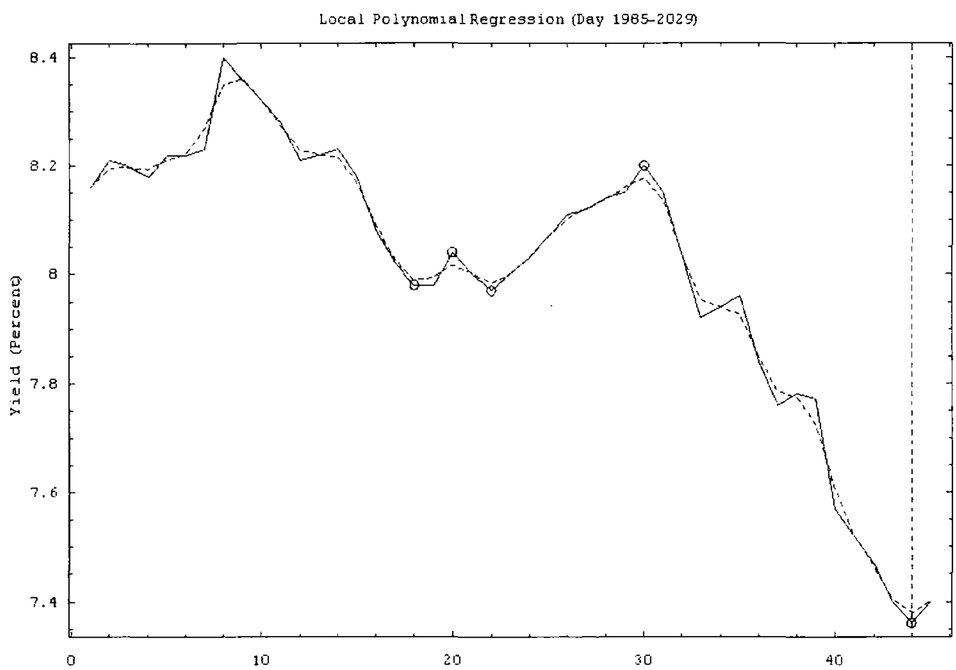


(b) Head-and-Shoulders Bottom

Figure 3.4: An Illustration of Broadening Pattern



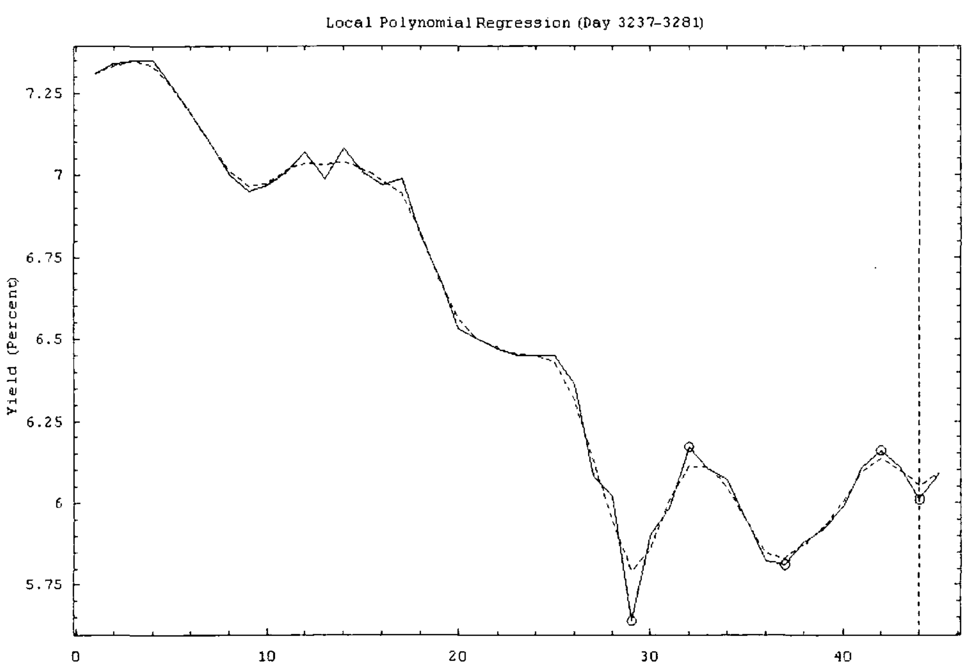
(a) Broadening Top



(b) Broadening Bottom

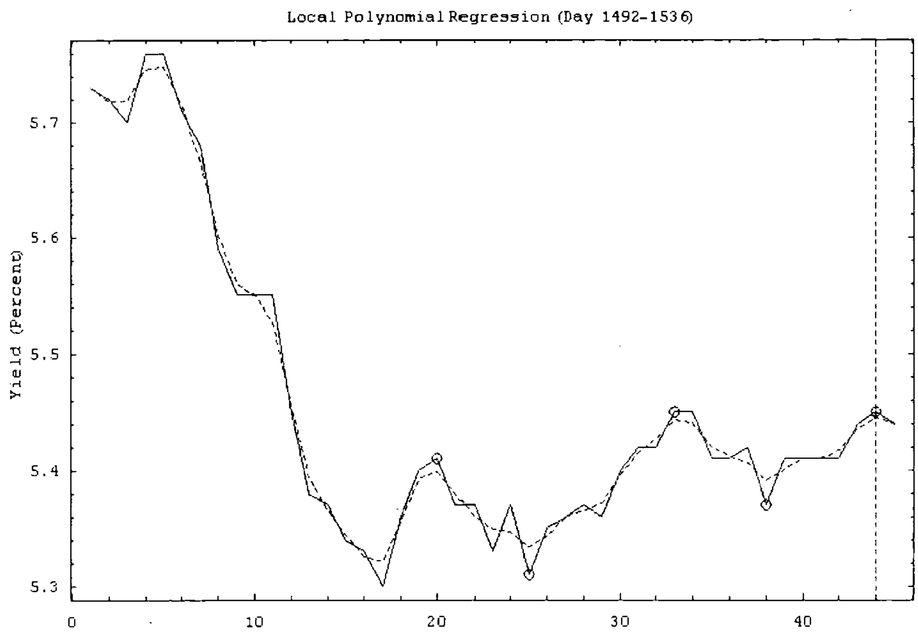
Figure 3.5: An Illustration of Triangle Pattern

(a) Triangle Top

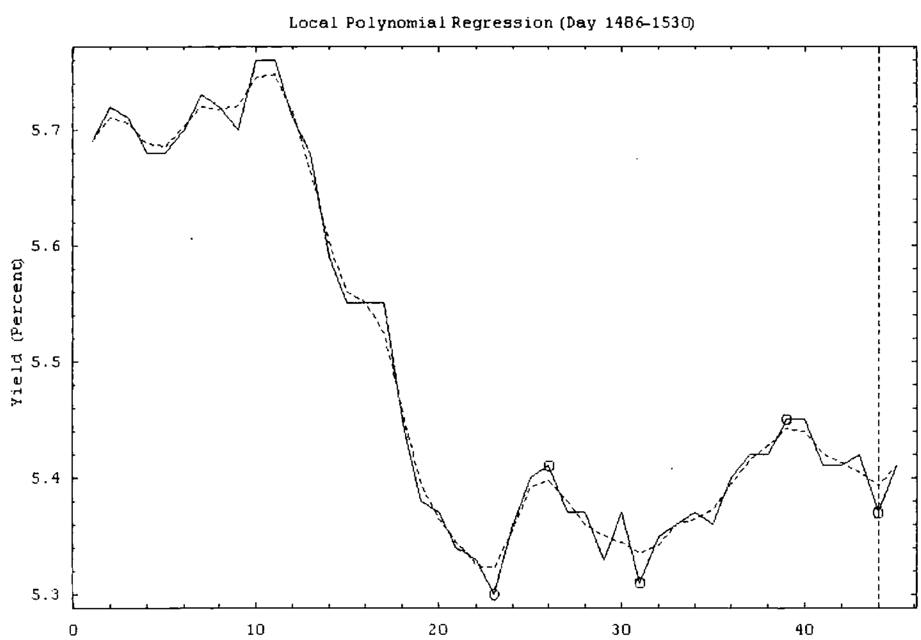


(b) Triangle Bottom

Figure 3.6: An Illustration of Rectangle Pattern

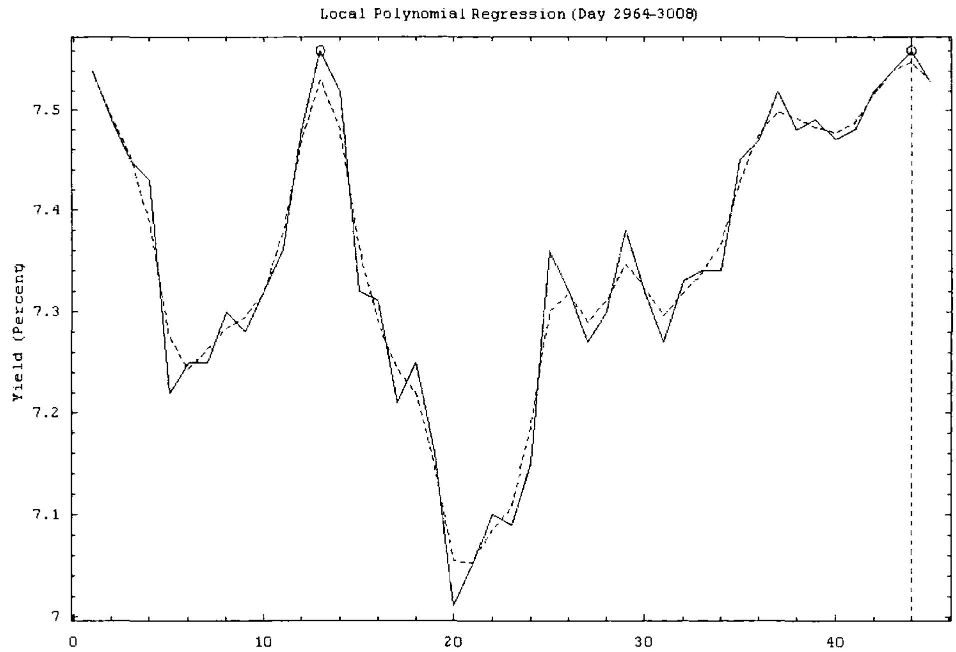


(a) Rectangle Top

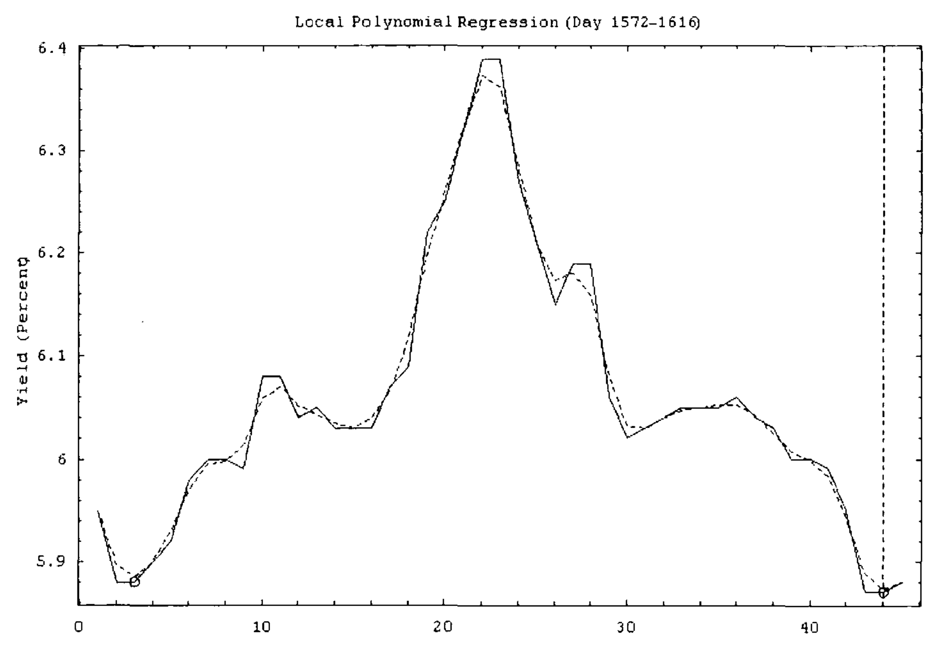


(b) Rectangle Bottom

Figure 3.7: An Illustration of Double Pattern

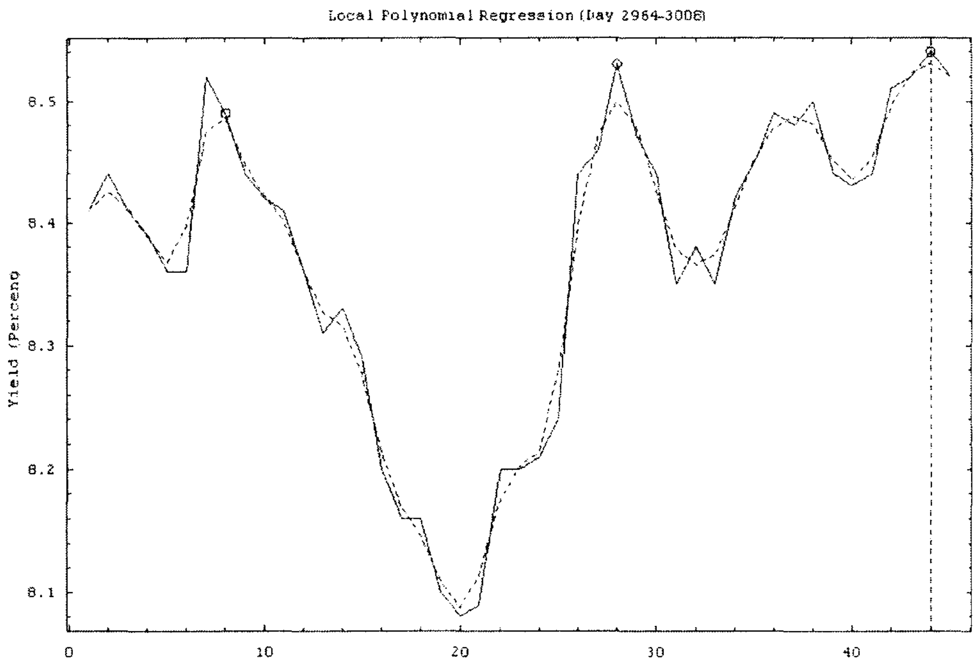


(a) Double Top

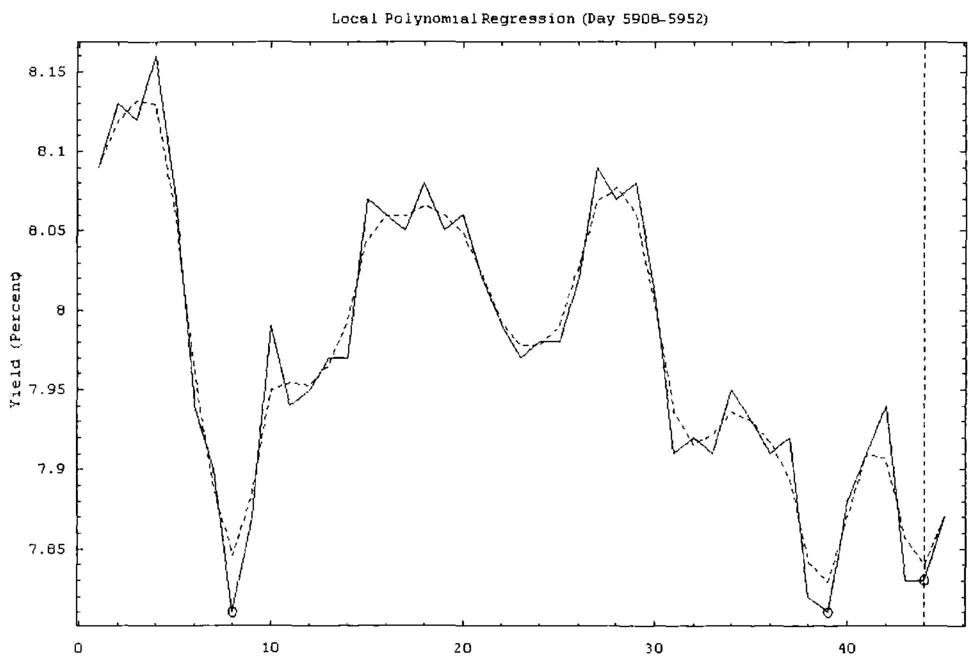


(b) Double Bottom

Figure 3.8: An Illustration of Triple Pattern



(a) Triple Top



(b) Triple Bottom

3.5 Empirical Evidence

3.5.1 Technical Chart Patterns in Bond Yields

This section presents the empirical results from the bond yield data. Table 3.2 and 3.3 display the pattern count from applying the Nadaraya-Watson and local polynomial regression respectively. The first row is the total sample count, and the second row is the results from the simulation from Vasicek model. The third and fourth row are counts where e_m is above the 45-day moving average (($\nearrow$) MA) and below moving average (($\searrow$) MA) respectively.

The total sample count from applying the Nadaraya-Watson regression shows that the most common chart pattern is Rectangle, with more than 3000 recorded, followed by Head-and-Shoulders and Double, with more than 1000 occurrences each. The rest of the chart patterns have counts in between 600-800. Interestingly, this result is different to LMW, who find the Double chart pattern to be the most observed in US equities, and Dawson and Steeley (2003) find Head-and-Shoulders to be the most observed pattern in the UK equity market. The country which displays the least number of chart patterns is Japan, with has only 856 count aggregated across all patterns, a substantially lower count than countries which have a similar number of raw data, such as Australia and Canada. When aggregating the bond yield series into three maturity brackets (short, medium and long), the most observed pattern count is still Rectangle, followed by Head-and-Shoulders and Double pattern, for all three maturities. When we separate the pattern count by the 45-day moving average, the difference with between ($\nearrow$) MA and ($\searrow$) MA, the Double pattern and Triple pattern show a stark difference, as we find nearly all Double and Triple top patterns lie above the moving average, and nearly all Double and Triple bottom patterns lie below the moving average. This shows that the moving average may have some use in differentiating top and bottom chart patterns. The only top pattern has a lower count with ($\nearrow$) MA is the Triangle pattern.

A further comparison of the number of chart patterns between the actual bond yields and simulated Vasicek yields shows that the total pattern count recorded from Vasicek simulation is higher than actual series for UK, Germany, Japan and Australia. For example, the number of patterns for Japan from the Vasicek series is nearly four times as many as the actual yields. One possible reason for the low pattern count in Japan is due to the level of bond yields. During the late nineties, the Japanese monetary authority has maintained the zero-interest rate policy for many years. With the bond yields languishing at near zero percent for such a considerable length of time, the consequence was few bond yields movements and thus no formation of chart patterns.[17] For US, Canada and Hong Kong markets, the pattern count from the actual yield is higher than the simulated Vasicek series. But whether this observation may carry the implication that technical traders are more active in these markets is difficult to conclude since we only conduct only one simulation from the Vasicek model. But having said that, our results do contrast significantly from LMW's estimation on the US equity markets, where they find that Head-and-Shoulders, Rectangle and Double chart patterns have much higher count than simulated geometric Brownian motion. This difference, however, may mean that chart traders are more active in US equity markets than in bond markets. For all simulated Vasicek series, the most frequently detected chart pattern is still the Rectangle pattern, followed by Head-and-Shoulders and Double chart pattern.

Further analysis between the results in Table 3.2 and Table 3.3 shows an interesting difference, in that the aggregate pattern count for the local polynomial regression is always higher. For example, the total chart pattern count for Nadaraya-Watson regression is 16,929, as compared to 21,334 for local polynomial regression. This implies that the boundary bias between the Nadaraya-Watson and local polynomial regression is important and has consequential results in matching chart patterns. When this boundary bias is reduced, more extrema are found near the right boundary to which we can identify the chart patterns, which contributed to the higher count. Similar to Nadaraya-Watson regression, the most frequently observed pattern for local polynomial regression is Rectangle, followed by Head-and-Shoulders and Double. The next step is to analyse whether higher pattern counts will provide more conclusive evidence on the informativeness of chart patterns.

To provide further intuitive results about the occurrence of the chart patterns across time and across the level of bond yield, Figures 3.5.1 provides two examples where the chart patterns are detected. Subfigure (a) shows the US 1-year bond yield while subfigure (b) shows the 2-year Japanese bond yield. Each empty circle signifies that one of the twelve chart patterns has occurred at that particular time.[18] In subfigure (a), it is noticeable that the distribution of patterns is not concentrated in any subperiods. The circles are fairly distributed across time periods and across yield levels, with possible exception during the period 1979-1981. On the other hand, subfigure (b) highlights a number of interesting features. One, the distribution of

[17]The late nineties witnessed a series of failures of Japanese financial institutions, such as the Long-Term Credit Bank and Nippon Credit Bank. As a result, Moody downgraded Japan's sovereign credit rating from AAA in November in 1998 and further downgrades in September 2000 and November 2001. These events prompted the Japanese central bank to maintain exceptionally low policy rate until recently.

[18]We omit the rest of the bond yields due to insufficient space.

chart patterns do cluster more than the US bond yield, especially around 1994 and 2005. Two, the level of bond yield may have some effects on the occurrence of chart patterns. When the yields are extremely stable at a particular level for an extended time period, as shown by Japan during 2001-2004 at zero percent, this implies that there is a lack of bond yield movements, which in turn means that no chart pattern can be formed at all. Three, when bond yields are experiencing a rapid movement in one direction (trending), this reduces chart formation which fit our pattern definition in Section 3.3.4, which is seen clearly in the US market during 1979-1981 and Japan during 1991, where few circles are recorded. Thus, the overall observation here is that when yields are very stable at some particular level, or very unstable over a relatively short time, it is difficult for chart patterns to form and hence our smoothing algorithm cannot detect them. In fact, when bonds yields are trending, a trend-following technical strategy might be a better choice than chart patterns, as we have discussed in Chapter 2.

Table 3.4 and 3.5 display the summary statistics of the one-day conditional yield return following the conclusion of a chart pattern for the two nonparametric regressions methods respectively. The asterisk (*) besides the mean return signifies that the return is significantly different from zero. The test statistic is given by equation (4.18). The mean and standard deviation of the unconditional returns have all been normalized to zero and one respectively. A comparison of the normalized conditional returns to the unconditional counterpart show some differences, but these differences seem to be randomly distributed across the chart patterns. For example, the HSTOP pattern is statistically different to zero for US and UK markets, but insignificant for the rest of the markets. Seven out of twelve chart patterns exhibit statistically significant mean return from the Nadaraya-Watson regression. When we have more conditional returns, as provided by local polynomial regression, there are now only five significant mean returns. So it seems that when a better technique is used to identify chart patterns (more sample count), the normalized mean returns are found to be less significant.

Furthermore, the signs of the mean returns do not conform to the expected sign. All top patterns are assumed to produce positive returns and bottom patterns are suppose to exhibit negative returns, since bond yields are inversely related to bond prices. An examination of the signs of mean returns across different countries and maturities does not yield any systematic pattern at all. For example, the mean return of the Head-and-Shoulders pattern is positively significant for US and UK, but negative for Australia market, highlighting the differences in the power of chart patterns across different bond markets. Conditioning on the moving average may not improve the results for both Nadaraya-Watson and local polynomial regressions. For example, the local polynomial regression result in Table 3.5 shows the UK BTOP, RTOP and RBOT pattern has significant return for both ($\nearrow$) MA and ($\searrow$) MA, while few of these patterns are significant in the US. But interestingly, we find that there are seven significant mean returns for ($\nearrow$) MA, which are HSTOP, TTOP, RTOP, HSBOT, BBOT, TBOT and RBOT. This result is consistent with our expectation if only the top patterns are significant, as all the top patterns *should* be above the 45-day moving average. But what is perplexing is that the bottom patterns (HSBOT, BBOT. TBOT and RBOT) are significant as well. This implies that bottom patterns that are already *above* the moving average continue in their upward trend while the bottom patterns below the moving average exhibit weaker reversals. The former patterns thus generate larger and statistically negative bond returns.

Table 3.6 and 3.7 presents the information test results for Nadaraya-Watson and local polynomial regression respectively. Panel A of both tables is the goodness-of-fit Chi-square test. The null hypothesis here is that each decile should contain an equal percentage of conditional yield return (10.0 percent). The last column is the Q-statistics and the numbers in parenthesis are the asymptotic z-values for each decile and p-value for the Q-statistics respectively. Panel B is the Kolmogorov-Smirnov statistics for each chart pattern. The numbers in parenthesis are the p-values for each γ statistic, given by equation (4.17).

The overall results from both regressions provide mixed support for the technical charts. The number of chart patterns that reject the goodness-of-fit test is seven and eight for Nadaraya-Watson and local polynomial regression respectively. The Rectangle pattern has the largest Q statistic. The results from local polynomial regression show only a limited improvement in the information tests, as evident from the p-values. For the Kolmogorov-Smirnov test, only five and six chart patterns reject the null hypothesis for Nadaraya-Watson and local polynomial regression respectively, a lower number than the goodness-of-fit test.[19] When examining the results for individual countries, it seems that there are no systematic pattern that bond traders can exploit, since most of the p-values are more than ten percent for most chart patterns. One possible exception maybe the Head-and-Shoulders Top (HSTOP) pattern in the US bond markets, which appear to reject both the goodness-of-fit and Kolmogorov-Smirnov null hypothesis, and for both Nadaraya-Watson and local polynomial regressions. The maturity of bond yields does not seem to produce any systematic results. Similarly, conditioning on moving average may not improve the results in any dramatic way, as shown by the insignificant p-values.

[19]-99.00 implies that less than three patterns are detected.

In summary of the results so far, the tentative conclusion seem to point to the fact that chart patterns do not provide return distribution that is systematically different to the unconditional counterpart.

Does the lack of statistical significance from our tests implies that technical charting contains no incremental information in the bond yields series for bond traders? Technical analysts may disagree with our results here. Their disagreement is largely based the mechanization procedure used to identify technical chart patterns. Traditional technical analysts have argued strenuously that a mechanical procedure, such as local polynomial regression, does not capture fully the spirit of *chartism* since these algorithms cannot acquire the sophistication that human cognitive ability possesses in recognizing complex patterns, as Edwards and Magee (1966, p.304) emphasized:

> ...[T]he stock market are driven by human emotion, as perhaps the most important of many variables influencing price. An human emotion and behaviour, its manic and its depressive elements, have not yet been quantified....The fact the chart analysis is not mechanizable is important. It is one reason chart analysis continues to be effective in the hands of a skilled practitioner. Not being susceptible to mechanization, counter-strategies cannot be brought against it, except in situations whose meaning is obvious to everyone, for instance, a large important Support or Resistance level or a glaringly obvious chart formation.

They may have a valid point, as we have shown that when bond yields are moving rapidly or very stable, few chart patterns can be captured by the nonparametric regressions. Furthermore, our algorithm is constrained by several parameters, including the fixed-window of $d = 45$ days and the bandwidth parameter $\hat{h}_{CV}$, which may be unsuitable in discovering chart patterns. For example, some chart patterns can take more than 45 days to form. There are also limitations as to what the nonparametric regression can capture. For example, Bulkowski (2005) has described four possible types of Double Top (DTOP), whereas the nonparametric regression here can only capture one type.

To alleviate these weaknesses, Jegadeesh (2000) suggests to let the computers to search for the optimal chart pattern from the historical data. This is akin to the optimization procedure used by technical system traders to find the best parameter for the trading system, as discussed in Chapter 2. This may not be as useful as investors had hoped since many genetic algorithm studies show that historically optimized strategy yield no better predictive results. See, for example, Neely, Weller and Dittmar (1997), Allen and Karjalainen (1999) and Neely and Weller (2003). Returning to the point about whether using statistical tools can mimic humans' extensive capability in recognizing chart patterns, it remains a work for the future to develop computer algorithms that can fully match the overall cognitive capabilities of human in recognizing complex technical chart patterns.

Table 3.2: Technical Pattern Count for Bond Yields (Nadaraya-Watson Kernel Regression). Row 1 and 2 are the number of patterns detected from the actual bond yield and Vasicek simulation respectively. Row 3 and 4 are the number of patterns detected which is above/below the 45-day Moving Average indicator respectively, shown by (↗) MA and (↘) MA. Column 3-14 present the results for each of the 12 different chart patterns respectively.

Sample	Total	HSTOP	BTOP	TTOP	RTOP	DTOP	TPTOP	HSBOT	BBOT	TBOT	RBOT	DBOT	TPBOT
						All Bond Yields							
Actual	16929	1841	634	736	3200	1180	645	1760	762	666	3552	1237	716
Vasicek	19962	2092	1063	976	3735	1350	751	2114	1066	933	3735	1458	689
(↗) MA	7846	1100	572	227	1993	1177	638	582	54	428	1071	0	4
(↘) MA	9083	741	62	509	1207	3	7	1178	708	238	2481	1237	712
						US, All Maturities							
Actual	5520	599	187	221	1090	442	222	605	223	186	1125	389	231
Vasicek	5183	546	375	334	793	368	179	549	359	317	793	410	160
(↗) MA	2649	360	170	75	684	441	219	210	21	113	355	0	1
(↘) MA	2871	239	17	146	406	1	3	395	202	73	770	389	230
						UK, All Maturities							
Actual	2909	328	84	113	603	162	88	302	101	107	703	186	132
Vasicek	3015	312	158	133	578	193	102	352	148	110	604	224	101
(↗) MA	1344	209	77	36	387	162	87	112	4	66	203	0	1
(↘) MA	1565	119	7	77	216	0	1	190	97	41	500	186	131
						Germany, All Maturities							
Actual	2496	299	83	105	476	146	92	275	110	89	534	186	101
Vasicek	3616	389	149	122	805	241	149	365	138	134	767	235	122
(↗) MA	1119	189	66	29	279	146	92	87	9	62	160	0	0
(↘) MA	1377	110	17	76	197	0	0	188	101	27	374	186	101
						Japan, All Maturities							
Actual	858	75	64	63	110	70	31	76	71	61	140	73	24
Vasicek	3226	326	98	108	707	179	126	358	112	90	758	207	157

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(continued)

Sample	Total	HSTOP	BTOP	TTOP	RTOP	DTOP	TPTOP	HSBOT	BBOT	TBOT	RBOT	DBOT	TPBOT
$(\nearrow)$ MA	402	41	60	24	67	68	31	23	4	39	43	0	2
$(\searrow)$ MA	456	34	4	39	43	2	0	53	67	22	97	73	22
Australia, All Maturities													
Actual	1863	201	70	42	319	145	95	178	101	60	419	146	87
Vasicek	2226	251	93	97	431	148	99	232	114	86	438	172	65
$(\nearrow)$ MA	892	129	67	11	214	145	93	60	4	43	126	0	0
$(\searrow)$ MA	971	72	3	31	105	0	2	118	97	17	293	146	87
Canada, All Maturities													
Actual	2289	257	93	126	433	144	77	225	110	108	445	172	99
Vasicek	2128	233	115	112	372	182	85	217	126	121	332	164	69
$(\nearrow)$ MA	1004	131	83	31	267	144	76	65	8	71	128	0	0
$(\searrow)$ MA	1285	126	10	95	166	0	1	160	102	37	317	172	99
Hong Kong, All Maturities													
Actual	994	82	53	66	169	71	40	99	46	55	186	85	42
Vasicek	568	35	75	70	49	39	11	41	69	75	43	46	15
$(\nearrow)$ MA	436	41	49	21	95	71	40	25	4	34	56	0	0
$(\searrow)$ MA	558	41	4	45	74	0	0	74	42	21	130	85	42
Short Maturity Yields (1-, 2- and 3-year)													
Actual	6156	623	281	301	1136	444	227	639	326	284	1230	432	233
Vasicek	7415	722	423	415	1331	494	280	754	433	398	1334	553	278
$(\nearrow)$ MA	2850	363	251	94	689	443	221	215	27	181	364	0	2
$(\searrow)$ MA	3306	260	30	207	447	1	6	424	299	103	866	432	231
Medium Maturity Yields (5- and 7-year)													
Actual	6048	662	201	278	1175	403	219	637	245	229	1298	440	261
Vasicek	7043	772	382	333	1313	493	254	760	383	316	1288	518	231
$(\nearrow)$ MA	2785	410	179	84	740	403	219	208	15	148	377	0	2
$(\searrow)$ MA	3263	252	22	194	435	0	0	429	230	81	921	440	259
Long Maturity Yields (10- and 30-year)													
Actual	4725	556	152	157	889	333	199	484	191	153	1024	365	222

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Sample	Total	HSTOP	BTOP	TTOP	RTOP	DTOP	TPTOP	HSBOT	BBOT	TBOT	RBOT	DBOT	TPBOT
Vasicek	5504	598	258	228	1091	363	217	600	250	219	1113	387	180
(↗) MA	2211	327	142	49	564	331	198	159	12	99	330	0	0
(↘) MA	2514	229	10	108	325	2	1	325	179	54	694	365	222

Table 3.3: Technical Chart Pattern Count for Bond Yields (Local Polynomial Kernel Regression)

Sample	Total	HSTOP	BTOP	TTOP	RTOP	DTOP	TPTOP	HSBOT	BBOT	TBOT	RBOT	DBOT	TPBOT
All Bond Yields													
Actual	21334	2297	831	893	4016	1483	818	2215	998	834	4462	1585	902
Vasicek	25178	2645	1380	1127	4693	1724	968	2639	1385	1139	4668	1911	899
(↗) MA	9910	1368	750	287	2526	1479	810	734	75	537	1340	0	4
(↘) MA	11424	929	81	606	1490	4	8	1481	923	297	3122	1585	898
US, All Maturities													
Actual	7025	749	246	269	1379	540	283	757	306	235	1444	516	301
Vasicek	6462	666	476	385	989	461	239	669	468	402	959	542	206
(↗) MA	3356	459	221	92	882	539	279	261	27	140	454	0	2
(↘) MA	3669	290	25	177	497	1	4	496	279	95	990	516	299
UK, All Maturities													
Actual	3680	407	108	137	771	214	117	362	143	143	871	242	165
Vasicek	3784	401	200	160	725	240	133	429	195	131	739	294	137
(↗) MA	1700	256	99	45	489	214	116	129	6	92	254	0	0
(↘) MA	1980	151	9	92	282	0	1	233	137	51	617	242	165
Germany, All Maturities													
Actual	3075	373	117	125	597	184	129	314	137	103	653	224	119
Vasicek	4530	477	189	144	997	295	186	453	176	158	973	317	165
(↗) MA	1412	223	94	40	364	184	129	99	12	70	197	0	0
(↘) MA	1663	150	23	85	233	0	0	215	125	33	456	224	119
Japan, All Maturities													
Actual	1101	95	80	77	136	88	39	106	96	78	170	104	32
Vasicek	4105	421	123	115	894	231	161	459	142	107	974	277	201
(↗) MA	519	57	75	30	82	86	39	36	9	49	54	0	2
(↘) MA	582	38	5	47	54	2	0	70	87	29	116	104	30
Australia, All Maturities													
Actual	2387	256	104	58	416	182	112	236	128	74	525	184	112

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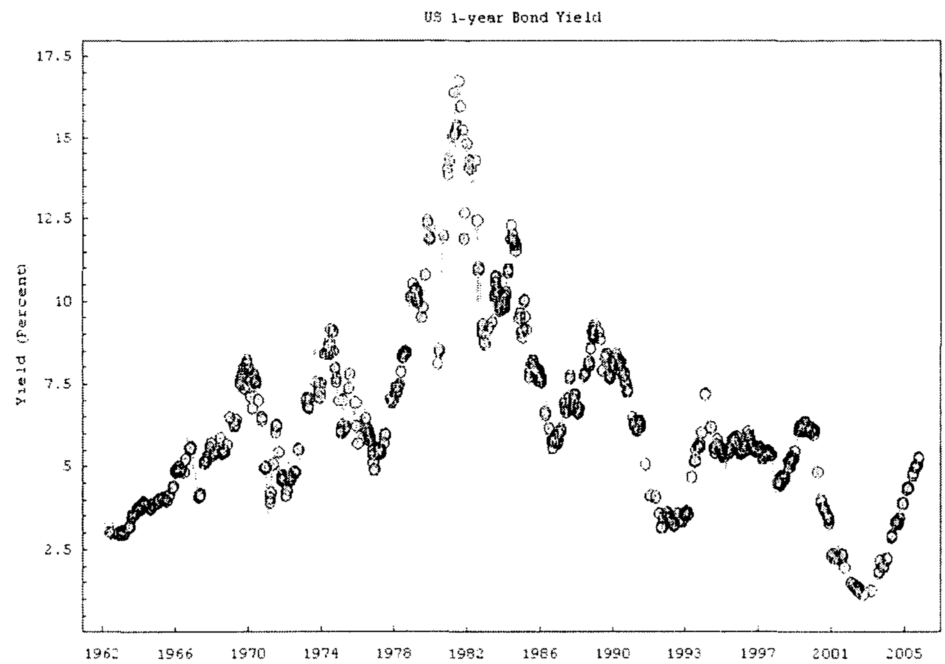
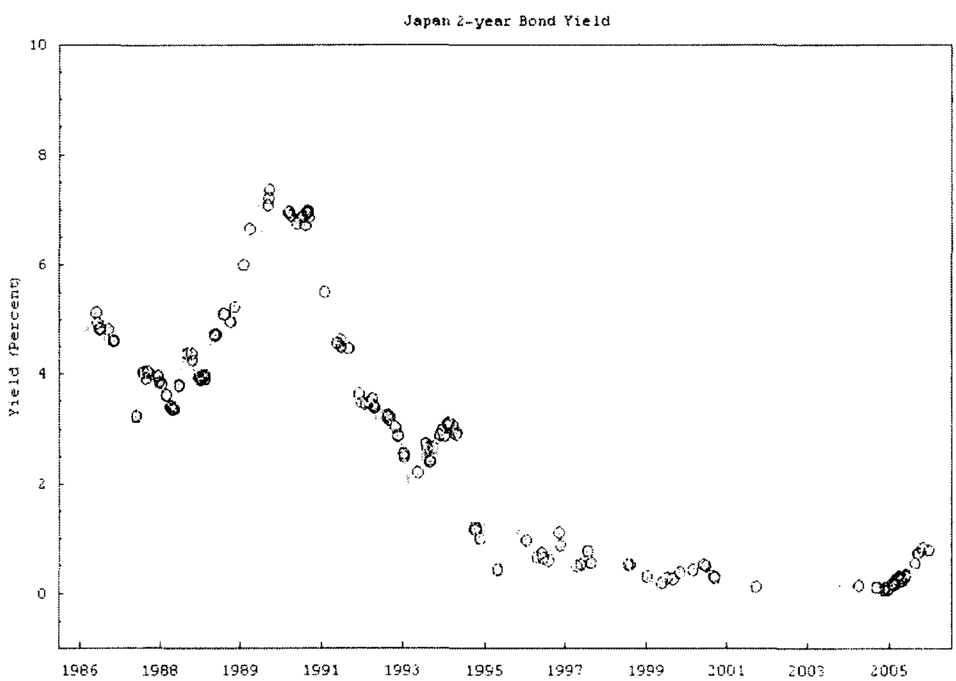
(*continued*)

Sample	Total	HSTOP	BTOP	TTOP	RTOP	DTOP	TPTOP	HSBOT	BBOT	TBOT	RBOT	DBOT	TPBOT
Vasicek	2838	329	132	114	551	202	124	288	149	115	537	210	87
(↗) MA	1138	161	99	15	277	181	110	78	7	53	157	0	0
(↘) MA	1249	95	5	43	139	1	2	158	121	21	368	184	112
Canada, All Maturities													
Actual	2810	308	115	142	510	190	93	300	129	132	562	203	126
Vasicek	2728	303	160	129	478	238	109	285	158	138	432	213	85
(↗) MA	1248	160	104	37	320	190	92	91	9	88	157	0	0
(↘) MA	1562	148	11	105	190	0	1	209	120	44	405	203	126
Hong Kong, All Maturities													
Actual	1256	109	61	85	207	85	45	140	59	69	237	112	47
Vasicek	731	48	100	80	59	57	16	56	97	88	54	58	18
(↗) MA	537	52	58	28	112	85	45	40	5	45	67	0	0
(↘) MA	719	57	3	57	95	0	0	100	54	24	170	112	47
Short Maturity Yields (1-, 2- and 3-year)													
Actual	7745	769	371	365	1404	561	275	807	415	351	1572	547	308
Vasicek	9333	906	558	472	1656	647	355	970	557	484	1660	718	350
(↗) MA	3579	442	333	123	859	559	269	267	34	230	460	0	3
(↘) MA	4166	327	38	242	545	2	6	540	381	121	1112	547	305
Medium Maturity Yields (5- and 7-year)													
Actual	7626	836	264	328	1461	505	282	805	331	292	1636	559	327
Vasicek	8989	980	503	383	1682	640	340	933	514	380	1621	696	317
(↗) MA	3516	511	236	99	923	505	282	267	27	187	478	0	1
(↘) MA	4110	325	28	229	538	0	0	538	304	105	1158	559	326
Long Maturity Yields (10- and 30-year)													
Actual	5963	692	196	200	1151	417	261	603	252	191	1254	479	267
Vasicek	6856	759	319	272	1355	437	273	736	314	275	1387	497	232
(↗) MA	2815	415	181	65	744	415	259	200	14	120	402	0	0
(↘) MA	3148	277	15	135	407	2	2	403	238	71	852	479	267

Figure 3.9: Illustrations of the Distribution of Chart Patterns



(a) US Bond Market



(b) Japan Bond Market

Table 3.4: Summary Statistics of Unconditional and Conditional Bond Returns (Nadaraya-Watson Kernel Regression). Row 1-4 are the first four moments of the normalized conditional mean return. Column 5 and 6 are the normalized mean return from above/below the 45-day Moving Average indicator. Column 3-14 are the 12 chart patterns.

Statistics	Unconditional Returns	HSTOP	BTOP	TTOP	RTOP	DTOP	TPTOP	HSBOT	BBOT	TBOT	RBOT	DBOT	TPBOT
						All Bond Yields							
Mean	0.000	0.051*	-0.006	0.112*	0.068*	-0.037	-0.039	-0.059*	0.067*	-0.155*	-0.023*	0.005	-0.001
S.D.	1.00000	0.920	1.033	0.847	0.837	0.839	0.957	0.869	0.958	1.003	0.802	0.866	0.775
Skew.	-0.1375	-0.852	-0.922	-0.218	-0.448	-1.114	-2.198	0.142	0.668	-0.675	-0.172	0.728	-0.641
Kurtosis	17.4359	18.010	10.670	3.073	8.411	9.705	19.560	6.088	10.640	5.028	3.340	10.800	4.117
$(\nearrow)$ MA	0.0000	0.055*	-0.013	0.145*	0.044*	-0.038	-0.047	-0.095*	0.342*	-0.221*	-0.052*	-	0.618
$(\searrow)$ MA	0.0000	0.044	0.050	0.097*	0.108*	0.447	0.739	-0.042	0.046	-0.037	-0.011	0.005	-0.004
						US, All Maturities							
Mean	0.0000	0.093*	-0.011	0.117*	0.097*	-0.068*	-0.172*	-0.040	0.008	-0.221*	-0.021	-0.123*	-0.093
S.D.	1.0000	1.081	1.054	0.872	0.877	0.843	0.963	0.815	0.970	1.040	0.771	0.851	0.775
Skew.	0.2348	-1.712	0.608	0.158	-0.108	-2.525	-2.795	0.147	-0.651	-1.176	-0.274	-0.186	-1.575
Kurtosis	10.3536	26.690	8.066	3.008	10.640	20.500	21.260	2.464	4.540	5.101	4.406	6.607	8.994
$(\nearrow)$ MA	0.0000	0.0961	-0.006	0.117	0.075*	-0.069*	-0.177*	-0.037	0.419	-0.311*	-0.012	-	0.001
$(\searrow)$ MA	0.0000	0.0879	-0.067	0.117	0.132*	0.130	0.167*	-0.042	-0.035	-0.084	-0.026	-0.123*	-0.094*
						UK; All Maturities							
Mean	0.0000	0.092*	0.155	0.118	0.112*	0.154*	0.112	-0.087*	0.117	-0.183	-0.067*	0.060	0.034
S.D.	1.0000	0.817	1.080	0.984	0.894	0.864	0.706	0.762	0.841	1.193	0.807	0.823	0.795
Skew.	0.1680	-0.143	-4.025	0.163	-1.010	0.783	-0.156	-0.316	0.569	-1.882	-0.236	0.469	0.139
Kurtosis	7.4571	1.545	28.080	1.254	9.450	1.830	0.785	1.487	0.975	5.151	2.269	1.860	0.314
$(\nearrow)$ MA	0.0000	0.070	0.144	0.445*	0.088*	0.154*	0.110	-0.133*	-0.355*	-0.373*	-0.139*	-	-0.016
$(\searrow)$ MA	0.0000	0.131*	0.286	-0.035	0.155*	-	0.276	-0.060	0.136	0.122	-0.038	0.060	0.035
						Germany, All Maturities							
Mean	0.0000	-0.009	0.067	0.119*	0.004	-0.185*	-0.096	-0.152*	-0.008	-0.130	-0.020	0.063	-0.023

continued next page

(*continued*)

Statistics	Unconditional Returns	HSTOP	BTOP	TTOP	RTOP	DTOP	TPTOP	HSBOT	BBOT	TBOT	RBOT	DBOT	TPBOT
S.D.	1.0000	0.849	0.957	0.704	0.770	0.927	0.981	0.888	0.934	0.805	0.778	0.787	0.747
Skew.	-0.3819	-0.256	-0.988	0.008	-0.382	-0.667	0.085	-1.136	0.472	-0.606	-0.202	-0.083	-0.438
Kurtosis	19.7031	5.010	4.171	0.294	3.289	2.164	0.314	6.076	1.716	1.092	2.062	1.804	1.890
(↗) MA	0.0000	-0.035	0.094	0.294*	-0.037	-0.185*	-0.096	-0.245*	0.424	-0.202*	-0.050	-	-
(↘) MA	0.0000	0.036	-0.040	0.052	0.062	-	-	-0.109	-0.046	0.035	-0.008	0.063	-0.023
Japan, All Maturities													
Mean	0.0000	0.036	0.010	0.067	-0.018	-0.058	-0.261	0.092	0.074	-0.029	-0.077	0.009	0.242
S.D.	1.0000	0.827	1.017	0.790	0.711	0.726	1.852	1.063	0.752	0.912	0.619	0.681	0.816
Skew.	-0.5683	-0.109	-0.471	-0.732	-1.164	0.117	-3.261	4.736	0.094	1.311	-0.147	-0.546	-1.270
Kurtosis	10.1088	3.031	1.471	2.786	7.016	0.070	13.610	32.500	0.094	6.551	2.879	2.469	3.605
(↗) MA	0.0000	0.001	0.038	0.108	-0.021	-0.078	-0.261	-0.159	0.516*	0.086	-0.212*	-	1.244*
(↘) MA	0.0000	0.079	-0.398	0.043	-0.013	0.606	-	0.200	0.047	-0.235	-0.018	0.009	0.151
Australia, All Maturities													
Mean	0.0000	-0.041	-0.087	0.149	0.048	0.009	0.136	0.045	0.076	-0.144	0.090*	0.070	0.136
S.D.	1.0000	0.860	0.836	1.085	0.843	0.900	0.943	1.020	1.007	0.986	0.936	0.776	0.901
Skew.	-0.3079	0.474	0.038	-0.382	-0.887	-0.862	0.076	0.179	-1.117	0.378	0.125	-0.472	0.042
Kurtosis	5.5083	5.104	0.338	1.875	6.016	3.381	3.522	1.062	4.642	2.559	3.084	2.391	1.453
(↗) MA	0.0000	-0.077	-0.104	0.386	-0.003	0.009	0.095	0.027	-0.012	-0.244	0.026	-	-
(↘) MA	0.0000	0.023	0.302	0.065	0.153*	-	2.011	0.054	0.079	0.108	0.117*	0.070	0.136
Canada, All Maturities													
Mean	0.0000	0.037	-0.061	0.015	0.053	-0.055	0.055	-0.154*	0.153*	-0.063	-0.076*	0.039	-0.028
S.D.	1.0000	0.883	1.220	0.747	0.805	0.760	0.758	0.978	0.869	0.876	0.884	1.007	0.723
Skew.	-0.2826	0.303	-1.686	-1.357	-0.192	-0.423	-0.108	-0.460	0.133	0.523	-0.168	0.059	-0.893
Kurtosis	6.9883	1.172	11.710	8.908	4.517	3.344	1.916	1.680	1.742	2.651	2.529	1.407	1.461
(↗) MA	0.0000	0.157*	-0.089	-0.127	0.063	-0.055	0.051	-0.224*	0.349	-0.115	-0.016	-	-
(↘) MA	0.0000	-0.089	0.166	0.061	0.036	-	0.373	-0.126	0.137	0.036	-0.099	0.039	-0.028
Hong Kong, All Maturities													

continued next page

(*continued*)

Statistics	Unconditional Returns	HSTOP	BTOP	TTOP	RTOP	DTOP	TPTOP	HSBOT	BBOT	TBOT	RBOT	DBOT	TPBOT
Mean	0.0000	0.075	-0.179	0.280	0.042	-0.008	0.078	0.074	0.195	-0.249	0.033	0.151	0.089
S.D.	1.0000	0.521	0.894	0.786*	0.664	0.612	0.547	0.651	1.474	1.127	0.564	1.095	0.506
Skew.	-0.9280	0.727	0.411	-0.999	-0.407	0.238	0.600	0.490	4.141	0.815	-1.261	5.542	0.690
Kurtosis	110.0890	1.262	3.232	1.926	3.879	1.299	2.978	3.384	22.040	3.832	5.863	41.360	0.753
(↗) MA	0.0000	0.183*	-0.233*	-0.157	-0.025	-0.008	0.078	0.215*	0.623*	-0.209	-0.127	-	-
(↘) MA	0.0000	-0.034	0.489	0.484*	0.129*	-	-	0.026	0.154	-0.314	0.103*	0.151	0.089
Short Maturity Yields (1-, 2- and 3-year)													
Mean	0.0000	0.009	0.041	0.093*	0.052*	-0.003	0.067	-0.089*	0.065	-0.111*	-0.012	-0.027	-0.038
S.D.	1.0000	0.960	1.089	0.810	0.718	0.798	0.872	0.836	1.000	0.924	0.719	0.907	0.730
Skew.	-0.2170	-2.458	-0.508	-0.132	-0.101	-0.350	0.220	-0.183	1.499	-0.463	0.233	1.801	-1.380
Kurtosis	19.1048	39.800	10.640	5.538	6.144	5.373	2.636	5.334	18.770	5.323	2.588	23.380	12.460
(↗) MA	0.0000	0.029	0.036	0.052	0.024	-0.004	0.047	-0.104*	0.206	-0.152	-0.083	-	0.418
(↘) MA	0.0000	-0.019	0.082	0.111*	0.095*	0.130	0.816	-0.081*	0.052	-0.040	0.018	-0.027	-0.042
Medium Maturity Yields (5- and 7-year)													
Mean	0.0000	0.101*	-0.047	0.100*	0.069*	-0.048	-0.077	-0.038	0.073	-0.181*	-0.031	0.017	0.055
S.D.	1.0000	0.851	0.954	0.919	0.888	0.883	1.127	0.915	0.889	1.005	0.829	0.815	0.746
Skew.	-0.0893	0.633	-2.573	-0.358	-1.094	-2.270	-3.969	0.639	-0.268	-0.524	-0.203	0.186	-0.288
Kurtosis	22.7280	3.747	17.680	2.204	12.540	18.180	27.880	9.303	4.142	3.670	4.213	1.297	1.436
(↗) MA	0.0000	0.119*	-0.052	0.090	0.064*	-0.048	-0.077	-0.116*	0.764*	-0.257*	-0.054	-	0.818
(↘) MA	0.0000	0.072	-0.006	0.104*	0.077*	-	-	-0.000	0.028	-0.041	-0.022	0.017	0.050
Long Maturity Yields (10- and 30-year)													
Mean	0.0000	0.037	-0.040	0.171*	0.088*	-0.068	-0.117*	-0.049	0.064	-0.198*	-0.027	0.026	-0.029
S.D.	1.0000	0.950	1.029	0.783	0.907	0.839	0.830	0.848	0.977	1.136	0.859	0.876	0.849
Skew.	-0.0687	-0.221	-0.132	0.048	0.130	-0.327	-0.226	-0.290	0.051	-0.978	-0.407	-0.143	-0.412
Kurtosis	6.8821	2.342	3.065	-0.259	3.355	1.377	0.893	0.930	0.681	5.360	2.443	2.288	0.848
(↗) MA	0.0000	0.005	-0.049	0.419*	0.042	-0.072	-0.119*	-0.055	0.121	-0.293*	-0.015	-	-
(↘) MA	0.0000	0.083	0.080	0.059	0.167*	0.606	0.276	-0.047	0.061	-0.025	-0.032	0.026	-0.029

Table 3.5: Summary Statistics of Unconditional and Conditional Bond Return (Local Polynomial Kernel Regression)

Statistics	Unconditional Returns	HSTOP	BTOP	TTOP	RTOP	DTOP	TPTOP	HSBOT	BBOT	TBOT	RBOT	DBOT	TPBOT
						All Bond Yields							
Mean	0.0000	0.063*	0.017	0.110*	0.064*	-0.022	-0.023	-0.044*	0.045	-0.096*	-0.015	0.007	-0.004
S.D.	1.0000	0.919	1.043	0.823	0.847	0.859	0.949	0.861	0.959	0.965	0.811	0.848	0.779
Skew.	-0.1375	-1.016	-0.910	-0.019	-0.728	-0.907	-2.109	0.174	0.542	-0.222	-0.042	0.772	0.238
Kurtosis	17.4359	18.730	9.478	2.754	10.410	7.920	18.350	5.720	8.944	4.418	3.623	10.750	4.652
(↗) MA	0.0000	0.065*	0.018	0.129*	0.041*	-0.023	-0.029	-0.072*	0.261*	-0.166*	-0.042*	-	0.538
(↘) MA	0.0000	0.060*	0.003	0.101*	0.102*	0.330	0.665	-0.030	0.028	0.030	-0.004	0.007	-0.006
						US, All Maturities							
Mean	0.0000	0.099*	-0.015	0.112*	0.073*	-0.062*	-0.145*	-0.022	-0.011	-0.123*	-0.009	-0.109*	-0.069
S.D.	1.0000	1.097	1.024	0.836	0.897	0.813	0.992	0.810	0.958	0.922	0.788	0.854	0.799
Skew.	0.2348	-1.940	0.472	0.143	-1.031	-2.266	-2.898	0.199	-0.232	-0.520	0.067	0.435	1.000
Kurtosis	10.3536	26.010	7.112	3.132	16.170	19.510	19.580	2.891	4.515	2.041	4.915	9.464	10.620
(↗) MA	0.0000	0.093	-0.002	0.066	0.050	-0.062*	-0.149*	-0.003	0.492*	-0.239*	-0.006	-	-0.168
(↘) MA	0.0000	0.109*	-0.131	0.137*	0.112*	0.130	0.162*	-0.032	-0.060	0.049	-0.011	-0.109*	-0.068
						UK, All Maturities							
Mean	0.0000	0.082*	0.236*	0.076	0.097*	0.127*	0.097	-0.039	0.061	-0.177*	-0.094*	0.032	-0.056
S.D.	1.0000	0.815	1.069	0.919	0.868	0.912	0.700	0.780	0.929	1.127	0.801	0.768	0.805
Skew.	0.1680	-0.397	-3.076	0.190	-0.903	0.161	-0.112	-0.087	0.220	-1.585	-0.452	0.414	0.039
Kurtosis	7.4571	2.230	24.320	1.589	8.487	1.791	0.397	0.985	3.083	4.956	2.558	2.103	0.315
(↗) MA	0.0000	0.054	0.228*	0.377*	0.082*	0.127*	0.095	-0.134*	-0.478*	-0.323*	-0.127*	-	-
(↘) MA	0.0000	0.129*	0.325*	-0.071	0.123*	-	0.276	0.013	0.084	0.088	-0.081*	0.032	-0.056
						Germany, All Maturities							
Mean	0.0000	0.026	0.029	0.110	0.021	-0.158*	-0.058	-0.105*	-0.034	-0.132	0.014	0.050	0.046
S.D.	1.0000	0.845	1.099	0.738	0.766	0.904	0.937	0.891	0.955	0.826	0.805	0.768	0.766
Skew.	-0.3819	-0.170	-1.731	0.179	-0.193	-0.625	0.038	-0.907	0.288	-0.353	-0.112	-0.363	-0.305

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(*continued*)

Statistics	Unconditional Returns	HSTOP	BTOP	TTOP	RTOP	DTOP	TPTOP	HSBOT	BBOT	TBOT	RBOT	DBOT	TPBOT
Kurtosis	19.7031	4.220	8.987	1.398	3.667	1.912	0.332	5.702	1.202	1.000	2.195	0.884	1.670
(↗) MA	0.0000	0.021	0.073	0.129	-0.025	-0.158*	-0.058	-0.186*	0.345	-0.194*	-0.041	-	-
(↘) MA	0.0000	0.032	-0.149	0.102	0.094*	-	-	-0.067	-0.070	-0.001	0.038	0.050	0.046
Japan, All Maturities													
Mean	0.0000	0.004	0.120	0.091	-0.001	-0.013	-0.279	0.081	0.017	0.036	-0.055	-0.006	0.161
S.D.	1.0000	0.770	1.051	0.728	0.694	0.756	1.653	0.941	0.800	0.872	0.612	0.740	0.750
Skew.	-0.5684	-0.044	-0.217	-0.584	-0.844	-0.399	-3.635	4.872	-0.469	1.067	-0.145	-0.742	-1.000
Kurtosis	10.1088	3.366	1.207	3.421	6.703	0.645	17.310	38.650	1.532	5.774	2.629	2.246	3.487
(↗) MA	0.0000	-0.023	0.127	0.098	0.038	-0.027	-0.279	-0.099	0.092	0.103	-0.186*	-	1.244*
(↘) MA	0.0000	0.046	0.015	0.086	-0.059	0.606	-	0.173	0.010	-0.078	0.006	-0.006	0.088
Australia, All Maturities													
Mean	0.0000	-0.047	-0.067	0.241	0.091*	0.022	0.175*	-0.013	0.064	-0.043	0.106*	0.121*	0.144
S.D.	1.0000	0.801	0.939	1.120	0.900	1.055	0.972	1.028	0.959	1.102	0.945	0.812	0.870
Skew.	-0.3079	0.467	-0.482	0.086	-0.453	-0.501	0.221	0.451	-1.231	1.275	0.065	-0.113	-0.074
Kurtosis	5.5083	5.570	1.931	1.881	4.632	3.295	3.025	1.737	5.088	5.388	2.557	2.930	1.413
(↗) MA	0.0000	-0.100	-0.098	0.653	0.055	0.022	0.142	0.016	-0.249	-0.111	0.048	-	-
(↘) MA	0.0000	0.042	0.540	0.097	0.161*	-0.022	2.011	-0.027	0.082	0.129	0.131*	0.121*	0.144
Canada, All Maturities													
Mean	0.0000	0.098*	-0.040	0.027	0.044	0.006	0.087	-0.125*	0.192*	-0.046	-0.064*	0.086	-0.030
S.D.	1.0000	0.904	1.164	0.726	0.830	0.807	0.782	0.954	0.906	0.835	0.879	0.978	0.700
Skew.	-0.2826	0.515	-1.595	-0.638	-0.247	-0.320	0.273	-0.574	0.306	0.505	0.210	0.038	-0.590
Kurtosis	6.9883	1.941	11.530	3.501	3.878	3.087	2.365	2.304	1.409	2.792	3.517	1.439	1.512
(↗) MA	0.0000	0.227*	-0.049	-0.057	0.028	0.006	0.084	-0.192*	0.366	-0.078	-0.022	-	-
(↘) MA	0.0000	-0.043	0.044	0.057	0.070	-	0.373	-0.097	0.179*	0.016	-0.080*	0.086	-0.030
Hong Kong, All Maturities													
Mean	0.0000	0.087*	-0.155	0.224*	0.039	-0.007	0.040	-0.007	0.165	-0.089	0.030	0.080	0.073
S.D.	1.0000	0.509	0.837	0.738	0.645	0.571	0.457	0.648	1.325	1.114	0.564	0.979	0.485
Skew.	-0.9280	0.574	0.348	-0.861	-0.517	0.072	-0.196	0.113	4.464	0.732	-1.032	6.029	0.776

continued next page

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Statistics	Unconditional Returns	HSTOP	BTOP	TTOP	RTOP	DTOP	TPTOP	HSBOT	BBOT	TBOT	RBOT	DBOT	TPBOT
Kurtosis	110.0890	0.831	3.959	1.920	3.851	1.535	1.661	3.345	27.020	3.325	5.430	51.160	1.105
$(\nearrow)$ MA	0.0000	0.172*	-0.175	-0.059	0.005	-0.007	0.040	0.084	0.535*	-0.104	-0.110	-	-
$(\searrow)$ MA	0.0000	0.009	0.245	0.363*	0.080	-	-	-0.044	0.131	-0.060	0.086*	0.080	0.073
Short Maturity Yields (1-, 2- and 3-year)													
Mean	0.0000	0.001	0.037	0.064	0.036*	-0.006	0.051	-0.061*	0.059	-0.081	-0.007	-0.005	0.016
S.D.	1.0000	0.981	1.016	0.794	0.757	0.836	0.843	0.833	0.966	0.915	0.760	0.896	0.736
Skew.	-0.2170	-2.689	-0.478	-0.282	-1.339	-0.351	0.131	0.070	1.189	0.015	0.294	2.053	1.761
Kurtosis	19.1048	38.480	10.850	5.818	17.650	4.824	2.680	5.511	17.200	6.803	4.544	22.760	14.150
$(\nearrow)$ MA	0.0000	0.012	0.033	0.032	-0.004	-0.006	0.033	-0.082*	0.132	-0.128*	-0.089*	-	0.167
$(\searrow)$ MA	0.0000	-0.014	0.072	0.081	0.099*	0.054	0.816	-0.051	0.052	0.010	0.028	-0.005	0.014
Medium Maturity Yields (5- and 7-year)													
Mean	0.0000	0.128*	0.048*	0.121	0.075*	-0.010	-0.054	-0.009	0.050	-0.107*	-0.015	-0.024	0.007
S.D.	1.0000	0.841	1.047	0.868	0.883	0.886	1.130	0.908	0.918	0.995	0.825	0.798	0.755
Skew.	-0.0893	0.628	-2.042	0.051	-1.116	-1.795	-3.586	0.526	0.214	-0.401	-0.020	0.090	-0.277
Kurtosis	22.7280	3.511	14.140	0.892	12.230	14.800	24.500	8.138	4.561	3.145	3.902	1.426	1.239
$(\nearrow)$ MA	0.0000	0.143*	0.063	0.105	0.074*	-0.010	-0.054	-0.072	0.445*	-0.189*	-0.030	-	1.652
$(\searrow)$ MA	0.0000	0.105*	-0.076	0.127*	0.075*	-	-	0.022	0.015	0.039	-0.009	-0.024	0.002
Long Maturity Yields (10- and 30-year)													
Mean	0.0000	0.054	-0.064	0.176*	0.083*	-0.058	-0.066	-0.067*	0.016	-0.109	-0.027	0.056	-0.041
S.D.	1.0000	0.935	1.090	0.799	0.902	0.858	0.831	0.833	1.003	1.010	0.853	0.846	0.854
Skew.	-0.0686	-0.244	-0.202	0.290	0.158	-0.415	-0.173	-0.328	-0.074	-0.270	-0.358	-0.311	-0.422
Kurtosis	6.88212	2.439	2.411	1.186	3.086	2.248	1.578	1.026	0.989	3.048	2.378	1.990	0.693
$(\nearrow)$ MA	0.0000	0.026	-0.067	0.349*	0.051	-0.061	-0.068	-0.059	0.223	-0.203*	-0.003	-	-
$(\searrow)$ MA	0.0000	0.096*	-0.026	0.093	0.143*	0.606	0.211*	-0.071	0.004	0.050	-0.038	0.056	-0.041

Table 3.6: Goodness-of-Fit Chi-Square Tests and Kolmogorov-Smirnov Distribution Tests (Nadaraya-Watson Kernel Regression). **Panel A**: Column 2-11 are the 10 deciles of the sorted normalized returns for each chart pattern, in percentage term. The null hypothesis is 10% for each decile. The last column is the Q-Statistic. Below the percentage result is the associated p-value for each of the ten deciles. **Panel B**: The γ statistic is the Kolmogorov-Smirnov statistic, tabulated for each chart pattern. Below the γ statistic is the associated p-value.

Panel A: Goodness-of-Fit Test											
Chart	Deciles										
Patterns	1	2	3	4	5	6	7	8	9	10	Q-Statistic
HSTOP	7.88	9.94	9.45	10.80	8.96	9.67	11.00	11.10	11.70	9.51	22.20
(p-value)	(-3.04)	(-0.09)	(-0.78)	(1.08)	(-1.48)	(-0.47)	(1.47)	(1.55)	(2.48)	(-0.71)	(0.008)
BTOP	9.62	8.83	12.00	11.50	7.89	9.15	9.94	10.10	10.60	10.40	8.52
(p-value)	(-0.32)	(-0.98)	(1.67)	(1.27)	(-1.77)	(-0.71)	(-0.05)	(0.08)	(0.48)	(0.34)	(0.482)
TTOP	6.93	8.29	9.24	10.50	8.70	11.10	8.56	13.50	11.50	11.70	26.00
(p-value)	(-2.78)	(-1.55)	(-0.69)	(0.42)	(-1.18)	(1.03)	(-1.30)	(3.12)	(1.40)	(1.52)	(0.002)
RTOP	6.50	8.28	10.10	11.70	9.38	11.80	10.90	11.30	11.30	8.84	86.50
(p-value)	(-6.60)	(-3.24)	(0.12)	(3.12)	(-1.18)	(3.36)	(1.71)	(2.53)	(2.36)	(-2.18)	(0.000)
DTOP	8.57	10.70	10.40	12.00	9.84	11.20	9.75	10.00	9.50	8.06	14.30
(p-value)	(-1.64)	(0.79)	(0.50)	(2.24)	(-0.18)	(1.37)	(-0.28)	(0.01)	(-0.57)	(-2.22)	(0.113)
TPTOP	9.61	10.40	9.15	9.92	11.00	12.60	8.99	10.20	9.61	8.53	7.73
(p-value)	(-0.33)	(0.33)	(-0.72)	(-0.07)	(0.85)	(2.17)	(-0.85)	(0.20)	(-0.33)	(-1.25)	(0.438)
HSBOT	10.10	11.20	10.60	10.40	10.30	10.70	10.80	9.49	8.69	7.78	17.60
(p-value)	(0.16)	(1.67)	(0.79)	(0.56)	(0.40)	(0.95)	(1.11)	(-0.72)	(-1.83)	(-3.10)	(0.041)
BBOT	9.20	9.20	9.59	10.20	9.33	8.67	10.40	11.40	11.00	10.90	5.85
(p-value)	(-0.74)	(-0.74)	(-0.37)	(0.23)	(-0.62)	(-1.22)	(0.35)	(1.32)	(0.95)	(0.83)	(0.255)
TBOT	13.80	11.70	11.10	9.01	11.00	9.16	6.16	10.10	11.00	7.06	30.40
(p-value)	(3.28)	(1.47)	(0.96)	(-0.85)	(0.83)	(-0.72)	(-3.31)	(0.05)	(0.83)	(-2.53)	(0.000)
RBOT	7.85	10.50	11.00	12.10	10.20	10.10	11.30	10.60	9.07	7.18	75.50
(p-value)	(-4.26)	(0.94)	(2.06)	(4.24)	(0.38)	(0.16)	(2.67)	(1.28)	(-1.86)	(-5.60)	(0.000)
DBOT	9.05	9.46	11.00	12.40	9.22	10.00	9.78	10.90	9.14	8.97	14.20

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(p-value)	(-1.11)	(-0.63)	(1.17)	(2.87)	(-0.92)	(0.03)	(-0.26)	(1.07)	(-1.01)	(-1.20)	(0.116)	
TPBOT	6.99	8.25	11.20	13.40	9.79	12.00	11.30	8.25	10.60	8.11	27.30	
(p-value)	(-2.68)	(-1.56)	(1.06)	(3.05)	(-0.19)	(1.81)	(1.18)	(-1.56)	(0.56)	(-1.68)	(0.001)	

Panel B: Kolmogorov-Smirnov Test

Statistics	HSTOP	BTOP	TTOP	RTOP	DTOP	TPTOP	HSBOT	BBOT	TBOT	RBOT	DBOT	TPBOT
						All Bond Yields						
γ	1.206	0.319	1.292	2.689	0.821	0.535	1.544	0.378	1.334	1.866	0.652	0.649
(p-value)	(0.109)	(1.000)	(0.071)	(0.000)	(0.510)	(0.937)	(0.017)	(0.999)	(0.057)	(0.002)	(0.789)	(0.793)
γ (↗) MA	1.096	0.214	1.024	1.577	0.839	0.661	2.248	1.292	1.809	1.608	-99.000	0.499
(p-value)	(0.181)	(1.000)	(0.245)	(0.014)	(0.483)	(0.774)	(0.000)	(0.071)	(0.003)	(0.011)	(0.000)	(0.965)
γ (↘) MA	1.144	0.381	0.860	2.222	-99.000	1.185	0.597	0.292	0.427	1.484	0.652	0.646
(p-value)	(0.146)	(0.999)	(0.450)	(0.000)	(0.000)	(0.120)	(0.869)	(1.000)	(0.993)	(0.024)	(0.789)	(0.798)
						US, All Maturities						
γ	1.640	0.358	0.609	2.150	0.553	0.838	0.686	0.237	0.790	1.136	1.047	0.859
(p-value)	(0.009)	(1.000)	(0.852)	(0.000)	(0.919)	(0.483)	(0.735)	(1.000)	(0.561)	(0.151)	(0.223)	(0.452)
γ (↗) MA	1.307	0.357	0.923	1.576	0.547	0.815	1.286	0.921	1.204	1.383	-99.000	-99.000
(p-value)	(0.066)	(1.000)	(0.362)	(0.014)	(0.926)	(0.519)	(0.073)	(0.364)	(0.110)	(0.044)	(0.000)	(0.000)
γ (↘) MA	0.960	0.401	0.572	1.117	-99.000	-99.000	0.371	0.444	0.475	1.112	1.047	0.850
(p-value)	(0.315)	(0.997)	(0.899)	(0.165)	(0.000)	(0.000)	(0.999)	(0.989)	(0.978)	(0.169)	(0.223)	(0.465)
						UK, All Maturities						
γ	0.893	0.877	0.509	1.151	0.496	0.715	1.002	0.504	0.477	1.364	0.280	0.402
(p-value)	(0.402)	(0.425)	(0.958)	(0.141)	(0.966)	(0.685)	(0.268)	(0.961)	(0.977)	(0.048)	(1.000)	(0.997)
γ (↗) MA	0.569	0.792	0.582	0.623	0.496	0.704	1.400	0.256	0.778	1.420	-99.000	-99.000
(p-value)	(0.903)	(0.557)	(0.887)	(0.833)	(0.966)	(0.704)	(0.040)	(1.000)	(0.580)	(0.036)	(0.000)	(0.000)
γ (↘) MA	0.793	0.332	0.268	1.442	-99.000	-99.000	0.452	0.542	0.379	0.689	0.280	0.395
(p-value)	(0.556)	(1.000)	(1.000)	(0.031)	(0.000)	(0.000)	(0.987)	(0.931)	(0.999)	(0.729)	(1.000)	(0.998)
						Germany, All Maturities						
γ	0.944	0.477	0.789	1.075	1.102	0.654	1.317	0.741	0.607	1.236	0.242	0.474
(p-value)	(0.335)	(0.977)	(0.562)	(0.198)	(0.176)	(0.786)	(0.062)	(0.642)	(0.855)	(0.094)	(1.000)	(0.978)
γ (↗) MA	0.920	0.562	0.327	0.944	1.102	0.654	1.017	0.516	0.973	0.282	-99.000	-99.000

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(*p*-value)	(0.365)	(0.910)	(1.000)	(0.335)	(0.176)	(0.786)	(0.252)	(0.953)	(0.300)	(1.000)	(0.000)	(0.000)
γ (↘) MA	0.638	0.429	0.554	0.994	-99.000	-99.000	0.870	0.616	0.326	1.282	0.242	0.474
(*p*-value)	(0.811)	(0.993)	(0.919)	(0.277)	(0.000)	(0.000)	(0.435)	(0.843)	(1.000)	(0.075)	(1.000)	(0.978)
Japan, All Maturities												
γ	0.172	0.735	0.232	0.581	0.377	0.610	0.305	0.200	0.528	1.173	0.325	0.530
(*p*-value)	(1.000)	(0.653)	(1.000)	(0.889)	(0.999)	(0.850)	(1.000)	(1.000)	(0.943)	(0.127)	(1.000)	(0.942)
γ (↗) MA	0.153	0.470	0.339	0.858	0.418	0.610	0.787	0.281	0.230	1.224	-99.000	-99.000
(*p*-value)	(1.000)	(0.980)	(1.000)	(0.454)	(0.995)	(0.850)	(0.566)	(1.000)	(1.000)	(0.100)	(0.000)	(0.000)
γ (↘) MA	0.264	0.751	0.160	0.323	-99.000	-99.000	0.380	0.328	1.097	0.515	0.325	0.467
(*p*-value)	(1.000)	(0.626)	(1.000)	(1.000)	(0.000)	(0.000)	(0.999)	(1.000)	(0.180)	(0.954)	(1.000)	(0.981)
Australia, All Maturities												
γ	0.463	0.821	0.611	1.283	0.429	0.733	0.575	0.689	0.852	0.817	0.686	0.878
(*p*-value)	(0.983)	(0.510)	(0.850)	(0.074)	(0.993)	(0.656)	(0.896)	(0.729)	(0.462)	(0.516)	(0.735)	(0.424)
γ (↗) MA	0.369	0.871	0.363	0.828	0.429	0.677	0.410	0.022	1.082	0.642	-99.000	-99.000
(*p*-value)	(0.999)	(0.433)	(0.999)	(0.500)	(0.993)	(0.750)	(0.996)	(1.000)	(0.193)	(0.805)	(0.000)	(0.000)
γ (↘) MA	0.265	-99.000	0.319	0.535	-99.000	-99.000	0.492	0.765	0.491	1.179	0.686	0.878
(*p*-value)	(1.000)	(0.000)	(1.000)	(0.937)	(0.000)	(0.000)	(0.969)	(0.602)	(0.969)	(0.124)	(0.735)	(0.424)
Canada, All Maturities												
γ	0.199	0.706	0.992	0.647	1.143	0.468	1.048	0.824	0.489	0.929	0.565	0.465
(*p*-value)	(1.000)	(0.701)	(0.279)	(0.797)	(0.146)	(0.981)	(0.222)	(0.506)	(0.971)	(0.354)	(0.907)	(0.982)
γ (↗) MA	0.876	0.747	0.478	0.553	1.143	0.452	1.002	0.409	0.659	0.617	-99.000	-99.000
(*p*-value)	(0.427)	(0.632)	(0.976)	(0.919)	(0.146)	(0.987)	(0.268)	(0.996)	(0.777)	(0.841)	(0.000)	(0.000)
γ (↘) MA	0.686	0.290	0.766	0.740	-99.000	-99.000	0.762	0.898	0.626	0.681	0.565	0.465
(*p*-value)	(0.734)	(1.000)	(0.600)	(0.644)	(0.000)	(0.000)	(0.607)	(0.396)	(0.828)	(0.743)	(0.907)	(0.982)
Hong Kong, All Maturities												
γ	0.564	0.773	1.228	0.307	0.450	0.508	0.470	0.494	1.386	1.142	0.469	0.413
(*p*-value)	(0.908)	(0.589)	(0.098)	(1.000)	(0.987)	(0.958)	(0.980)	(0.968)	(0.043)	(0.147)	(0.980)	(0.996)
γ (↗) MA	0.523	1.032	0.761	0.134	0.450	0.508	0.761	0.361	1.091	0.449	-99.000	-99.000
(*p*-value)	(0.947)	(0.237)	(0.609)	(1.000)	(0.987)	(0.958)	(0.608)	(0.999)	(0.185)	(0.988)	(0.000)	(0.000)
γ (↘) MA	0.571	0.447	2.025	0.683	-99.000	-99.000	0.478	0.656	0.763	1.215	0.469	0.413

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(p-value)	(0.900)	(0.988)	(0.001)	(0.740)	(0.000)	(0.000)	(0.976)	(0.782)	(0.606)	(0.105)	(0.980)	(0.996)
Short Maturity Yields (1-, 2- and 3-year)												
γ	0.615	0.207	0.896	2.146	0.651	0.537	1.052	0.339	0.758	1.152	0.750	0.830
(p-value)	(0.844)	(1.000)	(0.399)	(0.000)	(0.790)	(0.935)	(0.218)	(1.000)	(0.613)	(0.141)	(0.628)	(0.496)
γ (↗) MA	0.391	0.258	0.136	1.201	0.643	0.407	1.274	0.453	0.646	1.474	-99.000	-99.000
(p-value)	(0.998)	(1.000)	(1.000)	(0.112)	(0.802)	(0.996)	(0.078)	(0.986)	(0.798)	(0.026)	(0.000)	(0.000)
γ (↘) MA	0.695	0.324	0.716	1.522	-99.000	1.064	0.578	0.302	0.527	0.825	0.750	0.881
(p-value)	(0.719)	(1.000)	(0.685)	(0.019)	(0.000)	(0.208)	(0.893)	(1.000)	(0.944)	(0.505)	(0.628)	(0.419)
Medium Maturity Yields (5- and 7-year)												
γ	1.150	0.348	0.756	1.643	0.711	0.492	0.499	0.347	1.314	1.135	0.343	1.051
(p-value)	(0.142)	(1.000)	(0.617)	(0.009)	(0.693)	(0.969)	(0.965)	(1.000)	(0.063)	(0.152)	(1.000)	(0.219)
γ (↗) MA	0.868	0.410	0.569	1.301	0.711	0.492	1.214	1.359	1.341	0.881	-99.000	-99.000
(p-value)	(0.439)	(0.996)	(0.902)	(0.068)	(0.693)	(0.969)	(0.105)	(0.050)	(0.055)	(0.420)	(0.000)	(0.000)
γ (↘) MA	0.852	0.211	0.446	1.232	-99.000	-99.000	0.466	0.242	0.470	0.805	0.343	1.032
(p-value)	(0.462)	(1.000)	(0.988)	(0.096)	(0.000)	(0.000)	(0.982)	(1.000)	(0.980)	(0.536)	(1.000)	(0.238)
Long Maturity Yields (10- and 30-year)												
γ	1.128	0.339	0.802	1.078	0.777	0.816	0.628	0.464	0.648	0.963	0.346	0.520
(p-value)	(0.157)	(1.000)	(0.541)	(0.195)	(0.583)	(0.518)	(0.826)	(0.982)	(0.794)	(0.312)	(1.000)	(0.950)
γ (↗) MA	0.335	0.362	1.492	0.613	0.797	0.797	0.909	0.402	0.919	0.395	-99.000	-99.000
(p-value)	(1.000)	(0.999)	(0.023)	(0.846)	(0.549)	(0.550)	(0.380)	(0.997)	(0.367)	(0.998)	(0.000)	(0.000)
γ (↘) MA	1.181	0.111	0.412	1.266	-99.000	-99.000	0.436	0.411	0.408	0.866	0.346	0.520
(p-value)	(0.123)	(1.000)	(0.996)	(0.081)	(0.000)	(0.000)	(0.991)	(0.996)	(0.996)	(0.442)	(1.000)	(0.950)

Table 3.7: Goodness-of-Fit and Kolmogorov-Smirnov Distribution Tests (Local Polynomial Kernel Regression)

Panel A: Goodness-of-Fit Test

	Deciles										
Patterns	1	2	3	4	5	6	7	8	9	10	Q-Statistic
HSTOP	7.49	9.71	9.53	10.40	9.32	9.75	10.70	11.00	12.50	9.58	34.90
(p-value)	(-4.01)	(-0.47)	(-0.74)	(0.72)	(-1.09)	(-0.40)	(1.13)	(1.55)	(3.99)	(-0.67)	(0.000)
BTOP	9.99	8.42	11.00	11.10	8.30	9.75	10.10	9.39	10.30	11.70	8.96
(p-value)	(-0.01)	(-1.51)	(0.91)	(1.03)	(-1.63)	(-0.24)	(0.10)	(-0.59)	(0.34)	(1.61)	(0.441)
TTOP	6.72	8.40	8.85	10.50	9.41	11.80	8.73	12.90	12.00	10.80	29.30
(p-value)	(-3.27)	(-1.60)	(-1.15)	(0.52)	(-0.59)	(1.75)	(-1.26)	(2.87)	(1.97)	(0.75)	(0.001)
RTOP	6.65	8.22	10.00	11.10	9.56	11.90	11.30	11.30	11.10	8.76	104.00
(p-value)	-7.08)	(-3.77)	(0.02)	(2.39)	(-0.93)	(4.07)	(2.76)	(2.76)	(2.39)	(-2.61)	(0.000)
DTOP	8.70	10.60	10.60	10.60	9.24	10.90	9.78	11.20	10.20	8.16	13.50
(p-value)	(-1.67)	(0.75)	(0.75)	(0.75)	(-0.98)	(1.19)	(-0.29)	(1.53)	(0.32)	(-2.36)	(0.142)
TPTOP	9.17	9.41	9.90	9.78	10.80	11.90	10.10	10.30	9.78	8.92	5.25
(p-value)	(-0.79)	(-0.56)	(-0.09)	(-0.21)	(0.72)	(1.77)	(0.14)	(0.26)	(-0.21)	(-1.03)	(0.188)
HSBOT	9.98	10.90	9.89	11.10	9.62	11.40	10.60	9.62	9.16	7.77	22.70
(p-value)	(-0.04)	(1.38)	(-0.18)	(1.74)	(-0.60)	(2.16)	(0.96)	(-0.60)	(-1.31)	(-3.51)	(0.007)
BBOT	9.52	8.92	9.52	11.40	9.12	8.62	9.82	11.80	11.00	10.20	10.80
(p-value)	(-0.51)	(-1.14)	(-0.51)	(1.50)	(-0.93)	(-1.46)	(-0.19)	(1.92)	(1.08)	(0.23)	(0.291)
TBOT	12.40	11.80	11.00	9.59	9.47	9.71	6.71	10.20	11.50	7.67	23.9
(p-value)	(2.26)	(1.69)	(0.99)	(-0.39)	(-0.51)	(-0.28)	(-3.16)	(0.18)	(1.45)	(-2.24)	(0.004)
RBOT	7.87	10.20	10.80	12.10	10.20	10.40	11.30	10.80	8.92	7.33	92.40
(p-value)	(-4.75)	(0.39)	(1.89)	(4.73)	(0.44)	(0.99)	(2.93)	(1.74)	(-2.41)	(-5.95)	(0.000)
DBOT	8.64	9.53	10.90	12.30	8.96	10.20	10.90	10.50	9.65	8.39	20.80
(p-value)	(-1.80)	(-0.63)	(1.21)	(3.06)	(-1.38)	(0.29)	(1.21)	(0.63)	(-0.46)	(-2.14)	(0.014)
TPBOT	7.87	8.65	11.00	12.10	9.65	12.00	12.00	9.31	9.76	7.76	22.70
(p-value)	(-2.13)	(-1.35)	(0.98)	(2.09)	(-0.36)	(1.98)	(1.98)	(-0.69)	(-0.24)	(-2.24)	(0.007)

Panel B: Kolmogorov-Smirnov Test

continued next page

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Statistics	HSTOP	BTOP	TTOP	RTOP	DTOP	TPTOP	HSBOT	BBOT	TBOT	RBOT	DBOT	TPBOT
						All Bond Yields						
γ	1.645	0.669	1.633	2.345	0.764	0.371	1.531	0.345	1.562	2.192	0.739	0.824
(p-value)	(0.009)	(0.761)	(0.010)	(0.000)	(0.603)	(0.999)	(0.018)	(1.000)	(0.015)	(0.000)	(0.646)	(0.505)
γ (↗) MA	1.384	0.647	1.049	1.457	0.776	0.339	1.345	1.388	1.699	1.766	-99.000	0.262
(p-value)	(0.043)	(0.796)	(0.221)	(0.029)	(0.584)	(1.000)	(0.054)	(0.042)	(0.006)	(0.004)	(0.000)	(1.000)
γ (↘) MA	1.522	0.499	1.066	2.403	0.442	1.315	0.528	0.266	0.946	1.723	0.739	0.847
(p-value)	(0.019)	(0.965)	(0.206)	(0.000)	(0.990)	(0.063)	(0.943)	(1.000)	(0.332)	(0.005)	(0.646)	(0.470)
						US, All Maturities						
γ	1.928	0.157	0.814	1.237	0.728	0.660	0.737	0.262	0.738	1.425	1.169	0.799
(p-value)	(0.001)	(1.000)	(0.522)	(0.094)	(0.665)	(0.777)	(0.649)	(1.000)	(0.647)	(0.034)	(0.130)	(0.547)
γ (↗) MA	1.500	0.162	0.295	0.815	0.727	0.630	1.013	1.179	0.844	1.499	-99.000	-99.000
(p-value)	(0.022)	(1.000)	(1.000)	(0.521)	(0.666)	(0.822)	(0.256)	(0.124)	(0.474)	(0.022)	(0.000)	(0.000)
γ (↘) MA	1.209	0.679	0.682	1.247	-99.000	0.751	0.357	0.484	0.708	1.239	1.169	0.791
(p-value)	(0.107)	(0.745)	(0.740)	(0.089)	(0.000)	(0.625)	(1.000)	(0.973)	(0.698)	(0.093)	(0.130)	(0.559)
						UK, All Maturities						
γ	1.454	1.197	0.219	1.238	0.872	0.630	0.869	0.257	0.781	1.751	0.464	0.468
(p-value)	(0.029)	(0.114)	(1.000)	(0.093)	(0.432)	(0.822)	(0.437)	(1.000)	(0.576)	(0.004)	(0.982)	(0.981)
γ (↗) MA	0.816	1.099	0.732	0.760	0.872	0.620	1.375	0.139	1.083	1.554	-99.000	-99.000
(p-value)	(0.518)	(0.178)	(0.658)	(0.611)	(0.432)	(0.837)	(0.046)	(1.000)	(0.192)	(0.016)	(0.000)	(0.000)
γ (↘) MA	1.308	0.445	0.451	1.055	-99.000	-99.000	0.428	0.461	0.340	1.064	0.464	0.468
(p-value)	(0.065)	(0.989)	(0.987)	(0.216)	(0.000)	(0.000)	(0.993)	(0.984)	(1.000)	(0.208)	(0.982)	(0.981)
						Germany, All Maturities						
γ	0.601	0.518	0.773	1.262	0.982	0.510	1.296	0.416	0.904	1.057	0.329	0.526
(p-value)	(0.862)	(0.951)	(0.589)	(0.083)	(0.290)	(0.957)	(0.069)	(0.995)	(0.387)	(0.214)	(1.000)	(0.945)
γ (↗) MA	0.631	0.529	0.410	1.270	0.982	0.510	0.693	0.652	1.134	0.428	-99.000	-99.000
(p-value)	(0.821)	(0.942)	(0.996)	(0.080)	(0.290)	(0.957)	(0.723)	(0.788)	(0.152)	(0.993)	(0.000)	(0.000)
γ (↘) MA	0.498	0.797	0.737	1.146	-99.000	-99.000	0.973	0.415	0.333	1.024	0.329	0.526
(p-value)	(0.965)	(0.549)	(0.649)	(0.144)	(0.000)	(0.000)	(0.300)	(0.995)	(1.000)	(0.246)	(1.000)	(0.945)
						Japan, All Maturities						

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γ	0.307	0.772	0.463	0.732	0.433	0.555	0.585	0.235	0.324	1.247	0.401	0.384
(p-value)	(1.000)	(0.590)	(0.983)	(0.658)	(0.992)	(0.917)	(0.883)	(1.000)	(1.000)	(0.089)	(0.997)	(0.998)
γ ($\nearrow$) MA	0.289	0.797	0.561	0.615	0.481	0.555	0.741	0.365	0.160	1.377	-99.000	-99.000
(p-value)	(1.000)	(0.550)	(0.911)	(0.844)	(0.975)	(0.917)	(0.643)	(0.999)	(1.000)	(0.045)	(0.000)	(0.000)
γ ($\searrow$) MA	0.405	0.628	0.388	0.565	-99.000	-99.000	0.781	0.222	0.664	0.764	0.401	0.322
(p-value)	(0.997)	(0.826)	(0.998)	(0.907)	(0.000)	(0.000)	(0.575)	(1.000)	(0.771)	(0.604)	(0.997)	(1.000)
Australia, All Maturities												
γ	0.767	0.488	0.595	1.400	0.383	0.712	0.866	0.718	0.769	1.233	1.162	1.098
(p-value)	(0.599)	(0.971)	(0.870)	(0.040)	(0.999)	(0.691)	(0.442)	(0.681)	(0.595)	(0.095)	(0.134)	(0.179)
γ ($\nearrow$) MA	0.761	0.602	0.706	0.961	0.361	0.662	0.743	0.484	0.995	0.140	-99.000	-99.000
(p-value)	(0.608)	(0.861)	(0.701)	(0.314)	(0.999)	(0.774)	(0.638)	(0.973)	(0.276)	(1.000)	(0.000)	(0.000)
γ ($\searrow$) MA	0.509	0.342	0.335	0.694	-99.000	-99.000	0.436	0.721	0.597	1.521	1.162	1.098
(p-value)	(0.958)	(1.000)	(1.000)	(0.722)	(0.000)	(0.000)	(0.991)	(0.677)	(0.868)	(0.020)	(0.134)	(0.179)
Canada, All Maturities												
γ	0.427	0.483	0.665	0.616	0.756	0.558	1.391	0.916	0.555	1.175	0.632	0.567
(p-value)	(0.993)	(0.974)	(0.768)	(0.842)	(0.617)	(0.914)	(0.042)	(0.372)	(0.918)	(0.126)	(0.820)	(0.904)
γ ($\nearrow$) MA	1.201	0.452	0.490	0.672	0.756	0.544	0.768	0.338	0.622	0.618	-99.000	-99.000
(p-value)	(0.111)	(0.987)	(0.970)	(0.757)	(0.617)	(0.929)	(0.597)	(1.000)	(0.834)	(0.840)	(0.000)	(0.000)
γ ($\searrow$) MA	0.558	0.126	0.652	0.562	-99.000	-99.000	0.771	0.970	0.653	0.893	0.632	0.567
(p-value)	(0.915)	(1.000)	(0.788)	(0.911)	(0.000)	(0.000)	(0.592)	(0.303)	(0.787)	(0.403)	(0.820)	(0.904)
Hong Kong, All Maturities												
γ	0.739	0.833	1.214	0.518	0.509	0.645	0.525	0.321	0.960	1.337	0.541	0.454
(p-value)	(0.646)	(0.491)	(0.105)	(0.951)	(0.958)	(0.800)	(0.946)	(1.000)	(0.316)	(0.056)	(0.932)	(0.986)
γ ($\nearrow$) MA	0.719	0.978	0.597	0.190	0.509	0.645	0.331	0.483	0.689	0.522	-99.000	-99.000
(p-value)	(0.680)	(0.295)	(0.868)	(1.000)	(0.958)	(0.800)	(1.000)	(0.974)	(0.729)	(0.948)	(0.000)	(0.000)
γ ($\searrow$) MA	0.620	-99.000	1.440	0.621	-99.000	-99.000	0.504	0.488	0.445	0.867	0.541	0.454
(p-value)	(0.837)	(0.000)	(0.032)	(0.835)	(0.000)	(0.000)	(0.961)	(0.971)	(0.989)	(0.440)	(0.932)	(0.986)
Short Maturity Yields (1-, 2- and 3-year)												
γ	0.681	0.249	0.872	1.640	0.497	0.613	0.942	0.668	0.477	1.236	0.822	0.560
(p-value)	(0.743)	(1.000)	(0.433)	(0.009)	(0.966)	(0.847)	(0.338)	(0.763)	(0.977)	(0.094)	(0.509)	(0.912)

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γ ($\nearrow$) MA	0.372	0.245	0.426	1.014	0.482	0.496	1.287	0.637	0.533	1.393	-99.000	-99.000
(p-value)	(0.999)	(1.000)	(0.993)	(0.255)	(0.974)	(0.967)	(0.073)	(0.813)	(0.939)	(0.041)	(0.000)	(0.000)
γ ($\searrow$) MA	0.685	0.709	0.743	1.614	-99.000	1.064	0.469	0.668	0.524	0.855	0.822	0.543
(p-value)	(0.736)	(0.696)	(0.639)	(0.011)	(0.000)	(0.208)	(0.980)	(0.763)	(0.946)	(0.457)	(0.509)	(0.929)
Medium Maturity Yields (5- and 7-year)												
γ	1.484	0.896	1.007	2.028	0.582	0.462	0.453	0.277	1.218	1.402	0.831	0.785
(p-value)	(0.024)	(0.398)	(0.263)	(0.001)	(0.887)	(0.983)	(0.987)	(1.000)	(0.103)	(0.039)	(0.495)	(0.569)
γ ($\nearrow$) MA	1.270	1.053	0.838	1.608	0.582	0.462	0.605	1.031	1.242	0.935	-99.000	-99.000
(p-value)	(0.079)	(0.217)	(0.483)	(0.011)	(0.887)	(0.983)	(0.858)	(0.238)	(0.091)	(0.347)	(0.000)	(0.000)
γ ($\searrow$) MA	1.129	0.302	0.551	1.321	-99.000	-99.000	0.426	0.335	0.488	1.077	0.831	0.776
(p-value)	(0.156)	(1.000)	(0.922)	(0.061)	(0.000)	(0.000)	(0.993)	(1.000)	(0.971)	(0.196)	(0.495)	(0.584)
Long Maturity Yields (10- and 30-year)												
γ	1.359	0.458	0.937	1.188	0.721	0.695	1.101	0.372	1.254	1.167	0.883	0.571
(p-value)	(0.050)	(0.985)	(0.343)	(0.119)	(0.676)	(0.719)	(0.177)	(0.999)	(0.086)	(0.131)	(0.416)	(0.900)
γ ($\nearrow$) MA	0.273	0.398	1.338	0.734	0.714	0.673	0.948	0.758	1.470	0.482	-99.000	-99.000
(p-value)	(1.000)	(0.997)	(0.056)	(0.654)	(0.688)	(0.756)	(0.330)	(0.614)	(0.026)	(0.974)	(0.000)	(0.000)
γ ($\searrow$) MA	1.408	0.478	0.385	1.205	-99.000	-99.000	0.871	0.349	0.747	1.125	0.883	0.571
(p-value)	(0.038)	(0.976)	(0.998)	(0.110)	(0.000)	(0.000)	(0.434)	(1.000)	(0.633)	(0.159)	(0.416)	(0.900)

3.5.2 Technical Chart Patterns in Bond Yield Spreads

This section discusses the empirical results for bond yield spreads. Table 3.8 presents the pattern count for the Nadaraya-Watson kernel regression (Panel A) and local polynomial regression (Panel B) respectively. The top row is the aggregate count from all 43 yield spreads. We find the results here quite surprising because a comparison of the pattern count for bond yield spreads and bond yields show a substantial difference across all chart patterns, despite the fact that the number of raw data for yield spread is higher than bond yield. This seems to suggest that yield spreads behave more like a random walk than bond yields. Furthermore, the most frequently observed patterns are Triangle and Broadening patterns, rather than Rectangle, Double or Head-and-Shoulders that commonly found in equities or currencies markets. The fact that Broadening pattern count is higher than Head-and-Shoulders is even more perplexing in light of observations by Edwards and Magee (1966, p.148)

> It has been assumed in the past that Broadening Bottoms must exits, but the writer [Edwards] has never found a good one in his examination of thousands of individual stocks over many years and only one or two patterns which bore resemblance to it.

Similar to the results from bond yield, the pattern count for local polynomial regression is higher than Nadaraya-Watson regression. Out of 262,170 raw data, only 7,209 and 9,136 chart patterns are found by Nadaraya-Watson and local polynomial regression respectively, a considerable lower number than bond yield data. The least detected chart pattern is Triple pattern. The country that shows the lowest pattern count is Australia. A comparison of Vasicek simulation to actual yield series show no large difference for any particular pattern, results that are different to bond yields and other assets. Thus, it is conclusive to say that yield spreads data are fundamentally different to individual stocks, bond yield or currencies. The critical question now is whether technical charts can be applied to yield spreads as in other financial markets, in an attempt to gain any investment edge.

Next, Table 3.9 displays the summary results for the unconditional and conditional yield spread return from the long-spread strategy.[20] All the yield spread returns from the long spread strategy have been normalized to zero mean and unit standard deviation. Overall, the results here indicate some support for EMH since none of the overall mean return are statistically significant from zero, apart from HSTOP

[20]The mean, standard deviation and skewness results for the short-spread strategy have the opposite signs to the long spread strategy, but all the values remain the same.

for the local polynomial regression. None of the sign of the mean returns shows any systematic pattern that spread traders will be able to earn excess returns.

Lastly, Table 3.10 and 3.11 show the results for information tests from the two non-parametric regression respectively. Panel A of both tables are results from goodness-of-fit test, while panel B presents the results from the Kolmogorov-Smirnov test for all yield spreads. Unlike bond yield markets, only four chart patterns was able to reject the goodness-of-fit null hypothesis for Nadaraya-Watson regression in the yield spreads. There is, however, an improvement shown by local polynomial regression, where eight chart patterns are able to reject the goodness-of-fit null hypothesis that the unconditional and conditional distributions are the same. But the Kolmogorov-Smirnov test, for both regressions, rejects every single null hypothesis, apart from HSTOP pattern. Thus, it is fairly conclusive that the unconditional yield spread returns are not statistically different to the unconditional normalized returns. It is conceivable that spread traders may disagree with our results here, on the ground that even though chart patterns do not show statistically significant returns does not mean that other strategies will not earn excess returns. It may be true, but that is beside the point, since the objective here is to investigate whether chart pattern will provide additional information to spread traders. The answers to this question is negative.

Table 3.8: Technical Pattern Count for Bond Yield Spreads

Sample	Total	HSTOP	BTOP	TTOP	RTOP	DTOP	TPTOP	HSBOT	BBOT	TBOT	RBOT	DBOT	TPBOT
Panel A: Nadaraya-Watson Kernel Regression													
All Yield Spreads													
Actual	7209	409	983	1031	387	614	144	394	1124	1071	403	508	141
Vasicek	7223	318	1357	1177	217	506	77	273	1362	1183	222	449	82
US, All Spreads													
Actual	3141	211	397	425	196	259	61	206	497	412	186	230	61
Vasicek	3103	117	600	522	66	220	32	104	607	522	79	203	31
UK, All Spreads													
Actual	445	13	85	90	7	32	8	7	85	85	10	19	4
Vasicek	597	8	123	133	5	27	1	8	136	142	3	10	1
Germany, All Spreads													
Actual	1124	75	134	155	72	88	21	81	144	168	91	76	19
Vasicek	1162	83	173	135	70	101	20	74	174	127	84	97	24
Japan, All Spreads													
Actual	695	42	68	74	52	76	21	50	76	80	57	75	24
Vasicek	853	80	123	94	64	59	16	62	114	92	49	81	19
Australia, All Spreads													
Actual	393	5	71	56	11	46	8	4	77	85	0	23	7
Vasicek	474	11	111	104	3	25	1	7	98	94	1	17	2
Canada, All Spreads													
Actual	1019	45	170	178	32	75	15	31	187	176	43	50	17
Vasicek	680	10	161	127	4	47	3	14	149	141	2	19	3
Hong Kong, All Spreads													
Actual	392	18	58	53	17	38	10	15	58	65	16	35	9
Vasicek	354	9	66	62	5	27	4	4	84	65	4	22	2
Panel B: Local Linear Regression													
All Yield Spreads													
Actual	9136	511	1315	1254	488	813	194	481	1430	1283	518	674	175

continued next page

(*continued*)

Sample	Total	HSTOP	BTOP	TTOP	RTOP	DTOP	TPTOP	HSBOT	BBOT	TBOT	RBOT	DBOT	TPBOT
Vasicek	9022	403	1744	1405	291	628	109	359	1685	1437	292	563	106
						US, All Spreads							
Actual	3992	264	521	536	243	346	84	252	624	503	244	297	78
Vasicek	3870	158	756	629	96	267	43	135	758	641	102	244	41
						UK, All Spreads							
Actual	571	17	111	113	9	39	8	7	115	107	15	25	5
Vasicek	744	8	164	156	5	35	2	10	178	164	5	15	2
						Germany, All Spreads							
Actual	1401	89	179	182	94	119	30	90	182	197	114	102	23
Vasicek	1444	106	211	160	94	122	28	100	206	157	105	124	31
						Japan, All Spreads							
Actual	873	54	87	96	61	94	26	65	90	100	71	99	30
Vasicek	1077	96	166	108	81	83	23	81	132	113	66	105	23
						Australia, All Spreads							
Actual	525	10	112	64	16	62	12	5	100	92	4	39	9
Vasicek	598	12	145	126	3	31	1	9	125	117	2	24	3
						Canada, All Spreads							
Actual	1266	54	228	200	43	96	20	41	245	206	49	65	19
Vasicek	844	13	203	149	7	55	6	18	187	170	5	27	4
						Hong Kong, All Spreads							
Actual	508	23	77	63	22	57	14	21	74	78	21	47	11
Vasicek	445	10	99	77	5	35	6	6	99	75	7	24	2

Table 3.9: Summary Statistics of Conditional Bond Yield Spread Return (Long Spread Strategy)

Statistics	Unconditional Return	HSTOP	BTOP	TTOP	RTOP	DTOP	TPTOP	HSBOT	BBOT	TBOT	RBOT	DBOT	TPBOT
Panel A: Nadaraya-Watson Kernel Regression													
All Spreads, All Spreads													
Mean	0.0000	0.060	-0.004	0.023	0.024	0.038	0.018	0.032	-0.016	0.014	0.008	0.007	0.022
S.D.	1.0000	0.742	0.944	0.897	0.763	0.888	0.718	0.669	0.947	0.908	0.588	0.718	0.723
Skew.	0.1200	0.222	-1.449	-0.364	-1.140	-1.761	-0.008	0.108	-0.724	0.365	0.072	0.732	2.143
Kurtosis	38.7293	8.523	11.020	11.350	8.396	21.830	0.739	3.862	12.410	6.965	1.309	5.953	12.670
US, All Spreads													
Mean	0.0000	0.053	-0.012	0.041	0.066	0.011	0.111	0.068*	-0.077	0.071	0.030	0.005	0.027
S.D.	1.0000	0.752	1.016	0.914	0.879	0.883	0.819	0.739	1.004	0.858	0.619	0.738	0.598
Skew.	0.1030	0.014	-1.096	0.616	-1.075	-1.222	0.124	-0.186	-1.757	0.099	-0.261	1.335	0.254
Kurtosis	11.5246	3.371	5.683	7.407	7.168	9.387	-0.010	3.075	15.180	5.779	0.500	6.849	0.088
UK, All Spreads													
Mean	0.0000	0.563	0.204*	-0.071	0.024	0.050	-0.042	-0.497	-0.062	0.060	-0.152	0.080	0.092
S.D.	1.0000	1.412	0.719	1.304	0.831	0.624	0.701	0.847	0.905	1.196	0.449	0.766	0.671
Skew.	2.2468	2.664	0.586	-2.227	0.298	0.849	0.913	-1.880	-1.678	0.049	-0.367	-0.316	0.458
Kurtosis	68.6957	5.940	2.387	16.250	-0.890	0.595	0.068	1.801	7.610	7.016	-0.404	-0.424	-0.953
Germany, All Spreads													
Mean	0.0000	-0.078	-0.163	0.094	-0.136	0.174*	0.060	0.046	0.012	-0.068	-0.020	-0.082	-0.019
S.D.	1.0000	0.722	1.144	0.723	0.728	0.802	0.697	0.536	0.988	0.905	0.532	0.691	0.870
Skew.	-0.6763	-2.339	-2.663	1.280	-2.256	1.167	-0.957	1.160	-0.367	1.167	-0.196	-1.090	0.417
Kurtosis	68.7458	9.662	19.800	4.330	9.028	2.064	1.742	4.025	5.551	15.200	1.467	3.092	-0.140
Japan, All Spreads													
Mean	0.0000	0.156	-0.065	-0.088	0.011	0.041	-0.168	0.003	0.176	0.106	-0.061	-0.069	-0.014
S.D.	1.0000	0.641	0.842	0.750	0.466	0.738	0.757	0.592	0.969	1.103	0.676	0.722	0.560
Skew.	-0.0591	0.897	-2.468	-0.473	-0.351	-0.123	-0.548	1.366	0.598	0.991	1.099	-0.474	-0.277
Kurtosis	26.8662	2.367	12.430	-0.133	0.917	0.615	0.560	5.268	2.252	1.599	3.291	4.085	-0.091
Australia, All Spreads													

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Statistics	Unconditional Return	HSTOP	BTOP	TTOP	RTOP	DTOP	TPTOP	HSBOT	BBOT	TBOT	RBOT	DBOT	TPBOT
Mean	0.0000	-0.374	0.028	-0.034	0.178	0.288*	-0.136	-0.283	0.007	-0.000	-	0.316	0.445
S.D.	1.0000	1.305	0.725	0.693	0.974	0.984	0.449	0.587	0.631	0.846	-	0.893	2.030
Skew.	-0.3493	-0.968	-0.580	-0.153	0.423	2.119	0.288	0.108	-0.218	0.661	-	2.284	1.661
Kurtosis	13.8816	-0.468	7.309	1.535	-0.140	7.320	-1.104	-1.597	2.500	2.045	-	6.907	1.315
					Canada, All Spreads								
Mean	0.0000	0.133*	0.047	0.109	0.184*	-0.153	-0.062	-0.057	0.062	-0.027	0.061	0.055	-0.051
S.D.	1.0000	0.432	0.892	0.897	0.411	1.261	0.448	0.638	0.975	0.848	0.517	0.547	0.269
Skew.	-0.1623	-0.902	-0.445	-0.319	-0.068	-4.450	-0.802	0.894	1.852	0.082	0.519	-0.003	-0.381
Kurtosis	24.6661	0.968	4.671	3.520	-0.200	30.110	0.327	5.621	10.270	3.407	-0.007	1.867	0.394
					Hong Kong, All Spreads								
Mean	0.0000	0.066	-0.015	-0.248*	-0.143	-0.040	0.048	0.079	-0.025	-0.183*	0.100	0.066	-0.056
S.D.	1.0000	0.540	0.633	0.686	0.390	0.342	0.579	0.484	0.538	0.728	0.448	0.686	0.511
Skew.	-0.5951	-0.658	-1.187	-2.458	-0.023	0.430	0.656	-0.002	-0.543	-2.225	-0.533	1.580	-0.856
Kurtosis	206.748	0.591	4.480	10.280	-1.005	0.692	-0.137	-0.067	3.023	6.529	0.366	4.262	-0.573
					Panel B: Local Polynomial Regression								
					Long Spread, All Spreads								
Mean	0.0000	0.059*	-0.001	0.002	0.032	0.038	0.070	0.032	-0.045	0.025	0.016	0.024	0.021
S.D.	1.0000	0.732	0.938	0.879	0.755	0.799	0.756	0.670	0.976	0.954	0.643	0.759	0.684
Skew.	0.1200	0.065	-1.200	-0.504	-0.923	0.141	0.432	0.015	-1.210	0.445	-0.333	0.644	2.065
Kurtosis	38.7293	7.513	10.260	11.460	7.564	8.156	2.110	3.811	13.000	8.380	2.622	5.628	12.860
					US, All Spreads								
Mean	0.0000	0.055	-0.056	0.041	0.085	-0.007	0.219*	0.053	-0.118*	0.064	0.060	0.022	-0.016
S.D.	1.0000	0.758	1.014	0.899	0.874	0.871	0.865	0.741	1.028	1.033	0.659	0.748	0.591
Skew.	0.1030	-0.101	-1.223	0.482	-0.871	-0.709	0.532	-0.160	-1.929	0.505	-0.049	1.021	0.414
Kurtosis	11.5246	2.802	5.780	6.953	6.499	8.696	1.045	2.883	14.000	8.488	0.633	5.123	0.020
					UK, All Spreads								
Mean	0.0000	0.378	0.125*	-0.071	-0.301	-0.017	-0.042	-0.497	-0.051	0.004	-0.067	0.200	-0.005
S.D.	1.0000	1.284	0.709	1.280	1.000	0.625	0.701	0.847	0.871	1.162	0.632	0.955	0.620

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Statistics	Unconditional Return	HSTOP	BTOP	TTOP	RTOP	DTOP	TPTOP	HSBOT	BBOT	TBOT	RBOT	DBOT	TPBOT
Skew.	2.2468	2.994	0.799	-2.494	0.063	0.619	0.913	-1.880	-1.079	0.005	0.031	0.557	0.817
Kurtosis	68.7458	8.377	2.444	16.190	-0.648	0.819	0.068	1.801	7.257	6.395	-0.339	0.245	-0.523
						Germany, All Spreads							
Mean	0.0000	-0.080	-0.050	0.051	-0.085	0.060	-0.073	0.042	-0.031	-0.034	0.052	-0.015	0.012
S.D.	1.0000	0.722	1.087	0.711	0.723	0.764	0.664	0.538	1.083	0.891	0.507	0.653	0.803
Skew.	-0.6763	-2.122	-2.397	1.229	-1.799	1.207	-0.601	1.201	-2.001	0.820	-0.193	-1.170	0.344
Kurtosis	68.7458	8.703	19.200	4.231	7.646	2.429	0.975	3.687	14.770	14.060	1.596	3.595	0.159
						Japan, All Spreads							
Mean	0.0000	0.152*	0.030	-0.073	0.026	0.098	-0.008	-0.009	0.176*	0.178*	-0.187*	-0.144	0.046
S.D.	1.0000	0.591	0.960	0.721	0.453	0.677	0.723	0.664	0.953	1.036	0.801	0.800	0.544
Skew.	-0.0591	0.918	-1.608	-0.455	-0.468	0.413	1.135	0.001	0.333	0.865	-0.281	-0.747	-0.392
Kurtosis	26.8662	2.833	7.614	-0.111	0.572	1.089	2.182	5.256	2.307	1.630	3.845	2.924	-0.040
						Australia, All Spreads							
Mean	0.0000	-0.054	0.080	-0.084	0.054	0.275*	-0.079	-0.273	-0.060	0.005	-0.750	0.226	0.331
S.D.	1.0000	0.989	0.686	0.661	0.847	0.895	0.387	0.494	0.856	0.900	1.380	1.057	1.786
Skew.	-0.3493	-1.661	-0.146	-0.483	0.785	1.985	-0.048	-0.087	-1.257	0.555	-1.142	1.111	1.978
Kurtosis	13.8816	1.924	6.573	0.504	0.645	8.482	-0.894	-1.327	5.924	1.591	-0.677	4.952	2.724
						Canada, All Spreads							
Mean	0.0000	0.113*	0.053	0.042	0.148*	-0.008	-0.105	0.008	0.039	-0.015	0.079	0.118	-0.044
S.D.	1.0000	0.480	0.920	0.854	0.395	0.833	0.713	0.551	0.955	0.724	0.551	0.710	0.294
Skew.	-0.1624	-1.336	0.383	-0.312	-0.023	0.930	-1.966	1.724	1.491	-0.188	0.429	2.393	-0.342
Kurtosis	24.6661	2.610	7.237	3.744	-0.222	7.325	4.392	5.289	9.192	5.499	-0.412	12.050	-0.352
						Hong Kong, All Spreads							
Mean	0.0000	0.112	-0.016	-0.271*	-0.143	0.024	0.070	0.155	0.016	-0.113	0.067	0.074	0.111
S.D.	1.0000	0.521	0.589	0.703	0.349	0.423	0.563	0.426	0.520	0.699	0.358	0.541	0.426
Skew.	-0.5951	-0.700	-1.053	-2.152	-0.028	0.476	0.470	-0.437	-0.349	-2.221	-1.101	0.900	-1.243
Kurtosis	206.748	0.600	4.592	7.748	-0.638	0.128	-0.557	0.576	3.307	7.270	1.148	1.826	1.783

Table 3.10: Information Tests for Bond Yield Spreads (Nadaraya-Watson Kernel Regression)

Panel A: Goodness-of-Fit Test (Long Spread)											
	Deciles										
Patterns	1	2	3	4	5	6	7	8	9	10	Q-Statistic
HSTOP	5.38	9.05	9.29	8.07	10.80	12.50	12.70	13.90	11.20	7.09	27.00
p-value	(-3.12)	(-0.64)	(-0.48)	(-1.30)	(0.51)	(1.66)	(1.83)	(2.65)	(0.84)	(-1.96)	(0.001)
BTOP	9.36	11.00	9.05	7.73	9.77	9.56	11.00	11.00	12.10	9.46	14.10
p-value	(-0.67)	(1.03)	(-0.99)	(-2.37)	(-0.24)	(-0.46)	(1.03)	(1.03)	(2.20)	(-0.56)	(0.119)
TTOP	7.95	11.50	10.30	9.21	9.21	10.90	10.30	10.60	11.10	9.02	11.50
p-value	(-2.19)	(1.65)	(0.30)	(-0.84)	(-0.84)	(0.92)	(0.30)	(0.61)	(1.13)	(-1.05)	(0.246)
RTOP	7.49	7.49	9.30	9.04	13.20	12.90	10.60	10.60	10.90	8.53	14.01
p-value	(-1.64)	(-1.64)	(-0.46)	(-0.63)	(2.08)	(1.91)	(0.39)	(0.39)	(0.56)	(-0.97)	(0.122)
DTOP	7.82	9.45	9.77	9.61	13.80	10.10	8.96	10.60	10.10	9.77	13.20
p-value	(-1.80)	(-0.46)	(-0.19)	(-0.32)	(3.17)	(0.08)	(-0.86)	(0.48)	(0.08)	(-0.19)	(0.152)
TPTOP	8.33	12.50	5.56	10.40	14.60	9.03	10.40	9.72	7.64	11.80	8.64
p-value	(-0.67)	(1.00)	(-1.78)	(0.17)	(1.83)	(-0.39)	(0.17)	(-0.11)	(-0.94)	(0.72)	(0.471)
HSBOT	4.82	10.20	11.90	10.20	13.20	11.20	9.90	11.40	10.40	6.85	21.40
p-value	(-3.43)	(0.10)	(1.28)	(0.10)	(2.12)	(0.77)	(-0.07)	(0.94)	(0.27)	(-2.08)	(0.011)
BBOT	10.10	10.60	10.10	10.20	9.25	9.70	9.25	11.90	8.81	10.10	7.58
p-value	(0.16)	(0.66)	(0.06)	(0.26)	(-0.84)	(-0.34)	(-0.84)	(2.15)	(-1.33)	(0.06)	(0.423)
TBOT	9.43	11.70	9.24	7.84	10.60	10.60	9.80	11.00	10.20	9.62	11.00
p-value	(-0.62)	(1.82)	(-0.83)	(-2.35)	(0.60)	(0.70)	(-0.21)	(1.11)	(0.19)	(-0.42)	(0.273)
RBOT	5.96	9.93	11.70	7.94	12.20	12.20	11.40	15.60	7.20	5.96	36.50
p-value	(-2.71)	(-0.05)	(1.11)	(-1.38)	(1.44)	(1.44)	(0.95)	(3.77)	(-1.88)	(-2.71)	(0.000)
DBOT	7.09	11.80	11.00	9.65	11.20	9.65	11.00	8.86	13.60	6.10	22.80
p-value	(-2.19)	(1.36)	(0.77)	(-0.27)	(0.92)	(-0.27)	(0.77)	(-0.86)	(2.69)	(-2.93)	(0.007)
TPBOT	6.38	12.10	9.22	7.80	15.60	15.60	7.80	7.80	10.60	7.09	14.70
p-value	(-1.43)	(0.81)	(-0.31)	(-0.87)	(2.22)	(2.22)	(-0.87)	(-0.87)	(0.25)	(-1.15)	(0.100)
Panel B: Kolmogorov-Smirnov Test											

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Statistics	HSTOP	BTOP	TTOP	RTOP	DTOP	TPTOP	HSBOT	BBOT	TBOT	RBOT	DBOT	TPBOT
γ	1.118	0.280	0.484	0.943	0.526	0.268	1.057	0.282	0.698	0.985	0.761	0.422
p-value	(0.164)	(1.000)	(0.974)	(0.336)	(0.945)	(1.000)	(0.214)	(1.000)	(0.715)	(0.286)	(0.609)	(0.994)

Table 3.11: Information Tests for Bond Yield Spreads (Local Polynomial Kernel Regression)

Panel A: Goodness-of-Fit Test (Long Spread Strategy)

	Deciles										
Patterns	1	2	3	4	5	6	7	8	9	10	Q-Statistic
HSTOP	5.87	8.61	9.59	7.83	10.80	11.70	11.90	14.50	11.90	7.24	32.00
p-value	(-3.11)	(-1.05)	(-0.31)	(-1.64)	(0.58)	(1.31)	(1.46)	(3.38)	(1.46)	(-2.08)	(0.000)
BTOP	8.75	10.90	10.30	7.91	9.28	9.58	11.60	10.60	11.40	9.66	16.70
p-value	(-1.52)	(1.06)	(0.32)	(-2.53)	(-0.87)	(-0.51)	(1.98)	(0.78)	(1.70)	(-0.41)	(0.054)
TTOP	8.37	11.20	11.10	9.57	8.21	10.80	10.80	10.40	11.30	8.37	17.90
p-value	(-1.92)	(1.37)	(1.28)	(-0.51)	(-2.11)	(0.90)	(0.90)	(0.43)	(1.56)	(-1.92)	(0.037)
RTOP	7.38	6.76	10.20	9.22	13.50	11.90	10.00	11.30	11.90	7.79	21.50
p-value	(-1.93)	(-2.38)	(0.18)	(-0.57)	(2.60)	(1.39)	(0.03)	(0.94)	(1.39)	(-1.63)	(0.011)
DTOP	7.38	10.80	9.96	9.84	12.90	9.72	9.72	10.70	9.84	9.10	14.30
p-value	(-2.49)	(0.78)	(-0.04)	(-0.15)	(2.77)	(-0.27)	(-0.27)	(0.67)	(-0.15)	(-0.85)	(0.113)
TPTOP	7.22	11.90	4.12	12.90	12.90	9.28	11.90	9.79	8.25	11.90	14.10
p-value	(-1.29)	(0.86)	(-2.73)	(1.34)	(1.34)	(-0.34)	(0.86)	(-0.10)	(-0.81)	(0.86)	(0.117)
HSBOT	4.57	10.20	11.60	10.60	13.10	11.00	9.98	12.50	9.36	7.07	28.00
p-value	(-3.97)	(0.14)	(1.20)	(0.44)	(2.26)	(0.74)	(-0.02)	(1.81)	(-0.47)	(-2.14)	(0.001)
BBOT	10.30	10.80	10.10	10.10	9.16	10.30	9.44	11.50	8.67	9.58	8.64
p-value	(0.44)	(1.06)	(0.18)	(0.09)	(-1.06)	(0.35)	(-0.71)	(1.85)	(-1.67)	(-0.53)	(0.471)
TBOT	9.43	10.70	9.51	7.56	10.80	10.60	10.20	10.20	11.30	9.74	12.50
p-value	(-0.68)	(0.81)	(-0.59)	(-2.91)	(0.90)	(0.72)	(0.25)	(0.25)	(1.55)	(-0.31)	(0.186)
RBOT	6.95	9.27	10.20	7.72	12.50	11.80	11.00	15.80	7.34	7.34	38.30
p-value	(-2.31)	(-0.56)	(0.18)	(-1.73)	(1.93)	(1.35)	(0.76)	(4.42)	(-2.02)	(-2.02)	(0.000)
DBOT	7.12	11.60	9.79	9.64	11.40	9.94	11.00	9.64	13.20	6.68	23.80
p-value	(-2.49)	(1.36)	(-0.18)	(-0.31)	(1.23)	(-0.05)	(0.85)	(-0.31)	(2.77)	(-2.88)	(0.005)
TPBOT	5.14	13.10	10.90	6.86	13.70	14.90	8.57	9.71	10.90	6.29	17.20
p-value	(-2.14)	(1.39)	(0.38)	(-1.39)	(1.64)	(2.14)	(-0.63)	(-0.13)	(0.38)	(-1.64)	(0.046)

Panel B: Kolmogorov-Smirnov Test

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Statistics	HSTOP	BTOP	TTOP	RTOP	DTOP	TPTOP	HSBOT	BBOT	TBOT	RBOT	DBOT	TPBOT
γ	1.426	0.171	0.357	0.790	0.863	0.326	1.089	0.184	1.140	0.916	0.663	0.514
p-value	(0.034)	(1.000)	(1.000)	(0.560)	(0.445)	(1.000)	(0.186)	(1.000)	(0.149)	(0.371)	(0.771)	(0.954)

3.6 Conclusion

In this chapter, we examine the effectiveness of technical chart patterns in the bond markets. Specifically, we apply the charting algorithm to both bonds yield and bond yield spread markets. To the best of our knowledge, this is the first systematic evaluation of technical charts in the bond yields and bond yield spreads. Furthermore, we extend the capability of the nonparametric kernel regression by developing the nonparametric local polynomial kernel regression.

In summary of the results, we find that chart patterns exist in the bond yield markets, in a manner that can be captured by the chart algorithm. However, the results obtained from these chart patterns are broadly in supportive of the weak-formed EMH, meaning that chart patterns may have only limited information in trading bond securities. Some patterns, such as the Head-and-Shoulders, could have value in US bond markets. But for other markets, the value of this pattern declines.

In contrast to bond yields, relatively few chart patterns are detected by our non-parametric regression algorithms in the yield spread markets. Furthermore, the conditional returns obtained from these chart patterns provide no incremental information to traders at all. This shows that yield spread data are fundamentally different to individual stock or currencies. Perhaps other strategies are more suited in trading yield spreads than technical chart patterns.

In conclusion, it remains a challenge for technical analysis to explain how technical charts are useful to traders in forecasting bond prices and how it can be incorporated in the relative spread trading.

Appendix I: Maximum Likelihood Estimates of the Vasicek Model

This section presents the maximum likelihood estimates of the Vasicek (1977) model on bond yield and yield curve spreads data. The main purpose of the one-factor model is to provide a comparison using simulated yield and the actual yield. The Vasicek model is $dy_t = \lambda(\mu - y_t)dt + \sigma dW_t$, where (μ, λ, σ) are the model parameters, interpreted as long-run equilibrium level, speed of mean reversion and volatility of the state variable y_t respectively. The estimates are computed using equations (3.30) to (3.32) in Section 3.5. Panel A of Table 3.12 displays the results for bond yields, and Panel B presents the results for yield spreads. Panel C tabulates the results for sovereign yield spreads, which is the spread between a foreign country (UK, Germany, Japan, Australia, Canada and Hong Kong) and US.

An inspection of the results shows several interesting properties. One, bond yields have lower λ values, meaning that the yield spreads mean revert faster to the long-run equilibrium mean μ than bond yields. The autocorrelation statistics also show that yield spreads have lower persistency. Two, all bond yield spreads have positive mean value, which implies that on average the yield curve is upward sloping for all sample countries.

Table 3.12: Vasicek Model Parameter Estimates

Bond Yield	Obs.(T)	μ	σ	λ	Max	Min	$\rho(100)$
		Panel A: Bond Yields					
USBY1Y	11211	0.0625	0.0082	0.0005	0.1731	0.0088	0.9059
USBY2Y	7619	0.0697	0.0088	0.0005	0.1695	0.0108	0.9248
USBY3Y	11211	0.0668	0.0064	0.0005	0.1659	0.0132	0.9199
USBY5Y	11211	0.0689	0.0057	0.0005	0.1627	0.0203	0.9320
USBY7Y	9341	0.0751	0.0060	0.0005	0.1605	0.0263	0.9353
USBY10Y	11211	0.0711	0.0046	0.0005	0.1584	0.0312	0.9394
USBY30Y	7441	0.0794	0.0051	0.0005	0.1521	0.0417	0.9406
UKBY2Y	6962	0.0828	0.0081	0.0006	0.1549	0.0318	0.9220
UKBY5Y	6962	0.0845	0.0061	0.0006	0.1594	0.0356	0.9251
UKBY7Y	6962	0.0852	0.0055	0.0006	0.1580	0.0375	0.9349
UKBY10Y	6962	0.0852	0.0050	0.0005	0.1556	0.0391	0.9430
GERBY2Y	5341	0.0495	0.0029	0.0004	0.0927	0.0188	0.9409
GERBY3Y	4873	0.0510	0.0024	0.0004	0.0931	0.0218	0.9388
GERBY5Y	5341	0.0539	0.0027	0.0006	0.0914	0.0246	0.9218
GERBY7Y	4604	0.0565	0.0021	0.0005	0.0926	0.0274	0.9301
GERBY10Y	5341	0.0583	0.0020	0.0006	0.0913	0.0302	0.9248
JAPBY2Y	5250	0.0226	0.0012	0.0004	0.0849	0.0001	0.9482
JAPBY3Y	5250	0.0244	0.0012	0.0004	0.0845	0.0007	0.9454
JAPBY5Y	5250	0.0276	0.0017	0.0004	0.0849	0.0015	0.9394

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(*continued*)

Bond Yield	Obs.(T)	μ	σ	λ	Max	Min	$\rho(100)$
JAPBY10Y	5250	0.0338	0.0025	0.0006	0.0823	0.0044	0.9272
AUSBY2Y	5137	0.0780	0.0066	0.0008	0.1615	0.0382	0.9156
AUSBY3Y	5137	0.0792	0.0069	0.0007	0.1557	0.0404	0.9165
AUSBY5Y	5137	0.0812	0.0066	0.0008	0.1495	0.0431	0.9202
AUSBY10Y	5137	0.0833	0.0059	0.0007	0.1425	0.0459	0.9244
CANBY2Y	5157	0.0631	0.0081	0.0008	0.1329	0.0219	0.9108
CANBY3Y	5157	0.0651	0.0065	0.0007	0.1301	0.0244	0.9129
CANBY5Y	5157	0.0674	0.0059	0.0008	0.1257	0.0313	0.9164
CANBY7Y	5157	0.0699	0.0051	0.0008	0.1218	0.0344	0.9225
CANBY10Y	5157	0.0710	0.0048	0.0008	0.1196	0.0373	0.9231
HKBY2Y	3659	0.0487	0.0156	0.0018	0.1183	0.0057	0.8621
HKBY3Y	3182	0.0527	0.0144	0.0017	0.1142	0.0006	0.8728
HKBY5Y	2952	0.0570	0.0085	0.0014	0.1056	0.0229	0.8378
HKBY7Y	2662	0.0581	0.0136	0.0023	0.1055	0.0074	0.8488
HKBY10Y	2435	0.0598	0.0078	0.0017	0.1052	0.0333	0.8367
Total	204,816						
Panel B: Bond Yield Spreads							
USYS(1,5)	11211	0.0063	0.0030	0.0023	0.0258	-0.0271	0.7526
USYS(1,7)	9341	0.0089	0.0039	0.0020	0.0294	-0.0321	0.7448
USYS(1,10)	11211	0.0085	0.0038	0.0016	0.0339	-0.0344	0.7765
USYS(1,30)	7441	0.0129	0.0052	0.0013	0.0437	-0.0391	0.8017
USYS(2,5)	7619	0.0043	0.0019	0.0032	0.0164	-0.0171	0.7893
USYS(2,7)	7619	0.0064	0.0024	0.0024	0.0229	-0.0220	0.7962
USYS(2,10)	7619	0.0074	0.0025	0.0017	0.0274	-0.0241	0.8008
USYS(2,30)	7441	0.0095	0.0035	0.0013	0.0369	-0.0281	0.8185
USYS(3,7)	9341	0.0042	0.0016	0.0034	0.0181	-0.0130	0.7721
USYS(3,10)	11211	0.0043	0.0018	0.0023	0.0224	-0.0157	0.7940
USYS(5,10)	11211	0.0022	0.0009	0.0041	0.0119	-0.0091	0.7448
USYS(5,30)	7441	0.0053	0.0019	0.0021	0.0226	-0.0156	0.7994
USYS(10,30)	7441	0.0022	0.0009	0.0039	0.0113	-0.0084	0.8101
UKYS(2,5)	6962	0.0017	0.0017	0.0034	0.0166	-0.0135	0.7978
UKYS(2,7)	6962	0.0023	0.0030	0.0033	0.0199	-0.0169	0.7865
UKYS(2,10)	6962	0.0023	0.0043	0.0030	0.0287	-0.0216	0.7499
UKYS(5,10)	6962	0.0007	0.0015	0.0042	0.0187	-0.0090	0.5504
GERYS(2,5)	5341	0.0045	0.0021	0.0052	0.0195	-0.0084	0.8229
GERYS(2,7)	4604	0.0072	0.0014	0.0014	0.0226	-0.0095	0.8941
GERYS(2,10)	5341	0.0089	0.0024	0.0018	0.0271	-0.0130	0.8718
GERYS(3,7)	4604	0.0055	0.0007	0.0015	0.0174	-0.0071	0.8886
GERYS(3,10)	4873	0.0072	0.0014	0.0015	0.0211	-0.0098	0.8607
GERYS(5,10)	5341	0.0044	0.0017	0.0042	0.0141	-0.0085	0.7843
JAPYS(2,5)	5250	0.0050	0.0009	0.0042	0.0133	-0.0047	0.8036
JAPYS(2,10)	5250	0.0112	0.0019	0.0026	0.0256	-0.0072	0.8442
JAPYS(3,10)	5250	0.0094	0.0017	0.0032	0.0223	-0.0064	0.7984
JAPYS(5,10)	5250	0.0062	0.0013	0.0044	0.0142	-0.0067	0.7566
AUSYS(2,5)	5137	0.0032	0.0018	0.0039	0.0153	-0.0145	0.7988
AUSYS(2,10)	5137	0.0053	0.0036	0.0028	0.0277	-0.0240	0.7855
AUSYS(3,10)	5137	0.0041	0.0035	0.0048	0.0209	-0.0194	0.7289

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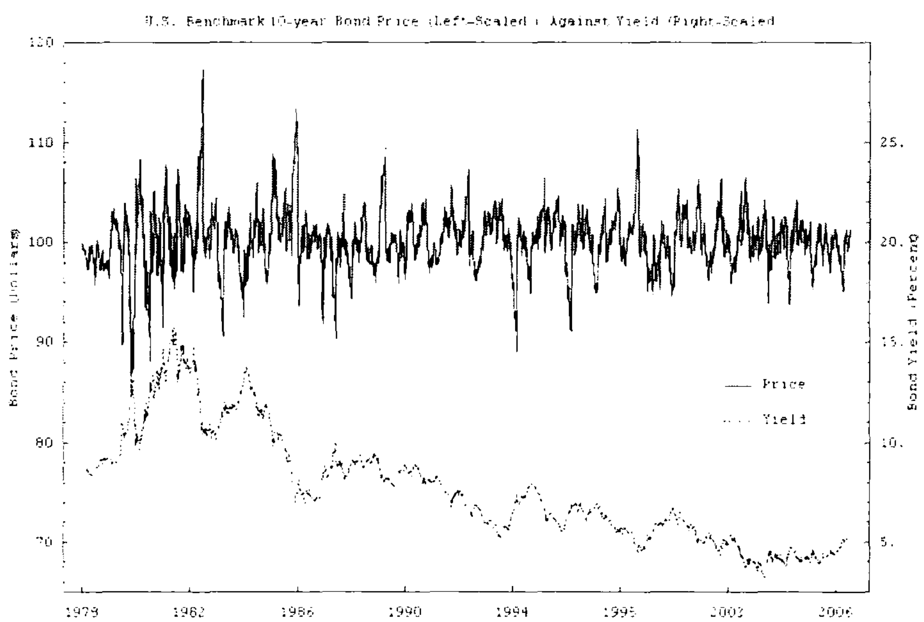
(*continued*)

Bond Yield	Obs.(T)	μ	σ	λ	Max	Min	$\rho(100)$
AUSYS(5,10)	5137	0.0020	0.0023	0.0080	0.0127	-0.0095	0.6890
CANYS(2,5)	5157	0.0043	0.0028	0.0058	0.0165	-0.0121	0.7736
CANYS(2,7)	5157	0.0068	0.0042	0.0047	0.0226	-0.0135	0.7848
CANYS(2,10)	5157	0.0079	0.0058	0.0045	0.0263	-0.0172	0.7921
CANYS(3,7)	5157	0.0048	0.0022	0.0049	0.0200	-0.0085	0.7733
CANYS(3,10)	5157	0.0059	0.0050	0.0065	0.0198	-0.0132	0.7806
CANYS(5,10)	5157	0.0037	0.0041	0.0172	0.0114	-0.0097	0.7470
HKYS(2,5)	2952	0.0084	0.0059	0.0085	0.0212	-0.0193	0.7109
HKYS(2,7)	2662	0.0113	0.0129	0.0096	0.0275	-0.0202	0.7666
HKYS(2,10)	2435	0.0142	0.0083	0.0040	0.0336	-0.0208	0.7924
HKYS(3,7)	2662	0.0079	0.0125	0.0209	0.0335	-0.0133	0.7739
HKYS(3,10)	2435	0.0107	0.0079	0.0070	0.0373	-0.0140	0.8053
HKYS(5,10)	2435	0.0061	0.0015	0.0047	0.0142	-0.0033	0.8381
Total	262,170						

Append II: Unconditional and Conditional Bond Returns

This Appendix briefly describes the methodology use to calculate the unconditional and conditional bond returns. Two important assumptions are needed to compute the bond returns. First, all benchmark bonds in our sample countries, apart from Germany, are assumed to pay semi-annual coupons to bond holders throughout the sample period. Second, benchmark bonds are assumed to trade at par. The first assumption is not controversial since the government coupon bonds usually maintain similar coupon payout methods for many years, especially for benchmark issues. To show why the second assumption is reasonable as well, we refer to the following Figure 3.10.

Figure 3.10: An Example of Historical Benchmark Bond Price and Bond Yield



This Figure displays the historical US 10-year benchmark bond price and the bond yield over period 1978-2006. The evidence here shows that the benchmark bond prices fluctuate permanently around \$100 while the bond yields vacillate between 3 and 15 percent. Although the bond prices deviate from par, in the long run, the average value of the bond price is close to par. As a matter of fact, the mean price in this example is \$100.17, which is not significantly different from \$100. Thus, it is reasonable for us to maintain the second assumption for other bonds of different maturities.

The next step is to compute the bond's duration. Despite the recent growth in modern financial engineering, the Macaulay duration by F. Macaulay (1938) is still the bedrock in measuring the price response of a bond to changes in interest rates. The basic equation for calculating the Macaulay duration D is given as:

$$D = \frac{\sum_{i=1}^{n} \frac{tC}{(1+y/2)^i} + \frac{nM}{(1+y/2)^n}}{P} \tag{3.33}$$

where y is the bond yield (semi-annual coupons), P is the bond price, M is the par value and n is the number of semi-annual periods. Given this Macaulay duration D we can proceed to calculate the Modified duration D^*:

$$D^* = \frac{D}{1+y} \tag{3.34}$$

By the virtue of the second assumption, the bond yield is equivalent to the coupon rate at par. This information enables us to compute the Modified duration D^* in equation (3.34) with $P = 100$, $M = 100$, $C = y$ and the bond yield y_t at time t and the maturity value. For example, the modified duration of a 10-year government bond at 5 percent yield and 5 percent coupon is $D^* = 7.7945$.[21] Armed with the modified duration D^*, it is possible for us to compute the approximate percentage bond price change of the bond with the following expression, even though we do not have the actual bond price data:

$$r_t = \frac{\Delta P}{P} = -D^* \times \Delta y \qquad t = 2, ..., T \tag{3.35}$$

where $\Delta P = P_t - P_{t-1}$, $\Delta y = y_t - y_{t-1}$, and $\Delta P/P$ is the percentage change in bond price, and Δy is the change in bond yield. This percentage bond price change is assumed to be the bond returns r_t at time t.[22] To provide further intuition to the percentage bond price change, we provide a graphical example of the unconditional bond returns r_t in Figure 3.11. The data used in this example is the US 10-year benchmark bond yield over the period 1962-2006. Basically, this Figure shows the daily normalized bond price returns change computed with the modified duration D^* and daily bond yield change Δy via equation (3.35).[23]

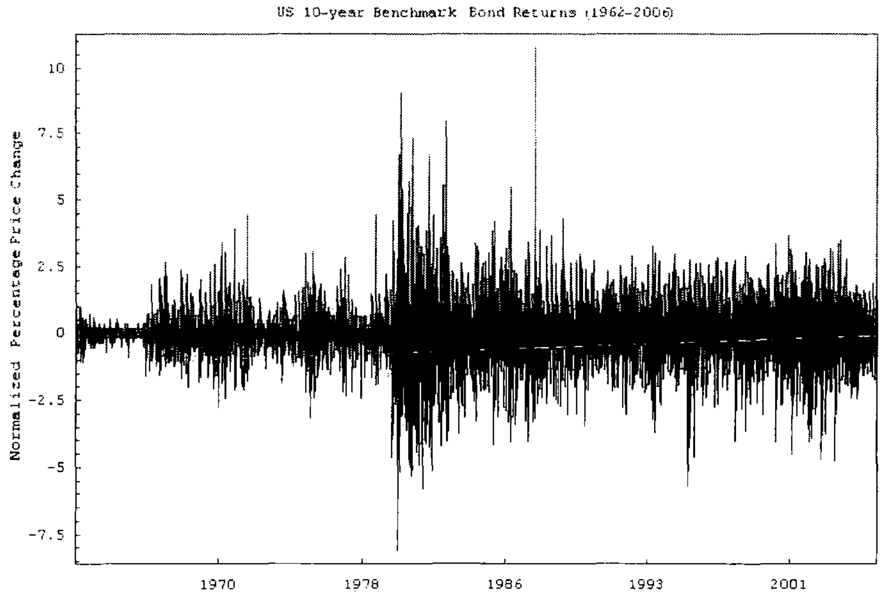
This figure shows that the unconditional bond price returns capture several well

[21] See Fabozzi (2001) and Campbell, Lo and Mackinlay (1997, Chapter 10) for more details.

[22] Another approach for approximating a bond's duration using the yield-to-maturity is derived by Shiller, Campbell and Schoenholtz (1983). Their approximation to the bond's duration that is selling close to par is given by: $D^\circ \approx \frac{1-\rho^n}{1-\rho}$, where $\rho = (1+y_t)^{-1}$ and n is the bond's maturity. This relationship becomes equality if the bond is selling at par. The log-linear bond returns is then given as: $r_{t+1} \approx D^\circ y_t - (D^\circ - 1)y_{t+1}$, where y_t is the yield-to-maturity at time t. See Campbell, Lo and Mackinlay (1997, p.408) and Hardouvelis (1994) for more details.

[23] The modified duration D^* will vary throughout our sample data because the level of bond yield is not constant. The normalization procedure is described in Section 3.2.

Figure 3.11: Daily Normalized Unconditional Benchmark Bond Price Changes Using Modified Duration



known stylized facts, such as the increased in bond price volatility during the US monetary tightening in 1978-1981, and the large positive spike in bond price during the October 1987 equity market crash. Because of their relative accuracy and to maintain consistency throughout our work, the method described here is used to calculate both the unconditional bond price returns and the one-day conditional bond price returns. After applying the Nadaraya-Watson and local polynomial regressions to each bond yield series, we have twelve sets of normalized conditional bond yield changes Δy, which we convert to bond price percentage returns r_t and compare these returns against the unconditional bond price returns from the whole sample period with the goodness-of-fit and Kolmogorov-Smirnov distribution tests.

Chapter 4

An Empirical Investigation of Price Gaps in the Financial Markets

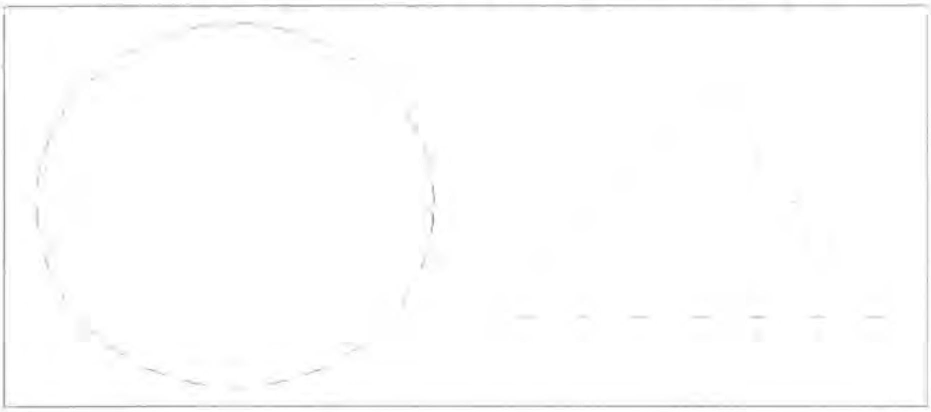
4.1 Introduction

It is well known that investors use technical analysis extensively to forecast future asset prices. (See Chapter 1) A significant part of technical analysis involves pattern recognition and evaluating images, such as extracting meaningful information from chart patterns like Head-and-Shoulders, which we have examined in Chapter 3. Therefore, human cognitive ability plays an important role in technical analysis. Early German psychologists have developed the *Gestalt laws of perceptual organization* to explain how humans, or technical traders in our case, perceive external objects. Among these Gestaltist laws, one cognitive theory hypothesized that there is a tendency for humans to visually complete fragmentary pictures and fill in the incomplete information. This is known as the *Law of Closure.*[1] To exemplify this law, we plot two objects in Figure 4.1(a). One could easily recognize the left and right figure as a circle and triangle respectively, even though no complete circle or triangle has been drawn. According to the Law of Closure, we mentally connect the dashed lines and fill the empty space between these dashed lines with imaginary lines, therefore forming the circular and triangular objects in our mind.

In relation to the dashed objects, such gaps (or empty space) can also occur between two trading periods in the financial markets, as shown in Figure 4.1(b). Price gaps are defined to be the vertical space created between the high and low prices in one trading period and the high and low prices in next trading period. They are marked by G in this sub-figure. For example, if the day-high at time t is lower

[1] See, for example, Wertheimer (1923, 1958) for a description of this and other cognitive laws. Early studies that verify the Law of Closure with simple incomplete geometric figures include Koffka (1935), Street (1931) and Leeper (1935). See also Barlett (1916, 1932).

Figure 4.1: Cognitive Psychology and Technical Analysis



(a) The Gestalt Law of Closure

(b) Price gaps (marked by G) in the financial markets

than the day-low at time $t+1$, an *upward* price gap has occurred. On the other hand, if the day-low at time t is higher than the day-high at time $t+1$, a *downward* price gap has occurred.

These price gaps have fascinated technical analysts for a long time, including Edwards and Magee (1966). Perhaps influenced by the Gestalt Law of Closure, technical analysts have prescribed that such gaps must be covered in the future, even though they cannot say why this must be so and when the gaps will be covered. In chartist parlance, a gap is *filled* when prices fall back to cover the entire space created by price gap, and *partially filled* when prices retrace to partially cover the gap. This Gap-Fill hypothesis is described by Pring (1987, p.87) as:

> There is an old principal that market abhors a vacuum and that all gaps are eventually filled.

The aim of this chapter is to evaluate whether this Gap-Fill hypothesis is empirically justified. Until now, price gaps have not been analyzed statistically. The price gap hypothesis has become a universal tool without any strong evidence, apart from the fact chartists know that gaps are important, as Edwards and Magee (1966, p.207) argue about this many years ago:

> These "holes" in the price trend graph were conspicuous. It was only natural that observers should attach importance to them, should try to assign some special significance to their occurrence. But the result was unfortunate, for there soon accumulate a welter of "rules" for their interpretation, some of which have acquired an almost religious force and are cited by the superficial chart reader with little understanding as to why they work when they work (and, of course, as is always the case with any superstition, an utter disregard of those instances where they don't work.)

Furthermore, no empirical study has provided any evidence on to whether gaps are sources of profitable technical indicators. The line of research in many previous technical analysis papers concentrate on [1] Profitability of simpler technical indicators like moving average, filters and calendar effects (See, for example, Brock, Lakonishok and LeBaron (1992), Kho (1996), Cooper (1999), Sullivan, White and Timmermann (1999, 2001) and Chapter 2), [2] Chart pattern recognition capability (See, for example, Osler (1998), Chang and Osler (1999), Lo, Mamaysky and Wang (2000), Dempster and Jones (2002), Dawson and Steeley (2003), Savin, Weller and Zvingelis (2003) and Chapter 3), [3] Neural network and artificial intelligence (See, for example, Neely, Weller and Dittmar (1997), Allen and Karjalainen (1999) and Neely and Weller (2003)) and [4] Theoretical models (See Treynor and Ferguson (1985), Brown and Jennings (1989) and Blume, Easley and O'Hara (1994)).[2]

Thus, this chapter extends the current literature on technical analysis by evaluating several hypothesis relating to price gaps:

1. Are price gaps filled, as technical analysts are universally led to believe?

2. Do price gaps provide an extra dimension of information to traders?

3. Do price gaps provide sources of profitable trading strategies?

Although price gaps are easy to identify, they can take several distinguishable forms. To test the information provided by these gaps, an objective method for identifying various types of price gaps is needed. Otherwise, various interpretations of the price gaps will arise. Thus, we pre-set various conditions for different types of

[2] See Park and Irwin (2004) for a complete review of the previous studies in technical analysis.

gaps and apply these conditions objectively to detect price gaps in financial markets. The goal of such a procedure is to reduce the subjective nature of our selection process.

To this end, we first categorize price gaps into five specific types commonly taught by chartists. There are Congestion gaps, Breakout gaps, Runaway gaps, Exhaustion gaps and Island gaps. The characteristics of each type of gap are carefully studied and described. The next step is translating these verbal descriptions into computationally feasible algorithms so as to detect and sort out the various price gaps. The final step is evaluating the conditional price returns obtained from these price gaps by comparing them to the unconditional returns.

Price gaps are usually not used as an isolated technical indicator. In fact, technical analysts commonly use other technical indicators in conjunction with price gaps when evaluating the significance of price trend. Indicators including various chart patterns and volume. Hence, we shall include both indicators in our price gap study.

First, to test whether conditioning on chart patterns provide further information to technical analysts, we use a statistical smoothing algorithm to extract potentially useful chart patterns in conjunction with price gaps, as in the spirit of Lo, Mamaysky and Wang (2000, thereafter LMW). The smoothing method we consider is known as the local polynomial regression. Using local polynomial regression has several attractive properties over the Nadaraya-Watson estimator used by LMW, such as reduced boundary bias. Moreover, by resorting to this regression technique, we can homogenized the appearance of chart pattern throughout the sample data. (See Chapter 3 for more details) Second, volume is hypothesized to contain information that is potentially useful to analysts. For example, the occurrence of a price gap together with increased volume is claimed to confirm a price trend while decreasing volume signifies that the price trend are more prone to reversal in the future. (See, Bulkowski (2005), Edwards and Magee (1966) and Blume, Easley and O'Hara (1994))

We test the Gap-Fill hypothesis and apply the technical charting algorithm to twenty-eight futures markets. The principal reason for this data choice is that short-selling is permitted in the futures markets. Investors could either enter into a long or short positions in the event of a price gap, which can be an upward or downward price gap. Furthermore, futures markets allow us to test the Gap-Fill hypothesis across different asset markets, such as equity, currencies, fixed income and commodities. As a matter of fact, some futures markets have higher liquidity than the underlying financial instruments, a characteristic which enhances price discovery and promotes market efficiency.

The rest of this chapter is as follows. The first part of Section 4.2 describes the various type of price gaps and its algorithmic identification. The second part of the same section describes the two conditioning variables used in conjunction with the price gaps, including chart patterns and volume. Next, Section 4.4 summarizes the underlying futures data and the adjustment technique used to extract the continuous time series. We also include a number of graphical examples to facilitate the understanding of the algorithm and the smoothing technique. Section 4.5 presents the empirical results. Finally, Section 4.6 concludes.

4.2 Identification of Price Gaps

4.2.1 Types of Price Gaps

Price gaps occur regularly in financial markets. The causes of prices gaps are many, some of which may be due to exogenous information shocks like the release of economic data which has an unexpected component, (See, for example, Fleming and Remonola (1999a and 1999b) and Fleming (2003)) or a clustering of buy/sell orders at certain technical price levels.[3] (See, for example, Osler (2003) and Kavajecz and Odders-White (2004)[4]) Technical analysts have grouped these price gaps into different categories so that it is possible to identify future price gaps and to derive forecasting properties from these gaps. Each type of gap offers a different hypothesis (see next section).[5]

In broad generalities, there are several types of price gap that market technicians have identified. (See, for example, Edwards and Magee (1966), Schwager (1996), Bulkowski (2005) and Kaufman (2005))

1. **Congestion gaps**. Occur within a congestion or consolidation level.
2. **Breakout gaps**. Occur when prices are breaking out of the congestion (trendless) area.
3. **Runaway gaps**. Occur when prices are rapidly moving in one direction.
4. **Exhaustion gaps**. Occur when the price trend is coming to an end or reversed itself.

[3]Our study here is not to investigate the causes of price gaps. Whether price gaps are predictable is an interesting issue, but outside the scope of our study here and a work for future research.

[4]In particular, Kavajecz and Odders-White (2004) find evidence that some technical indicators can capture changes in the state of the limit book orders, indicators such as moving average.

[5]The ex-dividend gaps are not included in the present study since they offers no new information as market participants know in advance the causes of the gaps.

5. **Island Gaps** Occur when there are upward and downward gaps in a matter of short-period, leaving an *island* of prices separated by two gaps from the rest of the prices.

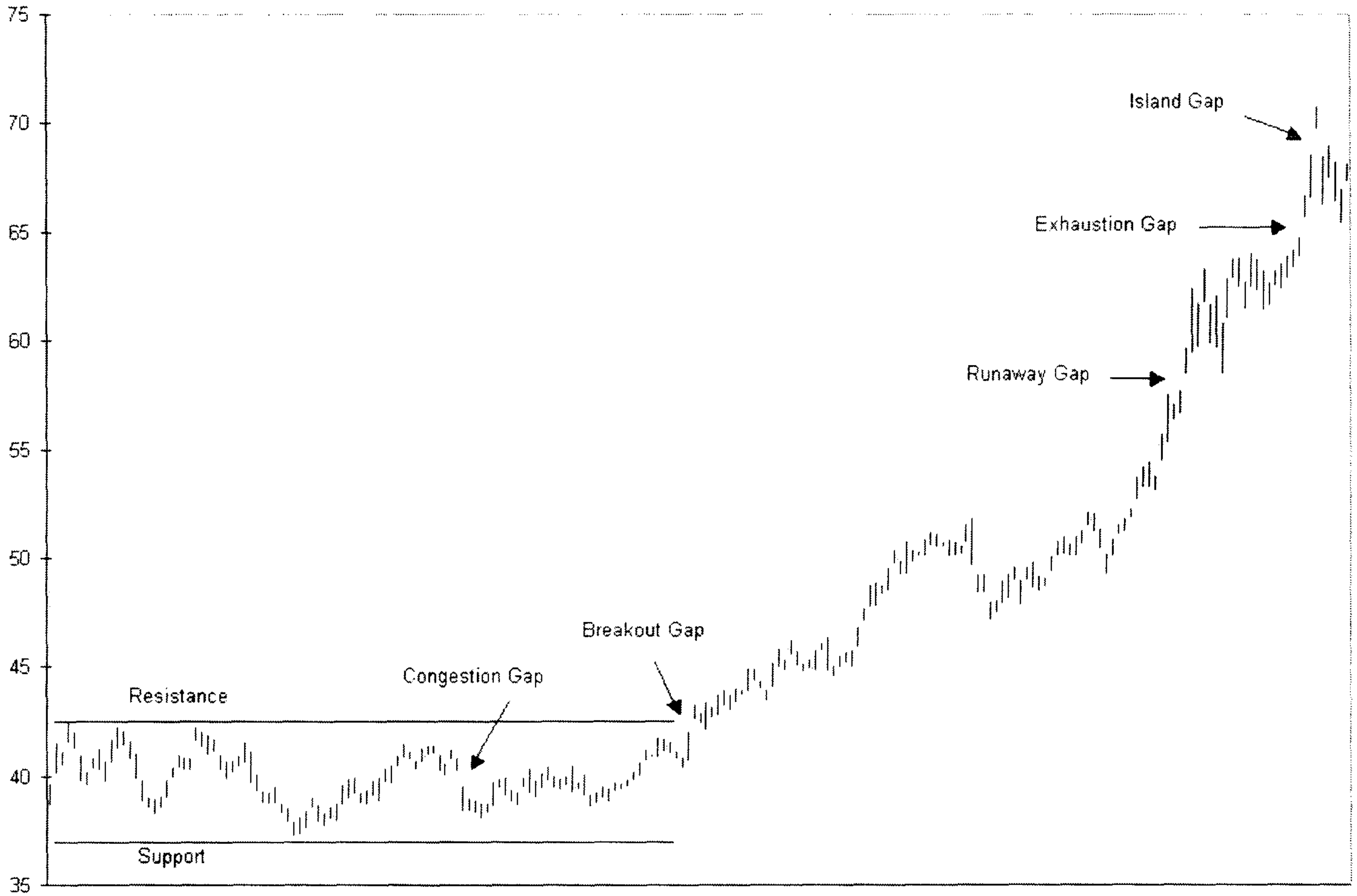
4.2.2 Observations on Different Price Gaps

This section provides more information about the various price gaps identified previously.

Congestion gaps occur frequently in financial data and can be attributed to the normal fluctuation of market noise. (Black (1986)). These gaps are commonly seen in areas of congestions, occurring below a critical resistance level and above an important support level, as shown in Figure 4.2.2. Simply, a resistance level is an area where prices can no longer advance due to excess supply of asset from sellers and a support level is a price level where prices do not fall further due to excess demand from buyers. These levels can be seen by the horizontal lines. The area bounded by the resistance and support levels is known as the "congestion" area. Therefore, the high and low prices on the day a congestion gap occurs should remained within the support and resistance level. Congestion gaps are said to be filled rapidly. Moreover, Edwards and Magee (1966, p.211) have described such gaps to have no value to traders, *"The forecasting significance of Common or Pattern Gaps is practically nil."* Thus, we should not expect such gaps to lent any forecasting capability to traders, neither should they provide any incremental information.

On the other hand, Breakout gaps often indicate the completion of some chart patterns and signal that a degree of bullishness or bearishness in asset prices is forthcoming. Patterns including Triangle or Rectangle. (See next section for more description of the chart patterns.) Usually, a Breakout gap is accompanied by heavier volume, and new highs (for up Breakout gap) and new lows (for down Breakout gap) on the day of the gap is made. The Breakout gap may be filled after the initial breakout. In Figure 4.2.2 an example of upward Breakout gap is given, which is shown to pierce through the resistance line. But what is the significance of Breakout gaps to investors? Edwards and Magee (1966) advise that if two securities are experiencing the same technical chart pattern, the security that breaks out of the pattern with a price gap has a higher probability of maintaining its direction over the security that does not have a gap. However, having said that, they also claim that (p.214) *"Except for the presumption of somewhat greater "steam" behind the move, the Breakaway gaps carries no particular measuring implication, nor any other forecasting significance."* For both Congestion and Breakout gaps, the congestion area bounded by a resistance and support line is presumed to span at least 10 trading days.

Figure 4.2: An Illustration of Various Price Gaps in the Financial Markets



Runaway gaps occur amidst a "strong" price advance or decline. To quantify what a strong price movement is, the prices before and on the day the Runaway gap occur should be new high (for an upward gap) or new low (for a downward gap). A Runaway gap is clearly seen in Figure 4.2.2, where the prices before the occurrence of the Runaway gap had increased rapidly. Prices after the occurrence of Runaway gaps are hypothesized to continue in the direction of the gap without pulling back to cover the gap in the short-term. To capture the characteristic of the strong price trend prior to Runaway gaps, we specify that prices must have at least two consecutive new highs or new lows before the day the gap occurs. The new highs or lows are compared to prices in the last 15 days.

Closely related to Runaway gaps are Exhaustion gaps, which are usually described as *"the last gasp"* after a strong price trend. The high or low price recorded during the Exhaustion gap must be new high or new low and possibly accompanied by higher than average volume. Exhaustion gaps are usually preceded by other price gaps, such as Runaway gaps, as shown in Figure 4.2.2. Exhaustion gaps are claimed to be filled quickly, most often within 2 to 5 days. Since Exhaustion gaps must be made after a significant price trend, we define the new high or new low over a longer time frame of 22 days.

Understandably, the hardest gaps to distinguish between are Runaway and Exhaustion gaps. This is because one is always uncertain whether the trend is terminating. It is only possible to differentiate these two gaps retrospectively, as Edwards and Magee (1966, p.216) point out that, *"this is fairly typical of many cases in which it is impossible to say whether Continuation or Exhaustion is being signaled until 2 or 3 days after the gap is made."* However, there are clues to distinguish between these two gaps, as described by the Edwards and Magee later in the same chapter (1966, p.221):

> An Exhaustion Gap is seldom the first gap in a runaway move; it is usually preceded by at least one Continuation Gap. Thus, you may ordinarily assume (unless the contrary appears from other and more weighty indications) that the first gap in a rapid advance or decline is a continuation Gap. But each succeeding gap must be regarded with more and more suspicion, especially if it is wider than its predecessor.

The problem for us now is deciding how many Continuation gaps must occurred before the gap can be categorized as an Exhaustion gap. For simplicity, we shall fixed the number at 1, meaning that at least one Runaway gap must occur in the near term before the current price gap is described as an Exhaustion gap. We define near term to be 7 trading days.

The last type of price gap is Island gap. An Island gap is an island of prices left out of the continuous fluctuations of price path separated by two gaps. This can be seen at the top right-hand corner in Figure 4.2.2. By itself, Island gaps are claimed not to be a major reversal indicator. Rather, they belong to minor tops in a larger chart formation, such as the Head in the Head-and-Shoulders formation. (Edwards and Magee (1966)) But given that interpretation, Island gaps are also said to predict some sort of retracement to earlier price movements after it occurs. Hence, if an Island top occurs, the general expectation is that near-term prices will decline. On the contrary, if an Island bottom occurs, the near-term prices will increase. Even Edward and Magee concede that it is not easy to make money by trading the Island gap pattern.

The next section transforms the above general descriptions algorithmically so that it is possible identify the price gaps.

4.2.3 Identification of Price Gaps

To define the above-mentioned price gaps, let O_t, H_t, L_t and C_t denote the open, high, low and close price at time t respectively. After a price gap is detected, it must be categorized into one of the first four price gaps without any overlapping definition. The only exception is Island gaps. This is because the Island gap contains two gaps, one up and one down, separated by a trading day.

The following are the conditions on each type of price gap.

Definition 1: (Congestion Gaps) Congestion gaps are bounded by a support level and a resistance level. The following defined both upward congestion gap (UCG)and downward congestion gap (DCG) respectively:

UCG1 $L_t > H_{t-1}$

UCG2 C_t and $O_t < \text{Max}(H_{t-1}, ..., H_{t-10})$

and

DCG1 $H_t < L_{t-1}$

DCG2 C_t and $O_t < \text{Min}(L_{t-1}, ..., L_{t-10})$

Definition 2: (Breakout Gaps) Breakout gaps occur when the gap forecast an initiation of a trend in prices. There are two types of possible breakaway gaps. The first case is when the body of the gap penetrates the resistant/support level, and the second case is when the gap skips entirely the resistance or support level. The following defines the upward breakout gap (UBG) and downward breakout gap (DBG) respectively[6]:

UBG1 $L_t > H_{t-1}$

UBG2 Either C_t or O_t or $L_t > \text{Max}(H_{t-1}, ..., H_{t-10})$

UBG3 $H_t > \sup(H_t : t = -1, ..., -10)$

and

DBG1 $H_t < L_{t-1}$

DBG2 Either C_t or O_t or $L_t < \text{Min}(L_{t-1}, ..., L_{t-10})$

DBG3 $L_t < \inf(L_t : t = -1, ..., -10)$

Definition 3: (Runaway Gaps) Runaway gaps continue the ongoing trend. It is characterized by strong price movements prior to the gap. The upward runaway gaps (URG) and downward runaway gaps (DRG) can be characterized by the following conditions respectively:

URG1 $L_t > H_{t-1}$

URG2a $H_{t-2} > \text{Max}(H_t : t = -2, ..., -2 - k)$ where $k = 15$

URG2b $H_{t-1} > \text{Max}(H_t : t = -1, ..., -1 - k)$ where $k = 15$

URG3 $H_t > \sup(H_t : t = -1, ..., -15)$

and

URG1 $H_t < L_{t-1}$

URG2a $L_{t-2} < \text{Min}(L_t : t = -2, ..., -2 - k)$ where $k = 15$

[6]From our perspective, the color of the body in candlestick charts does not matter, as long as either the close, open or low price penetrates the resistant/support level. Color here refers to whether the open price is higher than the close, and vice versa. If L_t penetrate the resistant/support level, it means that the gap completely skips the resistant/support. If either C_t or O_t penetrate the resistant/support level, the body of the bar penetrates the resistant/support level. Candlestick chartists may disagree with our presumption here, for example, Nison (1991). But to confirm our suspicions on the lack of profitability of candlestick charts, we cite a number of empirical studies evaluate numerous candlestick patterns, all of which find them to be unprofitable. See recent studies by Fock, Klein and Zwergel (2005) and Marshall, Young and Rose (2005).

URG2b $L_{t-1} < \text{Min}(L_t : t = -1, ..., -1-k)$ where $k = 15$

URG3 $L_t < \inf(L_t : t = -1, ..., -15)$

Definition 4: (Exhaustion Gaps) Exhaustion gaps occur near the end of a trend. One or more runaway gap must occur before in the last 7 days. The upward exhaustion gap (UEG) and downward exhaustion gap (DEG) can be characterized with the following conditions respectively:

UEG1 $L_t > H_{t-1}$

UEG2 One upward Runaway gaps must occur in the last 7 days.

UEG3 $H_t > \sup(H_t : t = -1, ..., -22)$

and

DEG1 $H_t < L_{t-1}$

DEG2 One downward Runaway gaps must occur in the last 7 days.

DEG3 $L_t < \inf(L_t : t = -1, ..., -22)$

Definition 5: (Island Reversal Gaps) Island gaps are marked by both an upward gap and downward gap over two consecutive days. The following is a possible characterization of the one-day upward island gap (UIG) and downward island gap (DIG) respectively:

UIG1 $L_{t-1} > H_{t-2}$

UIG2 $L_{t-1} > H_t$

UIG3 $H_{t-1} > \sup(H_t : t = -1, ..., -25)$

and

DIG1 $L_{t-2} > H_{t-1}$

DIG2 $L_t > H_{t-1}$

DIG3 $L_{t-1} < \inf(L_t : t = -1, ..., -25)$

4.2.4 Width of the Price Gaps

As a further evaluation on the information content of price gaps, we test whether the size of the price gap has any effects on the conditional returns. The hypothesis is that the larger the price gap, the more informative it is. We categorize the width of the price gaps into three sizes (Size 1, Size 2 and Size 3), all of which relate to the price range prior to the day the price gap occurs. First, we measure the size of the gap by $\text{gapdiff}_t = L_t - H_{t-1}$ for an upward gap, and $\text{gapdiff}_t = H_t - L_{t-1}$ for a downward gap. For Size 1, gapdiff is smaller or equal to the size of open and close price of the previous day. For Size 2, gapdiff is smaller or equal to the size of high and low price of the previous day. For Size 3, gapdiff is larger than the size of the high and low price of the previous day. More specifically,

1. (Size 1) $\text{gapdiff}_{t,1} \leq |O_{t-1} - C_{t-1}|$
2. (Size 2) $\text{gapdiff}_{t,2} \leq |H_{t-1} - L_{t-1}|$
3. (Size 3) $\text{gapdiff}_{t,3} > |H_{t-1} - L_{t-1}|$

where O_t, H_t, C_t are the open price, high price and close price at time t respectively.

4.2.5 Conditioning Variable 1: Chart Patterns

Local Polynomial Regression

Chart patterns are the foundation of technical analysis. It is frequently claimed that chart patterns provide additional value in forecasting financial prices. Indeed, LMW has provided some empirical evidence that chart patterns do alter the empirical distribution of the stock returns in the U.S. equity markets. (See Chapter 3 for more details.)

To identify the chart patterns objectively, we use a nonparametric smoothing algorithm known as local polynomial regression specified in Chapter 3. Local polynomial regression has several appealing properties over the Nadaraya-Watson kernel estimators. One advantage is the similar bias order along the boundary and in the interior, and this reduces the need to use specific boundary kernels. The other advantage is that we can estimate the regression parameters using least squares. (Fan and Gijbels (1996, Chapter 3) and Hastie, Tibshirani and Friedman (2001, Chapter 5))

It is assumed that the financial price, y, is generated by the function $f(\cdot)$:

$$y = f(x) + \epsilon \tag{4.1}$$

where ϵ's are independent white noise, that is, $E(\epsilon) = 0$ and $Var(\epsilon) = 1$. Assuming that the $(p+1)^{th}$ derivative of $f(x)$ at point x_0 exists, we can approximate the unknown regression function $f(x)$ locally by a polynomial of order p. A Taylor expansion for x in the neighborhood of x_0 gives:

$$f(x) \approx f(x_0) + f'(x_0)(x - x_0) + \frac{f''(x_0)}{2}(x - x_0)^2 + \ldots + \frac{f^{(p)}x_0}{p}(x - x_0)^p \tag{4.2}$$

This polynomial is fitted locally by a weighted least square regression, minimizing the following function:

$$\min_{\beta} \sum_{i=1}^{n} \left[y_i - \sum_{j=0}^{p} \beta_j (x_i - x_0)^j \right]^2 K_h\left(\frac{x_i - x_0}{h}\right) \tag{4.3}$$

where $K_h(\cdot)$ is the kernel function assigning weights to each datum point, and h is the bandwidth parameter controlling the size of the local neighborhood. Let $\hat{\beta}_j, j = 0, ..., p$ be the solution to this least squares problem, it is clear from the Taylor expansion that $\hat{f}_j(x_0) = j!\hat{\beta}_j$ is an estimator for $f^{(j)}(x_0)$, for $j = 0, 1, ..., p$. Denote $\mathbf{X}$ as the $(n \times p)$ design matrix:

$$\mathbf{X} = \begin{pmatrix} 1 & (x_1 - x_0) & \cdots & (x_1 - x_0)^p \\ 1 & (x_2 - x_0) & \cdots & (x_2 - x_0)^p \\ \vdots & \vdots & \ddots & \vdots \\ 1 & (x_n - x_0) & \cdots & (x_n - x_0)^p \end{pmatrix} \tag{4.4}$$

and let $\mathbf{W}$ be the $(n \times n)$ diagonal matrix of weights:

$$\mathbf{W} = \text{diag}\{K_h\left(\frac{x_i - x_0}{h}\right)\} \quad i = 1, ..., n \tag{4.5}$$

The weighted least square problem (4.3) can be written as:

$$\min_{\beta} (\mathbf{y} - \mathbf{X}\beta)'\mathbf{W}(\mathbf{y} - \mathbf{X}\beta) \tag{4.6}$$

where $\hat{\beta} = (\beta_0, \beta_1, ..., \beta_p)'$. The solution is provided by weighted least squares theory and is given by:

$$\hat{\beta} = (\mathbf{X}'\mathbf{W}\mathbf{X})^{-1}\mathbf{X}'\mathbf{W}\mathbf{y} \tag{4.7}$$

if $(\mathbf{X}'\mathbf{W}\mathbf{X})$ is invertible. The estimator $\hat{f}(\cdot)$ is the intercept term $\hat{\beta}_0$. To ensure that $(\mathbf{X}'\mathbf{W}\mathbf{X})$ is invertible, at least $(p + 1)$ different points with positive weights are required.

In our estimation, $\mathbf{y}$ is a vector of closing prices and $\mathbf{X}$ is a matrix of time point $1, 2, ..., n$, where n is the window of close prices to which we apply (4.7) to each data point τ in that window in order to obtain n smoothed prices. In this chapter, we fixed $n = 30$, implying that once a price gap is discovered at time t, the local polynomial regression is applied to prices at interval $\{y_{t-1}, ..., y_{t-30}\}$.[7]

[7] In chapter 3, the fixed length window is 45 days. The fixed length window is smaller in this study

After all $\hat{\beta}_0$ are computed, we determine the extrema in this window by checking the signs of $\{\hat{f}'(\tau)\}_{\tau=1}^{\tau=30}$. $\hat{f}'(\cdot)$ is given by parameter $\hat{\beta}_1$ in (4.7). All extrema are obtained by checking for the sign of $\hat{f}'(\tau)$ against $\hat{f}'(\tau-1)$. If $\hat{f}'(\tau) > 0$ and $\hat{f}'(\tau-1) < 0$, a minimum extrema is found at $\tau-1$. On the contrary, if $\hat{f}'(\tau) < 0$ and $\hat{f}'(\tau-1) > 0$, a maximum extrema is found at $\tau - 1$. If both $\hat{f}'(\tau) = 0$ and $\hat{f}'(\tau - 1) = 0$, we work backwards for each $\beta_{1,\tau}$ to determine whether the current stationary point is a maximum or minimum since the extrema always gives an alternating sequence between maximum and minimum. We label all extrema in a window to be $(e_1, ..., e_m)$

Asymptotic results prescribe that odd p has a clear advantage over even p, in the sense that the conditional bias for odd values of p are simpler that even values of p. (See Simonoff (1996) and Fan and Gijbels (1996)) Consequently, we shall use the first order only, $p = 1$, for all polynomial regression.

Smoothing Parameters

The key parameters in both nonparametric kernel and polynomial regression are the choice of kernel, size of bandwidth and definition of chart patterns. We shall discuss the first two in this section and leave the discussion of chart patterns to the next section.

There are many choices in choosing which the kernel functions $K_h(\cdot)$. The most common ones are Gaussian, Epanechnikov and uniform kernels. The advantage of Epanechnikov kernel is that it has compact support, but is not differentiable at 1.[8] Results by Fan and Gijbels (1996, Theorem 3.4) and Fan et al. (1995) prove that Epanechnikov kernel is the optimal kernel for all orders p, that is, it is the weight function that minimizes the asymptotic mean squared error of the local polynomial estimators. Thus in this chapter we use the Epanechnikov kernel as our primary kernel:

$$K(z) = \frac{3}{4}(1 - z^2)_+ \tag{4.8}$$

After deciding the kernel function, the next step is to choose the bandwidth parameter. There are numerous approaches to this, including rule-of-thumb, cross validation, nearest neighbour and plug-in methods. (See, for example, Hardle (1990), Simonoff (1996) and Jones, Marron and Sheather (1996) for some theoretical and

because price gaps are short-term indicators. Thus, the period to which we extract the patterns are shorter than just evaluating chart patterns alone.

[8] Alternatively, one could follow LMW and use the Gaussian kernel, defined as: $K(z) = \frac{1}{\sqrt{2\pi}}\exp(-z^2/2)$, or the Uniform kernel, defined as: $K(z) = 1_{[-0.5,+0.5]}(z)$.

simulation analyses of these methodologies.) Many of these methods rely on asymptotic results to justify their selection. But in this chapter, we are dealing with finite samples and rely heavily on visual approximation. This makes the asymptotic theoretical results less relevant, as Cleveland and Loaders (1996) argued that there is a gap between the asymptotic theory and the problems encountered in finite samples. In particularly, they argue that global bandwidth selection tend to perform worse than nearest neighbours methods in practice, which contradicts the asymptotic theory. Hence, no matter which method of computing the bandwidth, there is always a need to adjust the bandwidth visually by technical analysts.

Taking these considerations into account, we use the most common approach, the cross validation method: (See Silverman (1986) and Hardle (1990))

$$\hat{h}_{CV} = \frac{1}{n}\sum_{t=1}^{n}\left(y_t - \hat{f}_{h,t}\right)^2 \tag{4.9}$$

where

$$\hat{f}_{h,t} = \frac{1}{n}\sum_{\tau\neq t}^{n}\omega_{\tau,h}y_\tau \tag{4.10}$$

which is the omit the τ^{th} observation from local regression at the focal value y_i. Omitting the τ^{th} makes the fitted value independent of the observed value y_i. After each price gap is found, the cross validation (4.9) is computed on a window of n closing prices so that it can feed into the local polynomial regression. As such, $\hat{h}_{CV}$ is a local bandwidth rather than a global bandwidth. Similar to LMW, visual analysis of $\hat{h}_{CV}$ shows that this bandwidth value over-smooth data. Thus, there is a critical need to reduce the value of $\hat{h}_{CV}$. After some trial and error, we fixed the bandwidth at ($\hat{h}_{CV} \times 0.45$) for all data.

Chart Patterns

After obtaining the smoothing algorithm, the next step is defining the type of chart patterns of interest.[9] Given the extrema $(e_1, e_2, ..., e_m)$, where e_m is the last extrema in a window of 30 days (approximately six trading weeks), we define the following chart patterns, including Head-and-Shoulders, Triangle, Rectangle, Broadening and Double. The strategy in applying the local polynomial regression to identify chart

[9]The chart patterns defined here are slightly different to the patterns described in Chapter 3 because we alter the parameter values that define the patterns. For example, the shoulders extrema (e_{m-3}, e_{m-1}) in the Head-and-Shoulders pattern here are constrained to be less than 0.5 percent from their average, where as it is 1.0 percent in Chapter 3.

patterns is as follows. Step 1: we determine whether a price gap has occurred and whether it is an upward or a downward gap. Step 2(a): If the price gap is an upward gap, we check whether an *inverse* Head-and-Shoulders, Triangle, Rectangle, Broadening or Double has occurred in the last 30 days, that is, we check for the Bottom chart patterns by applying the regression to the closing prices. Step 2(b): If the price gap is an downward gap, we check whether a Head-and-Shoulders, Triangle, Rectangle, Broadening or Double Top has occurred in the last 30 days. The rationale for this difference is that an upward gap starts from a support level, and therefore a bottom pattern is more appropriate than a top pattern. Similarly, if a downward price gap occurs, a short-term top pattern reflects a change in price trend better.[10] Step 3: Analyze the conditional returns based on the information tests. (See Section 3)

The following describes the five commonly taught patterns, including Head-and-Shoulders Top (HSTOP) and Head-and-Shoulders Bottom (HSBOT), Triangle Top (TTOP) and Triangle Bottom (TBOT), and Rectangle Top (RTOP) and Rectangle Bottom (RBOT), Broadening Top (BTOP) and Bottom (BBOT) and Double Top (DTOP) and Bottom (DBOT). (See, for example, Chapter 3, Bulkowski (2005), Edwards and Magee (1966) and Kaufmann (2005) for some extensive description of chart patterns.) The extrema $(e_{m-4}, e_{m-3}, e_{m-2}, e_{m-1}, e_m)$ are the last five extrema before a price gap occurred. In our estimation, we only apply the regression to closing futures prices. One possible avenue for future research is to use both the high and low daily prices.

Pattern 1: (Head-and-Shoulders) The following conditions characterize the Head-and-Shoulders Top (HSTOP) and Bottom (HSBOT) respectively:

HSTOP1 e_m is a maximum.

HSTOP2 $e_{m-2} > e_{m-4}$ and $e_{m-2} > e_m$

HSTOP3 $\max |e_i - \bar{e}| \leq 0.005 \times \bar{e}$, where $i = (m-4, m)$ and $\bar{e} = \frac{e_{m-4}+e_m}{2}$

HSTOP4 $\max |e_i - \bar{e}| \leq 0.005 \times \bar{e}$, where $i = (m-3, m-1)$ and $\bar{e} = \frac{e_{m-3}+e_{m-1}}{2}$

and

HSBOT1 e_m is a minimum.

HSBOT2 $e_{m-2} < e_{m-4}$ and $e_{m-2} < e_m$

HSBOT3 $\max |e_i - \bar{e}| \leq 0.005 \times \bar{e}$, where $i = (m-4, m)$ and $\bar{e} = \frac{e_{m-4}+e_m}{2}$

[10] For robustness purpose, we also report the results for the Top patterns for downward price gaps and Bottom patterns for upward price gaps.

HSBOT4 $\max |e_i - \bar{e}| \leq 0.005 \times \bar{e}$, where $i = (m-3, m-1)$ and $\bar{e} = \frac{e_{m-3}+e_{m-1}}{2}$

Pattern 2: (Triangle) The following characterize the Triangle Top (TTOP) and Bottom (TBOT) with five extrema respectively:

TTOP1 e_m is a maximum.

TTOP2 $e_{m-4} > e_{m-2} > e_m$ and $e_{m-3} > e_{m-1}$

and

TBOT1 e_m is a minimum.

TBOT2 $e_{m-4} < e_{m-2} < e_m$ and $e_{m-3} < e_{m-1}$

Pattern 3: (Rectangle) The following conditions specify the Rectangle Top (RTOP) and Bottom (RBOT) respectively:

RTOP1 e_m is a maximum.

RTOP2 $\max |e_i - \bar{e}| \leq 0.005 \times \bar{e}$, where $i = (m-4, m-2, m)$ and $\bar{e} = \frac{e_{m-4}+e_{m-2}+e_m}{3}$

RTOP3 $\max |e_i - \bar{e}| \leq 0.005 \times \bar{e}$, where $i = (m-3, m-1)$ and $\bar{e} = \frac{e_{m-3}+e_{m-1}}{2}$

RTOP4 $\min(e_{m-4}, e_{m-2}, e_m) > \max(e_{m-3}, e_{m-1})$

and

RBOT1 e_m is a minimum.

RBOT2 $\max |e_i - \bar{e}| \leq 0.005 \times \bar{e}$, where $i = (m-4, m-2, m)$ and $\bar{e} = \frac{e_{m-4}+e_{m-2}+e_m}{3}$

RBOT3 $\max |e_i - \bar{e}| \leq 0.005 \times \bar{e}$, where $i = (m-3, m-1)$ and $\bar{e} = \frac{e_{m-3}+e_{m-1}}{2}$

RBOT4 $\max(e_{m-4}, e_{m-2}, e_m) < \min(e_{m-3}, e_{m-1})$

Pattern 4: (Broadening) The following conditions specify the Broadening Top (BTOP) and Bottom (BBOT) respectively:

BTOP1 e_m is a maximum.

BTOP2 $e_{m-4} < e_{m-2} < e_m$ and $e_{m-3} < e_{m-1}$

and

BBOT1 e_m is a minimum.

BBOT2 $e_{m-4} > e_{m-2} > e_m$ and $e_{m-3} > e_{m-1}$

Pattern 5: (Double) Double top and bottom patterns need the top two (e_{top1}, e_{top2}) and lowest two (e_{bot1}, e_{bot2}) prices in a 30-day window, with the time at which these extrema occurred to be $(e_{top1,t}, e_{top2,t})$ and $(e_{bot1,t}, e_{bot2,t})$ respectively. The following conditions specify the Double Top (DTOP) and Bottom (DBOT) respectively:

DTOP1 e_m is a maximum.

DTOP2 $\max|e_i - \bar{e}| \leq 0.0025 \times \bar{e}$, where $i = (e_{top1}, e_{top2})$ and $\bar{e} = \frac{e_{top1}+e_{top2}}{2}$

DTOP3 $\max|e_{top1,t} - e_{top2,t}| \geq 15$ days

and

DBOT1 e_m is a minimum.

DBOT2 $\max|e_i - \bar{e}| \leq 0.0025 \times \bar{e}$, where $i = (e_{bot1}, e_{bot2})$ and $\bar{e} = \frac{e_{bot1}+e_{bot2}}{2}$

DBOT3 $\max|e_{bot1,t} - e_{bot2,t}| \geq 15$ days

4.2.6 Conditioning Variable 2: Volume

From the technical analysis perspective, volume may provide a further confirmation of the current trend in addition to the price gaps. Theoretically, Blume, Easley and O'Hara (1994) has provided us with some insights on how this might be possible in a rational framework. The hypothesis here is rather simple: if a price gap is accompanied by higher volume, then it may reinforce the information of price gap and the direction of the price trend.

To simplify the role of volume in this paper, we assume that the price gaps are further conditioned by increasing or decreasing volume trend. To know whether the volume is increasing, we first compute the average of the volume in the last 22 days at the day when a price gap occur. If the current volume is higher than this average volume, the gap is categorized as an increasing volume (I.V.) price gap. On the other hand, if the volume is lower than the average volume in the last 22 days, then the gap is a decreasing volume (D.V.) price gap.

4.3 Return Measurement, Information Tests and Bootstrapping

4.3.1 Sampling Conditional and Unconditional Returns

For each price series, we apply the algorithm specified in the previous section to extract the conditional returns. In particular, once a price gap is detected at time t, we record the one-day continuously compounded returns from time t to $t+1$ using formula $r_t = \ln\left(\frac{P_{t+1}}{P_t}\right)$, where P_t is the time t closing price. As a result, we have 10 sets of conditional returns upon detection of each type of price gap. To obtain additional information, we also record the conditional returns from $t+2$ (day 2) to $t+4$ (day 5) to examine any abnormal behavior. Unlike the conclusion of technical chart patterns such as Head-and-Shoulders top in Chapter 3, detecting price gaps is rather immediate since there are less controversy about their formation. Hence, there is no requirement to wait for several days before measuring the conditional returns, as in LMW.

For each price series, we construct the *unconditional* continuously compounded returns and compare them to the conditional returns. To make comparison easier across different markets, both the conditional and unconditional returns are standardized by subtracting the mean and dividing by the standard deviation:

$$Z_{i,t} = \frac{r_{i,t} - \text{Mean}(r_{i,t})}{\text{S.D.}(r_{i,t})} \tag{4.11}$$

where the mean and standard deviation are computed for each individual price series. Moreover, to increase the power of the statistical tests, we join all the futures price contracts for the information tests describe in the next section.

4.3.2 Information and Statistical Tests

To conclude whether price gaps contain any particular information compared to the unconditional returns, we use the goodness-of-fit test and the Kolmogorov-Smirnov test as proposed by LMW. (See Chapter 3) The null hypothesis for these tests is that if price gaps are informative, conditioning on them will alter the empirical distribution of returns. On the other hand, if the information contained in such patterns has been incorporated into the returns, then the normalized conditional and unconditional return distribution should be similar.

For the goodness-of-fit test, the procedure is to compare the quantiles of the conditional returns with their unconditional counterparts. The first step is to compute the deciles of unconditional returns and tabulate the relative frequency $\hat{\delta}_j$ of conditional returns that fall into decile j of the unconditional returns, $j = 1, ..., 10$:

$$\hat{\delta}_j = \frac{\text{Number of conditional returns in decile } j}{\text{total number of conditional returns}} \tag{4.12}$$

The null hypothesis is that returns are independently and identically distributed and thus the conditional and unconditional return distribution are identical. The corresponding goodness-of-fit test statistic Q is given by:

$$\sqrt{T}(\hat{\delta}_j - 0.10) \sim N(0, 0.10(1 - 0.10)) \tag{4.13}$$

$$Q = \sum_{j=1}^{10} \frac{(T_j - 0.10T)^2}{0.10T} \sim \chi_9^2 \tag{4.14}$$

where n_j is the number of observations that fall in decile j and the T is the total number of observations and (4.13) is the asymptotic Z-values for each bin.

For the Kolmogorov-Smirnov test, the statistical basis is derived from the cumulative distribution function $F_1(z)$ and $F_2(z)$ with the null hypothesis that $F_1 = F_2$. Denote the empirical cumulative distribution function $\hat{F}_j(z)$ of both samples:

$$\hat{F}_j(z) = \frac{1}{T_i} \sum_{k=1}^{T_i} I(Z_{ik} \leq z), \quad i = 1, 2 \tag{4.15}$$

where $I(\cdot)$ is the indicator function and $(Z_{1t})_{t=1}^{T_1}$ and $(Z_{2t})_{t=1}^{T_2}$ are the two IID samples. The Kolmogorov-Smirnov statistic is given by the expression:

$$\gamma = \left(\frac{T_1 T_2}{T_1 + T_2}\right)^{1/2} \sup |\hat{F}_1(z) - \hat{F}_2(z)| \tag{4.16}$$

and the p-values are given by:

$$\text{Prob}(\gamma \leq x) = \sum_{k=-\infty}^{\infty} (-1)^k \exp(-2k^2x^2), \quad x > 0 \tag{4.17}$$

Under the null hypothesis, the statistic γ should be small. 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. (See Press et al. (2002, Section 14.3) and DeGroot (1986))

Apart from the information test, a simple t-statistic tests whether the unconditional mean returns are statistically significantly different from zero. The formula for the test-statistic is:

$$t = \frac{\bar{z}}{\sigma / \sqrt{T_z}} \tag{4.18}$$

where $\bar{z}$ is the mean normalized conditional returns, σ is the standard deviation of the normalized unconditional returns, and T_z is the number of observations for the conditional returns $\bar{z}$ for a particular price gap. The null hypothesis is $\bar{z} = 0$. We apply equation (4.18) to all mean returns.

4.3.3 Nonparametric Bootstrapping

For comparison purpose, we conduct a number of bootstrap trials to test whether the number of price gaps found is significantly different to the bootstrap distribution. According to Brock, Lakonishok and LeBaron (1992), bootstrapping has the advantage of performing a joint test of significance across different trading rules, and at the same time, accommodating the leptokurtic, autocorrelation and heteroscedasticity features of financial data. (See Efron (1979))

We employ the simple nonparametric bootstrap discussed in Levich and Thomas (1993) and Chapter 2. Nonparametric here refers to the fact that we are not imposing any form of statistical distribution to the time series.[11] The sampling procedure is as follows: First, given n returns, we scramble these returns to form a new n-dimensional array, and rebased each scrambled returns with initial price of 100. Since we are sampling *without replacement*, the distribution properties of each bootstrap series are exactly similar to the actual return. Moreover, the initial and final price are the same as the original sample data. Next, we apply the price gap identification algorithm to this scrambled futures prices to form the empirical distribution of the number of gap detected and the distribution of normalized conditional returns up to five days after a price gap is detected. The procedure is repeated 1000 times. Lastly, we compare the actual number of price gaps with this distribution. A simple null hypothesis for the nonparametric bootstrap can be stated as follows: if there is no information in the original futures price series, then the number of gaps should not be significantly different from the number of gaps obtained by the shuffled series. We set the rejection point of this hypothesis at α significance level. (We choose $\alpha = 10$ percent)

[11] Alternatively, Brock, Lakonishok and LeBaron (1992) impose and fit four null statistical models on the stock index data, which are random walk model, autoregressive $AR(1)$ model, GARCH-in-Mean model and Exponential-GARCH model.

4.4 Futures Data

4.4.1 Futures Data and Data Adjustments

The primary data in our investigation are daily futures data obtained from *Datastream*, which include daily open, high, low, close prices, and volume. We choose futures data rather than underlying stocks or bonds primarily due to the opportunity to hold short positions. Since the direction of price gaps can be either upward or downward, futures data alleviate the problem of short selling underlying assets in a downward gap. To some extent, a number of futures contracts has higher liquidity than the underlying instruments.

Table 4.1 displays the 28 futures contracts to which we evaluate the price gap hypotheses. There are four types of futures contracts, currencies, fixed income, stock index and commodities, each have more than 10 years of daily trading data. The total number of data is 164,288 daily futures prices, which is deemed sufficient for our evaluation.

Since futures contracts expire at delivery day, there is a need to join the successive contracts into a continuous price series. We follow the standard procedure similar to Levich and Thomas (1993), Kho (1996) and Sullivan, Timmermann and White (1999, Section V) in splicing futures contracts. A continuous artificial returns data is created by taking logarithmic returns from the nearby (front) futures contract. For all financial futures contracts, the nearby months are March, June, September and December contracts, and for commodity contracts, the nearby contracts vary. For example, the returns data for US T-Bond March 2004 contract is collected from December 2003 to February 2004, and for June 2004 contract, returns data is collected from March 2004 to May 2004, and so on. The futures contract is switched on the last trading day before the current contract enters into the delivery month to avoid the complications arising during the delivery months, such as excess volatility, illiquidity and the presence of various options for fixed income futures. (See, for example, Milonas (1986), Johnston, Kracaw and McConnell (1991) and Ma, Mercer and Walker (1992))

Next, after obtaining all the *actual* returns series of the futures contracts, with the open, high and low prices as a fraction of the close actual futures prices for each trading day, we then rebased the returns series into a continuous price series, assuming an initial price based index as 100. The returns are converted back to prices with the expression: $P_t = P_{t-1}e^{r_t}$ for $t = 1, ..., n$ and $P_0 = 100$, where r_t is the actual return at time t and P_t is the price index at time t. The open, high and low prices are then

Table 4.1: Futures Contracts

Futures Contracts	Sample Period	Contracts Months	Observations
	Currencies		
US-Yen	Jan. 78-Jun. 06	3,6,9,12	7184
US-CHF	Jan. 78-Jun. 06	3,6,9,12	7186
US-GBP	Jan. 78-Jun. 06	3,6,9,12	7184
US-AUS	Jun. 88-Jun. 06	3,6,9,12	4555
US-CAN	Sep. 87-Jun. 06	3,6,9,12	4744
	Fixed Income		
US 2Y T-Bond	Jun. 90-Jun. 06	3,6,9,12	4014
US 5Y T-Bond	May. 88-Jun. 06	3,6,9,12	4539
US 10Y T-Note	May. 82-Jun. 06	3,6,9,12	6074
US 30Y T-Bond	Jan. 78-Jun. 06	3,6,9,12	7167
EuroDollar	Dec. 81-Jun. 06	3,6,9,12	6182
UK Long Gilts	Dec. 82-Jun. 06	3,6,9,12	5954
JAP. JGB	Dec. 86-Jun. 06	3,6,9,12	4704
AUS. 3Y T-Note	May. 88-Jun. 06	3,6,9,12	4579
AUS. 10Y T-Bond	Dec. 84-Jun. 06	3,6,9,12	5456
CAN. 10Y Bond	Sep. 89-Jun. 06	3,6,9,12	4211
	Stock Indices		
S&P 500	Apr. 82-Jun. 06	3,6,9,12	6095
FTSE 100	May. 84-Jun. 06	3,6,9,12	5593
Nikkei 225	Sep. 88-Jun. 06	3,6,9,12	4378
Dax	Nov. 90-Jun. 06	3,6,9,12	3938
	Commodities		
Gold	Jan. 79-Jun. 06	2,4,6,8,10,12	6894
Silver	Jan. 79-Jun. 06	3,5,7,9,12	6908
Cotton	Jan. 79-Jun. 06	3,5,7,10,12	6894
Crude Oil	Apr. 83-Jun. 06	1-12	5782
Heating Oil	Jul. 80-Jun. 06	1-12	6507
Cocoa	Jan. 79-Jun. 06	3,5,7,9,12	6886
Coffee	Jan. 79-Jun. 06	3,5,7,9,12	6880
Wheat	Jan. 79-Jun. 06	3,5,7,9,12	6928
Sugar	Jan. 79-Jun. 06	3,5,7,10	6882
	Total Observations		164,288

Source: *Datastream*

obtained by multiplying the actual fraction to this close price index.[12]

Figure 4.3 provides a comparison of the actual and rebased price series. The chart type is candlestick, where white bar means the close price is higher than open price and black bar means that the close price is lower than open price. Evidently, there is little difference between the charts, apart from the level of prices. The returns and the open, high, low prices, as a ratio to the closing price, are similar to one another. The rebased future price series have all the actual returns from the nearest futures contract prices, and the open, high and low are also of the same dimension as the actual futures prices. Consequently, when we conduct the empirical tests on the rebased futures prices, the results should be similar to the actual prices, at least in the short term. A gap in the actual price series will also exhibit itself in the rebased price series. As a robustness check, we have also spliced the futures data with another procedure based on expiry day, assuming that the futures contract is switch 10 days before the front contract expires. The results from this method are similar to the results from the first splicing procedure. For future research, it will be interesting to test the Gap-Fill hypothesis on intra-day data, as day traders rely heavily on technical indicators in their trading decisions. Moreover, intraday data allows us to observe the distribution of the volume throughout trading hours.

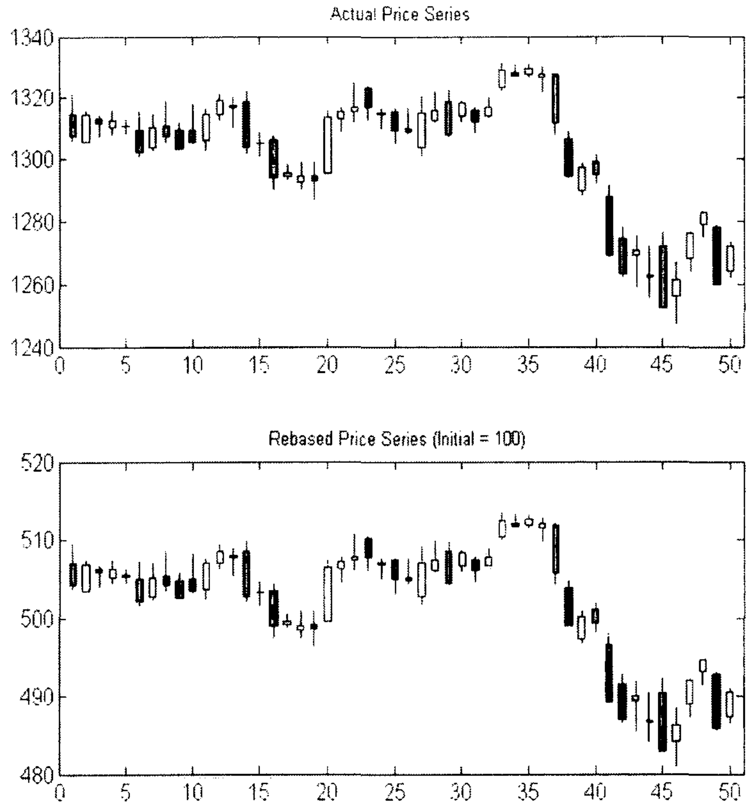
One particular concern about using futures data is the level of rebased futures prices. Arguably, the rebased futures prices are not an exact replica of the underlying cash prices or cash index. Therefore, we can only evaluate the Gap-Fill hypothesis in the short-term, since over the long-term the cumulative difference between the rebased futures price level and actual price level differs substantially. It remains a work for future research to test the Gap-Fill hypothesis on cash asset prices directly.

4.4.2 Empirical Examples of Price Gaps and Chart Patterns

In this section, we provide a visual sample of all price gaps detected using the algorithm specified in Section 4.2. The futures data to which we applied the price gap identification algorithm is the US 30-year bond futures contract over the entire sample period shown in Table 4.1. There are ten figures, one for each type of price gap detected (See Figure 4.4 to Figure 4.8). In each figure, the vertical dashed line is the

[12] In addition to the forward splicing method used here, we have also tried the backward splicing method for robustness check. Backward splicing uses the latest price as the initial price and multiplies the futures returns backward from T to $t = 1$ to obtain the futures prices. Even though the price level is different (because the initial price is different), the empirical results obtained from applying the price gaps algorithm on this dataset is the same, since the returns used for both methods are similar. See Chapter 2 for more description about the backward splicing procedure. In the Appendix I, we present a graphical view of all the rebased price series.

Figure 4.3: Actual and Rebased Price Series of S&P 500 Index Futures (June 2006 contract, 21/03/06-31/05/06)



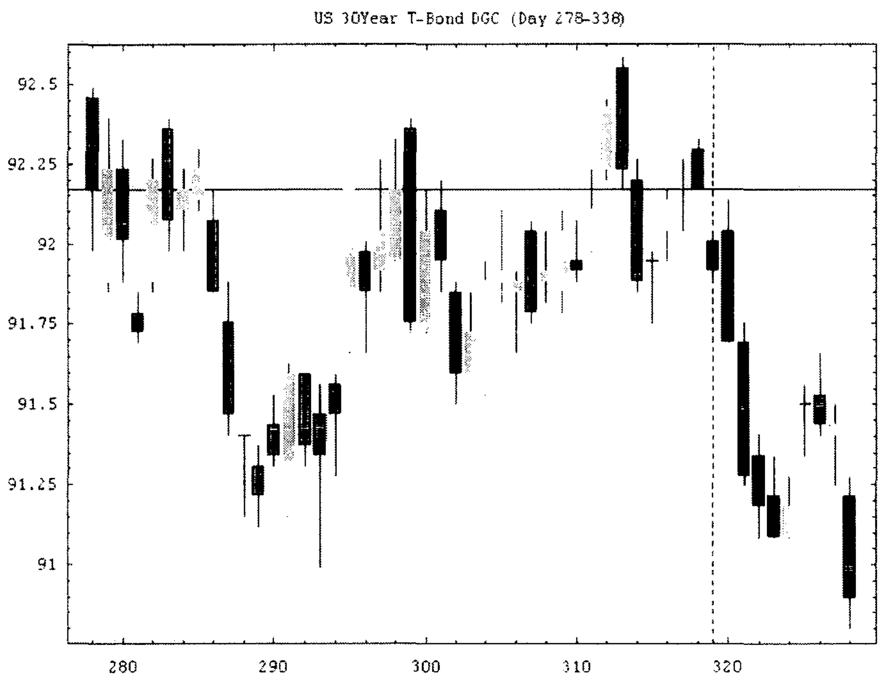
day at which a price gap occurred. The solid horizontal line highlights the level of price relative to the price gap. The dark bar means that the close price is lower than the open price and grey bar is the opposite.

In summary, Figure 4.4 shows the Congestion gaps are detected *in-between* some resistance and support levels and Figure 4.5 shows the Breakout gaps *penetrating* key resistance and support levels. The Runaway gaps in Figure 4.6 show that a strong price movements occurred before the price gap is detected. The Exhaustion gaps in Figure 4.7 show that a Runaway gap must occur in the last 7 days before it can be classified as an Exhaustion gap. Lastly, Figure 4.8 depicts the Island gaps.

The next set of figures (Figure 4.9 to Figure 4.13) are price gaps conditioned on one of the ten chart patterns discussed in Section 2.4. The thick dashed line is the smoothed prices obtained from applying the local polynomial regression $\hat{f}(\cdot)$ with cross validated bandwidth ($\hat{h}_{CV} \times 0.45$) to the closing prices. The vertical dashed line is the day when a particular price gap occurred. As before, the darker candlesticks are trading days where the open price is lower than the closing price. For upward price gap, we apply the inverse chart patterns, and for downward price gap, we apply the top chart patterns. For example, a downward price gap in Figure 4.9(a) is shown to be accompanied by a Head-and-Shoulders Top, while an upward price gap is accompanied by a Head-and-Shoulders Bottom in Figure 4.9(b). Obviously, not all Head-and-Shoulders patterns are as symmetrical as the one shown in this Figure. One weakness of kernel regression and local polynomial regression is the inability of the extrema $(e_1, ..., e_m)$ to match the actual turning points in closing prices precisely. Nevertheless, the local polynomial regression does provide us with a powerful indication that a chart pattern has indeed formed prior to the price gap.

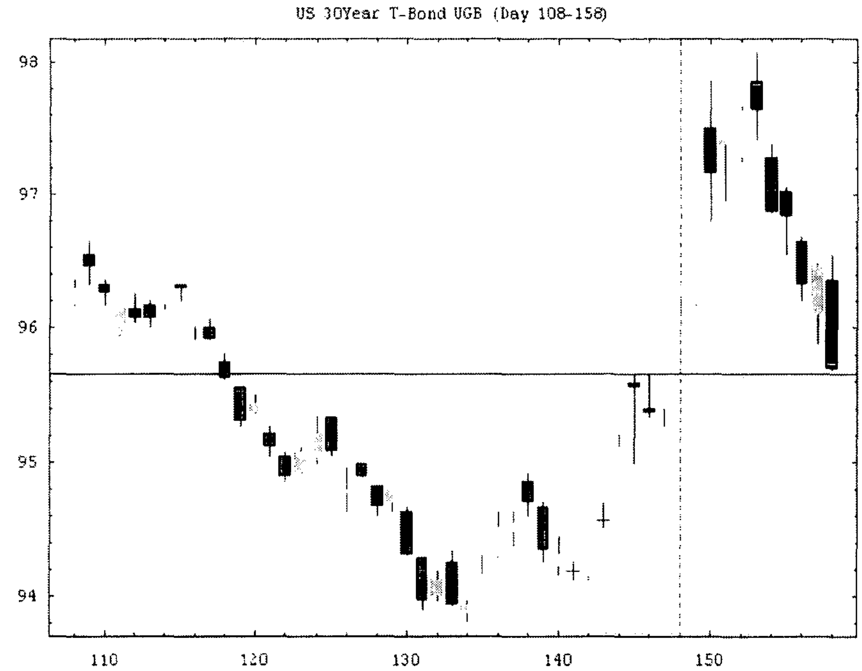
Figure 4.4: An Illustration of Congestion Gaps. The dotted line is the day the price gap is detected and categorised.

(a) Upward Price Gap: Congestion

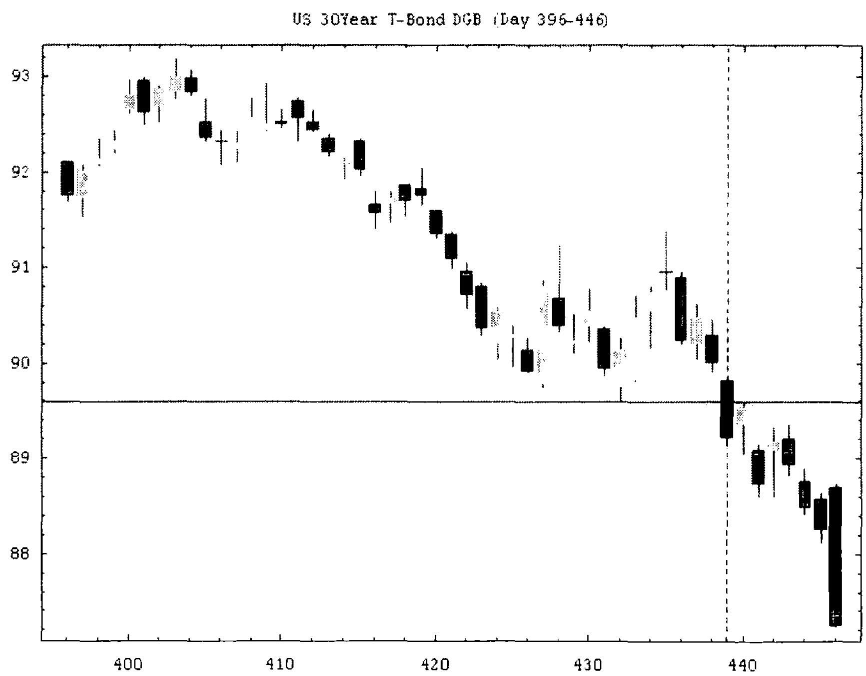


(b) Downward Price Gap: Congestion

Figure 4.5: An Illustration of Breakout Gaps

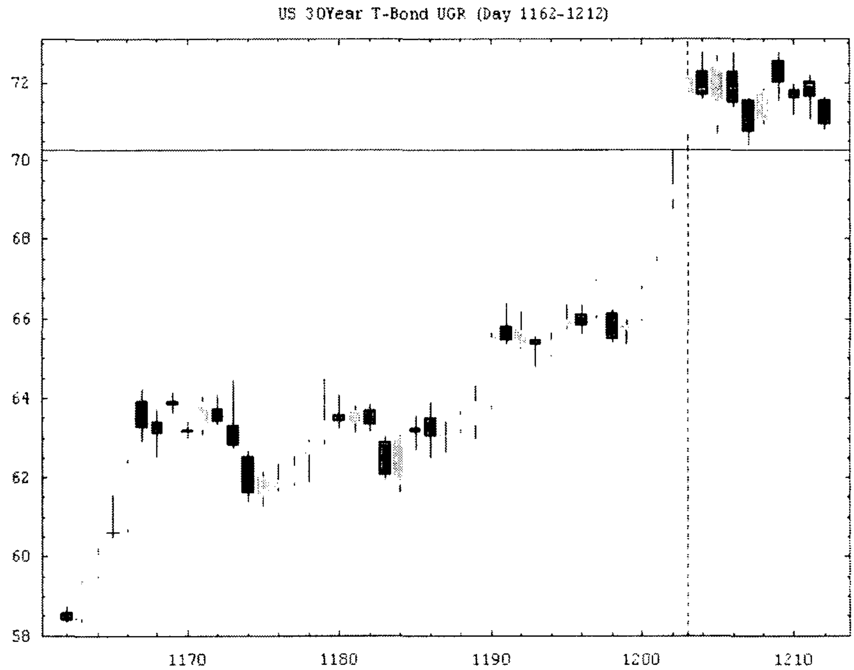


(a) Upward Price Gap: Breakout



(b) Downward Price Gap: Breakout

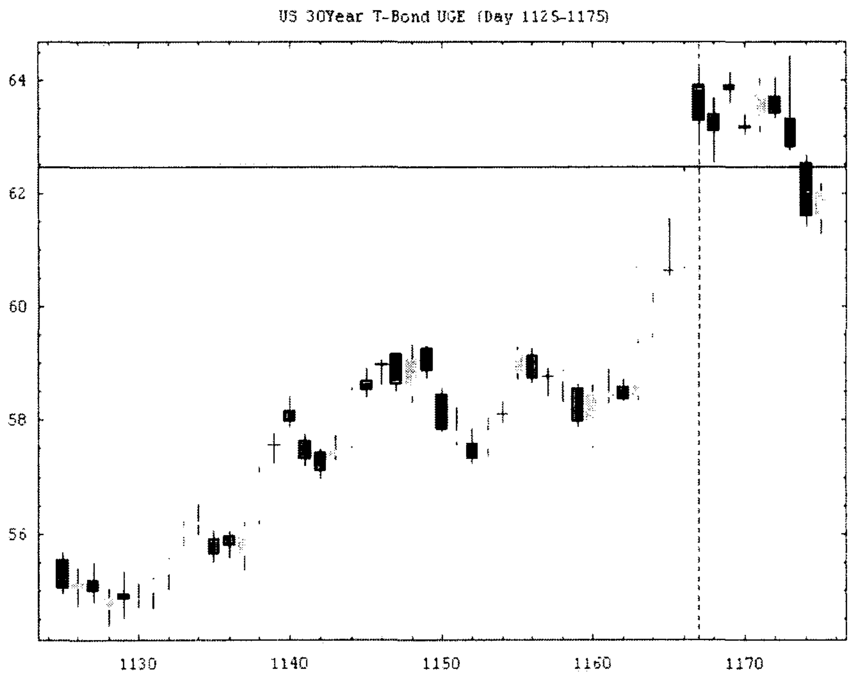
Figure 4.6: An Illustration of Runaway Gaps



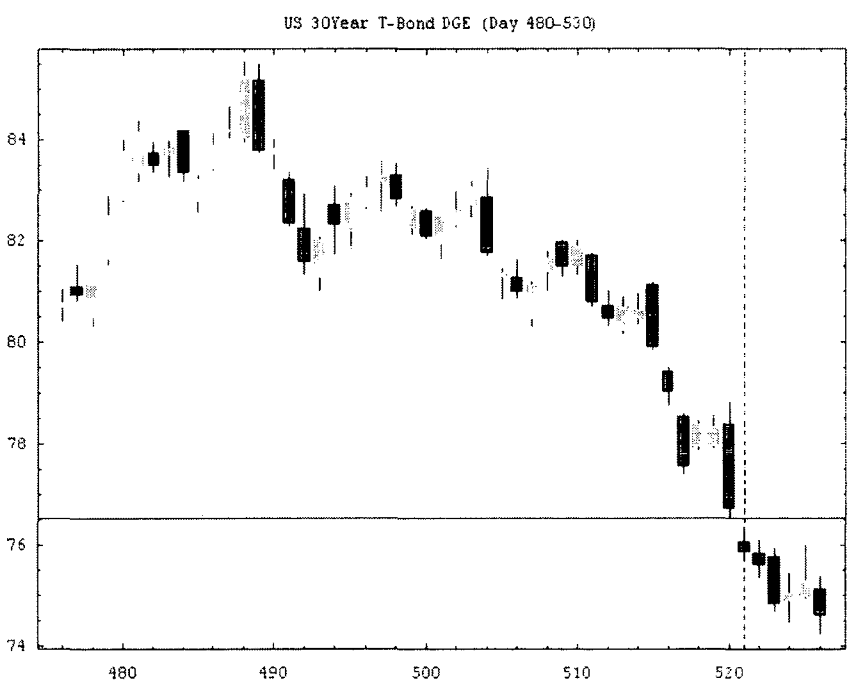
(a) Upward Price Gap: Runaway

(b) Downward Price Gap: Runaway

Figure 4.7: An Illustration of Exhaustion Gaps

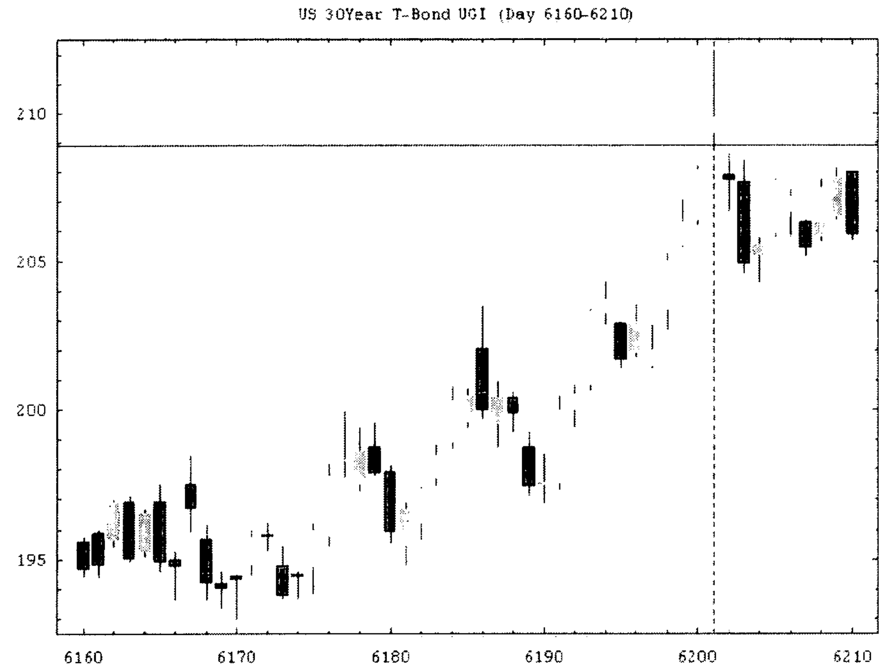


(a) Upward Price Gap: Exhaustion

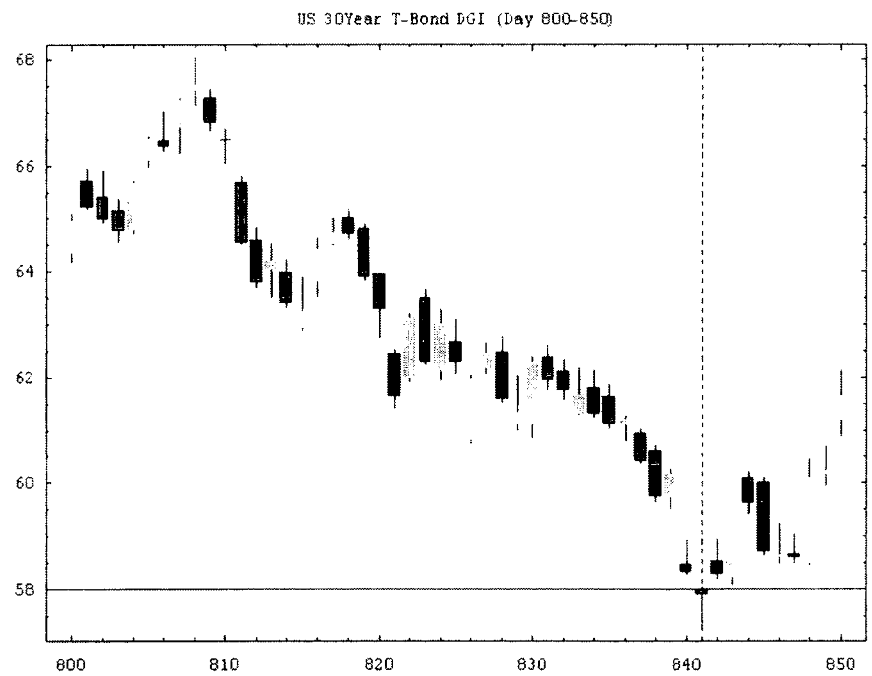


(b) Downward Price Gap: Exhaustion

Figure 4.8: An Illustration of Island Gaps

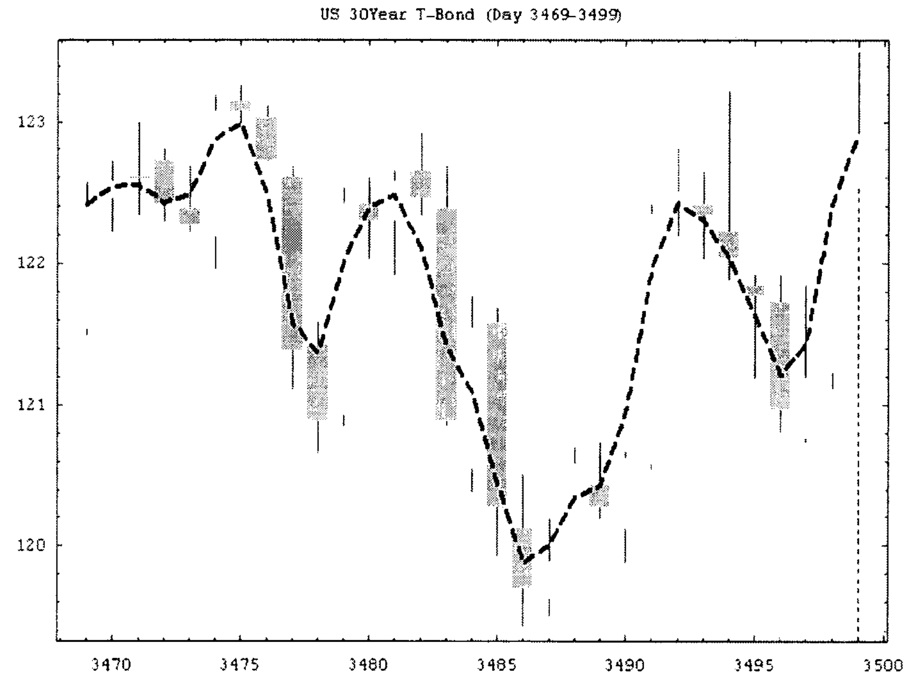


(a) Upward Price Gap: Island

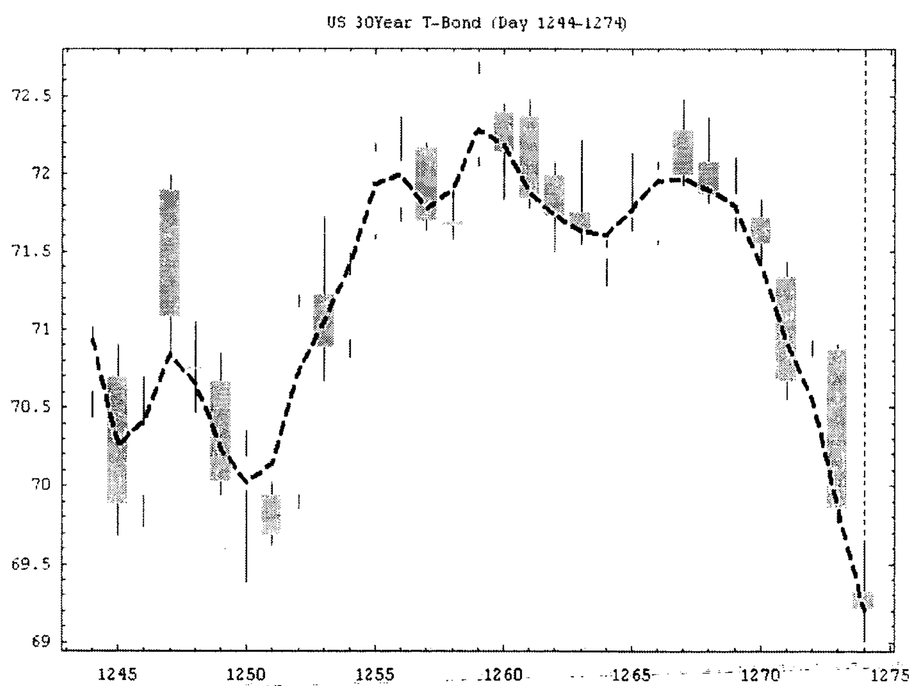


(b) Downward Price Gap: Island

Figure 4.9: An Illustration of Price Gaps With Head-and-Shoulder Chart Pattern. The thick dotted line is derived form the local polynomial regression and which satisfied the conditions for the Head-and-Shoulders chart pattern.

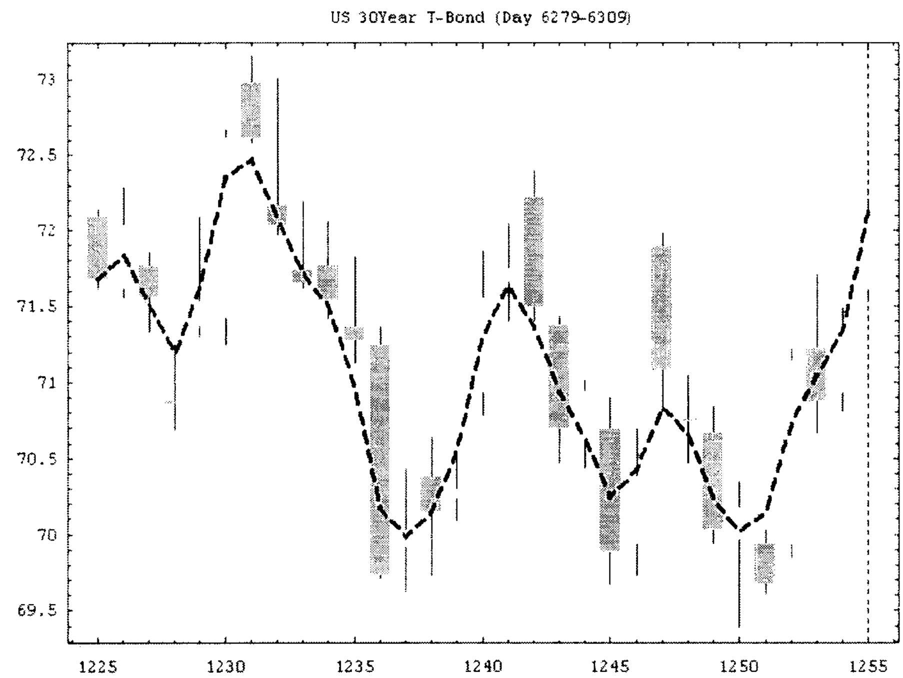


(a) Upward Price Gap With Head-and-Shoulders Bottom

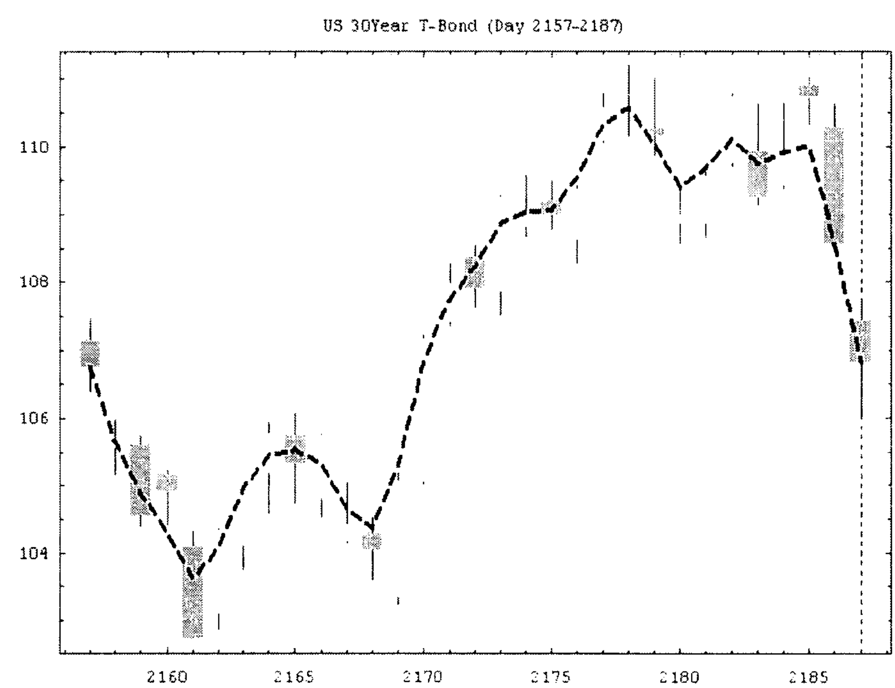


(b) Downward Price Gap With Head-and-Shoulders Top

Figure 4.10: An Illustration of Price Gaps With Rectangle Chart Pattern

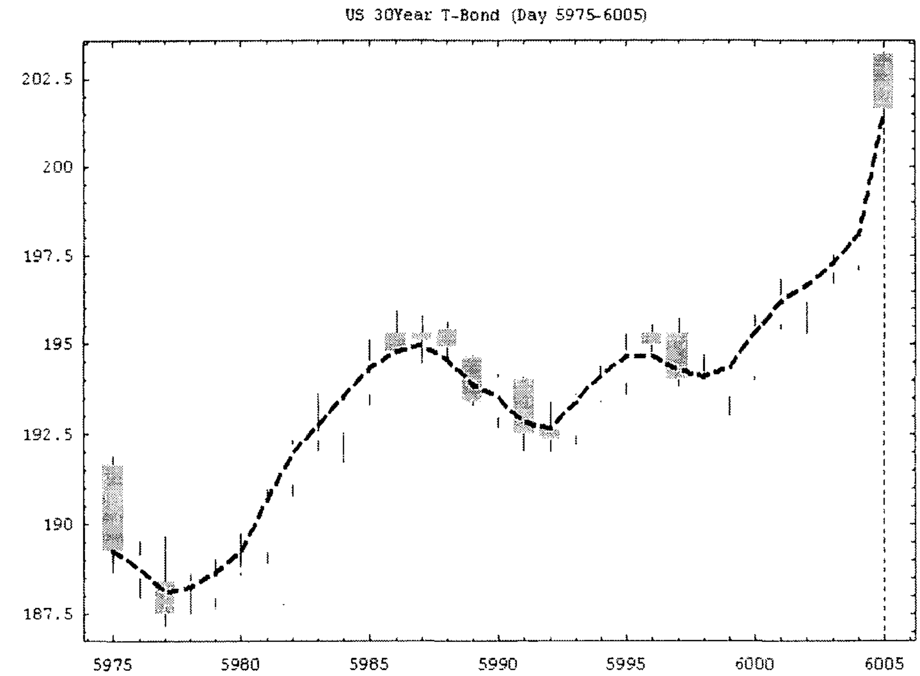


(a) Upward Price Gap With Rectangle Bottom

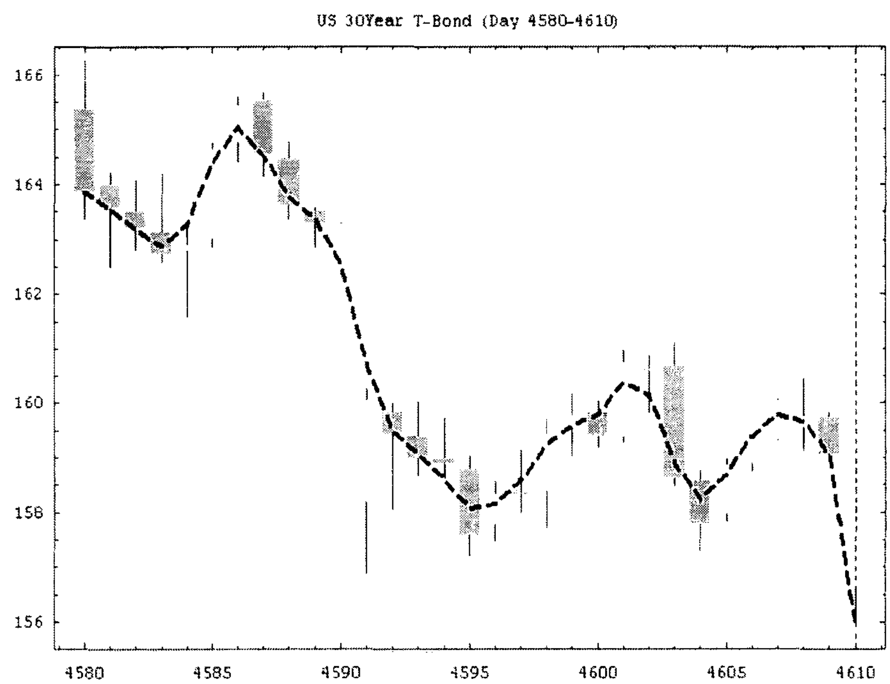


(b) Downward Price Gap With Rectangle Top

Figure 4.11: An Illustration of Price Gaps With Triangle Chart Pattern

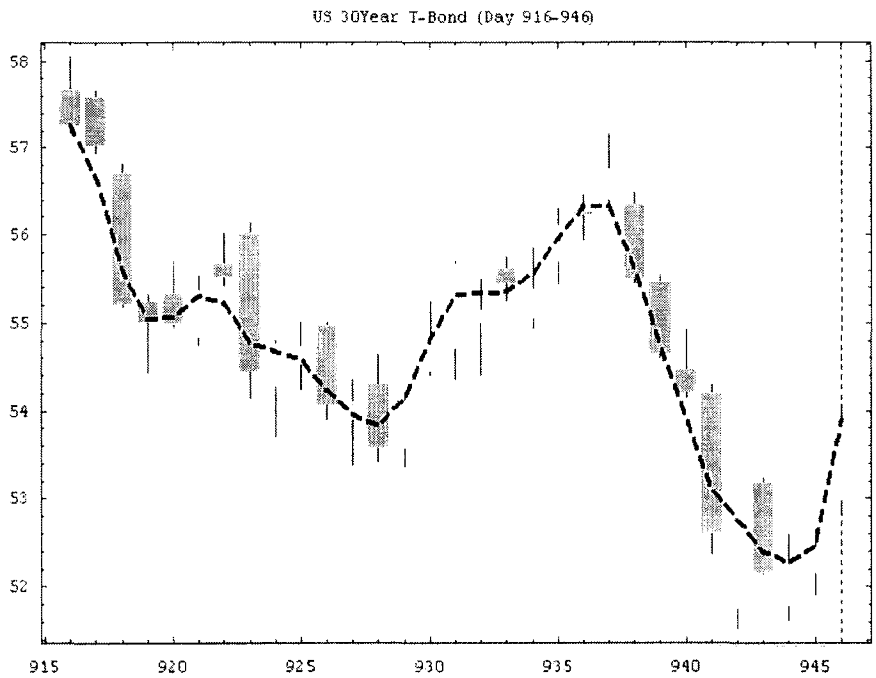


(a) Upward Price Gap With Triangle Bottom

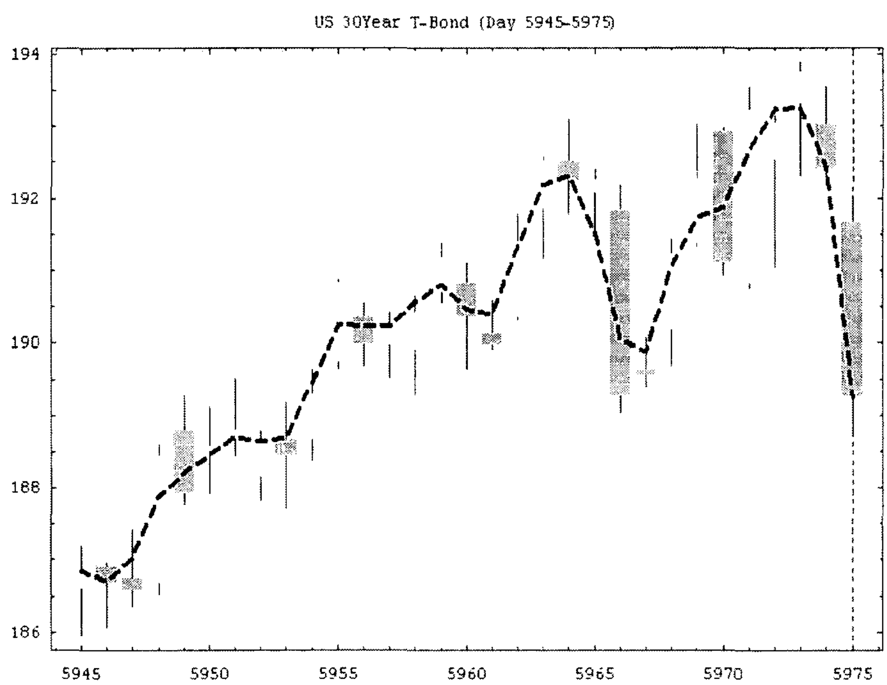


(b) Downward Price Gap With Triangle Top

Figure 4.12: An Illustration of Price Gaps With Broadening Chart Pattern

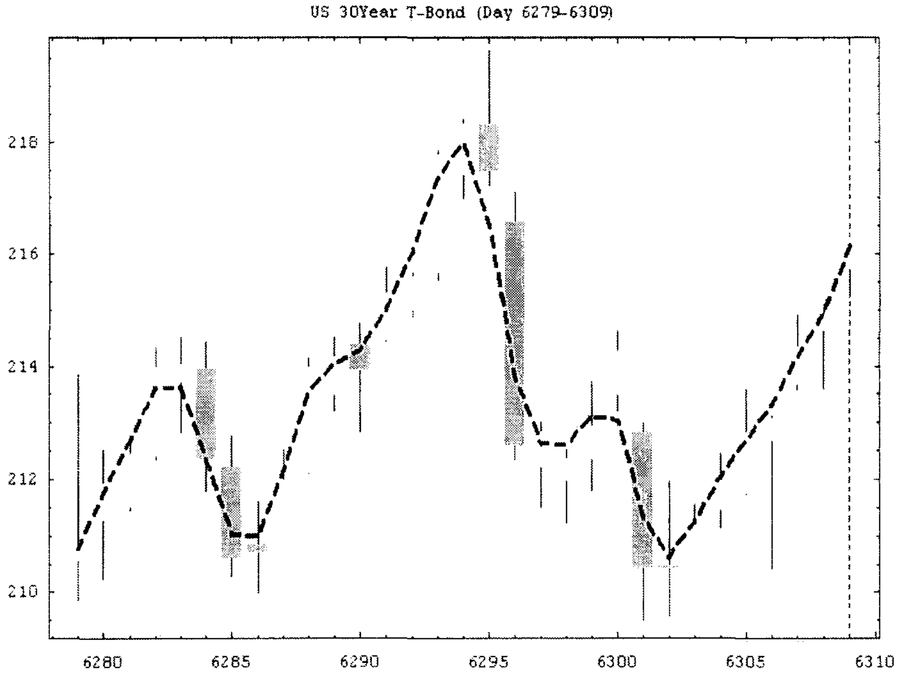


(a) Upward Price Gap With Broadening Bottom

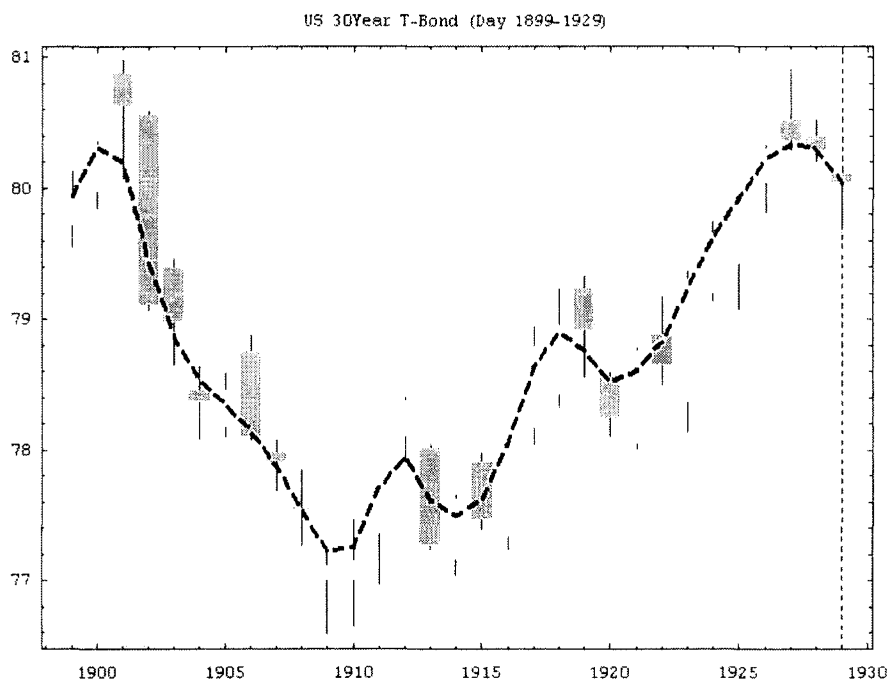


(b) Downward Price Gap With Broadening Top

Figure 4.13: An Illustration of Price Gaps With Double Chart Pattern



(a) Upward Price Gap With Double Bottom



(b) Downward Price Gap With Double Top

4.5 Empirical Evidence

4.5.1 The Price Gap-Fill Hypothesis

Table 4.2 presents the empirical results from applying the price gaps identification algorithm described in Section 2 to the rebased futures data. The first three rows in Panel A are the total upward and downward price gaps detected, sorted across by the 10 gap patterns, and also conditioned on increasing volume (I.V.) and decreasing volume (D.V.). Following this is the result for each individual futures contract, where the first row is the number of gaps detected and the second row is the median number of price gaps from 1000 nonparametric bootstraps.

The greatest number of price gaps is Congestion gaps, followed by Breakout, Runaway, Exhaustion and Island gaps. This observation is similar for both upward and downward gaps, and for many individual contracts. The number of upward and downward gaps are roughly balanced across the data. For example, the total number of upward price gaps is 11,547 against 10,922 downward price gaps. For fixed income and stock index futures, however, the total number of upward price gaps is always all higher than the downward price gaps. This is due to the increasing futures prices in the last decades for these contracts. For example, lower interest rates in the last decades has led to large increases in bond prices, which created more upward price gaps. This can be seen clearly in the Appendix A, where we plot all the futures prices.

When conditioned on volume, it seems that price gaps are more associated with increasing volume (I.V.) than decreasing volume (D.V.). For example, the total number of upward price gaps conditioned on I.V. is 6,578 compared to 4,966. If we breakdown the type of price gaps according to volume (See Row 2 and 3, Panel A), two contrasting effects appear. First, the number of Congestion gaps (UCG and DCG) with D.V. is higher than I.V. What this may suggests is that congestion gaps are more prone to price reversals in the near future, since price gap is less significant (as proxied by lower volume). Second, Breakout (UBG and DBG), Runaway (URG and DRG) and Exhaustion gaps (UEG and DEG) show that the number of gaps with I.V. is almost twice the number conditioned on D.V.. For example, the number of I.V. for UBG is 3,002 compared to 1,404 for D.V., and for UEG is 292 against 151. This indicates that these price gaps are more significant since more trading occurs when these gaps occurred.

As we inspect the individual futures contracts, it is noticeable that the S&P 500 index futures displays the least number of price gaps among all the futures contracts. For example, a comparison of S&P 500 futures to US10Y bond futures reveal that it has nearly forty percent less price gaps (329 for S&P 500 and 523 for US10Y bond) than US10Y bond despite the fact that both contracts has similar number of raw data. One speculative reason for this could be that S&P index futures is the most efficient futures. But we cannot affirm this hypothesis here.

A comparison of the number of gaps detected in actual series and to the median number in 1000 bootstrap series show that we cannot reject the null hypothesis that the price gaps count from the actual price are equal to the bootstrap series. What this implies is that the number of price gaps shown by the actual futures prices may not be unusually high or low. In other words, the formation of price gaps may be due to randomness because if traders' actions or information news shock are causes of price gaps, then we should expect that the number of gaps from actual price series to be much higher than the randomly reshuffled series. But this is not the result displayed here.

Turning to the Gap-Fill hypothesis, Panel B of Table 4.2 presents the percentage of the price gaps filled as a percentage of the total number of gaps recorded in that particular category and aggregated over all futures contracts.[13] To provide information about the distribution of the number of days taken to fill the price gaps, we split the price gap sample into 9 categories, shown on the most left column in Panel B. On the right are the percentages of the gaps in each category (see total sample count in that category in Panel A). The fill here is taken to be complete fill and not partial fill.

The percentage of price gaps being filled within a short period of time after their occurrence is high. For example, the percentage of price gaps covered within 1 day vary from 20.70 to 33.80 percent, and the percentage of gaps covered within the next four days vary from 26.50 to 31.90 percent. Cumulative results shows that 70 percent of gaps across all categories are covered within 20 days and 80 percent of price gaps are filled within 50 days for all price gaps. This provides quite strong support for the Gap-Fill hypothesis. Surprisingly, it is noted that only less than six percent of all gaps are not filled at all, which is a small percentage. One further observation is that Breakout gaps have the lowest percentage filled in 1-day (row 1 in Panel B), which may indicates that the Breakout gaps capture prices that are breaking out of some important resistance or support levels. Therefore, prices continue to move in the same direction to the Breakout gap the following day rather than retracing to fill the gap.

[13] The results for each individual contracts are available upon request.

Armed with some strong evidence that price retrace to fill the price gap after their occurrence. The next question is whether such predictability give traders a risk-free method to generate excess returns. To answer this important question, Table 4.3 displays the summary statistics of the normalized conditional returns from day 1 to day after the price gap is identified, and sorted by the various price gaps. The first column is the unconditional normalized return with zero mean and unit standard deviation. Conditional mean return with asterisk (*) implies that it is significantly different from unconditional mean return at 10 percent significance level. Statistical significance here is measured using the simple test-statistic in equation (4.18). At the bottom of each row is the conditional mean return for increasing (I.V.) and decreasing (D.V.) price gap.

An analysis of the results for shows an interesting observation. The consequence of high percentage of gaps being filled in the short term means that four out of five upward gap's mean returns are negative on day 1. But after day 1, the average mean normalized returns aggregated from all futures data for these five types of price gaps demonstrate no persistent bias in either direction. As previously mentioned, Breakout gaps have lowest filled percentage at 1-day. The statistics in row 1 of Table 4.3 support this fact. First, the unconditional mean returns at day 1 for UBG and DBG are of the expected signs (positive and negative) respectively. Moreover, the mean returns on day 1 are statistically significant and largest in absolute terms among all the five days conditional Breakout gap mean returns.

Turning to Runaway gaps, URG shows some persistence in the mean return, which is positive from day 2 to day 5, while DRG exhibit negative mean return from day 3 to day 5. The average standard deviation of the conditional returns for both URG and DRG are shown to be slightly higher than Congestion and Breakout gaps. For Exhaustion gaps (UEG and DEG), its standard deviation are highest as compared to the rest of the price gaps. Lastly, the one-day Island gaps display results that are contrary to the hypothesis that UIG should have negative mean returns while DIG should have positive returns. In fact, it is more common to see negative returns for both UIG and DIG.

Regarding the information given by volume, both increasing (I.V.) and decreasing (D.V.) mean return show no consistent patterns across all price gaps, apart from day 1, which we observe that increasing volume has a tendency to increase the value of mean return in the same direction as the total mean return for all price gaps. For example, the mean return for UBG is 0.0453 compared to 0.0522 for I.V., and the mean return for URG is -0.0719, which is less negative than the I.V. with mean return of -0.1390.

Other than this, the mean returns for other days (2-5) show inconstant signs. Perhaps the effects of volume last for only 1 day, after which the effects disappear. This is partially consistent with the results presented by Cooper (1999), who produces evidence that increasing volume stocks exhibit weaker reversal than decreasing volume stocks in the US equity markets.

Table 4.2: The Gap-Fill Hypothesis. Panel A of the following Table (row 1 to row 3) shows the total number of price gaps identified by the price gap algorithm. The results horizontally placed are the 10 different types of price gaps. Row 2 (I.V.) and row 3 (D.V.) display the total number of price gaps conditioned on increasing volume and decreasing volume respectively. The rest of Panel A present the results for each individual contract. The median number is the median number of price gaps from 1000 nonparametric bootstrap simulations. Panel B shows the time period taken by the price gap to be filled. The column on the left is the 9 periods which we measure the time taken for the gaps to be filled. The results on the right hand side of Panel B is the percentage of the price gaps for each type of price gap, for each corresponding time period.

Futures	Total Up Gaps	Total Down Gaps	UCG	UBG	URG	UEG	UIG	DCG	DBG	DRG	DEG	DIG
Panel A: Price Gap Count												
Total	11547	10922	5812	4406	648	446	235	5579	4264	515	322	242
I.V.	6578	6304	2713	3002	431	292	140	2640	3013	354	183	114
D.V.	4966	4618	3099	1404	217	151	95	2939	1251	161	139	128
Currencies												
USYen	811	905	400	284	46	46	35	412	351	52	55	35
(Median)	837	932	445	293	42	30	27	484	314	56	46	32
USCHF	605	658	304	208	42	33	18	296	255	47	41	19
(Median)	595	656	308	218	36	20	13	333	231	47	29	16
USGBP	685	616	320	259	48	41	17	301	246	31	21	17
(Median)	703	664	353	257	46	29	18	350	239	37	22	16
USAUS	596	579	312	216	30	23	15	314	202	20	19	24
(Median)	643	580	336	210	38	35	24	320	195	26	20	19
USCAN	317	293	158	122	21	12	4	159	116	13	2	3
(Median)	316	284	162	118	22	9	5	153	108	14	5	4
Fixed Income												
US2Y	284	193	150	110	14	6	4	120	64	7	2	0

continued next page

(continued)

Futures	Total Up Gaps	Total Down Gaps	UCG	UBG	URG	UEG	UIG	DCG	DBG	DRG	DEG	DIG
(Median)	303	228	150	112	24	12	5	137	73	11	4	3
US5Y	216	157	119	87	6	1	3	96	53	6	1	1
(Median)	242	181	118	92	21	8	3	101	64	11	3	2
US10Y	287	236	138	126	14	7	2	136	92	6	0	2
(Median)	318	236	144	132	28	10	4	126	90	15	3	2
US30Y	323	302	152	142	17	8	4	145	129	16	9	3
(Median)	326	287	152	134	28	9	3	140	118	21	6	2
ED	277	259	136	114	16	8	3	143	91	13	10	2
(Median)	89	326	189	174	16	6	4	189	121	10	3	3
UKLG	288	238	134	119	23	11	1	128	99	7	2	2
(Median)	304	257	147	122	23	8	4	132	103	16	4	2
JGB	473	374	215	181	39	32	6	205	130	18	13	8
(Median)	478	352	217	182	41	29	9	190	131	17	8	6
AUS3Y	562	437	307	202	26	13	14	267	141	9	5	15
(Median)	586	471	307	201	33	27	18	287	143	18	10	13
AUS10Y	714	633	406	247	21	14	26	388	194	20	10	21
(Median)	721	613	396	229	41	33	22	369	185	25	16	18
CAN10Y	324	292	173	120	14	12	5	169	93	17	8	5
(Median)	320	268	156	120	25	13	6	150	94	14	6	4
Stock Indices												
S&P500	176	153	94	70	12	0	0	87	60	5	0	1
(Median)	205	153	89	89	21	5	1	76	64	10	2	1
FTSE100	405	309	211	148	24	16	6	166	112	12	5	14
(Median)	402	314	200	150	31	15	5	169	118	17	6	4
N225	399	344	220	141	23	11	4	172	135	17	10	10
(Median)	383	360	198	138	25	15	7	172	140	26	14	8
DAX	276	213	148	98	20	6	4	119	76	12	3	3

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Futures	Total Up Gaps	Total Down Gaps	UCG	UBG	URG	UEG	UIG	DCG	DBG	DRG	DEG	DIG
(Median)	283	204	139	107	23	11	3	108	79	11	4	2
					Commodities							
Gold	507	529	260	185	29	22	11	272	204	26	15	12
(Median)	534	541	280	204	27	13	10	280	211	27	13	10
Silver	401	426	189	140	27	35	10	197	170	25	27	7
(Median)	431	438	221	162	28	12	8	216	175	27	11	8
Cotton	408	433	200	167	19	17	5	191	215	16	7	4
(Median)	426	410	215	162	31	13	5	203	157	32	13	5
Crude	348	338	172	140	17	11	8	161	139	23	9	6
(Median)	321	274	157	126	25	9	4	146	104	16	5	3
Heat	417	421	201	155	29	23	9	202	164	27	19	9
(Median)	402	369	200	152	31	13	6	198	133	24	9	5
Cocoa	428	520	218	176	21	7	6	246	237	17	12	8
(Median)	432	506	224	159	30	13	6	242	194	42	21	7
Coffee	360	384	153	169	16	15	7	175	184	18	3	4
(Median)	347	370	177	136	23	8	3	180	149	27	10	4
Wheat	282	297	138	125	14	3	2	150	130	14	3	0
(Median)	276	283	136	113	20	5	2	129	117	27	8	2
Sugar	378	383	184	155	20	13	6	162	182	21	11	7
(Median)	407	378	203	158	30	12	4	185	150	29	10	4
					Panel B: Price Gap Being Filled (Percentage of Total)							
1-Day			33.80	20.70	32.90	30.30	24.30	33.80	22.10	30.60	27.60	32.20
2-5 Day			28.90	30.20	27.00	26.50	31.90	30.10	29.20	28.10	29.40	26.90
6-10 Day			9.39	11.00	8.49	13.70	11.10	9.42	11.70	10.50	12.10	9.09
11-20 Day			7.78	9.33	7.72	7.17	7.23	7.25	9.08	6.59	6.50	7.44
21-50 Day			6.07	8.56	6.17	6.95	7.66	6.88	9.41	6.01	7.12	8.26
51-75 Day			2.15	3.20	2.62	4.48	2.98	2.08	2.55	2.71	1.55	3.72

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Futures	Total Up Gaps	Total Down Gaps	UCG	UBG	URG	UEG	UIG	DCG	DBG	DRG	DEG	DIG
76-100 Day			1.14	1.86	2.16	1.79	1.70	1.36	1.97	1.36	0.93	1.24
101-200 Day			2.51	3.68	4.78	4.93	3.40	2.24	3.44	3.88	3.41	2.07
>200 Day			3.92	5.81	3.55	1.57	5.53	4.08	7.16	6.01	7.12	6.61
No Fill			4.37	5.70	4.63	2.69	4.26	2.76	3.37	4.26	4.33	2.48

Table 4.3: Summary Statistics of Unconditional and Conditional Normalized Returns. The following Table shows the summary statistics of the normalized conditional futures returns for each price gap, from day 1 to day 5 after the occurrence of the price gap. On the second column is the normalized unconditional futures returns with zero mean and unit variance respectively. The summary statistics display from row 1 to row 4 are mean, standard deviation, skewness and excess kurtosis respectively. Row 5 and 6 is the conditional mean return for increasing volume and decreasing volume price gap respectively. The asterisk (*) besides the mean return imply that the return is statistically significant at 10% significant level.

Statistics	Unconditional	UCG	UBG	URG	UEG	UIG	DCG	DBG	DRG	DEG	DIG
					Day 1						
Mean	-0.0000	-0.0318*	0.0453*	-0.0719*	-0.0400	-0.0822	0.0010	-0.0315*	0.1206*	0.0929	-0.0133
S.D.	1.0000	1.0282	1.0788	1.1298	1.3820	1.1788	1.0369	1.0520	1.2709	1.4456	1.1430
Skew.	-0.2344	0.3711	0.6315	0.6084	-0.5856	-0.6478	-0.3016	-0.4919	0.0632	0.3690	0.7113
Kurt.	10.6242	6.9602	9.3443	5.9317	5.2325	3.2534	4.1404	3.7185	7.1327	2.6084	5.7712
I.V. Mean	-	-0.0723*	0.0522*	-0.1390*	-0.1300*	-0.0331	0.0167	-0.0498*	0.1850*	0.0952	-0.0301
D.V. Mean	-	0.0037	0.0306	0.0611	0.1300*	-0.1550*	-0.0131	0.0125	-0.0219	0.0898	0.0017
					Day 2						
Mean	-0.0000	0.0010	-0.0164	0.1298*	0.1065*	-0.0103	-0.0276	0.0266*	0.1168*	-0.0426	-0.0058
S.D.	1.0000	1.0346	1.0255	1.1307	1.3194	1.1763	1.0330	1.1062	1.4541	1.3191	1.0862
Skew.	-0.2344	0.2831	0.7056	0.1394	-0.1640	0.6341	-0.2651	-0.8739	2.8380	0.1470	0.3561
Kurt.	10.6242	5.7559	8.5284	2.3264	2.5668	6.5731	3.9813	11.3040	23.5890	1.1235	1.2055
I.V. Mean	-	-0.0002	0.0231	0.0943	0.0851*	0.0256	-0.0555*	0.0304*	0.1290*	-0.0026	-0.0710
D.V. Mean	-	0.0020	-0.1010	0.2010	0.1470*	-0.0632	-0.0026	0.0173	0.0901	-0.0952	0.0523
					Day 3						
Mean	-0.0000	-0.0047	-0.0073	0.0259	0.1149*	-0.0890	0.0022	-0.0021	-0.0579	-0.1413*	-0.0326
S.D.	1.0000	1.0382	1.1001	1.2186	1.3801	1.1951	1.0307	1.0882	1.1866	1.4197	1.0885
Skew	-0.2344	0.2225	1.9764	-0.2092	-0.6943	-0.0230	-0.1636	-0.3828	-0.3985	-0.0896	0.4653
Kurt.	10.6242	6.2587	35.7200	3.2971	5.7672	2.8202	3.8251	6.6020	3.5091	1.3153	1.2454
I.V. Mean	-	-0.0048	-0.0002	0.0103	0.0637	-0.0843	-0.0334*	-0.0131	-0.0661	-0.0935	-0.1520*
D.V. Mean	-	-0.0046	-0.0224	0.0567	0.2120*	-0.0960	0.0342*	0.0244	-0.0399	-0.2040*	0.0738

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Statistics	Unconditional	UCG	UBG	URG	UEG	UIG	DCG	DBG	DRG	DEG	DIG
					Day 4						
Mean	-0.0000	-0.0207	0.0305*	0.0172	0.0361	0.0783	-0.0038	-0.0141	-0.0100	-0.1371*	-0.1350*
S.D.	1.0000	1.0014	1.0323	1.1368	1.4166	1.2659	1.0484	1.0835	1.2240	1.2860	1.0673
Skew	-0.2344	-0.2766	0.1337	-0.8971	-0.6516	1.4280	0.0394	0.4846	-0.1579	-0.0692	-0.7017
Kurt.	10.6242	3.3699	4.3381	4.6530	2.0531	14.6780	4.3037	6.7417	2.7071	0.5615	2.9010
I.V. Mean	-	-0.0022	0.0314*	0.0338	0.0084	0.1190*	-0.0033	-0.0082	0.0265	-0.2110*	0.0389
D.V. Mean	-	-0.0368*	0.0285*	-0.0158	0.0886*	0.0182	-0.0043	-0.0284	-0.0900	-0.0401	-0.2900*
					Day 5						
Mean	-0.0000	-0.0047	-0.0346*	0.0455	-0.0073	0.1826*	0.0254*	-0.0177	-0.0285	-0.1499*	0.1407*
S.D.	1.0000	1.0402	1.0629	1.1350	1.4190	1.1147	1.0567	1.1020	1.2477	1.3062	0.9887
Skew	-0.2344	0.3308	0.2158	-0.3628	-0.6638	1.6552	0.2906	-0.1463	-0.2711	0.1004	0.7280
Kurt.	10.6242	7.9087	4.9763	2.1136	2.9466	13.9570	7.6124	3.5132	4.7005	1.4448	1.2514
I.V. Mean	-	0.0073	-0.0321	0.0368	0.0206	0.1950	0.0515	-0.0058	-0.0006	-0.0683	0.0474
D.V. Mean	-	-0.0153	-0.0400	0.0627	-0.0601	0.1640	0.0020	-0.0463	-0.0901	-0.2570	0.2240

4.5.2 Information Content of Price Gaps

This section presents the information tests results of the price gaps. The two main tests are goodness-of-fit and Kolmogorov-Smirnov distribution tests described in Section 4.2. Table 4.4 tabulates the empirical results from the goodness-of-fit tests, aggregated across all futures contracts and sorted vertically according to the type of price gaps, from day 1 to day 5 after the occurrence of the price gaps. The result horizontally placed is the ten deciles of the normalized conditional returns in percentage form. According to the goodness-of-fit null hypothesis, the percentage for each bin is 10.00 percent. The number in parenthesis below each percentage is the asymptotic z-values given in equation (4.13). The last column is the goodness-of-fit Q-statistic computed using equation (4.14), and the number in parenthesis below the Q-statistic is the p-value.

The large Q-statistics for all price gaps on day 1 (except DIG) imply that we can reject the hypothesis that the distribution of unconditional and conditional normalized returns are equal. But as we move further along from day 2 to day 4, there is a slight increase in the p-values, especially for UCG and UIG, implying that some of the conditional return distributions are indistinguishable to the unconditional distributions one day after the price gap occurs. Comparing across all price gaps, the highest Q-statistics are shown by Exhaustion gaps (UEG and DEG), and the price gap that has the lowest Q-statistic is DIG.

One particular feature of Table 4.4 is the variation in the distribution of the normalized returns display by different price gaps. For Congestion and Breakout gaps, the distribution of the returns seldom venture more than 1.5 percentage points from the null of 10.00 percent for each decile, for all five days. On the other hand, the difference from the null increases for Runaway gaps (URG and DRG), sometimes this difference is more than three percentage points. For Exhaustion gaps (UEG and DEG), the percentage deciles range from 4.93 to 20.90, in stark contrast to Congestion and Breakout gaps. The basic observation is that the weight of the distribution tend to push to both ends of the deciles as we compare from UCG to UEG, which resulted in larger Q-statistic.

Next, Table 4.5 presents the Kolmogorov-Smirnov two sample distribution tests aggregated from all futures contracts, sorted across by the type of price gaps, and from day 1 to day 5. The parameter γ is the Kolmogorov-Smirnov statistic given in equation (4.16) and the numbers in parenthesis are the p-values. I.V. and D.V. represents the increasing volume and decreasing volume respectively when the price gaps occur.

For Congestion gaps (UCG and DCG), the day 1 p-values are 0.000 and 0.021 respectively. But the results for day 2 to day 5 are seemingly different from day 1, because the p-values increase to more than 10 percent for these days. This shows that any unusual price gaps effects for UCG and DCG dissipated after one day.

For Breakout gaps, the opposite conclusion is found. On day 1, both UBG and DBG produce insignificant p-values at 0.400 and 0.111 respectively. But from day 2 to day 5, the p-values decline to less than 10 percent. This provides some evidence that prices continue to behave abnormally for a few more days after the penetration of key support or resistant level. For Runaway gaps (URG and DRG), the results show that any dissimilarities between the conditional and unconditional returns dissipate by day 3 and day 1 for URG and DRG respectively.

The results for Exhaustion price gaps (UEG and DEG) are fairly strong, where the p-values are statistically significant (ranging from 0.000 to 0.064) for all days, thereby rejecting the null hypothesis that the conditional return distribution are similar to the unconditional normalized returns. The overall conclusion from both the goodness-of-fit test and the Kolmogorov-Smirnov tests suggests that there may be some unusual information contained in the Exhaustion price gaps that investors can use.

Similar to the goodness-of-fit tests, the only price gaps that do not show statistically insignificant for most days are UIG and DIG, implying that there are no extra information that traders can use even after these type of gaps appear in the financial markets. This also confirms Edwards and Magee's forecast described earlier, that Island gaps are very difficult to trade on.

Contrary to the hypothesis about the role of volume advocated by market technician, the results in Table 4.5 (row 2 and 3) does not seem to support the hypothesis that increasing volume on price gap days decreases the p-value for γ consistently, neither do decreasing volume exhibit any particularly striking results. For example, it was noted earlier that the number of increasing volume price gaps are more common than decreasing volume price gaps. The Kolmogorov-Smirnov statistic for increasing volume, however, is not always higher than decreasing volume. For example, the I.V. γ for UEG is 1.37 compared to D.V. γ of 1.60. What this suggests is that a higher number of gaps may not necessarily produce returns that are unusual compared to the unconditional returns.

Table 4.4: Goodness-of-Fit Information Tests. The following Table displays the Chi-square information test. The normalized returns are separated into 10 deciles. The null percentage for each decile is 10%. The number in parenthesis for the deciles for each decile is the asymptotic p-values given by equation (??). The last column shows the Q-statistic computed using equation (4.14). The number in parenthesis is the p-value for the Q-statistic.

	Decile										
Gaps	1	2	3	4	5	6	7	8	9	10	Q-Statistic
					Day 1						
UCG	10.50	10.50	11.30	10.70	9.93	9.41	10.00	8.69	9.05	9.93	32.60
	(1.26)	(1.26)	(3.31)	(1.70)	(-0.18)	(-1.50)	(0.08)	(-3.33)	(-2.41)	(-0.18)	(0.000)
UBG	8.65	10.10	10.70	11.60	11.00	9.12	9.44	8.87	8.85	11.70	55.000
	(-2.99)	(0.12)	(1.48)	(3.54)	(2.28)	(-1.94)	(-1.24)	(-2.49)	(-2.54)	(3.79)	(0.000)
URG	11.30	13.10	11.30	11.30	12.00	9.26	7.25	7.87	5.71	11.00	32.800
	(1.07)	(2.65)	(1.07)	(1.07)	(1.73)	(-0.63)	(-2.33)	(-1.81)	(-3.64)	(0.81)	(0.000)
UEG	16.40	11.20	8.30	8.30	6.50	5.83	9.87	9.64	7.62	16.40	55.20
	(4.48)	(0.85)	(-1.20)	(-1.20)	(-2.46)	(-2.94)	(-0.09)	(-0.25)	(-1.67)	(4.48)	(0.000)
UIG	14.00	10.20	13.60	8.94	6.81	4.68	7.23	9.79	12.80	11.90	20.70
	(2.07)	(0.11)	(1.85)	(-0.54)	(-1.63)	(-2.72)	(-1.41)	(-0.11)	(1.41)	(0.98)	(0.014)
DCG	11.40	9.43	9.27	9.55	8.46	9.70	10.40	10.40	10.80	10.60	37.80
	(3.49)	(-1.42)	(-1.83)	(-1.11)	(-3.83)	(-0.75)	(0.99)	(1.12)	(1.92)	(1.43)	(0.000)
DBG	12.00	9.22	9.12	8.75	9.76	9.85	10.60	10.60	10.30	9.87	33.10
	(4.32)	(-1.70)	(-1.91)	(-2.73)	(-0.53)	(-0.33)	(1.20)	(1.36)	(0.59)	(-0.28)	(0.000)
DRG	13.60	7.96	6.21	6.41	7.96	8.93	12.80	10.90	10.50	14.80	41.80
	(2.72)	(-1.54)	(-2.86)	(-2.72)	(-1.54)	(-0.81)	(2.13)	(0.66)	(0.37)	(3.60)	(0.000)
DEG	15.80	8.70	7.76	6.52	7.45	6.21	7.76	10.60	11.50	17.70	45.30
	(3.49)	(-0.78)	(-1.34)	(-2.08)	(-1.52)	(-2.27)	(-1.34)	(0.33)	(0.89)	(4.61)	(0.000)
DIG	14.90	7.02	8.68	10.30	9.09	9.09	11.60	8.26	11.60	9.50	10.70
	(2.53)	(-1.54)	(-0.69)	(0.17)	(-0.47)	(-0.47)	(0.81)	(-0.90)	(0.81)	(-0.26)	(0.295)
					Day 2						

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	Decile										
Gaps	1	2	3	4	5	6	7	8	9	10	Q-Statistic
UCG	10.70	10.50	10.50	9.43	8.88	9.31	9.76	9.86	10.30	10.70	22.00
	(1.78)	(1.39)	(1.26)	(-1.45)	(-2.85)	(-1.76)	(-0.62)	(-0.36)	(0.82)	(1.78)	(0.009)
UBG	9.94	10.30	11.10	11.30	10.20	9.53	9.71	9.83	8.35	9.78	26.40
	(-0.13)	(0.72)	(2.33)	(2.83)	(0.42)	(-1.03)	(-0.63)	(-0.38)	(-3.65)	(-0.48)	(0.002)
URG	9.72	8.80	12.00	8.18	7.56	8.95	9.26	8.64	11.40	15.40	32.400
	(-0.24)	(-1.02)	(1.73)	(-1.55)	(-2.07)	(-0.89)	(-0.63)	(-1.15)	(1.20)	(4.61)	(0.000)
UEG	13.70	8.52	8.97	10.10	5.83	6.73	7.85	6.95	12.80	18.60	62.70
	(2.59)	(-1.04)	(-0.73)	(0.06)	(-2.94)	(-2.30)	(-1.52)	(-2.15)	(1.96)	(6.06)	(0.000)
UIG	13.60	11.50	8.09	9.36	7.23	8.94	9.79	7.23	13.20	11.10	11.10
	(1.85)	(0.76)	(-0.98)	(-0.33)	(-1.41)	(-0.54)	(-0.11)	(-1.41)	(1.63)	(0.54)	(0.270)
DCG	11.60	9.64	9.79	9.32	9.55	9.16	10.10	10.60	10.10	10.10	25.40
	(4.02)	(-0.89)	(-0.53)	(-1.69)	(-1.11)	(-2.09)	(0.36)	(1.52)	(0.27)	(0.14)	(0.003)
DBG	11.20	9.47	8.54	9.62	8.75	8.54	10.50	10.60	10.80	12.10	55.70
	(2.53)	(-1.14)	(-3.19)	(-0.84)	(-2.73)	(-3.19)	(1.10)	(1.20)	(1.77)	(4.47)	(0.000)
DRG	14.80	7.57	6.41	8.16	8.93	8.93	9.90	10.30	11.50	13.60	32.00
	(3.60)	(-1.84)	(-2.72)	(-1.40)	(-0.81)	(-0.81)	(-0.07)	(0.22)	(1.10)	(2.72)	(0.000)
DEG	18.00	8.39	9.01	6.52	8.39	7.76	7.76	9.01	12.10	13.00	33.40
	(4.79)	(-0.97)	(-0.59)	(-2.08)	(-0.97)	(-1.34)	(-1.34)	(-0.59)	(1.26)	(1.82)	(0.000)
DIG	12.00	13.60	10.30	8.68	8.68	9.09	8.68	7.44	8.26	13.20	10.50
	(1.03)	(1.89)	(0.17)	(-0.69)	(-0.69)	(-0.47)	(-0.69)	(-1.33)	(-0.90)	(1.67)	(0.313)
						Day 3					
UCG	10.80	10.60	9.67	10.40	9.17	9.27	9.76	9.76	9.77	10.70	19.00
	(2.09)	(1.52)	(-0.84)	(1.13)	(-2.11)	(-1.85)	(-0.62)	(-0.62)	(-0.58)	(1.87)	(0.025)
UBG	10.50	11.00	10.10	10.20	9.17	8.81	9.69	10.20	9.37	10.90	21.60
	(1.12)	(2.28)	(0.17)	(0.52)	(-1.84)	(-2.64)	(-0.68)	(0.37)	(-1.39)	(2.08)	(0.010)
URG	11.70	9.26	11.40	8.95	6.48	8.80	8.64	9.26	12.50	13.00	24.60
	(1.47)	(-0.63)	(1.20)	(-0.89)	(-2.99)	(-1.02)	(-1.15)	(-0.63)	(2.12)	(2.51)	(0.003)
UEG	12.80	9.87	8.07	8.30	6.05	8.30	9.87	8.52	7.40	20.90	71.20

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Gaps	1	2	3	4	5	6	7	8	9	10	Q-Statistic
	Decile										
	(1.96)	(-0.09)	(-1.36)	(-1.20)	(-2.78)	(-1.20)	(-0.09)	(-1.04)	(-1.83)	(7.64)	(0.000)
UIG	14.50	11.10	8.09	10.60	7.23	11.50	7.66	13.20	6.38	9.79	15.00
	(2.28)	(0.54)	(-0.98)	(0.33)	(-1.41)	(0.76)	(-1.20)	(1.63)	(-1.85)	(-0.11)	(0.091)
DCG	10.90	10.20	10.10	9.16	8.64	10.10	9.48	10.40	10.20	10.90	26.00
	(2.15)	(0.41)	(0.36)	(-2.09)	(-3.39)	(0.14)	(-1.29)	(0.94)	(0.45)	(2.33)	(0.002)
DBG	10.90	10.70	10.10	9.36	8.77	9.90	9.64	9.10	10.20	11.30	25.10
	(1.97)	(1.61)	(0.23)	(-1.40)	(-2.67)	(-0.22)	(-0.79)	(-1.96)	(0.49)	(2.74)	(0.003)
DRG	13.20	11.80	9.51	10.70	8.74	8.54	7.57	7.57	9.71	12.60	19.000
	(2.42)	(1.40)	(-0.37)	(0.51)	(-0.95)	(-1.10)	(-1.84)	(-1.84)	(-0.22)	(1.98)	(0.026)
DEG	20.20	8.70	9.01	6.21	11.20	6.21	8.07	7.45	8.39	14.60	54.90
	(6.09)	(-0.78)	(-0.59)	(-2.27)	(0.71)	(-2.27)	(-1.15)	(-1.52)	(-0.97)	(2.75)	(0.000)
DIG	14.00	10.30	12.40	10.30	7.85	8.26	7.85	7.02	9.92	12.00	11.50
	(2.10)	(0.17)	(1.24)	(0.17)	(-1.11)	(-0.90)	(-1.11)	(-1.54)	(-0.04)	(1.03)	(0.245)
	Day 4										
UCG	10.20	10.50	10.10	10.20	9.33	9.53	10.50	9.79	9.67	10.10	8.43
	(0.52)	(1.35)	(0.30)	(0.60)	(-1.71)	(-1.19)	(1.17)	(-0.53)	(-0.84)	(0.34)	(0.495)
UBG	10.40	9.42	9.85	9.74	9.19	9.15	10.10	10.30	10.80	10.90	16.10
	(0.92)	(-1.29)	(-0.33)	(-0.58)	(-1.79)	(-1.89)	(0.32)	(0.77)	(1.88)	(1.98)	(0.065)
URG	10.60	10.30	8.33	8.64	10.20	9.57	9.41	9.57	9.10	14.20	15.80
	(0.55)	(0.29)	(-1.41)	(-1.15)	(0.16)	(-0.37)	(-0.50)	(-0.37)	(-0.76)	(3.56)	(0.072)
UEG	17.50	7.62	6.73	5.83	7.40	5.61	7.85	11.90	10.50	19.10	92.10
	(5.27)	(-1.67)	(-2.30)	(-2.94)	(-1.83)	(-3.09)	(-1.52)	(1.33)	(0.38)	(6.38)	(0.000)
UIG	11.10	10.20	8.94	8.51	8.09	11.10	7.23	11.10	10.60	13.20	6.74
	(0.54)	(0.11)	(-0.54)	(-0.76)	(-0.98)	(0.54)	(-1.41)	(0.54)	(0.33)	(1.63)	(0.336)
DCG	11.20	10.50	10.00	9.52	8.94	8.96	9.84	9.68	9.86	11.40	35.60
	(3.04)	(1.25)	(0.09)	(-1.20)	(-2.63)	(-2.58)	(-0.40)	(-0.80)	(-0.35)	(3.57)	(0.000)
DBG	12.10	11.00	9.87	9.38	8.02	8.91	9.31	10.00	10.70	10.70	52.40
	(4.57)	(2.07)	(-0.28)	(-1.35)	(-4.31)	(-2.37)	(-1.50)	(0.08)	(1.56)	(1.51)	(0.000)

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	Decile										
Gaps	1	2	3	4	5	6	7	8	9	10	Q-Statistic
DRG	12.20	11.70	11.30	7.38	8.16	7.77	9.90	8.35	9.71	13.60	20.70
	(1.69)	(1.25)	(0.95)	(-1.98)	(-1.40)	(-1.69)	(-0.07)	(-1.25)	(-0.22)	(2.72)	(0.014)
DEG	19.30	10.60	7.45	7.45	7.76	11.80	5.90	7.76	8.39	13.70	46.70
	(5.54)	(0.33)	(-1.52)	(-1.52)	(-1.34)	(1.08)	(-2.45)	(-1.34)	(-0.97)	(2.19)	(0.000)
DIG	11.20	15.30	11.60	8.68	5.79	9.50	11.20	12.00	4.96	9.92	19.90
	(0.60)	(2.74)	(0.81)	(-0.69)	(-2.19)	(-0.26)	(0.60)	(1.03)	(-2.61)	(-0.04)	(0.019)
					Day 5						
UCG	10.80	10.30	10.00	9.84	9.14	9.79	9.84	10.10	9.76	10.30	10.60
	(2.09)	(0.87)	(0.03)	(-0.40)	(-2.19)	(-0.53)	(-0.40)	(0.30)	(-0.62)	(0.87)	(0.300)
UBG	11.80	10.70	11.50	9.42	8.40	9.06	8.40	9.28	10.80	10.60	61.50
	(4.04)	(1.63)	(3.28)	(-1.29)	(-3.55)	(-2.09)	(-3.55)	(-1.59)	(1.83)	(1.28)	(0.000)
URG	10.80	10.20	10.00	8.64	8.49	6.79	10.50	10.20	10.20	14.20	21.40
	(0.68)	(0.16)	(0.03)	(-1.15)	(-1.28)	(-2.72)	(0.42)	(0.16)	(0.16)	(3.56)	(0.011)
UEG	17.90	10.50	8.30	6.28	4.93	6.95	6.05	6.95	12.80	19.30	104.00
	(5.59)	(0.38)	(-1.20)	(-2.62)	(-3.57)	(-2.15)	(-2.78)	(-2.15)	(1.96)	(6.53)	(0.000)
UIG	8.09	9.36	11.90	4.68	8.09	6.81	11.90	8.51	16.60	14.00	27.20
	(-0.98)	(-0.33)	(0.98)	(-2.72)	(-0.98)	(-1.63)	(0.98)	(-0.76)	(3.37)	(2.07)	(0.001)
DCG	10.50	10.30	10.20	9.73	8.21	9.91	9.28	9.66	10.60	11.60	40.90
	(1.16)	(0.72)	(0.41)	(-0.66)	(-4.46)	(-0.22)	(-1.78)	(-0.84)	(1.61)	(4.07)	(0.000)
DBG	11.80	10.30	10.50	8.91	7.67	9.43	9.47	10.60	10.10	11.10	53.80
	(4.01)	(0.69)	(1.15)	(-2.37)	(-5.07)	(-1.25)	(-1.14)	(1.31)	(0.23)	(2.43)	(0.000)
DRG	14.20	10.10	9.51	8.93	7.96	7.96	7.57	10.50	10.30	13.00	21.80
	(3.16)	(0.07)	(-0.37)	(-0.81)	(-1.54)	(-1.54)	(-1.84)	(0.37)	(0.22)	(2.28)	(0.009)
DEG	18.00	12.10	7.14	8.39	7.45	9.63	8.70	8.39	8.07	12.10	31.70
	(4.79)	(1.26)	(-1.71)	(-0.97)	(-1.52)	(-0.22)	(-0.78)	(-0.97)	(-1.15)	(1.26)	(0.000)
DIG	9.09	10.70	9.50	9.09	9.09	9.92	7.02	9.50	11.60	14.50	8.41
	(-0.47)	(0.39)	(-0.26)	(-0.47)	(-0.47)	(-0.04)	(-1.54)	(-0.26)	(0.81)	(2.31)	(0.493)

Table 4.5: Kolmogorov-Smirnov Distribution Tests. The following Table displays the Kolmogorov-Smirnov test for all 10 normalized conditional price gap returns, up to 5 days after the occurrence of the price gap. Row 1 is the Kolmogorov-Smirnov γ statistic given by equation (4.16) and row 2 is the p-values for each corresponding statistic given by equation (4.17). Row 3 and 5 are the γ statistic for increasing volume and decreasing volume respectively, while row 4 and 6 are the corresponding p-value.

Statistics	UCG	UBG	URG	UEG	UIG	DCG	DBG	DRG	DEG	DIG
					Day 1					
γ	2.46	0.89	1.42	1.31	0.77	1.51	1.20	1.45	1.64	0.51
p-value	(0.000)	(0.400)	(0.036)	(0.064)	(0.598)	(0.021)	(0.111)	(0.031)	(0.009)	(0.955)
I.V. γ	1.66	1.34	1.58	1.37	0.78	1.32	1.29	1.41	0.96	0.73
p-value	(0.008)	(0.056)	(0.014)	(0.048)	(0.572)	(0.060)	(0.071)	(0.039)	(0.316)	(0.658)
D.V.γ	1.04	0.31	0.69	1.60	1.20	0.68	0.36	1.27	1.06	0.42
p-value	(0.226)	(0.000)	(0.734)	(0.012)	(0.110)	(0.737)	(1.000)	(0.079)	(0.208)	(0.995)
					Day 2					
γ	0.91	1.48	1.48	2.26	0.85	1.19	2.15	1.12	1.47	0.76
p-value	(0.376)	(0.024)	(0.025)	(0.000)	(0.463)	(0.120)	(0.000)	(0.166)	(0.027)	(0.614)
I.V. γ	0.83	0.85	1.12	1.77	0.49	1.23	1.97	0.96	1.11	1.01
p-value	(0.492)	(0.460)	(0.166)	(0.004)	(0.967)	(0.099)	(0.001)	(0.320)	(0.166)	(0.263)
D.V.γ	0.25	1.54	1.17	1.50	0.48	0.32	0.82	0.64	0.99	0.43
p-value	(1.000)	(0.017)	(0.127)	(0.023)	(0.973)	(1.000)	(0.515)	(0.801)	(0.282)	(0.992)
					Day 3					
γ	0.95	1.27	1.36	2.12	0.91	1.09	1.01	1.20	2.03	1.01
p-value	(0.325)	(0.080)	(0.050)	(0.000)	(0.383)	(0.185)	(0.263)	(0.111)	(0.001)	(0.257)
I.V. γ	0.44	0.94	0.63	1.54	0.80	1.74	0.74	1.14	1.23	1.12
p-value	(0.990)	(0.341)	(0.825)	(0.018)	(0.544)	(0.005)	(0.645)	(0.148)	(0.098)	(0.161)
D.V.γ	1.09	0.75	1.33	1.39	0.52	1.03	1.14	0.92	1.38	0.35
p-value	(0.189)	(0.624)	(0.057)	(0.043)	(0.946)	(0.236)	(0.151)	(0.361)	(0.044)	(1.000)
					Day 4					
γ	0.80	1.56	0.79	1.95	0.55	1.18	2.03	0.98	1.73	0.62

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Statistics	UCG	UBG	URG	UEG	UIG	DCG	DBG	DRG	DEG	DIG
p-value	(0.538)	(0.015)	(0.564)	(0.001)	(0.927)	(0.122)	(0.001)	(0.290)	(0.001)	(0.840)
I.V. γ	0.17	1.41	0.96	1.43	0.41	1.21	1.59	0.94	1.44	0.69
p-value	(0.000)	(0.037)	(0.311)	(0.034)	(0.995)	(0.105)	(0.012)	(0.337)	(0.032)	(0.735)
D.V.γ	0.75	0.52	0.52	1.62	0.30	0.62	1.08	0.92	1.17	1.08
p-value	(0.635)	(0.952)	(0.952)	(0.011)	(1.000)	(0.843)	(0.192)	(0.362)	(0.127)	(0.193)
Day 5										
γ	1.00	2.54	0.82	2.43	1.55	1.42	1.41	1.04	1.83	0.96
p-value	(0.268)	(0.000)	(0.506)	(0.000)	(0.016)	(0.035)	(0.037)	(0.231)	(0.003)	(0.311)
I.V. γ	0.35	1.72	1.09	1.84	1.59	1.50	0.66	1.14	1.15	0.22
p-value	(0.000)	(0.005)	(0.187)	(0.002)	(0.012)	(0.022)	(0.777)	(0.146)	(0.145)	(1.000)
D.V.γ	1.14	1.09	0.88	1.75	0.37	0.74	1.24	1.05	1.67	1.19
p-value	(0.151)	(0.185)	(0.423)	(0.004)	(0.999)	(0.643)	(0.093)	(0.221)	(0.007)	(0.119)

4.5.3 Does the Size of Price Gap Matter?

Table 4.6 presents the results with gap size categorization. Panel A shows the number of price gap count for each size (Size 1 to Size 3), and sorted by the type of price gap (UCG to DIG). Recall the Size 1 gaps are price gaps that has lower absolute value than the difference between the open and close price of the previous trading day, the result in Panel A shows that such gaps are the most common, followed by Size 2 and Size 3 respectively. For Island gaps (UIG and DIG), no count is recorded for Size 2 and Size 3, hence we cannot tests the hypothesis whether the size of price gaps will affect the results in the previous section. An interesting observation is that for Exhaustion gaps (UEG and DEG) the percentage of Size 3 over the total sample size is more than 20 percent, at $\frac{115}{446} \approx 25.8$ percent and $\frac{98}{322} \approx 30.4$ percent respectively, a percentage larger than other types of price gaps. For Breakaway gap, for example, the percentage of Size 3 over the total sample is $\frac{765}{4406} \approx 17.36$ percent and $\frac{732}{4264} \approx 17.17$ percent for upward and downward gap respectively.

Panel B of the same Table presents the summary statistics and the information test results for each size. To conserve space, the p-values for both the goodness-of-fit Q and Kolmogorov-Smirnov γ statistics are omitted. Instead, an asterisk (*) is shown beside the statistic if the p-values are more than 10 percent. This also applies to the mean return t-tests.

Previously we noted that the mean returns on UCG, UBG, URG and UEG are statistically negative on day 1, which is a result from the prices retracing to cover the gaps. When we split the size of price gaps, some interesting facts emerge. One, the congestion gaps (UCG) mean returns are all negative for all sizes. Surprisingly, the mean return for Size 1 is more negative than Size 2 or 3. It seem to suggest that a contrarian strategy might be profitable here. Two, all upward Breakout gaps have positive mean returns and all downward Breakout gaps have negative mean returns. This means that a trend-following strategy is more appropriate when a Breakout gap appears. Three, for both upward Runaway and Exhaustion gaps, the Size 1 and Size 2 mean returns are negative, but it is positive for Size 3. Moreover, the mean return for Size 3 is the largest compared to Size 1 or 2. The opposite signs are observed for the downward Runaway and Exhaustion gaps. What this is saying is that if the size of the price gap is large enough, then strong momentum effect may result from it. The large standard deviation for Size 3 Runaway and Exhaustion gaps also implies that these momentum effects are accompanied with increased volatility. A further implication of this fact suggests that even though traders can earn higher returns by trading the URG, UEG, DRG and DEG price gaps, these higher returns are accompanied by higher risks (as measured by higher standard deviation). In other words, the high return-high risk relationship still prevails. Furthermore, a casual look at the pattern count for Size 3 for these four gaps show that it is not a large number. It is undoubtedly fairly difficult to trade all these gaps over twenty-eight futures contract over a span of 25 years. Fourth, all Size 3 downward gaps (DCG, DBG, DRG and DEG) show negative mean returns. This means that downward momentum effects is strong when the size of the downward gap is large.

For other days (2-4), the Congestions gaps (UCG and DCG) do not show any unusual results for all sizes. The p-values for Q and γ statistic for both UCG and DCG vary during these days. For Breakout gaps (UBG and DBG), the Q and γ statistics are randomly significant for three sizes. For example, on day 3 the Size 1 UBG Q statistic is significant at 6.810, but on day 5, it is significant at 40.700. Moving to Runaway gaps (URG and DRG), the mean test statistic, Q and γ statistics are all significant on day 1. After which, such strong results disappear from day 2 onwards, and are inconsistent for all sizes.

Turning to the Exhaustion gaps (UEG and DEG), we observed that all the Q and γ statistics are significant at 10 percent level for all sizes at day 1. After day 1, however, Size 3 remains the only category that shows significant Q and γ statistics consistently for five days after the occurrence of the price gaps. Moveover, the conditional normalized mean return for Size 3 show the most consistent direction, which is negative for DEG and positive for UEG (except day 5). Lastly, Island gaps (UIG and DIG) have very unreliable results for all days. This is consistent with our earlier findings.

In summary, the results here support the hypothesis that the size of the price gap will improve the information content of the price gap on day 1. We also show that Exhaustion gaps seem to be the only type of gaps that show statistically significant results. Judging by the results shown here and in the previous sections, the unusual effects exhibited by Exhaustion gaps may be caused by the short-term momentum effects in the futures prices. For example, Jegadeesh and Titman (1993, 2001) report strong momentum effects in the US equity markets. Moreover, Moskowitz and Grinblatt (1999) find industry momentum effects. Recently, George and Hwang (2004) present evidence that stocks that are near the 52-Week exhibit momentum effects that are greater than Jegadeesh and Titman's results. Since our categorisation of the Exhaustion gap requires the current price to be either a new high (for upward gap) or a new low (for downward gap) over a period of 22 days. Our results here may just be a manifestation of the short-term momentum effects documented by these studies. Adding the large shocks (as measured by Size 3 gap), we therefore find that

Exhaustion conditional returns to be statistically different from the unconditional returns.

Table 4.6: Price Gap Size Evaluation. Table 4.6 displays the results according to the size of price gaps. The first three rows of the Table shows the total number of price gaps for each size, for each type of price gap. Row 2 and row 3 are the results for increasing and decreasing volume respectively. The rest of the table displays the summary statistics and the distribution tests results for each price gap, for up to five days after the occurrence of the price gap. To save space, the p-values for Chi-square and Kolmogorov-Smirnov distribution tests are omitted, to be replaced by an asterisk (*) if the p-values are more than 10%. Dashed (-) means that no price gap is detected for that particular size.

Gap Size	Statistics	UCG	UBG	URG	UEG	UIG	DCG	DBG	DRG	DEG	DIG
Size 1	Count	3397	2563	435	216	235	3153	2440	303	146	242
Size 2	Count	1739	1078	142	115	0	1731	1092	148	78	0
Size 3	Count	676	765	71	115	0	695	732	64	98	0
						Day 1					
Size 1	Mean	-0.0469*	0.0382*	-0.1139*	-0.1173*	-0.0822	0.0203	-0.0053	0.0941	0.2224*	-0.0133
	S.D	1.0285	1.0088	1.0834	1.2124	1.1788	1.0422	1.0592	1.1216	1.2450	1.1430
	Q	31.600*	36.300*	15.600*	19.100*	20.700*	30.600*	16.700*	16.600*	24.000*	10.700
	γ	2.257*	0.856	1.343*	0.980	0.768	1.565*	0.728	1.294*	1.390*	0.512
Size 2	Mean	-0.0095	0.0332	-0.2665*	-0.2856*	-	0.0124	-0.0438	0.2717*	0.2158*	-
	S.D.	1.0050	1.0590	0.9254	1.4610	-	0.9924	0.9841	1.3025	1.3621	-
	Q	11.000	14.800*	18.400*	11.200	-	8.170	12.100	22.100*	22.300*	-
	γ	0.793	0.670	1.553*	0.947	-	0.735	0.551	1.348*	1.244*	-
Size 3	Mean	-0.0129	0.0862*	0.5752*	0.3508*	-	-0.1151*	-0.1006*	-0.1035	-0.1980*	-
	S.D.	1.0846	1.3094	1.5110	1.5240	-	1.1122	1.1217	1.7555	1.7328	-
	Q	4.800	22.000*	52.000*	91.300*	-	20.200*	27.400*	26.600*	25.500*	-
	γ	0.176	1.004	1.429*	2.237*	-	1.131	0.952	1.106	1.546*	-
						Day 2					
Size 1	Mean	-0.0028	-0.0629*	0.1372*	0.0005	-0.0103	-0.0275	0.0162	0.1058*	0.0457	-0.0058
	S.D	1.0544	0.9698	1.0798	1.2260	1.1763	1.0688	1.1197	1.4227	1.1915	1.0862
	Q	25.500*	31.600*	17.000*	18.200*	11.100	26.200*	41.500*	16.200*	6.470	10.500

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Gap Size	Statistics	UCG	UBG	URG	UEG	UIG	DCG	DBG	DRG	DEG	DIG
	γ	0.759	2.207*	1.079	0.849	0.851	1.001	1.486	0.861	0.360	0.758
Size 2	Mean	-0.0082	0.0105	0.0992	0.0978	-	-0.0254	0.0410	0.1824*	-0.1067	-
	S.D.	0.9989	0.9818	1.0912	1.2401	-	0.9583	1.0219	1.4978	1.2616	-
	Q	9.480	7.400	11.800	21.400*	-	2.860*	12.100	16.600*	17.400*	-
	γ	0.168	0.550	0.773	0.828	-	0.372	0.792	0.814	1.293*	-
Size 3	Mean	0.0433	0.1014*	0.1461	0.3140*	-	-0.0332	0.0397	0.0173	-0.1231	-
	S.D.	1.0245	1.2364	1.4787	1.5357	-	1.0488	1.1808	1.5141	1.5333	-
	Q	12.500	15.500*	31.100*	50.000*	-	8.550	18.200*	7.880	45.100*	-
	γ	0.758	0.946	1.059	1.840*	-	0.471	0.669	0.713	1.703*	-
						Day 3					
Size 1	Mean	0.0026	0.0174	-0.0142	0.0058	-0.0890	0.0083	-0.0232	-0.0877	-0.0391*	-0.0326
	S.D	1.0354	1.0159	1.2537	1.2234	1.1951	1.0338	1.1017	1.1083	1.4153	1.0885
	Q	11.100	6.810	12.800	21.800*	15.000*	22.200*	19.100*	17.500*	29.500*	11.500
	γ	0.776	0.461	0.774	0.649	0.907	1.038	1.346	1.070	0.922	1.012
Size 2	Mean	-0.0251	0.0029	0.1150	0.0120	-	0.0112	0.0200	-0.0656	0.0012	-
	S.D.	1.0474	1.0120	1.1132	1.5463	-	0.9856	0.9905	1.1860	1.2701	-
	Q	15.000*	14.700*	11.800	11.500	-	14.200	6.610	18.600*	9.950	-
	γ	0.972	0.355	0.979	0.821	-	0.831	0.506	0.563	0.513	-
Size 3	Mean	0.0113	-0.1045*	0.0929	0.4225*	-	-0.0476	0.0350	0.1007	-0.4070*	-
	S.D.	1.0288	1.4359	1.2059	1.4465	-	1.1221	1.1781	1.5121	1.5140	-
	Q	12.400	30.200*	12.500	68.400*	-	11.500	9.040	13.200	40.800*	-
	γ	0.427	1.971*	0.799	1.784*	-	0.498	0.785	0.798	2.043*	-
						Day 4					
Size 1	Mean	-0.0099	0.0323*	0.0217	-0.0519	0.0783	0.0000	-0.0353*	0.0447	0.0275	-0.1350*
	S.D	1.0044	0.9689	1.1179	1.3474	1.2659	1.0852	1.0826	1.1389	1.1358	1.0673
	Q	4.800	8.020	11.400	29.900*	6.740	42.500*	43.900*	14.700	12.400	19.900*
	γ	0.282	0.714	0.668	1.089	0.546	1.200	2.005*	0.765	0.547	0.617
Size 2	Mean	-0.0455*	0.0082	0.0930	-0.0075	-	-0.0294	0.0534*	-0.0601	-0.2151*	-

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Gap Size	Statistics	UCG	UBG	URG	UEG	UIG	DCG	DBG	DRG	DEG	DIG
	S.D.	0.9801	1.0946	1.0792	1.4375	-	0.9688	1.1067	1.3178	1.2458	-
	Q	12.200	13.400	11.800	16.400*	-	11.400	17.300*	23.800*	17.600*	-
	γ	1.106	0.659	0.811	0.626	-	0.266	0.587	0.985	1.237*	-
Size 3	Mean	-0.0109	0.0559	-0.1623	0.2449*	-	0.0427	-0.0444	-0.1528	-0.3204*	-
	S.D.	1.0403	1.1426	1.3441	1.5107	-	1.0686	1.0482	1.3833	1.4944	-
	Q	7.990	19.900*	4.920	79.200*	-	17.600*	8.870	8.500	47.100*	-
	γ	0.430	0.818	0.628	2.088*	-	0.679	0.886	0.627	1.894*	-
					Day 5						
Size 1	Mean	0.0104	-0.0152	0.0325	0.0525	0.1826*	0.0209	-0.0204	-0.0372	-0.0522	0.1407*
	S.D	1.0107	1.0490	1.0897	1.5127	1.1147	1.0361	1.1271	1.2744	1.2862	0.9887
	Q	9.660	40.700*	14.300	68.900*	27.200*	34.400*	44.100*	8.520	7.700	8.410
	γ	0.753	0.987	1.026	2.061*	1.554*	1.040	1.198	0.616	0.953	0.964
Size 2	Mean	-0.0392	-0.0765*	0.0145	-0.0049	-	0.0418*	0.0122	-0.0264	0.0051	-
	S.D.	1.0786	1.0337	1.0649	1.2150	-	1.0704	1.0396	1.1139	1.2015	-
	Q	9.920	16.300*	8.990	13.300	-	7.060	7.690	8.620	3.790*	-
	γ	1.007	1.236	0.434	0.676	-	0.525	0.518	0.452	0.454	-
Size 3	Mean	0.0080	-0.0406	0.1868	-0.1218	-	0.0051	-0.0529	0.0076	-0.4186*	-
	S.D.	1.0842	1.1463	1.4960	1.4310	-	1.1146	1.1079	1.4209	1.3860	-
	Q	18.300*	19.400*	24.900*	53.300*	-	12.700	22.000*	21.900*	39.100*	-
	γ	0.863	0.958	1.509*	1.358*	-	0.360	0.736	0.854	1.788*	-

4.5.4 Conditioning on Chart Patterns

Table 4.7 displays the results for the statistical test of price gaps conditioned on the occurrence of one of the chart patterns. (See Section 2.4) The results are aggregated over all futures contracts. Column 1 to 10 are the price gaps (UCG to DIG) and for each row represents the results for each chart pattern (HSBOT to DTOP).

In Panel A, we provide the pattern count for all ten chart patterns for each type of price gap. For upward gaps, the Bottom chart patterns (HSBOT, RBOT, TBOT, BBOT, DBOT) are patterns where the last extrema e_m is a minimum in the 30-day window. (See Section 4.4.2 for some graphical examples.) Recall our hypothesis that an upward price gap is assumed to be followed after a Bottom chart pattern. But not every e_m for an upward price gap is a minima. In fact, a large number of upward gaps have the last extrema to be maxima. Rather than discarding these price gaps, we test whether these polynomial regressions satisfy any of the Top chart pattern. The pattern counts from this exercise is shown by HSTOP, RTOP, TTOP, BTOP and DTOP for the upward gaps in Table 4.7 (column 3 to 7). A similar procedure is undertaken for downward price gaps as well and shown by HSBOT, RBOT, TBOT, BBOT and DBOT in column 8 to 12.

The evidence in Panel A shows that a large number of extrema e_m do indeed satisfy the chart formation conditions for a Top pattern even when an upward price gap occurs. As a matter of fact, the count for HSTOP is higher than HSBOT for upward Congestion price gap (UCG) and the count for HSBOT is higher than HSTOP for downward Congestion price gap (DCG), observations that are contrary to our expectations.[14]

For upward Congestion gap (UCG), the most frequently seen pattern is Rectangle (RBOT, RTOP) followed by Head-and-Shoulders and Double chart pattern. The difference in the pattern count between RBOT (432) and RTOP (405) is low. For upward Breakout gap (UBG), the largest pattern count is RBOT (631), followed by HSBOT (469) and TBOT (219). Similarly, for downward Breakout gap (DBG), RTOP (492) has the largest count, followed by HSTOP (394) and TTOP (235). A comparison between the Congestion and Breakout gaps shows an interesting feature about the shift of bottom pattern count to top pattern count. For example, for upward Congestion gaps, the total number of bottom patterns (HSBOT, RBOT, TBOT, BBOT, DBOT) is 1,102 and the total number of top patterns (HSTOP,

[14]In comparison to LMW, the definitions of the chart patterns as specified in Section 2.4 are more stringent. For example, for Head-and-Shoulders, Rectangle and Double patterns, the difference in prices during the extrema points are fixed to be 0.5 percent. Because of such strict definitions, the algorithm detects less patterns in our sample data than in LMW.

RTOP, TTOP, BTOP, DTOP) is 997, a difference of only 105. On the other hand, for upward Breakout gaps, the total number of bottom chart pattern is 1,586, but the total number of top pattern is only 315, a difference of 1,271. This implies that upward Breakout gaps (and to a large extent, Runaway and Exhaustion gaps) experienced some form of 'bottoming-out' before an upward price gap occurs. The opposite can be said for downward Breakaway gaps, where prices experience some form of 'topping' before a downward gap happens.

Panel B displays all the summary statistics and information tests results for each pattern. Like previous section, the p-values for Q and γ statistics are omitted to conserve space and replaced by asterisk (*) if it is more than 10 percent. Basically, the results show that statistically significant p-values are randomly distributed among the price gaps and across all ten chart patterns. This evidence seems to suggest that not one chart pattern is capable of producing reliable results, in terms of statistically significant p-values for Q and γ statistics that reject the hypothesis that the conditional returns are similar to unconditional returns. For example, on day 1, the Q statistic for RBOT is significant for UCG, UBG and DBG, but not the rest of price gaps. On day 4, the same pattern is now significant for UIG and DEG. Furthermore, it is difficult to discover any patterns that exhibit significant statistics for the goodness-of-fit, Kolmogorov-Smirnov and t-tests together, even for Exhaustion gaps.

However, one main concern about the distribution tests is the low power of these tests, which is due to the extremely low number of pattern count for some price gaps. The only way to alleviate this problem is to include more data. But even including more data may not necessarily increases the pattern count if the asset prices do not exhibit the chart pattern as defined in Section 4.2. As a result, one has to be careful in drawing conclusion about the results shown in this section.

Table 4.7: Price Gaps and Technical Chart Patterns. Panel A shows the number of chart patterns detected conditioned upon the occurrence of each of the 10 price gaps. Panel B presents the summary statistics of the normalized conditional futures returns and the Chi-square and Kolmogorov-Smirnov distribution tests statistic. To save space, the p-values for Chi-square and Kolmogorov-Smirnov distribution tests are omitted, to be replaced by an asterisk (*) if the p-values are more than 10%. Dashed (-) means that no chart pattern was detected for that particular price gap.

Chart Patterns	Statistics	UCG	UBG	URG	UEG	UIG	DCG	DBG	DRG	DEG	DIG
						Panel A: Pattern Count					
HSBOT	Count	190	469	76	28	26	260	38	0	0	0
RBOT	Count	432	631	79	22	35	400	116	2	2	0
TBOT	Count	82	219	31	23	15	105	20	0	0	0
BBOT	Count	152	71	7	3	4	84	40	1	6	0
DBOT	Count	246	196	11	4	9	141	77	3	4	0
HSTOP	Count	282	46	0	0	0	155	394	59	23	31
RTOP	Count	405	143	2	2	0	436	492	75	23	37
TTOP	Count	80	19	0	0	0	77	235	34	9	13
BTOP	Count	88	43	5	4	0	158	81	12	1	3
DTOP	Count	142	64	2	4	0	214	138	11	4	5
						Panel B: Summary Statistics and Information Tests					
						Day 1					
HSBOT	Mean	-0.0063	-0.0204	-0.0377	-0.1646	-0.0266	-0.0930	-0.2407	-	-	-
	S.D.	0.8382	0.9239	0.9209	1.0705	0.9993	0.8729	0.8590	-	-	-
	Q	15.700*	11.800	9.530	11.300	10.200	10.800	7.790	-	-	-
	γ	0.401	0.845	0.507	0.826	0.629	0.969	0.729	-	-	-
RBOT	Mean	-0.0361	0.0435	-0.0901	-0.4781*	-0.2650	-0.0146	-0.1772*	0.0895	0.3622	-
	S.D.	0.7749	0.9001	1.2453	0.8647	0.9151	0.8698	0.7423	0.7824	0.5811	-
	Q	47.500*	25.100*	9.480	12.500	7.000	11.500	16.200*	8.000	8.000	-
	γ	0.988	0.918	0.799	1.415*	0.937	0.423	1.293*	0.376	0.046	-

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Chart Patterns	Statistics	UCG	UBG	URG	UEG	UIG	DCG	DBG	DRG	DEG	DIG
TBOT	Mean	0.2076*	0.1008	-0.1606	-0.1786	-0.0027	-0.0510	-0.2748	-	-	-
	S.D.	0.8033	0.9847	1.3275	1.1908	1.0877	1.0282	0.8268	-	-	-
	Q	8.240	17.300*	6.740	7.870	8.330	5.950	10.000	-	-	-
	γ	0.720	0.566	0.718	0.410	0.493	0.171	1.021	-	-	-
BBOT	Mean	0.0215	0.0617	-0.4887	-1.1006*	-0.8925*	-0.1432	0.3737	0.2897	0.7870	-
	S.D.	0.8552	1.0166	1.5814	0.5567	0.6904	1.0813	1.2060	-	1.3488	-
	Q	6.290	13.100	5.860	13.700	6.000	1.950*	8.500	9.000	7.330	-
	γ	0.315	0.214	0.761	1.406*	0.697	0.300	0.867	0.424	0.477	-
DBOT	Mean	-0.0231	-0.0027	0.2316	0.6437	0.0138	0.0026	-0.0772	-0.4676	0.6874	-
	S.D.	0.7863	0.7737	0.6997	0.5156	0.9553	0.9891	1.0666	0.2008	0.7737	-
	Q	8.720	18.300*	6.270	11.000	5.440	11.000	2.610*	7.000	11.000	-
	γ	0.528	0.572	0.232	0.835	0.352	0.214	0.294	0.263	0.691	-
HSTOP	Mean	-0.0919	0.0003	-	-	-	-0.0583	-0.0091	0.0513	0.0985	-0.1562
	S.D.	0.9496	1.0170	-	-	-	0.8735	0.9615	0.8114	1.0108	0.8093
	Q	11.600	4.430	-	-	-	11.500	6.710	4.900	9.610	5.450
	γ	0.875	0.175	-	-	-	0.637	0.252	0.499	0.360	0.640
RTOP	Mean	0.0838*	0.0820	0.1016	-0.4632	-	-0.0699	-0.0588	0.0913	0.2006	-0.0811
	S.D.	0.8189	1.0491	0.6311	0.0430	-	0.8616	0.9160	0.9596	0.6448	0.8487
	Q	14.800*	38.900*	8.000	18.000*	-	15.400*	9.220	11.500	8.740	14.100
	γ	0.996	1.051	0.297	0.394	-	0.853	0.726	0.745	0.382	0.705
TTOP	Mean	-0.1162	-0.3052*	-	-	-	-0.1157	-0.0188	0.4143	-0.0315	-0.3441
	S.D.	1.1211	2.0072	-	-	-	1.1566	1.0416	0.9476	0.7471	1.1284
	Q	14.500	8.890	-	-	-	14.000	8.700	16.000*	7.670	12.400
	γ	0.969	0.649	-	-	-	0.366	0.277	0.828	0.329	0.763
BTOP	Mean	-0.1316	-0.1633	-0.1293	0.0161	-	0.1046	-0.1192	0.4228	0.1350	-0.5573
	S.D.	0.9961	0.9739	0.5850	0.5414	-	0.9785	1.1432	1.1586	-	0.2346
	Q	5.410	15.800	9.000	6.000	-	3.270	11.500	19.700*	9.000	7.000
	γ	0.679	0.619	0.290	0.174	-	0.469	0.564	1.012	0.521	0.296

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Chart Patterns	Statistics	UCG	UBG	URG	UEG	UIG	DCG	DBG	DRG	DEG	DIG
DTOP	Mean	0.1171	0.1053	0.5564	0.0509	-	-0.0712	-0.0913	0.4629	0.9307*	0.2201
	S.D.	0.8321	0.8730	0.0121	0.5941	-	0.9862	0.9847	0.7657	1.9268	1.3771
	Q	12.500	7.250	18.000*	16.000*	-	6.000	9.970	8.090	11.000	5.000
	γ	0.454	0.409	0.420	0.022	-	0.450	0.590	0.808	0.527	0.353
					Day 2						
HSBOT	Mean	-0.0329	-0.0722	0.0915	-0.0855	-0.0632	0.0159	-0.2005	-	-	-
	S.D.	0.9071	0.8909	0.9236	1.1636	0.8155	0.9679	1.0888	-	-	-
	Q	11.300	12.200	1.370*	7.710	2.460*	7.380	6.740	-	-	-
	γ	0.430	1.095	0.248	0.533	0.237	0.546	0.610	-	-	-
RBOT	Mean	0.0464	-0.0471	0.0151	0.0190	-0.3707	-0.0713	-0.2119*	-0.4538	0.1807	-
	S.D.	0.9037	0.8923	0.8931	0.9305	0.9750	0.8743	1.1366	0.7309	1.1582	-
	Q	3.420*	35.800*	4.160*	6.180	19.000*	9.050	21.200*	8.000	8.000	-
	γ	0.247	1.451*	0.139	0.579	1.157	0.818	1.492*	0.748	0.475	-
TBOT	Mean	0.1910*	0.0390	0.0443	0.4264*	-0.0223	-0.1034	-0.1663	-	-	-
	S.D.	1.1011	1.0949	0.9837	1.2024	0.8282	0.8732	0.7656	-	-	-
	Q	7.020	5.430	8.680	9.610	3.000*	7.100	6.000	-	-	-
	γ	0.491	0.178	0.354	1.018	0.203	0.436	0.471	-	-	-
BBOT	Mean	-0.0441	0.1623	-0.4127	-0.1356	0.1419	-0.1143	-0.0712	-0.0143	0.1800	-
	S.D.	1.0022	1.0134	1.1663	0.7944	1.4622	1.1437	1.2299	-	0.6613	-
	Q	18.000*	2.940*	8.710	7.000	6.000	6.950	17.000*	9.000	7.330	-
	γ	1.257*	0.253	0.697	0.425	0.456	0.707	0.393	0.622	0.289	-
DBOT	Mean	0.0488	-0.0067	0.0323	0.0920	-0.1165	-0.1326	0.1383	0.1002	1.2587*	-
	S.D.	0.8642	0.7766	0.9865	0.5037	0.7579	0.8151	1.0273	0.1841	1.0659	-
	Q	14.200	10.100	6.270	6.000	9.890	19.500*	4.170*	7.000	11.000	-
	γ	0.232	0.745	0.373	0.290	0.864	0.942	0.261	0.236	1.021	-
HSTOP	Mean	0.0444	-0.0824	-	-	-	0.0191	-0.0305	-0.0590	-0.1134	0.0817
	S.D.	1.0210	1.1605	-	-	-	1.0342	0.9826	0.8902	0.6479	1.3569
	Q	15.000*	7.910	-	-	-	8.940	14.100	11.300	20.900*	10.600

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Chart Patterns	Statistics	UCG	UBG	URG	UEG	UIG	DCG	DBG	DRG	DEG	DIG
	γ	0.209	0.846	-	-	-	0.486	0.547	0.705	0.694	0.383
RTOP	Mean	0.0098	-0.1200	0.2730	0.1475	-	-0.0148	-0.0951	-0.0470	0.1283	0.1872
	S.D.	0.9063	0.9695	0.9210	1.0848	-	1.0085	0.9992	0.8717	0.5925	1.0504
	Q	14.400	18.900*	8.000	8.000	-	20.700*	12.100	8.330	22.700*	6.510
	γ	0.671	1.491*	0.321	0.465	-	0.401	0.600	0.648	0.771	0.242
TTOP	Mean	0.1139	-0.0459	-	-	-	-0.0375	-0.0270	-0.0286	0.3834	-0.2938
	S.D.	0.9956	1.0309	-	-	-	0.9306	1.0305	1.3467	1.0267	0.7554
	Q	2.000*	8.890	-	-	-	14.600	6.400	6.590	7.670	6.230
	γ	0.415	0.490	-	-	-	0.299	0.338	0.683	0.510	0.622
BTOP	Mean	0.1030	-0.1710	0.4200	-0.2969	-	-0.0480	0.0764	0.2494	0.5384	0.3128
	S.D.	0.9456	0.9841	1.2098	0.5652	-	0.9436	1.1174	1.0593	-	0.3955
	Q	8.140	15.800*	9.000	6.000	-	7.950	4.310	9.670	9.000	7.000
	γ	0.623	0.467	0.158	0.391	-	0.496	0.292	0.405	0.299	0.230
DTOP	Mean	0.0430	0.1095	-0.4073	0.2671	-	-0.0384	-0.0893	-0.1021	-0.6232	-0.1124
	S.D.	0.8461	1.1510	0.0411	0.7437	-	1.0060	0.9047	0.7732	0.5246	2.5386
	Q	8.850	10.100	8.000	11.000	-	8.150	7.650	4.450	21.000*	13.000
	γ	0.469	0.418	0.361	0.157	-	0.102	0.782	0.238	0.948	0.955
						Day 3					
HSBOT	Mean	0.0962	-0.0486	0.0232	-0.5324*	0.0394	0.0716	-0.1542	-	-	-
	S.D.	0.9866	0.9568	1.1625	1.1411	1.2364	0.8815	0.6622	-	-	-
	Q	14.200	18.900*	8.470	20.600*	10.200	5.770	7.260	-	-	-
	γ	1.132	0.549	0.812	1.168	0.726	0.367	1.014	-	-	-
RBOT	Mean	-0.0045	-0.0200	-0.0200	0.3249*	0.0034	-0.0069	0.0448	-0.6476	-2.4453*	-
	S.D.	0.8948	0.9024	1.0441	0.8259	1.1977	0.8663	0.9969	0.9476	1.7203	-
	Q	11.500	10.500	12.300	13.500	2.430*	14.400	12.600	8.000	18.000*	-
	γ	0.400	1.199	0.534	0.665	0.360	0.340	0.580	0.881	1.398*	-
TBOT	Mean	0.0031	0.0274	0.0729	0.4032*	-0.0786	-0.0608	-0.2756	-	-	-
	S.D.	0.9850	1.1167	1.8144	1.7284	0.9208	0.9233	0.7958	-	-	-

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Chart Patterns	Statistics	UCG	UBG	URG	UEG	UIG	DCG	DBG	DRG	DEG	DIG
	Q	9.710	6.620	13.800	7.000	7.000	16.600*	8.000	-	-	-
	γ	0.305	0.484	0.624	0.395	0.341	0.188	0.694	-	-	-
BBOT	Mean	0.0109	0.1987	0.4597	-0.2879	1.0576*	-0.0251	0.0795	0.2573	0.4989	-
	S.D.	0.9727	1.0633	1.1785	1.1949	1.0284	1.1737	0.8796	-	0.5185	-
	Q	18.100*	10.800	8.710	7.000	11.000	7.670	4.500	9.000	7.330	-
	γ	0.280	0.504	0.311	0.583	0.986	0.644	0.180	0.444	0.445	-
DBOT	Mean	-0.0148	0.0737	0.6057	1.1572*	-0.3069	0.0334	0.2071*	0.4746	-2.1442*	-
	S.D.	0.7814	0.8547	0.9694	1.8441	1.2837	0.9679	0.8788	0.4869	1.4412	-
	Q	7.660	15.300*	11.700	11.000	9.890	4.040*	7.290	7.000	21.000*	-
	γ	0.417	1.030	0.684	0.536	0.730	0.465	0.905	0.349	1.704*	-
HSTOP	Mean	-0.0267	-0.2490	-	-	-	-0.0921	-0.0279	-0.2428	0.3094	-0.0414
	S.D.	0.9631	1.0100	-	-	-	1.0345	1.0032	0.8678	0.9383	0.9833
	Q	6.940	11.000	-	-	-	9.450	4.020*	9.980	28.700*	3.520*
	γ	0.420	0.526	-	-	-	0.493	0.492	1.060	0.747	0.710
RTOP	Mean	0.0373	-0.1698*	0.1998	-0.0583	-	-0.0490	-0.0114	0.1169	0.2074	-0.0947
	S.D.	0.8444	0.9996	0.0012	0.3636	-	1.0546	0.9887	0.8855	0.7479	0.9700
	Q	6.780	18.300*	18.000*	8.000	-	6.200	10.400	11.800	18.300*	8.140
	γ	0.398	0.973	0.176	0.277	-	0.309	0.631	0.388	0.720	0.802
TTOP	Mean	-0.0778	-0.3134	-	-	-	0.1781	0.0019	0.0714	0.7084*	-0.1110
	S.D.	0.9890	0.6642	-	-	-	1.2394	0.9969	1.1515	1.0567	1.0899
	Q	7.750	19.400*	-	-	-	19.000*	11.200	4.240	12.100	10.800
	γ	0.610	0.617	-	-	-	0.530	0.195	0.211	0.793	0.652
BTOP	Mean	0.0425	-0.2226	0.4605	-0.2611	-	-0.1630	-0.0407	-0.1996	0.0941	0.2215
	S.D.	0.9333	0.9000	0.7229	0.5612	-	0.9161	0.9478	0.9011	-	0.5809
	Q	10.400	9.330	9.000	6.000	-	12.800	0.358*	8.000	9.000	7.000
	γ	0.393	0.779	0.270	0.454	-	1.104	0.227	0.610	0.546	0.222
DTOP	Mean	0.0219	-0.1478	-0.1630	-0.4131	-	-0.0801	-0.0034	-0.3251	0.3064	0.4758
	S.D.	0.7580	0.8105	0.5142	0.5114	-	0.9260	1.1099	1.5677	0.4102	0.9599

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Chart Patterns	Statistics	UCG	UBG	URG	UEG	UIG	DCG	DBG	DRG	DEG	DIG
	Q	8.420	16.600*	8.000	6.000	-	6.650	9.830	2.640*	6.000	5.000
	γ	0.701	0.918	0.414	0.886	-	0.925	0.410	0.583	0.329	0.317
					Day 4						
HSBOT	Mean	0.0136	0.1082*	-0.0964	0.1240	-0.2092	-0.1505*	0.1575	-	-	-
	S.D.	0.9721	0.9191	1.1355	0.9449	1.1672	1.0061	1.2532	-	-	-
	Q	16.000*	9.780	7.950	22.700*	6.310	16.200*	13.100	-	-	-
	γ	0.300	0.631	0.386	0.643	0.420	1.212	0.495	-	-	-
RBOT	Mean	0.0413	0.0509	0.1074	0.1921	0.0909	0.0290	-0.0260	-0.3751	-0.1666	-
	S.D.	0.9449	0.8673	0.9219	1.1332	0.9581	0.9534	0.9249	0.2984	1.1699	-
	Q	7.770	10.900	5.430	8.000	3.570*	8.050	9.690	8.000	8.000	-
	γ	0.334	0.723	0.371	0.233	0.234	0.450	0.695	0.447	0.611	-
TBOT	Mean	-0.1287	0.0461	0.1860	-0.3755*	0.2110	-0.0398	-0.4816	-	-	-
	S.D.	0.8213	0.9571	0.8327	1.2520	0.6725	1.1202	1.2808	-	-	-
	Q	4.100*	13.600	6.740	12.200	4.330	3.480*	13.000	-	-	-
	γ	0.458	0.627	0.276	1.019	0.494	0.305	0.797	-	-	-
BBOT	Mean	0.0364	0.0021	-0.1076	-0.9722*	0.3224	0.0738	0.3097	0.6190	-0.1737	-
	S.D.	1.0996	1.1589	0.5863	1.6920	2.0336	1.0587	0.9788	-	0.3696	-
	Q	7.740	15.600*	5.860	7.000	6.000	13.100	4.500	9.000	14.000	-
	γ	0.239	0.249	0.244	1.027	0.567	0.441	0.518	0.265	0.049	-
DBOT	Mean	0.0456	0.0608	0.1118	-0.3279	0.0264	0.0012	-0.1174	-0.0456	0.5689	-
	S.D.	0.8524	0.9237	0.7187	1.0365	1.6009	0.9888	0.9966	0.5577	0.4895	-
	Q	11.200	8.390	9.910	6.000	9.890	6.020	8.840	7.000	6.000	-
	γ	0.513	0.545	0.437	0.530	0.697	0.299	0.428	0.436	0.654	-
HSTOP	Mean	-0.0307	0.3304*	-	-	-	0.0062	-0.1230	-0.1213	0.1287	0.1063
	S.D.	0.9345	1.2498	-	-	-	1.0333	0.9644	0.8813	1.0516	0.9644
	Q	6.370	10.500	-	-	-	12.500	14.800*	4.900	14.800*	15.800*
	γ	0.368	0.610	-	-	-	0.239	0.596	0.741	0.391	0.384
RTOP	Mean	-0.0438	0.0152	-0.0787	-0.2886	-	-0.0401	-0.1185	0.0071	-0.2852	-0.1114

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Chart Patterns	Statistics	UCG	UBG	URG	UEG	UIG	DCG	DBG	DRG	DEG	DIG
	S.D.	0.8352	0.9999	0.0676	0.8668	-	0.9842	1.0132	0.7908	0.7467	0.8245
	Q	16.400*	4.200	18.000*	8.000	-	12.000	16.300*	13.700	22.700*	11.400
	γ	0.738	0.320	0.123	0.582	-	0.533	0.686	0.282	0.960	0.885
TTOP	Mean	-0.1196	0.2525	-	-	-	-0.1205	-0.0696	0.1747	-0.2231	-0.2735
	S.D.	1.0099	0.9903	-	-	-	1.2142	1.0806	1.2992	1.1476	0.7657
	Q	8.500	6.790	-	-	-	4.950	6.660	20.100*	9.890	13.900
	γ	0.762	0.553	-	-	-	0.644	1.100	0.661	0.475	0.739
BTOP	Mean	-0.0125	0.0552	-1.1684	0.1530	-	-0.0270	-0.1262	-0.3066	-0.7464	0.1304
	S.D.	0.9553	0.9682	2.2502	0.4804	-	1.0379	1.0024	1.6020	-	0.2938
	Q	8.360	7.930	17.000*	11.000	-	8.080	18.400*	13.000	9.000	7.000
	γ	0.575	0.299	0.733	0.400	-	0.342	1.004	0.587	1.015	0.143
DTOP	Mean	-0.1191	0.1258	0.5893	0.0554	-	0.0141	-0.0848	0.1563	0.1085	-0.0743
	S.D.	0.8099	0.7685	0.8772	0.6400	-	0.8811	0.8638	0.7161	1.2354	0.6661
	Q	11.100	17.300*	8.000	11.000	-	7.310	6.640	13.500	6.000	5.000
	γ	1.021	0.447	0.047	0.242	-	0.328	0.545	0.212	0.345	0.443
						Day 5					
HSBOT	Mean	-0.0331	-0.0064	-0.1126	-0.1594	0.3666*	0.0366	-0.0233	-	-	-
	S.D.	0.8760	1.0217	1.0664	1.4323	0.8719	0.8968	0.6576	-	-	-
	Q	5.580	5.180	8.210	19.100*	17.800*	14.200	16.200*	-	-	-
	γ	0.483	0.492	0.471	0.913	0.462	0.447	0.523	-	-	-
RBOT	Mean	-0.0316	-0.1393*	0.2936*	0.0556	-0.0104	-0.0458	-0.0942	-0.3994	0.1876	-
	S.D.	0.8516	0.9799	1.1107	1.0382	0.7853	0.8483	0.8139	0.4960	0.6684	-
	Q	13.200	14.600	10.500	5.270	8.710	7.550	9.340	8.000	8.000	-
	γ	0.772	1.365	0.711	0.407	0.359	0.646	0.723	0.525	0.254	-
TBOT	Mean	0.0373	-0.1038	0.3689	-0.1775	-0.2388	0.0002	0.1049	-	-	-
	S.D.	0.9106	1.0260	1.1859	1.2595	1.0879	1.0844	1.1164	-	-	-
	Q	14.800	8.810	7.390	12.200	12.300	16.600*	4.000*	-	-	-
	γ	0.126	0.513	0.497	1.068	0.767	0.472	0.429	-	-	-

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(*continued*)

Chart Patterns	Statistics	UCG	UBG	URG	UEG	UIG	DCG	DBG	DRG	DEG	DIG
BBOT	Mean	-0.0249	-0.0203	-0.3147	0.5525	-0.1855	0.1305	-0.1695	-0.1900	-0.7844	-
	S.D.	0.9542	1.0390	1.2435	0.5550	0.9206	0.9274	1.1192	-	0.3536	-
	Q	21.000*	13.600	8.710	7.000	11.000	5.760	12.000	9.000	14.000	-
	γ	0.383	0.297	0.739	0.287	0.508	0.778	0.858	0.751	0.195	-
DBOT	Mean	0.0185	-0.1314*	0.2976	-0.7402	0.0682	0.0342	-0.0103	-1.0475*	0.0245	-
	S.D.	0.8405	0.8293	0.6929	1.4001	0.9539	0.9816	0.8256	1.0858	0.6035	-
	Q	10.200	10.300	19.000*	11.000	9.890	2.330*	15.100*	7.000	6.000	-
	γ	0.290	1.186	0.744	1.056	0.515	0.286	0.578	1.110	0.173	-
HSTOP	Mean	-0.0045	0.1562	-	-	-	0.0475	-0.0657	0.1047	0.1813	0.0463
	S.D.	1.1871	0.6927	-	-	-	0.9139	0.9668	0.8644	1.2168	0.7075
	Q	5.870	12.300	-	-	-	6.740	11.500	5.580	10.500	9.320
	γ	0.711	0.494	-	-	-	0.370	0.496	0.275	0.323	0.447
RTOP	Mean	0.1387*	0.0862	-0.4442	-0.0761	-	0.0082	-0.0611	0.0338	-0.0647	0.2263
	S.D.	0.7868	0.8524	0.3980	0.3243	-	0.8446	0.9922	1.0442	0.8763	0.9746
	Q	24.900*	11.100	8.000	8.000	-	9.140	8.200	2.730*	10.500	10.300
	γ	1.374*	0.588	0.515	0.269	-	0.713	0.760	0.135	0.197	0.922
TTOP	Mean	0.3009*	-0.2379	-	-	-	0.1031	0.0134	0.4369	-0.1972	0.4588
	S.D.	1.0732	1.4879	-	-	-	1.2506	1.1880	1.3664	1.0400	0.8525
	Q	8.500	13.100	-	-	-	11.700	14.100	16.000*	9.890	15.500*
	γ	0.839	0.492	-	-	-	0.575	0.400	1.086	0.412	0.842
BTOP	Mean	0.0299	-0.1221	-0.1517	-0.7588	-	0.1730	-0.0081	-0.4705	-1.3468*	-0.0539
	S.D.	0.9827	1.1464	0.4752	0.2938	-	0.8258	1.0188	0.8612	-	1.0491
	Q	12.000	6.530	9.000	16.000*	-	10.900	11.200	9.670	9.000	7.000
	γ	0.494	0.807	0.618	0.290	-	1.365*	0.664	0.877	1.143	0.440
DTOP	Mean	0.0733	0.0778	-0.4325	0.4766	-	-0.0983	0.0901	0.3295	0.3579	0.9470*
	S.D.	0.9527	1.0862	0.4146	0.9119	-	0.9027	0.9414	0.8956	0.1809	1.5035
	Q	6.590	6.940	8.000	6.000	-	15.000*	10.800	8.090	16.000*	5.000
	γ	0.492	0.360	0.515	0.181	-	1.315*	0.755	0.510	0.768	0.290

4.6 Conclusion

This chapter evaluates an old principle proposed by market technicians: the Gap-Fill hypothesis. Market technicians have hypothesized that when a price gap occurs, it will be *filled* in the future. Furthermore, price gaps are said to contain important information in evaluating the current price movements. To test this Gap-Fill hypothesis, we first categorize the all the price gaps into five type of price gaps commonly taught by chartists, including Congestion gap, Breakout gap, Runaway gap, Exhaustion gap and one-day Island gap. We then examine this Gap-Fill hypothesis in the futures markets. Apart from studying the information on the price gaps, we also include a number of conditioning variables in our tests for further evaluation since price gaps are seldom analyze alone. The conditioning variables include chart patterns and volume. To extract the chart patterns systematically, we applied a methodology known as local polynomial regression to the futures prices whenever a price gap is detected.

There are several empirical results in our study are interesting and which contribute to the literature on technical analysis. First, our results provide support for the Gap-Fill hypothesis. The percentage of price gaps filled within 20 days is more than 75 percent across all types of gaps, including both upward and downward price gaps.

Second, we examine whether such predictability in price retracement give chartists an edge in trading. Broadly speaking, these retracements in prices provide only partial reliable sources of information for chartists, especially one day after the occurrence of the gaps. On day 2 to day 4, Many of the conditional returns generated from these price gaps have distributions that are not statistically different from the distribution of the unconditional returns aggregated over all futures markets.

Third, we study whether price gaps are sources of profitable indicators. The overall conclusion is yet unclear. Even though many of conditional mean returns are statistically significant (using test statistics), especially on day 1, the direction of these conditional mean returns varies differently from day 2 to day 5. Thus, it may not be profitable for investors if they were to trade with price gaps alone. Furthermore, the evidence shows that volume does not provide any useful information in ascertaining the direction of price gaps, apart from day 1.

Fourth, the effects of the size of price gaps is also analyzed. We find that Exhaustion price gaps are statistically significant across all five days for the largest gap size category (Size 3). Moveover, the direction of the conditional mean returns is also largely consistent for Size 3, which is negative for downward gaps and positive for upward gaps. Other types of price gaps show less reliable results.

Lastly, we also find that conditioning on the chart patterns produces conditional returns that are indistinguishable from the unconditional returns. This implies that chart patterns are less useful, informative and profitable when combine with price gaps, results that are quite different to LMW. One may argue that our results may be plagued by small sample problem due to the low number of pattern count. But a comparison of the results with patterns that have larger counts do not provide any more consistent results.

In conclusion, it is evident that not every price gaps are useful to investors. As a matter of fact, many price gaps may be caused predominantly by market noise and indistinguishable to the rest of the market movements. On rare occasions, however, some price gaps are found to provide important information to investors. It remains a challenge for technical analysis to explain why price gaps should be important and how it can be exploited by investors in a profitable manner.

Appendix: Splicing Futures Contract

The aim of the splicing procedure is to join all successive futures contracts together without any of the gaps between different futures contracts. In Figure 4.14, we plot all the rebased price series with initial 100. We observe that all fixed income futures have experienced higher prices in the last decade, which is a direct consequence of lower interest rates in developed economies. On the contrary, equity futures display substantial variation in prices, especially during the recent euphoria in technology sector.[15] The commodity futures show signs of rapid increased in prices after nearly two decades of decreasing prices.

[15] In those days, a mere change in a firm's name to .com will generate some unusual returns, as discovered by Cooper, Dimitrov and Rau (2001). See also Ofek and Richardson (2002) and Barber and Odean (2001).

Figure 4.14: Rebased Futures

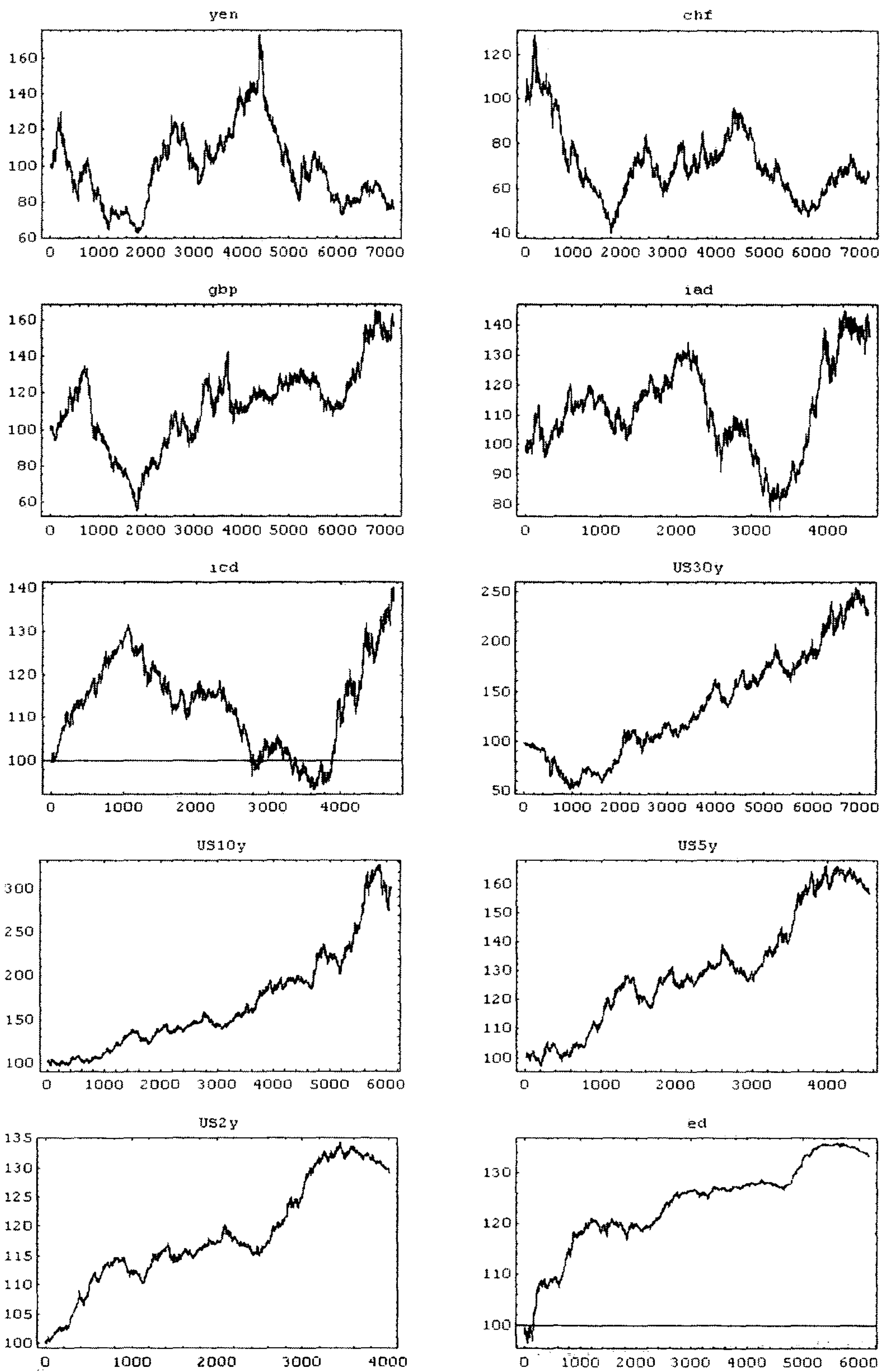


Figure 4.14: Rebased Futures (cont)

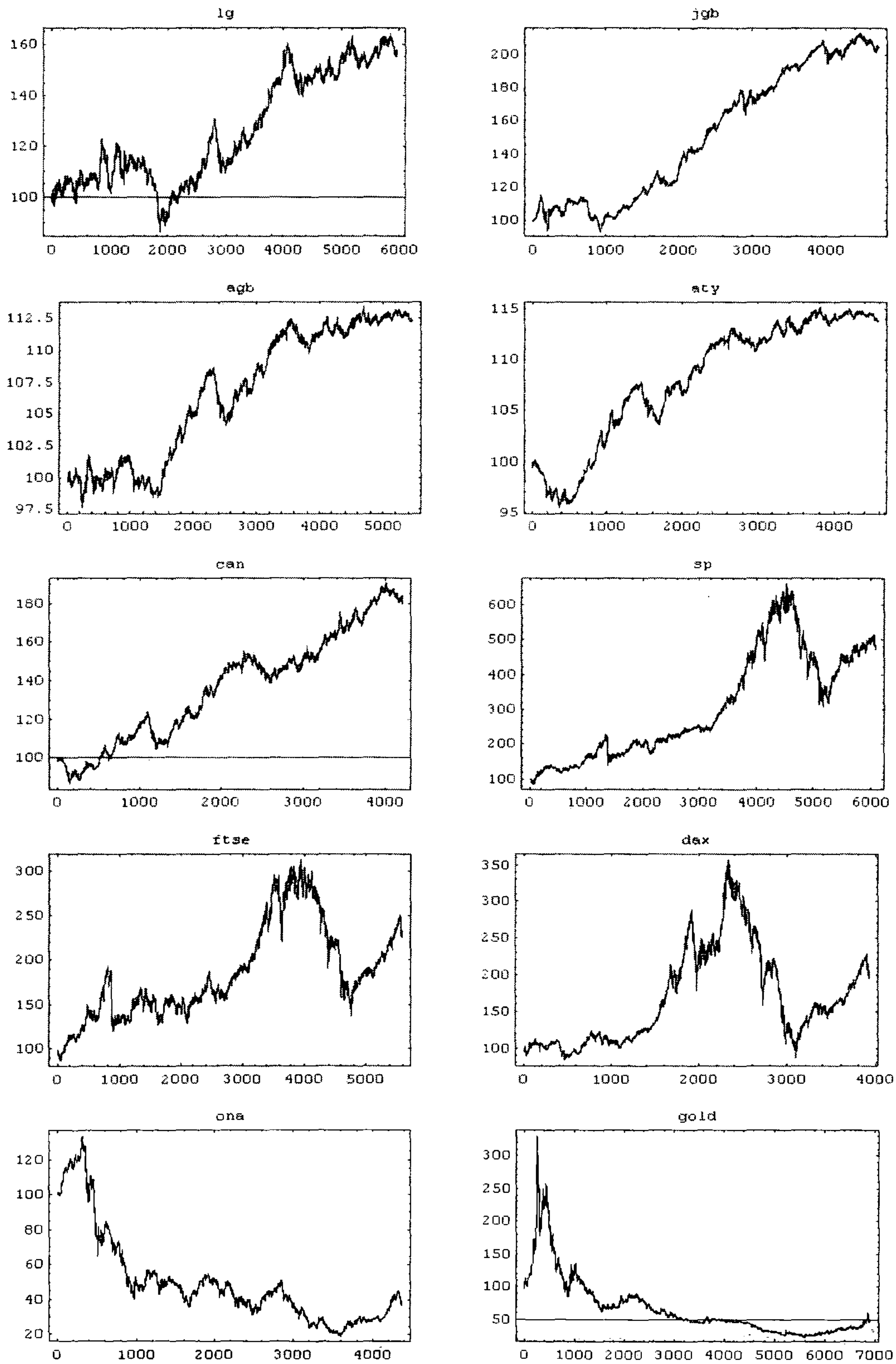
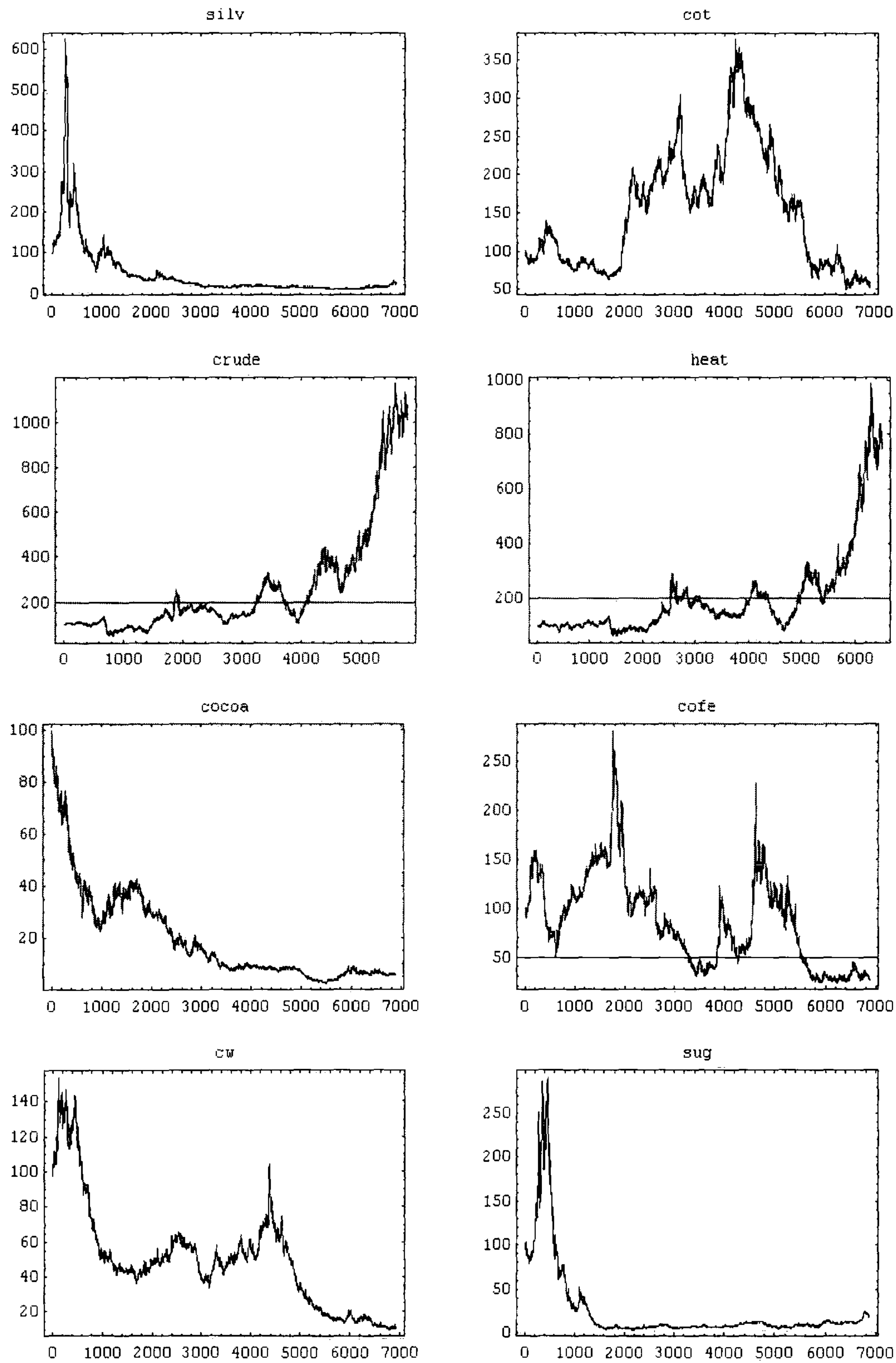


Figure 4.14: Rebased Futures (cont)



Chapter 5

Conclusion

This thesis evaluates the effectiveness of technical trading systems in the financial markets, with main applications to the fixed income sector. Specifically, we attempt to answer whether technical indicators are able to provide a systematic strategy for bond traders to earn excess returns in the bond markets, and whether technical indicators, such as technical charts and price gaps, are able to provide additional information to investors.

We have analysed several aspects of technical analysis. First, we investigate the profitability of a large number of technical trading systems in the bond futures markets. Second, we examine the informativeness of technical chart patterns in the bond yield markets and bond yield spread markets. Third, we categorize and test the information contained in price gaps in the futures markets.

In summary of the above empirical results, we document the following major results:

1. Technical trading systems are useful in capturing trends in interest rates and bond futures prices. But the profitability of these systems varies over time and across different trading strategies. The issue of data snooping may not be solved by evaluating additional trading systems since the final results vary substantially over different bond markets. We also find the profitability of trading systems has decreased in recent years, but we cannot affirm whether this is due to a more efficient market or due to lower volatility.

2. Technical chart patterns may not provide additional information to bond traders. This is because we find the unconditional and conditional bond returns are not systematically different from each other in the bond yield markets. Occasionally, some patterns may appear to generate incremental information in some bond markets. But we cannot address why this is so. A more negative result is

especially acute for bond yield spread markets since we show that yield spread data are fundamentally different to traditional price series such as equity prices or currencies. Far fewer chart patterns are found in bond yield spread than bond yield, and the conditional returns obtained from yield spreads are not statistically significant to unconditional returns. This implies other investment strategies may be more suitable for bond traders than technical chart patterns.

3. Generally, some financial price gaps are found to contain significant information for investors. But the unusual effects displayed by most price gaps are short-term. In other words, traders may have to act quickly to be able to take advantage of the gaps. Since our sample data contains twenty-eight futures contracts over a period of nearly twenty-five years, we opine that it will be a challenging task for traders to trade on every gap over such a long period of time.

In view of the above results, it is clear that using the technical indicators specified in this thesis may not be the panacea that investors have been searching for in order to earn excess returns consistently over time. We opine that such a strategy is difficult to find, which may be due reasonably efficient financial markets. Robert Shiller (2002, p.23) summarises this view:

> The basic problem with efficient markets is that it is a half-truth. Presenting market efficiency as a concept to students and amateur investors is useful lest they come to believe that it is easy to get rich quickly. It is not easy to get rich quickly by trading in speculative markets.

Perhaps the only way to earn excess returns is to consistently develop a competitive advantage, which may be a combination suitable trading strategy, astute capital management and sound risk management. Because the profitability of investment strategies tend to vary over time and across different markets, no prediction will be good for very long. Mistakes will be made, even by the standard of the best investment managers such as Warren Buffett or George Soros.[1]

One possible extension of this thesis is to examine how market psychology and the technical indicators interacts, given the importance of market and investors' psychology in asset pricing.[2] For example, investors are known to exhibit the characteristic of

[1] See, for example, the 1989 Berkshire Hathaway Annual Chairman's report to shareholders, in which Warren Buffett detailed the investment mistakes he made in the last 25 years. Ironically, the first mistake he made was buying Berkshire Hathaway!

[2] As famously described by Maynard Keynes in *Treatise on Money* (1930):

> The vast majority of those who are concerned with buying and selling of securities

"over-confidence" (Daniel, Hirshleifer and Subrahmanyam (2001)) and tend to over-trade as a result. (Odean (1999)).[3] Controlling for these behaviour is important in assessing whether technical analysis can provide genuine value to investors.

Lastly, technical analysis may not be suitable for every investors. Some investors will prefer fundamental information to technical indicators, and some investors may prefer short-term trading to long-term investing. The crux of the matter is that investors must choose and develop the strategies for themselves in order to survive in the financial 'jungles', and this is what economic historian David Landes (1998) advocates from his important work on trade development:

> It always helps to attend and respond to the market. But just because markets give signals does not mean that people will respond to timely or well. Some people do this better than others, and culture can make all the difference.

The only action he discovers that everyone (investors in our case) must do is (p.524):

> The one lesson that emerges is the need to keep trying. No miracles. No perfection. No millennium. No apocalypse. We must cultivate a skeptical faith, avoid dogma, listen and watch well, try to clarify and defined ends, and better to choose means.

know almost nothing whatever about what they are doing. They do not possess even the rudiments of what is required for a valid judgement, and are the prey of hope and fears easily aroused by transient events and as easily dispelled. This is one of the odd characteristics of the capitalist system under which we live, which, when we are dealing with the real world, is not to be overlooked.

[3]For other biases, see, for example, Barberis and Thaler (2002) and Shleifer (2000).

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